TESIS DOCTORAL

ESCUELA INTERNACIONAL DE DOCTORADO

Programa de Doctorado en Ciencias Sociales

On the impact and relative importance of financial literacy on financial resilience: New evidence from Europe during the COVID-19 crisis

Autor:

Diba Erdem, M.Sc.

Directores:

Prof. Dr. Joachim Rojahn, CFA

Prof. Dr. Laura Nieto Torrejón

Murcia, Septiembre 2023

TESIS DOCTORAL

ESCUELA INTERNACIONAL DE DOCTORADO

Programa de Doctorado en Ciencias Sociales

On the impact and relative importance of financial literacy on financial resilience: New evidence from Europe during the COVID-19 crisis

Autor:
Diba Erdem, M.Sc.

Directores:
Prof. Dr. Joachim Rojahn, CFA
Prof. Dr. Laura Nieto Torrejón

Murcia, Septiembre 2023

EIDUCAM
Escuela Internacional
de Doctorado

UCAM
UNIVERSIDAD CATÓLICA
DE MURCIA

AUTHORIZATION OF THE DIRECTORS OF THE THESIS FOR SUBMISSION

Prof. Dr. Laura Nieto Torrejón and Prof. Dr. Joachim Rojahn as Directors [(1)] of the Doctoral Thesis "On the impact and relative importance of financial literacy on financial resilience: New evidence from Europe during the COVID-19 crisis" by Ms. Diba Erdem in the Programa de Doctorado en Ciencias Sociales, **authorize for submission** since it has the conditions necessary for her defense.

Sign to comply with the Royal Decree 99/2011, in Murcia, September 10, 2023.

Joachim Rojahn

Prof. Dr. Joachim Rojahn, CFA

Prof. Dr. Laura Nieto Torrejón

[(1)] If the Thesis is directed by more than one Director, both of them must sign this document.

UCAM EIDUCAM
Escuela Internacional
de Doctorado

RESUMEN

Esta tesis estudia cómo el impacto y la importancia relativa de la educación financiera explica la resiliencia financiera durante la crisis de la enfermedad del coronavirus 2019 (COVID-19). Para ello, se utiliza el conjunto de datos COVID-19 de la Encuesta sobre salud, envejecimiento y jubilación en Europa (SHARE), se analizan siete países europeos, así como un amplio conjunto de determinantes adicionales.

La literatura existente sobre educación financiera y resiliencia financiera indica que las personas con educación financiera están más protegidas de los shocks macroeconómicos. Sin embargo, la mayoría de los estudios no utilizan muestras de datos que cubran esos períodos de crisis. Además, la investigación empírica que investiga la influencia de la educación financiera en la resiliencia financiera durante la pandemia de COVID-19 se lleva a cabo predominantemente en el contexto de Estados Unidos y es relativamente limitada en Europa. Además, la mayoría de los estudios anteriores emplean técnicas de clasificación única y se centran en la influencia de la alfabetización financiera en la resiliencia financiera, descuidando la importancia de la alfabetización financiera en el fomento de la resiliencia financiera.

Este estudio emplea múltiples métodos que comprenden técnicas tradicionales y de minería de datos para (i) evaluar el impacto de la educación financiera en la resiliencia financiera y (ii) determinar la importancia relativa de la educación financiera en la predicción de la resiliencia financiera, que puede variar según la técnica aplicada.

La metodología incluye la regresión logística, seguida de la regresión logística multinomial, PPOR (partial proportional odds regression) y árboles de regresión, que sirven como controles de robustez. Además, para tener en cuenta la endogeneidad, se utiliza tanto un modelo de regresión de variables instrumentales (IV), en el que los instrumentos son las habilidades lingüísticas y matemáticas de los encuestados a la edad de diez años, como valores rezagados de la variable independiente, es decir, la educación financiera.

El análisis se basa en el SHARE que cubre los años 2017 y 2020 y comprende 10.464 observaciones de Bélgica, Estonia, Francia, Alemania, Italia, Eslovenia y

España. Los análisis también se realizan a nivel de país para descubrir la posible heterogeneidad entre países en el impacto y la importancia de la educación financiera en la resiliencia financiera.

Los hallazgos revelan que las variables más importantes para explicar la resiliencia financiera son variables ficticias que reflejan los ingresos y el país de residencia de los encuestados. La educación financiera aumenta la resiliencia financiera y se ubica en el medio campo en términos de importancia variable entre todas las variables explicativas. Los hallazgos son consistentes entre las comprobaciones de robustez y no están sesgados por la endogeneidad. Los análisis a nivel de país revelan heterogeneidad en la importancia de la educación financiera para predecir la resiliencia financiera. A modo de ejemplo, en Italia la educación financiera se encuentra entre las variables más importantes para explicar la resiliencia financiera, mientras que en España se encuentra entre las menos importantes.

Como implicación para la práctica, los resultados revelan las características más importantes que mejoran la resiliencia financiera, permitiendo así intervenciones específicas para aumentar la preparación para futuras crisis. Dado que la educación financiera es uno de los pocos determinantes de la resiliencia financiera que se pueden moldear activamente, una combinación de políticas de educación financiera que promuevan el conocimiento financiero y la confianza financiera, la regulación, la arquitectura de elección y el refuerzo positivo pueden ayudar a aumentar la educación financiera y, posteriormente, la resiliencia financiera.

PALABRAS CLAVE

Educación financiera, Resiliencia financiera, COVID-19, Importancia variable, Regresión logística, Endogeneidad, Regresión logística multinomial, Regresión de probabilidades proporcionales parciales, Bosque aleatorio condicional

ABSTRACT

This dissertation examines financial literacy's impact and relative importance in explaining financial resilience during the coronavirus disease 2019 (COVID-19) crisis. Using the novel COVID-19 dataset of the Survey of Health, Ageing, and Retirement in Europe (SHARE), seven European countries are analyzed while controlling for a broad set of additional determinants.

Extant literature on financial literacy and financial resilience indicates that financially literate individuals are more protected from macroeconomic shocks. However, most previous studies do not utilize data samples covering such crisis periods. Furthermore, empirical research examining the influence of financial literacy on financial resilience during the COVID-19 pandemic is predominantly conducted in the U.S. context and is relatively limited in Europe. Moreover, most previous studies employ single classification techniques and focus on the influence of financial literacy on financial resilience, neglecting the variable importance of financial literacy in fostering financial resilience.

This study employs multiple methods comprising traditional and data mining techniques to (i) assess the impact of financial literacy on financial resilience and (ii) determine the relative importance of financial literacy in predicting financial resilience, which may vary depending on the technique applied.

The methodology covers logistic regression, followed by multinomial logistic regression, partial proportional odds regression, and conditional random forest, which serve as robustness checks. Furthermore, to account for endogeneity, both an instrumental variables (IV) regression model, with the instruments being respondents' language and mathematical skills at the age of ten, and lagged values of the independent variable, i.e., financial literacy, are used.

The analysis relies on the SHARE covering 2017 and 2020 and comprises 10,464 observations from Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain. The analyses are additionally performed at the country level to uncover potential cross-country heterogeneity in financial literacy's impact and importance on financial resilience.

The findings reveal that the most important variables for explaining financial resilience are dummy variables reflecting respondents' income and respective country of residence. Financial literacy increases financial resilience and ranks in the midfield regarding its variable importance among all predictor variables. The findings are consistent among the robustness checks and are not biased by endogeneity. The analyses at the country level reveal heterogeneity in financial literacy's importance in predicting financial resilience. To illustrate, in Italy, financial literacy is among the most important predictors of financial resilience, while it is among the least important in Spain.

As an implication for practice, the results disclose the most important features that increase financial resilience, thereby allowing for targeted interventions to increase preparedness for future crises. As financial literacy is among the few determinants of financial resilience that can be actively shaped, a mix of policy measures of financial education promoting financial knowledge and financial confidence, regulation, choice architecture, and nudging may help increase financial literacy and, subsequently, financial resilience.

KEYWORDS

Financial literacy, Financial resilience, COVID-19, Variable importance, Logistic regression, Endogeneity, Multinomial logistic regression, Partial proportional odds regression, Conditional random forest

ACKNOWLEDGEMENTS

I would like to express my gratitude to those who have significantly contributed to the completion of my doctoral thesis. Their support and guidance have been invaluable throughout my academic journey.

First and foremost, I express my deepest gratitude to my esteemed thesis advisor, Prof. Dr. Joachim Rojahn. His unwavering commitment, reliability, insightful feedback, and outstanding mentoring have shaped and contributed to the successful completion of this dissertation. Further, his exceptional guidance and supervision have contributed to the expansion of my knowledge in the realm of scientific research. I would also like to thank Prof. Dr. Laura Nieto Torrejón for her insightful feedback during this dissertation, which invaluably contributed to my completion of this work. Moreover, I am grateful to the Universidad Católica de Murcia and FOM University of Applied Sciences for allowing me to write this doctoral thesis. Particularly, I thank Prof. Dr. Mercedes Carmona Martínez, Prof. Dr. Gonzalo Wandosell Fernández de Bobadilla, and Kristin Westphal for their continuous guidance and support throughout my research.

Beyond academics, I am deeply grateful to my family and friends for their unwavering encouragement and patience during this journey. I want to thank my sister, brother, and parents for their persistent understanding, support, and love throughout my life. Their values have shaped my character and commitment to academic excellence. I am particularly grateful to my mother and husband, who always had my back and walked me through the ups and downs of my doctoral journey with untiring devotion and love. I am forever grateful for their love and sacrifices. Finally, I extend my deepest thanks to my daughter, who is the driving force of my life and has been a constant source of motivation throughout this endeavor.

Frankfurt am Main, September 10, 2023

Diba Erdem

Diba Erdem, M.Sc.

For my parents, Saida Baiza and Nasim Afzali

“Knowing is not enough; we must apply. Willing is not enough; we must do.”

- Johann Wolfgang von Goethe (1749-1832) -

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

2SLS	Two-stage least squares
Adj.	Adjusted
AME	Average marginal effect
AUC	Area under the curve
COVID-19	Coronavirus Disease 2019
ECB	European Central Bank
EPV	Events per variable
Eq.	Equation
GDP	Gross domestic product
GNI	Gross National Income
GVIF	Generalized variance inflation factor
IIA	Independence of Irrelevant Alternatives
ISCED	International Standard Classification of Education
IV	Instrumental Variable
Logit	Logistic regression
Max.	Maximum value
Min.	Minimum value
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
OOB	Out-of-bag
Probit	Probit regression
ROC	Receiver Operating Characteristic
S&P Global FinLit Survey	Standard & Poor's Ratings Services Global Financial Literacy Survey

SHARE	Survey of Health Ageing and Retirement in Europe
Std. dev.	Standard deviation
TNR	True negative rate
TPR	True positive rate
U.S.	United States
UN	United Nations
UNESCO	United Nations Education, Scientific, and Cultural Organization

LIST OF FIGURES, TABLES, EQUATIONS, SYMBOLS, AND APPENDIXES

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

LIST OF SYMBOLS

\$	U.S. Dollar
€	Euro
$AGE_{i,t-1}$	Age of individual i at time t-1
$BELGIUM_{i,t-1}$	Belgium being the domicile of individual i at time t-1
$CH_{i,t-1}$	Number of children of individual i at time t-1
Df	Number of degrees of freedom
$EDU\text{-}MED_{i,t-1}$, $EDU\text{-}HIGH_{i,t-1}$	Level of education of individual i at time t-1
$EMPL_{i,t}$	Employment status of individual i at time t
$ESTONIA_{i,t-1}$	Estonia being the domicile of individual i at time t-1
f	Mathematical function
$FEMALE_{i,t-1}$	Gender of individual i at time t-1
$FL_{i,t-1}$	Financial literacy of individual i at time t-1
$FR_{i,t}$	Financial resilience of individual i at time t
$FRANCE_{i,t-1}$	France being the domicile of individual i at time t-1
$GERMANY_{i,t-1}$	Germany being the domicile of individual i at time t-1
H1, H2, H3, H4	Alternative hypothesis one, two, three, and four
$IFL\text{-}LAN_{i,t-1}$	Initial financial literacy in reading and writing of individual i at time t-1
$IFL\text{-}MAT_{i,t-1}$	Initial financial literacy in math of individual i at time t-1
$IN\text{-}MED_{i,t}$, $IN\text{-}HIGH_{i,t}$	Income of individual i at time t

$ITALY_{i,t-1}$	Italy being the domicile of individual i at time t-1
ln	Natural logarithm
n	Number of observations in a sample
p	P(robability)-value
$P\text{-}FIH_{i,t-1}$	Experienced period of financial hardship of individual i at time t-1
$PLAN_{i,t-1}$	Planning horizon of individual i at time t-1
R^2	Coefficient of Determination
$RET_{i,t-1}$	Retirement status of individual i at time t-1
$SLOVENIA_{i,t-1}$	Slovenia being the domicile of individual i at time t-1
$SPAIN_{i,t-1}$	Spain being the domicile of individual i at time t-1
t	Time period
x	Independent variable
$\chi 2$	Chi-square
Y	Dependent variable
z	Z-score

LIST OF APPENDIXES

I – INTRODUCTION

I - INTRODUCTION

1.1. RESEARCH MOTIVATION AND PRACTICAL RELEVANCE

Numerous households worldwide were already financially fragile well before the outbreak of the coronavirus disease 2019 (COVID-19) crisis (Clark, Lusardi, and Mitchell, 2020; Demertzis, Domínguez-Jiménez, and Lusardi, 2020; Lusardi, Hasler, and Yakoboski, 2020; Lusardi, Schneider, and Tufano, 2011). Studies in the United States and Europe disclose that, on average, one out of three households lacks financial resilience (Demertzis et al., 2020; Lusardi et al., 2020). Financial resilience is the ability to cope with an unexpected financial shock or to recover quickly from periods of financial adversity by accessing emergency funds from any available source (Lusardi et al., 2011; Mcknight and Rucci, 2020).

The COVID-19 pandemic caused widespread financial instability and uncertainty worldwide. The shutdowns seeking to slow the spread of the virus led to severe financial challenges for several households, including unemployment, reduced income and investment wealth, and other adverse effects that strained household finances (Hasler, Lusardi, Yagnik, and Yakoboski, 2023; Mitchell, Clark, and Lusardi, 2022; Nguyen et al., 2022). The challenging financial conditions induced by the COVID-19 crisis highlighted the importance of households' financial resilience, which can lead to more effective resource allocation and higher financial stability at both the micro and macro levels (Nguyen et al., 2022).

A key factor that significantly contributes to enhancing financial resilience is financial literacy (Erdem and Rojahn, 2022; Hasler and Lusardi, 2019; Hasler, Lusardi, and Oggero, 2018; Hasler et al., 2023; Kass-Hanna, Lyons, and Liu, 2022; Lusardi et al., 2011, 2020; Nguyen et al., 2022, among others). Financial literacy refers to the knowledge, skills, and attitudes needed to make informed and effective decisions regarding personal finances (Huston, 2010) and is associated with various financial outcomes, such as better comprehension of debt concepts (Lusardi and Tufano, 2009) or more effective retirement planning (Bucher-Koenen and Lusardi, 2011; Lusardi and Mitchell, 2011b). Furthermore, superior decisions regarding saving, spending, and investment (Babiarz and Robb, 2014; Klapper and

Lusardi, 2020; Lusardi et al., 2020; Lusardi and Mitchell, 2014) and better portfolio diversification (Guiso and Jappelli, 2009; Von Gaudecker, 2015) are attributed to greater financial literacy, indicating that financial literacy is crucial in explaining financial resilience during economic crises.

However, a substantial portion of the preceding research is based on datasets not collected during times of financial turmoil. Some exceptions are Klapper, Lusardi, and Panos (2012), who report that during the financial crisis of 2009 in Russia, increasing financial literacy was linked to a decreased likelihood of adverse income shocks. Further, Bucher-Koenen and Ziegelmeyer (2011) find that German households with lower financial literacy were more likely to realize losses when selling their assets in response to the financial market crisis. Moreover, in the early stages of the COVID-19 crisis, Lusardi et al. (2020) highlighted the potential advantages of financial literacy, as financial resilience was particularly low in population groups that were severely affected by the economic consequences of the COVID-19 pandemic. Similarly, Clark et al. (2020) disclose that individuals with higher financial literacy levels were more resilient to financial shocks.

Research based on datasets obtained during the COVID-19 pandemic is limited in scope. Hasler et al. (2023) use data in the U.S. context from 2021 and report that those who are more financially literate are more likely to be financially resilient and less likely to be constrained by debt. Likewise, Clark and Mitchell (2022) reveal that Americans with greater financial literacy were more resilient to pandemic-induced financial shocks, utilizing data from 2020 and 2021. Furthermore, Nguyen et al. (2022) report that for individuals in Vietnam, those who are more financially literate were less susceptible to financial instabilities during the peak of the COVID-19 pandemic in 2021. In the European context, Andreou, Anyfantaki, and Atkinson (2023) disclose that financial literacy is a strong precursor of Cypriot households' tendency to be financially resilient, employing data from 2021. Similarly, Cziriak (2022) finds that financial literacy is associated with lower financial fragility and mitigates the negative consequences of income losses on the ability to cope with emergency expenditures for German households using data collected in 2020 and 2021.

In conclusion, financial literacy can be expected to evolve as an essential variable in explaining financial resilience, especially during times of economic hardship, such as the COVID-19 crisis, which posed several financial difficulties for individuals worldwide. As financial literacy can be actively shaped, for example, by financial education, it may be one channel through which financial resilience could be increased.

Although financial education's effectiveness is debated in research, much of the debate stems from early findings, such as those of Fernandes, Lynch, and Netemeyer (2014), who reveal that financial education, like other forms of education, fades over time. However, recently, empirical studies on financial education are increasing. In a relatively comprehensive meta-analysis, Kaiser, Lusardi, Menkhoff, and Urban (2022) account for this increase and find no evidence to support a rapid decay in the realized treatment effects of financial education. Furthermore, they find that financial education has positive causal treatment effects on financial knowledge and financial behaviors. They estimate an effect of financial education interventions that is more than five times as large as the effect reported by Fernandes et al. (2014). Additionally, they document that the effects are similar across age groups and hold across countries. Moreover, they report that the estimates of statistical effect sizes are economically significant and that numerous financial education interventions are cost effective.

Consequently, determining the variable importance of financial literacy and other factors in contributing to financial resilience would not only help policymakers and researchers better understand the role of financial literacy in promoting financial resilience but also allow for the development of targeted interventions and policies to enhance individuals' financial well-being and ability to cope with economic challenges.

Therefore, this thesis aims to contribute to the growing body of literature concerning the influence of financial literacy on financial resilience by determining financial literacy's importance on financial resilience while controlling for an extensive set of additional explanatory variables using data gathered in Europe during the COVID-19 pandemic. In this context, this study is not only motivated by the need to better understand the role of financial literacy in promoting financial resilience during times of crisis but also aims to quantify the importance of financial literacy and various features in predicting financial resilience. Thus, not only the direction, strength, and significance of a selected set of predictor variables, including financial literacy, are considered, the relative variable importance is further assessed.

1.2. RESEARCH OBJECTIVE AND DELIMITATION

This doctoral thesis aims to add to the emerging scholarly work on financial literacy's impact on financial resilience in crisis periods by determining the variable importance of financial resilience in Europe during the COVID-19 crisis. Specific research gaps identified in the literature are addressed through the following three primary considerations:

First, within continental Europe, the COVID-19 pandemic triggered a severe health crisis that quickly became a financial crisis affecting numerous households. During the initial pandemic wave, there were extensive lockdowns and layoffs across Europe (Gros, 2020). However, empirical research examining the influence of financial literacy on financial resilience during this crisis period is predominantly performed in the U.S. and is relatively limited in Europe (Clark and Mitchell, 2022; Hasler et al., 2023).[1]

In this context, Europe is crucial for the global economy, representing the third-largest economy in the world by GDP in nominal terms in 2022 after the United States and China (International Monetary Fund, 2023). Furthermore, the European area covers a heterogeneous cross-border environment because (i) the COVID-19 pandemic affected countries differently (Bergsen, Billon-Galland, Kundnani, Ntousas, and Raines, 2020) and (ii) diverse degrees of financial resilience are observed in numerous countries (Demertzis et al., 2020; OECD, 2020). Consequently, this study might produce results that differ from those of U.S. studies and contribute to the current state of research. Therefore, this analysis uses a dataset obtained from the Survey of Health, Ageing and Retirement in Europe

[1] For a detailed outline of the analyzed countries in the financial resilience literature during the COVID-19 crisis, see Section 2.3.

(SHARE[2]) and draws on the individual-level information provided by respondents from the seven eurozone countries of Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

Second, a considerable proportion of prior studies analyzing financial literacy's impact on financial resilience relies on datasets not gathered during the COVID-19 crisis.[3] This study covers a crucial period from June 9, 2020, to August 10, 2020, reflecting the economic status and financial circumstances of the respondents following the initial wave of the COVID-19 pandemic. Hence, this thesis extends earlier contributions focusing on the situation in Europe, which rely on information collected before the crisis (Demertzis et al., 2020; Midões, 2020; Midões and Seré, 2022).

Third, a comprehensive review of the literature reveals that most empirical studies concerning financial resilience tend to employ a single classification method, usually via a logistic or probit regression analysis (Clark et al., 2020; Lusardi et al., 2011).[4] However, the assessment of variable importance and prediction performance, particularly concerning error rates of misclassification, may exhibit variations depending on the applied technique (Bolón-Canedo, Sánchez-Maroño, and Alonso-Betanzos, 2013; Dietterich, 1998; Luebke and Rojahn,

---

[2] When using data from this dataset, the following has to be cited: "This study used data obtained from SHARE Wave 7 (https://doi.org/10.6103/SHARE.w7.711) and the SHARE COVID-19 survey (https://doi.org/10.6103/SHARE.w8cabeta.001), see (Bergmann, Scherpenzeel, and Börsch-Supan, 2019) and (Börsch-Supan et al., 2013) for details on the methodology. The SHARE data collection was funded by the European Commission via FP5 (QLK6-CT-2001–00360), FP6 (SHARE-I3: RII-CT-2006–062193, COMPARE: CIT5-CT-2005–028857, SHARELIFE: CIT4-CT-2006–028812), FP7 (SHARE-PREP: GA N8211909, SHARE-LEAP: GA N8227822, SHARE M4: GA N8261982, DASISH: GA N8283646), Horizon 2020 (SHARE-DEV3: GA N8676536, SHARE-COHESION: GA N8870628, SERISS: GA N8654221, SSHOC: GA N8823782), and by DG Employment, Social Affairs and Inclusion. Additional funding from the German Ministry of Education and Research, Max Planck Society for the Advancement of Science, US National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553–01, IAG_BSR06-11, OGHA_04–064, HHSN271201300071C), and various national funding sources are gratefully acknowledged (see www.share-project.org)."

[3] For a detailed overview of the analyzed period in the financial resilience literature, see Section 2.3.

[4] For a detailed review of the applied methodologies in the financial resilience literature, see Section 2.3.

2016). Therefore, different classification techniques are applied to examine the importance of various features in explaining financial resilience. In this context, the employed methodologies are supplemented by a machine learning technique. Although machine learning has been widely used in finance (e.g., Bazarbash, 2019; Bracke, Datta, and Jung, 2019; Dixon, Halperin, and Bilokon, 2020), research that combines traditional regression techniques with machine learning techniques to examine the relationship between financial literacy and financial resilience is limited.

This study builds upon the author's previous work (Erdem and Rojahn, 2022) and extends the analysis to a broader range of classification techniques, aiming to provide a more comprehensive understanding of the role of financial literacy in fostering financial resilience during the challenging circumstances of the COVID-19 pandemic. Three statistical models and one machine learning model are compared. The basic findings are based on a conventional logistic regression unaffected by biases stemming from endogeneity. Moreover, multinomial logistic regression and partial proportional odds regression are employed to enable the consideration of alternative definitions of financial resilience. Finally, a conditional random forest model, a tree structure machine learning model, is used. Although a conditional random forest has no individual coefficients that can be interpreted, it enables the determination of the predictor's variable importance. The combination of both methods, procedures that provide individual coefficients for the variables under review and machine learning techniques that are superior in variable importance determination, complements the literature by allowing the quantification of the association between independent and dependent variables as well as the determination of their importance (Gehrke, 2022; Levantesi and Zacchia, 2021).

1.3. STRUCTURE OF THE DISSERTATION

Figure 1 illustrates the structure of this doctoral study, which is organized into five sections. Section One introduces the research topic and its relevance, followed by the overall objectives and delimitation of the research.

A comprehensive literature review is conducted in Section Two to (i) explicate the concepts of financial resilience and financial literacy, including approaches to their measurement; (ii) delineate the status quo on individuals' financial resilience and financial literacy levels; and (iii) present the current state of the empirical research on the drivers of financial resilience followed by financial literacy's linkage to financial resilience and the identification of research gaps. Finally, Section Two is concluded by proposing the research questions and hypotheses.

Section Three outlines the empirical analysis to cover this thesis' contributions to the literature, especially concerning the identified research gaps. After describing the data, the techniques employed for modeling and predicting the variable importance of financial resilience are introduced. First, the analysis applies a traditional logistic regression model and an instrumental variable regression to account for potential endogeneity. Subsequently, three robustness checks are conducted, including a multinomial logistic regression, partial proportional odds model, and conditional random forest analysis.

Section Four presents the results of the basic regression and robustness checks based on the total and country-level samples, compares the results from the different applied techniques regarding the variable importance, and discusses the findings.

Finally, Section Five concludes the dissertation by summarizing the main empirical findings, addressing the limitations of the thesis, and proposing avenues for further research.

Figure 1. Structure of the thesis

Introduction

Section 1 - Introduction

- Introduction to the topic, problem statement, research objective and delimitation, and structure of the thesis

Literature review, delineation of status quo, identification of research gaps

Section 2 - Review of literature

- Definition and measurement of financial resilience and financial literacy
- Presentation of financial resilience and financial literacy levels worldwide
- Overview of empirical studies on the drivers of financial resilience
- Linking financial literacy with financial resilience
- Theoretical underpinnings through the development of research hypotheses

Empirical analysis, findings, and discussion

Section 3 - Empirical Analysis	*Section 4 - Results and Discussion*
• Sample and data • Research methdodology - Application of different classification techniques	• Findings of basic regression and robustness checks • Comparison of regression results and variable importance and discussion

Conclusion

Section 5 - Summary and Conclusion

- Summary of the main findings, limitations, and future research

Note. This figure presents the structure of the doctoral thesis.

[Source: Own representation]

II – THEORETICAL FRAMEWORK AND EMPIRICAL FOUNDATIONS

II - THEORETICAL FRAMEWORK AND EMPIRICAL FOUNDATIONS

2.1. FUNDAMENTALS ON FINANCIAL RESILIENCE

2.1.1. Concept and measurement approaches of financial resilience

The concept of resilience is not restricted to finance and can be found in several disciplines, including behavioral science (Norris, 2010), psychology (Buikstra et al., 2010; Donnellan, Conger, McAdams, and Neppl, 2009), or economics (Briguglio, Cordina, Farrugia, and Vella, 2014; Hallegatte, 2014; Pant, Barker, and Zobel, 2014). Resilience refers to an individual's ability to recover from adverse events and adapt to changing circumstances in the face of environmental stress (Abbott-Chapman, Denholm, and Wyld, 2008) and encompasses various interconnected dimensions that change over time (Buikstra et al., 2010). These dimensions can include biological, psychological, social, and cultural factors that interact with one another to determine how one responds to stressful events (Southwick, Bonanno, Masten, Panter-Brick, and Yehuda, 2014) and may evolve as a function of development and individuals' interaction with their environment (Kim-Cohen and Turkewitz, 2012). Therefore, resilience is a dynamic process characterized by adaptability as opposed to stability (Adger, 2000; Bonanno, 2005), involving recovering from harm rather than being immune to it (Norris, 2010).

Five potential outcomes in response to adverse events are documented in the extant literature, which include (i) bouncing back better, i.e., benefiting from the adverse event; (ii) resistance, i.e., remaining unaffected; (iii) resilience, i.e., being able to draw on appropriate resources to sustain a stable equilibrium; (iv) recovery, i.e., loss of equilibrium before gradually returning fully or partially to pre-event levels; and (v) reconfiguration, i.e., not adapting to the adverse event and performing major changes to normal behavior (DFID, 2011; Lepore and Revenson, 2014; Norris, 2010).

Resilience depends on access to appropriate internal and external resources. Internal resources are personal characteristics that protect individuals from stress (Norris, 2010) and are not necessarily unalterable innate attributes but rather dynamic features that evolve with individuals' social context (Donnellan et al., 2009). Such stress-suppressing personal characteristics include cognitive skills, positivity, and optimism (Donnellan et al., 2009; Ensel and Lin, 1991; Masten, 2001; Norris, 2010).

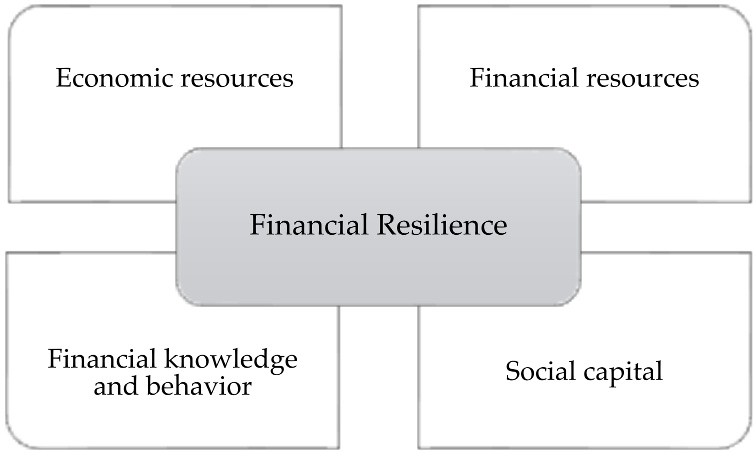
External resources can be categorized into money and relationships (Tomyn and Cummins, 2011). While money is self-explanatory, relationships refer to social capital, defined as an individual's network of relationships that can help provide access to and sources of information, advice, and support (Morrow, 2008), thereby fostering adaptation under changing circumstances (Norris, 2010).

Most existing research on financial resilience focuses on organizational financial resilience, which can be defined as an organization's resilience when firms face shock related to their financial management (Steccolini and Jones, 2014; Zahedi, Salehi, and Moradi, 2022). The concept of household financial resilience is relatively recent in the literature and emerged after the 2007–2008 financial market crisis to improve existing understandings of whether households' vulnerability to unforeseen financial shocks could, by itself, cause financial instability (Demertzis et al., 2020; Mundi and Vashisht, 2023). The concept has gained importance in recent years, particularly owing to the unpredictable shocks induced by the COVID-19 pandemic (OECD, 2020). In this context, the term financial resilience explicitly denotes household financial resilience, which serves as the central focus of this analysis.

Financial resilience describes the ability to cope with and recover from unexpected adverse economic shocks by relying on internal and external financial resources, including emergency savings, family, friends, or loans to handle financial shocks (Bialowolski, Cwynar, and Weziak-Bialowolska, 2022; Demertzis et al., 2020; Hasler et al., 2018; Mcknight and Rucci, 2020; Nguyen et al., 2022; Salignac, Marjolin, Reeve, and Muir, 2019). Hence, financial resilience is defined by households' capacity to obtain and draw on emergency reserves from any source, either from internal capabilities or external resources, in times of financial adversity (Lusardi et al., 2011; Salignac et al., 2019; Tahir, Shahid, and Richards, 2022).

As proposed by Salignac et al. (2019), financial resilience can be conceptualized using a multidimensional model comprising the following four components: Economic resources, financial resources, financial knowledge and behavior, and social capital (Figure 2).

Figure 2. Financial resilience framework



Note. This figure provides an overview of the components of the financial resilience framework. [Source: Own representation based on Salignac et al. (2019, p. 23)]

The *economic resources* component encompasses financial aspects that impact an individual's capacity to manage financial challenges, including income, savings, debt management, coping with cost-of-living expenses, and having emergency funds. Savings enable the management of cash flow (Cull, Ehrbeck, and Holle, 2014), and access to credit can have a positive impact on spending habits (Demirgüç-Kunt, Klapper, Singer, and Van Oudheusden, 2015). Proper debt management enables access to formal credit products and helps avoid reliance on alternative high-cost and high-interest loans (Anderloni and Vandone, 2008). An inability to meet one's cost-of-living expenses, which refers to expenses related to goods and services necessary to retain a particular standard of living (Jacobs, Perera, and Williams, 2014), indicates economic insecurity and can erode resilience (Conger and Conger, 2002; Orthner, Jones-Sanpei, and Williamson, 2004).

The *financial resources* component refers to access to financial products and services, including bank accounts, affordable credit, and general insurance (Connolly, 2012).

The *financial knowledge and behavior* component examines individuals' knowledge of and confidence in using financial products and services. Furthermore, this component includes the willingness to seek financial advice and engage in proactive financial behaviors. High levels of financial capability enable individuals to apply their acquired knowledge, skills, and tools to identify suitable financial products and services, facilitating effective financial management (Serido, Shim, and Tang, 2013; Taylor, 2011; Von Stumm, O'Creevy, and Furnham, 2013). However, financial knowledge and behaviors are not exclusively individuals' responsibility because they are also influenced by the availability of financial information. Thus, improving financial knowledge and behavior depends on addressing internal and external factors.

Finally, *social capital* is another essential resource for dealing with financial shocks, as individuals also rely on their social connections (i.e., friends and family) for financial assistance during emergencies (Demirgüç-Kunt, Klapper, Singer, and Ansar, 2022). Similarly, access to community and government support services contributes to resilience as it can provide support in times of financial hardship (Orthner et al., 2004; Seccombe, 2002).

The financial resilience framework exemplifies the challenge of quantifying financial resilience because it is a multidimensional and dynamic concept. Therefore, various ways to measure financial resilience exist in the literature, which focuses on objective and subjective financial resilience measures (Hasler and Lusardi, 2019; Mcknight and Rucci, 2020).

Objective measures of financial resilience include numerous forms of individuals' or households' liquidity or debt ratios to assess their coping capacity (Ampudia, Van Vlokhoven, and Żochowski, 2016; Bi and Montalto, 2004; Brown and Taylor, 2008; Brunetti, Giarda, and Torricelli, 2016; Faruqui, 2008; Jappelli, Pagano, and Di Maggio, 2013; Mcknight and Rucci, 2020). Common measures include the sufficiency of savings and liquid financial assets in terms of ratios of monthly income. For example, the number of months a household could meet its expenditure needs by drawing on its existing savings if its income fell to zero, with typical values set at three or six months (Bhargava and Lown, 2006; Bialowolski et al., 2022; Chieffe and Rakes, 1999; Clark and Mitchell, 2022; Johnson and Widdows, 1985; Smythe, 1968).

Other measures examine the opposite of financial resilience, capturing aspects of financial distress and utilizing financial debt-to-income ratios, credit-to-income ratios, financial assets-to-debt ratios, and debt overburden or over-indebtedness indicators (Ampudia et al., 2016; Brown and Taylor, 2008; Christelis, Jappelli, Paccagnella, and Weber, 2009; Clark and Mitchell, 2022; Cumming and Hubert, 2021; Room and Merikull, 2017).

Subjective measures of financial resilience look at individuals' perceived ability to cope with unexpected financial shocks and are most commonly used in empirical studies (Anderloni, Bacchiocchi, and Vandone, 2012; Andreou et al., 2023; Clark et al., 2020; Deevy, Streeter, Hasler, and Lusardi, 2021; Demertzis et al., 2020; Hasler et al., 2018, 2023; Lusardi et al., 2011, 2020; Mcknight and Rucci, 2020; Wiersma, Alessie, Kalwij, Lusardi, and Van Rooij, 2020).

One frequently used measure asks respondents to self-assess their confidence in obtaining \$2,000 in the event of an unforeseen financial necessity within 30 days (Clark et al., 2020; Deevy et al., 2021; Hasler et al., 2023; Lusardi et al., 2011). This \$2,000 threshold represents a midsize financial shock measuring unexpected expenses like automobile repairs, legal fees, or home maintenance (Lusardi et al., 2011). This financial resilience indicator offers several advantages. It obviates the need for an extensive collection of data on respondents' assets and liabilities, which is often challenging to obtain in surveys owing to non-responses to financial questions (Cziriak, 2022; Demertzis et al., 2020). Essentially, the indicator is independent of sensitive data regarding individuals' assets or borrowing capacity (Hasler et al., 2018). Moreover, it effectively characterizes the state of balance sheets because it captures hidden elements of a respondent's financial situation, such as their knowledge of their payment obligations, asset allocation for dependents, and availability of resources for unexpected needs (Hasler and Lusardi, 2019). Additionally, the question assesses households' ability to navigate financial shocks, encompassing their reliance on social networks comprising family and friends, which may be influenced by cultural distinctions (Demertzis et al., 2020).

Further related research points in the same direction and assesses the financial resilience of households by inquiring whether they can manage an unexpected expense equating to one month's income of those at the risk-of-poverty threshold. The precise amount of this unanticipated expenditure varies by country (Ampudia et al., 2016; Anderloni et al., 2012; Andreou et al., 2023; Brunetti et al., 2016; Christelis et al., 2009; Del Río and Young, 2005; Demertzis et al., 2020; Room and Merikull, 2017; Worthington, 2003).

Another commonly used subjective measure of financial resilience related to the $2,000 in 30 days metric (Lusardi et al., 2011), is the ability to make ends meet in a month (Christelis et al., 2009; Chua and Chin, 2022; Hasler et al., 2018; Lusardi, 2011; Lusardi et al., 2020; Sconti, 2022; Yakoboski, Lusardi, and Hasler, 2020b, 2021, 2022, 2023). Alternatively, other related studies ask respondents to state whether their debt obligations hinder them from effectively managing other financial obligations and participating in regular retirement savings (Lusardi et al., 2020; Yakoboski et al., 2020, 2022, 2023).

2.1.2. Financial resilience levels worldwide

The Global Findex Database 2021 provides an extensive cross-country assessment of individuals' financial resilience levels worldwide. The Global Findex Survey has been conducted since 2011 and provides insights into how adults worldwide use financial services, from payments to savings and borrowing, and manage financial events, such as a major expense or a loss of income. The indicators in the Global Findex database are drawn from survey data carried out in 2021 and cover about 128,000 people in 123 economies aged 15 and above (Demirgüç-Kunt et al., 2022).

Regarding the operationalization of financial resilience, the Global Findex 2021 Survey adopts subjective financial resilience measures, as outlined in Section 2.1.1., to evaluate respondents' ability to manage financial shocks that fall outside the routine and expected living costs. Two indicators of financial resilience are used in the Global Findex 2021 Survey, specifically, a thirty-day and a seven-day measure. However, this study exclusively presents the findings based on the thirty-day indicator for the following two reasons: First, it is identical to the timeframe of the commonly utilized subjective measures that assess financial resilience (Section 2.1.1). Second, the time frame of thirty days constrains respondents' opportunities and the cost of the methods that they can rely upon (Lusardi et al., 2011). Three questions assess the difficulty that a respondent would encounter in a hypothetical emergency in obtaining an amount equal to five percent of the gross national income (GNI) per capita in local currency within a thirty-day timeframe.

Furthermore, the primary source that the respondents would use to obtain that amount is inquired (Demirgüç-Kunt et al., 2022). If a respondent can come up with emergency funds in thirty days with no difficulty or somewhat difficulty, the observation is classified as financially resilient. If a respondent cannot obtain emergency funds in thirty days or it is very difficult for the individual to generate that amount, the observation is classified as financially fragile.

Table 1 provides an overview of the Global Findex 2021 Survey results and is structured as follows: Panel A reports the total samples' share of financially resilient individuals, while Panel B (Panel C) displays the ten most financially resilient (fragile) economies in descending order. Panel D presents financial resilience levels by region in descending order, with each country classified into a geographic region according to the Statistics Division of the United Nations Secretariat (UN). The UN uses these geographic regions to obtain greater homogeneity in population sizes, demographic circumstances, and the accuracy of demographic statistics (United Nations Statistics Division, n.d.). Finally, Panel E lists financial resilience levels by income categories in descending order, with each country classified into one of the following four income groups: High, upper-middle, lower-middle, and low. The income groups reflect the World Bank income group classifications from 2023. They are based on gross national income (GNI) per capita in U.S. dollars and are converted from local currency using the World Bank Atlas conversion factor to reduce the impact of exchange rate fluctuations in the cross-country comparison of national incomes (World Bank, 2023). A list of the included countries, individual country-level financial resilience levels, and region and income group assignments are provided in APPENDIX 1.

Table 1 reveals that financial resilience levels vary widely across countries. Panel A indicates that, on average, 60% of individuals were financially resilient in 2021. Thus, during the COVID-19 pandemic, for 40% of adults worldwide, it was very difficult or impossible to obtain emergency funds in thirty days.

Panel B demonstrates that internationally, Austria, Denmark, Estonia, Finland, Hong Kong, Iceland, Norway, Sweden, Taiwan, and the United Kingdom have the most financially resilient individuals, with more than 85% of adults being financially resilient. Sweden leads the ranking, with 94% financially literate respondents.

Table 1. Global financial resilience levels

Sample	Financially resilient individuals (%)
Panel A: Total sample	60
Panel B: Top ten financially resilient countries	
Sweden	94
Denmark, Finland, Norway	89
Hong Kong SAR, Iceland, Taiwan	88
Austria, Estonia, United Kingdom	86
Panel C: Top ten financially fragile countries	
South Sudan	16
Zambia	21
Pakistan	30
India	31
Mali, Zimbabwe	32
Lao PDR	33
Namibia	35
Nigeria, Sierra Leone	36
Panel D: Financial resilience by regions	
Oceania	85
Northern Europe	84
Eastern Asia	81
Northern America, Western Europe	79
Eastern Europe	74
Southern Europe	69
Western Asia	60
Central Asia, South-eastern Asia	58
Latin America & Caribbean	50
Northern Africa	46
Southern Asia	45
Sub-Saharan Africa	43
Panel E: Financial resilience by income groups	
High income	77
Upper middle income	56
Lower middle income	51
Low income	38

Note. This table provides an overview of financial resilience levels worldwide based on data from the Global Findex 2021 Survey.

[Source: Own representation]

By contrast, Panel C indicates that India, Lao PDR, Mali, Namibia, Nigeria, Pakistan, Sierra Leone, South Sudan, Zambia, and Zimbabwe have the most financially fragile individuals. South Sudan and Zambia with only 16% and 21%, respectively, accommodate the most financially fragile individuals worldwide.

Panel D uncovers considerable heterogeneity in financial resilience levels between regions. The regions with the highest rates of financial resilience are Oceania (Australia and New Zealand), Northern Europe (mainly consisting of Scandinavian countries), and Eastern Asia, where, on average, greater than 80% of individuals are financially resilient, followed by Northern America (Canada and the United States), Western Europe, and Eastern Europe, where, on average, greater than 70% of the individuals are financially resilient. By contrast, Northern Africa, Southern Asia, and Sub-Saharan Africa house the countries with the lowest financial resilience levels, where, on average, greater than half of the adults are financially fragile. Moreover, financial resilience rates vary widely within each economic region, such as Europe, revealing that heterogeneity in financial resilience levels exists between and within the regions. For example, in Northern Europe, financial resilience rates vary from 94% in Sweden to 63% in Lithuania. Similarly, financial resilience rates differ within Southern Europe, with 81% of respondents in Malta being financially resilient, down to only 58% in North Macedonia (not reported in Table 1).

Finally, Panel E discloses that financial resilience levels are the highest in high-income economies and lowest in low-income economies. On average, 77% of individuals in high-income countries are financially resilient compared to 56% (51%) in upper-middle-income (lower-middle-income) countries. The gap is considerably larger in low-income economies, where, on average, only 38% of individuals are financially resilient, comprising less than half of the proportion of financially resilient individuals in high-income economies.

Another finding from the Global Findex 2021 Survey is that the preferred source of emergency money varies among income groups (not presented in Table 1). In high-income economies, savings is the preferred source of financing in an emergency, with 46% of the adults stating that they would primarily use their savings to come up with emergency money in thirty days. By contrast, for low- and lower-middle-income economies, the most common emergency fund source is money from family or friends, with 32% and 39% of adults, respectively, relying on their social network as their primary source of emergency money. However, personal social networks, such as family and friends, are often unreliable, particularly during the COVID-19 pandemic, when numerous members of the same family or community had simultaneously lost their jobs or income, making it challenging to help friends or relatives (Demirgüç-Kunt et al., 2022).

The findings of the Global Findex 2021 Survey highlight that disparities in financial resilience levels across countries, beyond stemming from income, are likely to be influenced by country contexts, including cultural factors, policies, and financial development. This context can include variations in the financial infrastructure, government policies, or social welfare systems (Demirgüç-Kunt et al., 2022; Wiersma et al., 2020).

2.1.3. Determinants of financial resilience

Prior research on financial resilience indicates that individuals' financial resilience is associated with a range of socio-demographic characteristics, which are described in the following:

- *Income.* Research reveals that income plays a protective role for financial resilience (Cziriak, 2022). Low-income households tend to exhibit a higher susceptibility to financial fragility due to their markedly reduced capacity to navigate unforeseen health and financial shocks (Andreou et al., 2023; Bialowolski et al., 2022; Clark et al., 2020; Daud, Marzuki, Ahmad, and Kefeli, 2019; Hasler et al., 2018; Wiersma et al., 2020, among others).
- *Education.* Education increases one's capacity to navigate financial shocks (Andreou et al., 2023; Cziriak, 2022; Daud et al., 2019; Hasler et al., 2018; Lusardi et al., 2011; Wiersma et al., 2020), as it facilitates adequate income and resource management (Ali, Khan, and Ahmad, 2020; Bialowolski et al., 2022; Hasler and Lusardi, 2019; Lusardi et al., 2020). Individuals with higher educational levels tend to have a greater understanding of financial concepts (Lusardi and Mitchell, 2014) and are more likely to engage in financial planning and saving behaviors (Hilgert, Hogarth, and Beverly, 2003). Furthermore, education improves individuals' employability and income potential, thus contributing to greater financial stability and resilience (Behrman, Mitchell, Soo, and Bravo, 2012).

- *Age.* Younger respondents are less likely to be financially resilient (Andreou et al., 2023; Clark et al., 2020; Daud et al., 2019; Klapper and Lusardi, 2020; Lusardi et al., 2011; Tahir et al., 2022) because they tend to borrow more (Hansen, Slagsvold, and Moum, 2008) and to hold risky assets because of inadequate experience (Emmons and Noeth, 2013), thus accumulating lower wealth levels than older adults.
- *Children.* Households with more children are less likely to be financially resilient due to the associated expenses linked to childcare and education. These costs considerably and negatively affect the financial resources of these households (Andreou et al., 2023; Clark et al., 2020; Cziriak, 2022; Hasler and Lusardi, 2019; Hasler et al., 2018).
- *Employment.* The empirical evidence on employment's impact on financial resilience is mixed. Studies find that unemployed individuals face an elevated risk of encountering financial difficulties (Clark et al., 2020; Hasler et al., 2018; Mundi and Vashisht, 2023; Wiersma et al., 2020) due to their lack of sufficient savings to address unforeseen expenses during periods of crisis (Lusardi et al., 2020). By contrast, Clark and Mitchell (2022) document a positive relationship between unemployed individuals and financial resilience, analyzing 2021 data and ascribing it to the unemployment benefit checks provided during COVID-19 to protect the unemployed. Furthermore, households in atypical employment situations, such as those undergoing marginal employment, i.e., possessing mini-jobs (Cziriak, 2022), or individuals in precarious employment or those dissatisfied with their employment hours, i.e., people who only work odd jobs or are underemployed (Salignac et al., 2019), were found to be financially fragile. Relatedly, Salignac et al. (2019) suggest that being employed might be insufficient to support financial resilience if the hours of work and related income are insufficient to cover an individual's needs**.**
- *Retired.* Similarly, the findings for retired individuals are miscellaneous. Pensioners encounter difficulties managing an unexpected financial shock if their pension funds fall short of acting as a financial cushion. This funding gap may result from inadequate retirement planning or the premature withdrawal of retirement account funds (Hasler and Lusardi, 2019; Lusardi et al., 2011; Wiersma et al., 2020, among others). By contrast, Erdem and

Rojahn (2022) document a positive relationship between retired individuals and financial resilience, suggesting that retirees' pension income is less vulnerable to a sudden income loss or the risk of unemployment during the COVID-19 crisis.

- *Planning horizon.* Prior studies demonstrate that financial fragility can arise from short-term financial planning and inadequate savings (Clark and Mitchell, 2022; Goyal, Kumar, Rao, Colombage, and Sharma, 2021; Hoffmann and McNair, 2019; Huffman, Maurer, and Mitchell, 2019).
- *Gender.* Empirical evidence regarding gender's effect on financial resilience is mixed. Some studies find that single women are less likely to be financially resilient than single men (Demertzis et al., 2020; Hasler and Lusardi, 2019; Hasler et al., 2018; Lusardi et al., 2011). Others disclose a positive relationship between women and financial resilience (Cziriak, 2022).

  However, others report no significant association between gender and financial resilience, indicating that any variations in financial resilience between men and women are more likely to be linked to other factors, such as income, age, and educational disparities, rather than being solely attributed to gender (Clark et al., 2020; Wiersma et al., 2020). Cziriak (2022) bridges these mixed findings by demonstrating that the operationalization of financial literacy is critical in this regard. While he uncovers a significantly positive relationship between women and financial resilience when he controls for financial literacy based on questions assessing basic financial literacy, the association of gender and financial resilience becomes insignificant when a broader measure, assessing advanced financial literacy, is utilized.
- *Financial hardship.* Learning curve effects suggest that experienced financial difficulties can foster the development of financial resilience. However, as individuals confront prolonged periods of financial hardship, their savings and assets often diminish as they are depleted over time (Browning and Crossley, 2001). Accordingly, research identifies a negative relationship between an extended period of financial hardship and financial resilience (Hasler et al., 2018; O'Connor et al., 2019).

- *Financial literacy.* Another key determinant of financial resilience is financial literacy. Several studies document a positive relationship between financial literacy and financial resilience (Anderloni et al., 2012; Andreou et al., 2023; Babiarz and Robb, 2014; Clark et al., 2020; Cziriak, 2022; Deevy et al., 2021; Despard, Friedline, and Martin-West, 2020; Hasler et al., 2018; Loschiavo and Graziano, 2022; Lusardi et al., 2020; Lyons, Kass-Hanna, Liu, Greenlee, and Zeng, 2020; Singh and Malik, 2022; Woodyard, Robb, Babiarz, and Jung, 2017, among others).

  Individuals with higher financial literacy levels are more likely to engage in behaviors that promote financial resilience, such as farsighted budgeting, emergency savings, or adequate insurance coverage (Lusardi and Mitchell, 2014; Mcknight and Rucci, 2020). Furthermore, reportedly, financial literacy is associated with reduced financial stress and improved overall financial well-being, such as being less debt-constrained, spending less time thinking regarding issues related to personal finances, being less likely to overdraw checking accounts, tracking spending, saving and planning for retirement, and having non-retirement savings (Hastings and Mitchell, 2020; Van Rooij, Lusardi, and Alessie, 2011b; Yakoboski, Lusardi, and Hasler, 2018, 2019; Yakoboski et al., 2021, 2022, 2023).

  To further elaborate on the concept of financial literacy and its crucial role in fostering financial resilience, the following section provides a detailed financial literacy assessment, covering its definition, measurement approaches, and impact on financial outcomes. Furthermore, international levels of financial proficiency are reported to present an overview of the status quo, and the link between financial literacy and potential endogeneity bias is discussed.

2.2. CONSTRUCT OF FINANCIAL LITERACY

2.2.1. Definition and operationalization of financial literacy

The abundant literature on financial literacy proposes several conceptual definitions. However, a universally accepted notion of the meaning of financial literacy is lacking (Aren and Dinç Aydemir, 2014; Hung, Parker, and Yoong, 2009; Huston, 2010; Ouachani, Belhassine, and Kammoun, 2021; Stolper and Walter, 2017). Table 2 illustrates the range of conceptual definitions of financial literacy drawn from various studies chronologically.

Table 2. Conceptual definitions of financial literacy

Publication	**Conceptual definition**
Noctor, Stoney, and Stradling (1992)	Financial literacy is the *financial knowledge* that leads to informed decision making.
Hilgert et al. (2003)	Financial literacy is defined as *financial knowledge.*
Moore (2003)	Financial literacy is obtained through *practical experience* and *active integration of knowledge.*
Lusardi and Mitchell (2007c)	Financial literacy is *knowledge* that results in *sound financial decisions.*
The President's Advisory Council on Financial Literacy (PACFL, 2008)	Financial literacy is the *ability to use knowledge* and skills to manage financial resources effectively.
Huston (2010)	Financial literacy is personal *financial knowledge* and personal *financial application.*
Lusardi and Mitchell (2014)	Financial literacy is the *ability to* process economic information and *make informed financial decisions.*
Organisation for Economic Cooperation and Development (OECD, 2014)	Financial literacy is the *knowledg*e and understanding of financial concepts and the *confidence to apply such knowledge* to make effective decisions in the financial context.

Note. This table provides an overview of different conceptual definitions of financial literacy drawn from various studies. Italics have been added throughout to emphasize key definitional components.

[Source: Own representation]

Among the first to define the financial literacy concept were Noctor, Stoney, and Stradling (1992), according to whom financial literacy is the financial knowledge that leads to informed decision-making. Comparably, Hilgert et al. (2003) and Lusardi and Mitchell (2007c) emphasize the financial knowledge component of financial literacy, which results in sound financial decisions. Thus, this definition includes two dimensions, financial knowledge and the ability to use such knowledge appropriately to make informed decisions (Ouachani et al., 2021). Furthermore, Moore (2003) includes the active integration of financial knowledge and argues that financial literacy is obtained through practical experience.

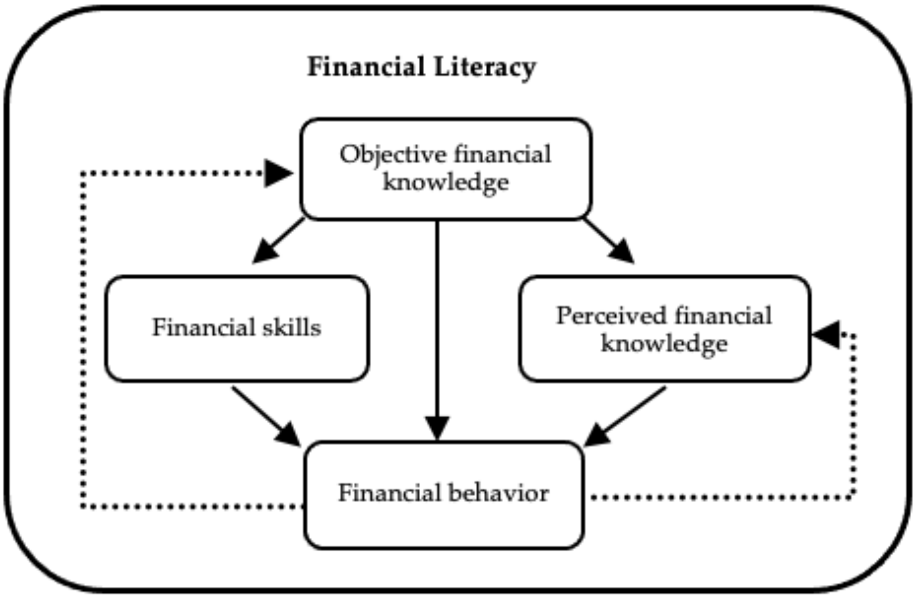
The President's Advisory Council on Financial Literacy (PACFL) highlight, in their definition of financial literacy, the ability to use financial knowledge and not merely its existence (PACFL, 2008). Likewise, Huston (2010, p. 306) dissociates those two dimensions, suggesting that financial literacy measures must integrate both financial knowledge and financial decision-making and defines financial literacy as a measure of an individual's "understanding (personal finance knowledge) and use (personal finance application)." The understanding dimension describes knowledge acquired through education and experience related to personal financial concepts and products, whereas the application dimension refers to the ability and confidence to effectively use that knowledge to make financial decisions (Huston, 2010).

Similarly, Lusardi and Mitchell (2014) conceptualize financial literacy as surpassing financial knowledge, including the ability to analyze economic information and confidence in informed financial decision-making. In the same vein, the Organisation for Economic Cooperation and Development (OECD) provides a definition that includes both the understanding and application dimension, stating that "financial literacy is knowledge and understanding of financial concepts and risks, and the skills, motivation, and confidence to apply such knowledge and understanding in order to make effective decisions across a range of financial contexts, to improve the financial well-being of individuals and society, and to enable participation in economic life" (OECD, 2014, p. 33-34).

Overall, Table 2 illustrates that the most common basis in the various definitions of financial literacy is financial knowledge and the confidence to apply such knowledge.

Hung et al. (2009, p. 12) combine the various definitions in the literature and propose an all-encompassing conceptualization of financial literacy considering financial knowledge, skills, and behavior, as well as their mutual relationships, specifying it as the "knowledge of basic economic and financial concepts, as well as the ability to use that knowledge and other financial skills to manage financial resources effectively for a lifetime of financial well-being." They argue that objective financial knowledge represents the foundation of financial literacy, reflected in both perceived financial knowledge and financial skills. Financial behavior results from objective financial knowledge, perceived financial knowledge, and financial skills. Ultimately, the experience gained through financial behavior feeds back to objective and perceived financial knowledge. Figure 3 presents a conceptual model of a composite definition of financial literacy that builds from the extant literature and incorporates the relationships among the components of financial literacy.

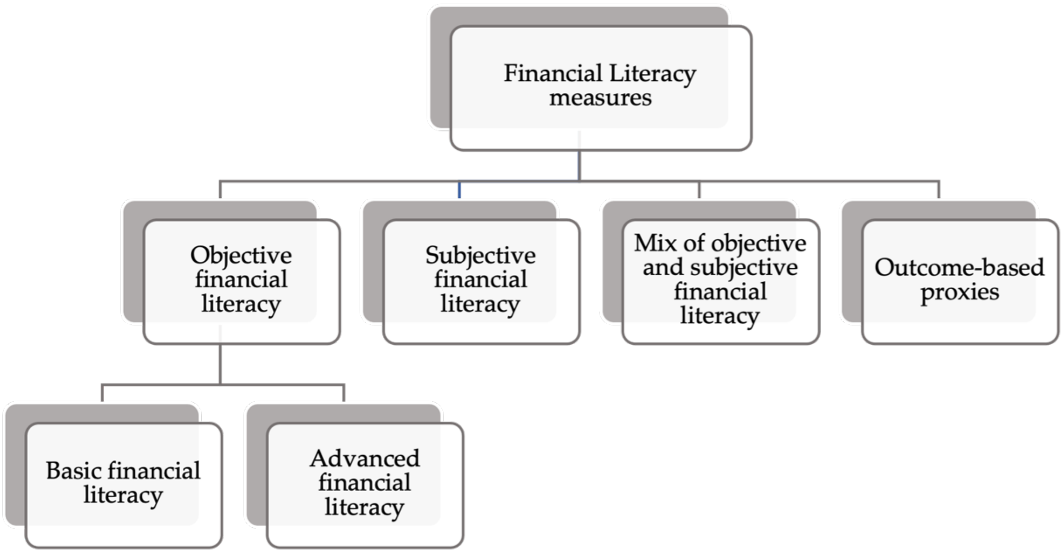
Figure 3. Conceptual model of financial literacy



Note. This figure provides a conceptual model of financial literacy.
[Source: Own representation based on Hung (2009, p. 12)]

Financial literacy can be measured in three ways, reflected in four strands of literature, as presented in Figure 4.

Figure 4. Financial literacy measures



Note. This figure provides an overview of the financial literacy measures.
[Source: Own representation]

The first strand of literature assesses *objective financial literacy*, predominantly performed utilizing test-based measures (Hung et al., 2009; Huston, 2010; Ouachani et al., 2021). The test items can be classified according to their sophistication level and evaluate basic or advanced financial literacy levels.

When designing questions that assess *basic financial literacy*, Lusardi and Mitchell (2014) stress that questions should relate to concepts pertinent to individuals' day-to-day financial decisions over their life cycle and capture general rather than context-specific ideas. Consequently, basic financial literacy covers fundamental economic concepts, such as basic numeracy, the functioning of interest rates and interest compounding, inflation, and risk diversification (Aren and Dinç Aydemir, 2014; Grohmann, 2018; Liao, Xiao, Zhang, and Zhou, 2017; Lusardi, 2019; Van Rooij, Lusardi, and Alessie, 2011a).

Advanced financial literacy, first proposed by van Rooij et al. (2011), distinguishes professional knowledge from basic financial literacy and covers more complex questions related to investment and portfolio choice. The questions focus on specific financial products, such as bonds, stocks, and mutual funds; the function of the stock market; the concept of risk diversification; and the relationship between bond prices and interest rates (Liao et al., 2017; Van Rooij et al., 2011b).

Ultimately, the individual level of basic or advanced financial literacy is obtained using different means of aggregating the questions. Most literature calculates a financial literacy index based on the amount of correct answers to the financial literacy questions (Angrisani, Burke, Lusardi, and Mottola, 2023; Stolper and Walter, 2017). Test-based measures have become the international benchmark for assessing objective financial literacy because they are primarily knowledge-based, target fundamental concepts crucial for informed financial decisions, and are less prone to subjective biases (Hung et al., 2009). However, reservations can be raised against their use as they are sensitive to framing. Thus, the wording of the question matters, and some correct answers may result from simple guessing (Lusardi and Mitchell, 2011a; Van Rooij et al., 2011b).

Regarding the operationalization of objective financial literacy, Hung et al. (2009), Huston (2010), and Ouachani et al. (2021) document, in their extensive review of financial literacy measures, that several scales are utilized (i.e., the specific questions asked, economic concepts covered, and number of questions) and vary within the literature (Aren and Dinç Aydemir, 2014; Ouachani et al., 2021; Rieger, 2020; Stolper and Walter, 2017).

Table 3 presents an overview of the most commonly used test items suggested in the literature to measure basic financial literacy. The enumeration does not include all questions raised in the past but rather locates the most frequently used questions in this field. Furthermore, as this thesis analyzes individuals' basic financial literacy, the advanced financial literacy test items are not discussed in detail.

Table 3. Economic concepts covered by basic financial literacy measures

(1) Basic financial literacy measures and publications using those	(2) Economic concepts						(3) Number of items
Publication / measure	Interest rates and compounding	Inflation	Risk diversification	Numeracy	Knowledge of financial products	Debt	
Clark and Mitchell (2022); Grohmann (2018); Lusardi (2019); Lusardi and Mitchell (2006),(2008), (2011b), (2011a), (2014); Sconti (2022) / **Big Three**	X	X	X	X			3
Anderson, Baker, and Robinson (2017); Angrisani et al. (2023); Hastings, Madrian, and Skimmyhorn (2013); Mitchell and Lusardi (2022) / **Big Five**	X	X	X	X			5
Klapper and Lusardi (2020); Klapper, Lusardi, and Van Oudheusden (2017) / **S&P global financial literacy index**	X	X	X	X			5
Kunovskaya, Cude, and Alexeev (2014)	X	X		X			6
Bianchi (2018)	X	X		X	X		7
Burke and Manz (2014)	X	X			X		4
Gathergood and Weber (2017)	X			X		X	4
Van Ooijen and Van Rooij (2016)	X	X	X	X		X	6
Bialowolski et al. (2022); Christelis, Jappelli, and Padula (2010); Erdem and Rojahn (2022); Jappelli and Padula (2013) / **SHARE financial literacy index**	X			X			4

Note. This table provides an overview of various basic financial literacy measures and the economic concepts that they cover.

[Source: Own representation]

Column (1) in Table 3 lists the authors that have utilized the specific financial literacy questions, while column (2) classifies the different categories of economic concepts that are covered by the specific questions. This includes interest rates and interest compounding; inflation rates; risk diversification; numeracy; knowledge of financial products, such as stocks, bonds, or mutual funds; and debt. Finally, column (3) provides an overview of the number of questions asked to assess basic financial literacy.

Lusardi and Mitchell (2014) suggest compliance with the following four principles when designing questions that assess basic financial literacy: (i) simplicity, (ii) relevance (i.e., the questions should relate to concepts pertinent to individuals' day-to-day financial decisions, as discussed above); (iii) brevity (i.e., the number of questions must be short to ensure widespread adoption); and (iv) capacity to differentiate (i.e., the questions should distinguish financial knowledge to allow comparisons across individuals). Accordingly, they designed a standard set of three questions, the so-called "Big Three," which were first used in the 2004 US Health and Retirement survey. The Big Three test respondents' understanding of four fundamental financial concepts, specifically, numeracy related to the ability to conduct interest rate calculations and understand interest compounding, inflation, and risk diversification (Lusardi, 2019; Lusardi and Mitchell, 2011c).

Although the Big Three are widely used in the literature to measure basic financial literacy (Clark and Mitchell, 2022; Grohmann, 2018; Lusardi, 2019; Lusardi and Mitchell, 2008, 2011a, 2011b; Sconti, 2022, among others), subsequent analyses extended surveys by additional questions beyond the Big Three to capture further nuances of knowledge and abilities related to personal finance matters (Stolper and Walter, 2017).

Hastings, Madrian, and Skimmyhorn (2013) utilize a set of five financial literacy questions, also known as the "Big Five," covering fundamental economic and financial concepts. The Big Five aim at evaluating an individual's competence in basic interest calculations and understanding of the relationship between interest rates and bond prices. Furthermore, they assess respondents' understanding of the impact of mortgage length on overall interest paid and the risk diversification concept. Along with the Big Three, the Big Five are among the most frequently used basic financial literacy measures (Angrisani et al., 2023; Klapper and Lusardi, 2020; Mitchell and Lusardi, 2022).

Other researchers and surveys have implemented elements of the Big Three or Big Five in their research or further extended the questions to capture other dimensions of financial literacy, including debt and knowledge of financial products, such as bonds and stocks (Bianchi, 2018; Burke and Manz, 2014; Gathergood and Weber, 2017; Klapper and Lusardi, 2020; Kunovskaya et al., 2014; Van Ooijen and Van Rooij, 2016); knowledge of asset pricing (Lusardi and Mitchell, 2014); or other questions assessing numeracy (Klapper et al., 2017).

In the European context, the SHARE provides a measure of basic financial literacy first used in the 2004 SHARE Wave 1. The index comprises four financial and numerical questions. The first and second questions cover percentage calculation; the third question evaluates the rule of proportion and fractions, and the fourth question assesses interest rate compounding in a savings account and is commonly considered a good proxy for financial literacy, being one of the Big Three financial literacy questions (Lusardi and Mitchell, 2008; Lusardi, Mitchell, and Curto, 2010).

Overall, Table 3 illustrates that despite deviations in the literature regarding the number of questions asked and their framing, most of the applied questions that aim to measure basic financial literacy cover the same financial concepts relevant to individuals' everyday financial decision-making. Specifically, the economic concepts of interest rates and interest compounding, inflation, and numeracy are covered by most of the questions. Thus, most of the test items aiming at assessing subjective financial literacy comply with the principle of relevance suggested by Lusardi and Mitchell (2014). Moreover, Rieger (2020) finds that most basic financial literacy measures used in the literature significantly positively correlate. Thus, even though the content of the questions in the scales differs, most of the scales remain related.

The second strand of literature (see Figure 4) assesses *subjective financial literacy*, which refers to individuals' self-assessed or perceived financial knowledge (Bellofatto, D'Hondt, and De Winne, 2018; French and McKillop, 2016). Concerning subjective financial literacy measures, a consensus exists among researchers regarding the items. Several studies evaluate individuals' subjective financial literacy by addressing a single question with a Likert scale assessing how respondents perceive their financial literacy level (Allgood and Walstad, 2016; Bayrakdaroğlu and Şan, 2014; Lusardi and Mitchell, 2007b; Lusardi and Tufano, 2009; Moore, 2003, among others). The corresponding item is usually worded as follows: "On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall financial knowledge?" (Lusardi and Mitchell, 2014, p. 15).

The third strand of literature combines *both objective and subjective financial literacy* (Allgood and Walstad, 2016; Anderson et al., 2017; Guiso and Jappelli, 2009; Müller and Weber, 2010; Robb and Woodyard, 2011; Van Rooij, Lusardi, and Alessie, 2007). The comparison between the two measures helps assess individuals' confidence in their financial knowledge (Bayrakdaroğlu and Şan, 2014; Lusardi and Mitchell, 2007b) and reveals that individuals tend to be overconfident regarding how much they know (Agnew and Szykman, 2005; Porto and Xiao, 2016; Xia, Wang, and Li, 2014). Furthermore, Rieger (2020) criticizes that subjective and objective financial literacy have little in common because individuals compare their knowledge with their peers and, therefore, state a relative level of knowledge compared to people with similar backgrounds.

An alternative approach to capture financial literacy is examining individuals' observable financial behavior and using their financial decisions as a proxy for their financial literacy. Such *outcome-based proxies* for financial literacy form the fourth strand of literature, which include factors such as previous investment experience (Goetzmann and Kumar, 2008; Nicolosi, Peng, and Zhu, 2009; Seru, Shumway, and Stoffman, 2010), the extent of risk diversification in equity portfolios (Goetzmann and Kumar, 2008; Grinblatt and Keloharju, 2001), or the proclivity to invest in complex financial instruments (Genesove and Mayer, 2001; Goetzmann and Kumar, 2008). However, few studies use outcome-based proxies to measure financial literacy because differentiating the individual effect of financial literacy from the independent effect of the proxy variable can be challenging (Aren and Dinç Aydemir, 2014).

In summary, among the available measures of financial literacy, test-based measures assessing objective financial literacy outperform indicators of subjective financial literacy and outcome-based proxies of financial literacy owing to their validity and data availability. Objective financial literacy measures are not biased by overconfidence, reflect financial concepts related to individuals' day-to-day financial decision-making, allow comparisons across individuals regarding sophistication level, and are obtainable in terms of data availability because they are implemented in numerous surveys. Accordingly, the SHARE financial literacy measure, which is commonly used in the European context (Bialowolski et al., 2022; Christelis et al., 2010; Erdem and Rojahn, 2022; Jappelli and Padula, 2013), is the scale of choice in this doctoral thesis. Details on the questions and construction of the financial literacy indicator are provided in APPENDIX 3.

2.2.2. International financial literacy proficiency

Few studies provide a cross-country assessment of individuals' basic financial literacy levels across different countries; to date, only one survey assesses individuals' financial literacy levels globally, that is the Standard & Poor's Ratings Services Global Financial Literacy Survey (S&P Global FinLit Survey). The S&P Global FinLit Survey, which provides a direct cross-country comparison of financial literacy levels, was conducted in 2014. Five test questions assess the basic financial literacy of about 150,000 individuals aged 15 and above in 148 countries worldwide (S&P, 2014). A person is classified as financially literate when they answer at least three of the five test questions correctly. Basic financial literacy is measured using questions assessing knowledge pertaining to the four economic concepts: Numeracy, interest compounding, inflation, and risk diversification (Klapper and Lusardi, 2020; Klapper et al., 2017). Although the S&P Global FinLit Survey figures are from 2014, the financial literacy levels are unlikely to have changed significantly to date since recent research on the evolution of financial literacy indicates that financial literacy stagnates and remains relatively stable over time (Angrisani et al., 2023; Hasler et al., 2023; Lusardi, 2019; Yakoboski et al., 2023).

Table 4 provides an overview of the findings of the S&P Global FinLit Survey and is structured as follows: Panel A reports the total samples' proportion of financially literate individuals, while Panel B (Panel C) lists the ten most financially literate (illiterate) countries in descending order. Panel D presents financial literacy levels by region in descending order, with each country being classified into a geographic region following the UN (United Nations Statistics Division, n.d.). Finally, Panel E displays financial literacy levels by income categories in descending order, which reflects the World Bank income group classifications from 2023 (World Bank, 2023). A list of the included countries, individual country-level financial literacy levels, and region and income group assignments are provided in APPENDIX 2.

Table 4. Global financial literacy levels

Sample	Financially literate individuals (%)
Panel A: Total sample	37
Panel B: Top ten financially literate countries	
Denmark, Norway, Sweden	71
Canada, Israel	68
United Kingdom	67
Germany, Netherlands	66
Australia	64
Finland	63
Panel C: Top ten financially illiterate countries	
Yemen Republic	13
Afghanistan, Albania	14
Angola, Somalia	15
Tajikistan	17
Armenia, Cambodia, Haiti, Nepal	18
Panel D: Financial literacy by regions	
Northern America, Oceania	63
Northern Europe	60
Western Europe	57
Eastern Europe	40
Eastern Asia	38
Northern Africa, Southern Europe	35
South-eastern Asia	34
Sub-Saharan Africa, Western Asia	33
Latin America & Caribbean	30
Central Asia	28
Southern Asia	27
Panel E: Financial literacy by income groups	
High income	49
Upper middle income	32
Lower middle income	30
Low income	28

Note. This table provides an overview of financial literacy levels worldwide based on data from the S&P Global FinLit Survey.

[Source: Own representation]

Table 4 discloses considerable heterogeneity in financial proficiency levels across the countries. Panel A indicates that, on average, 37% of individuals worldwide are financially literate; thus, only one in three adults correctly answers at least three of the five questions.

Panel B reveals that, internationally, Australia, Canada, Denmark, Finland, Germany, Israel, the Netherlands, Norway, Sweden, and the United Kingdom have the highest financial literacy levels, with 63% or more of adults being financially literate. With 71% financially literate individuals, Scandinavian countries (Denmark, Norway, and Sweden) lead the ranking.

By contrast, Panel C displays that the most financially illiterate individuals are from Afghanistan, Albania, Angola, Armenia, Cambodia, Haiti, Nepal, the Republic of Yemen, Somalia, and Tajikistan. With less than 15% financially literate citizens, Afghanistan, Albania, and the Republic of Yemen score the lowest.

Panel D uncovers disparities in financial literacy proficiency between regions. The regions with the highest financial literacy rates are Northern America (Canada and the United States), Oceania (Australia and New Zealand), Northern Europe, and Western Europe, where approximately 57% or more individuals are financially literate. By contrast, Central Asia and Southern Asia house the countries with some of the lowest financial literacy scores, where, on average, less than 30% of adults are financially literate. Moreover, financial literacy rates vary widely within economic regions, such as Europe. The understanding of basic financial concepts is highest in Northern and Western Europe, with 60% and 57% of respondents being financially literate, respectively.

By contrast, financial literacy proficiency is significantly lower in Eastern and Southern Europe, with an average of 40% and 35% of individuals being financially literate, respectively. Even within the same region, financial literacy rates differ broadly, such as in Southern Europe, where financial proficiency varies from 49% in Spain to only 14% in Albania. Similarly, financial literacy rates in Eastern Europe vary from 58% in the Czech Republic to 22% in Romania (not reported in Table 4).

Panel E reveals that financial proficiency levels are the highest in high-income countries and lowest in low-income countries. On average, 49% of the survey participants in high-income countries are financially literate compared to 32% (30%) for upper-middle-income (lower-middle-income) countries and 28% for low-income economies.

In summary, financial proficiency is, on average, low worldwide, and distinct differences between geographical regions emerge. Furthermore, although relative differences exist in financial literacy levels between high- and low-income groups, in absolute values, higher national income levels do not equate to a more financially literate population because, on average, only half of the individuals from high-income economies (i.e., 49%) are financially literate.

2.2.3. Financial literacy's impact on financial outcomes

Several studies conducted in various countries provide evidence associating financial literacy with sound financial decision-making and financial well-being (e.g., Angrisani et al., 2023; Christelis et al., 2010; Cole, Sampson, and Zia, 2011; Hwang and Park, 2022; Lusardi, 2012; Van Rooij et al., 2011a). Table 5 provides an overview of the key findings of financial literacy's influence on financial outcomes.

Extensive research has explored financial literacy's positive influence on retirement planning (Alessie, Van Rooij, and Lusardi, 2011; Angrisani et al., 2023; Bernheim, 1998; Bucher-Koenen and Lusardi, 2011; Hasler et al., 2023; Hauff, Carlander, Gärling, and Nicolini, 2020; Kalmi and Ruuskanen, 2018; Lusardi and Mitchell, 2007a, 2008, 2011b; Sekita, 2011; Van Rooij, Lusardi, and Alessie, 2011a; Van Rooij et al., 2011b; Van Rooij, Lusardi, and Alessie, 2012; Yeh, 2022). Furthermore, several studies report a positive relationship between financial literacy and savings behavior (Babiarz and Robb, 2014; Behrman et al., 2012; Chan and Stevens, 2008; Clark et al., 2020; Hasler and Lusardi, 2019; Hastings and Mitchell, 2020; Letkiewicz and Fox, 2014; Lusardi and Mitchell, 2011c, 2014; Wiersma et al., 2020) and financial planning behavior (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2015; Arrondel, Debbich, and Savignac, 2014). De Bassa Scheresberg (2013) finds that financially literate consumers are more likely to hold precautionary savings, which is, reportedly, a prominent method of preparation for financial shocks (Lusardi et al., 2011).

Table 5. Key findings of financial literacy's influence on financial outcomes

Publication	Findings on financial outcomes
Alessie et al. (2011); Angrisani et al. (2023); Bernheim (1998); Bucher-Koenen and Lusardi (2011); Hasler et al. (2023); Hauff et al. (2020); Kalmi and Ruuskanen (2018); Lusardi and Mitchell (2007a), (2008), (2011b); Sekita (2011); Van Rooij et al. (2011a), (2011b), (2012); Yeh (2022).	Financial literacy's positive impact on *retirement planning*
Agarwal et al. (2015); Arrondel et al. (2014); Babiarz and Robb (2014); Behrman et al. (2012); Chan and Stevens (2008); Clark et al. (2020); de Bassa Scheresberg (2013); Hasler and Lusardi (2019); Hastings and Mitchell (2020); Letkiewicz and Fox (2014); Lusardi and Mitchell (2011b), (2014); Wiersma et al. (2020).	Positive relation between financial literacy and *savings* behavior and *financial planning*
Al-Tamimi and Bin Kalli (2009); Alessie et al. (2011); Almenberg and Dreber (2015); Amari and Jarboui (2017); Arrondel et al. (2014); Balloch et al. (2015); Christelis et al. (2010); Clark et al. (2017); Kimball and Shumway (2010); Sivaramakrishnan et al. (2017); Thomas and Spataro (2018); Van Rooij et al. (2011a), (2012); Xia et al. (2014); Yoong (2011).	Financially literate individuals are more likely to *participate in the stock market* and hold mutual funds.
Bilias et al. (2010); Bucher-Koenen and Ziegelmeyer (2014); Calvet et al. (2007), (2009); Clark et al. (2017); Deuflhard et al. (2017); Feng and Seasholes (2005); Goetzmann and Kumar (2008); Guiso and Jappelli (2009); Guiso and Viviano (2015); Hoffmann et al. (2013); Müller and Weber (2010); Von Gaudecker (2015).	*Investment choices and performance:* Financial literacy's positive impact on trading behavior, less investment mistakes, more likely to correctly assess the risk profile of their fund investments, better portfolio diversification, excess stock returns, and higher returns on savings accounts
Disney and Gathergood (2013); Hasler et al. (2023); Lusardi and de Bassa Scheresberg (2013); Lusardi and Tufano (2009), (2015); Moore (2003).	Low financial literacy levels are associated with *high-cost borrowing*, such as higher transaction costs and fees.
Allgood and Walstad (2013); Lusardi and Tufano (2009), (2015); Mottola (2013); Stango and Zinman (2009).	Negative relation between financial literacy and costly credit card practices and *excessive debt accumulation*.

Note. This table provides an overview of key findings on financial literacy's impact on financial outcomes. Italics have been added throughout to emphasize key financial behavior.

[Source: Own representation]

Moreover, the financially literate are more likely to participate in financial markets and invest in stocks (Al-Tamimi and Bin Kalli, 2009; Alessie et al., 2011; Almenberg and Dreber, 2015; Amari and Jarboui, 2017; Arrondel et al., 2014;

Balloch et al., 2015; Christelis et al., 2010; Clark et al., 2017; Kimball and Shumway, 2010; Sivaramakrishnan et al., 2017; Thomas and Spataro, 2018; Van Rooij et al., 2011b, 2012; Xia et al., 2014; Yoong, 2011).

Furthermore, the literature reveals a positive relationship between financial literacy and sound investment decisions. For example, the more financially literate tend to invest more efficiently (Calvet et al., 2007, 2009), as they commit fewer investment mistakes and better assess the risk profile of their fund investments (Bilias, Georgarakos, and Haliassos, 2010; Bucher-Koenen and Ziegelmeyer, 2014; Feng and Seasholes, 2005; Guiso and Viviano, 2015; Hoffmann, Post, and Pennings, 2013; Müller and Weber, 2010). Additionally, financially literate individuals are more likely to have excess stock returns (Clark et al., 2017) and higher returns on savings accounts (Deuflhard et al., 2017). Moreover, the financially literate perform better portfolio diversification (Calvet et al., 2007; Clark et al., 2017; Goetzmann and Kumar, 2008; Guiso and Jappelli, 2009; Von Gaudecker, 2015), the optimal benefits of which unfold in times of crises.

However, financial literacy not only impacts savings and investment decisions but also influences financing decisions and is an essential predictor of debt (Hasler et al., 2023). Previous research reveals that individuals with higher financial literacy levels better comprehend debt-related concepts, as low financial literacy levels are linked to high-cost borrowing and suboptimal mortgage choices (Disney and Gathergood, 2013; Lusardi and De Bassa Scheresberg, 2013; Lusardi and Tufano, 2009, 2015; Moore, 2003).

Further, individuals with low financial literacy levels are less likely to use their credit cards efficiently (Allgood and Walstad, 2013; Lusardi and Tufano, 2009, 2015; Mottola, 2013) and are more likely to accumulate excessive debt (Stango and Zinman, 2009), features that are both essential for financial resilience, as individuals may need to access credit through various means, such as credit cards or retirement account loans (Lusardi et al., 2011) to buffer themselves against shocks. Thus, a poor understanding of debt management and high levels of indebtedness contribute to financial fragility (Hasler and Lusardi, 2019; Hasler et al., 2018; Mcknight and Rucci, 2020).

2.2.4. Financial literacy and endogeneity

As established in Section 2.2.3., financial literacy positively influences sound financial behavior. However, as evidence on financial literacy's impact on financial decision-making is generally based on non-experimental data, endogeneity presents a prevalent issue that should be considered when analyzing financial literacy's role in financial outcomes (Stolper and Walter, 2017).

Endogeneity arises in regression models when the assumption of exogeneity (i.e., the independent variable is uncorrelated with the error term) is violated. In the case of endogeneity, the independent variable is correlated with the error term, and the estimated coefficients suffer from endogeneity bias and do not reflect true values (Antonakis, Bendahan, Jacquart, and Lalive, 2010). Thus, endogeneity does not preclude the possibility that financial literacy improves individuals' financial decision-making but rather introduces complexity in assessing the accurate magnitudes of the estimated effects as they are often upwardly biased (Hastings et al., 2013).

Endogeneity issues may arise from reverse causality, omitted variables, or measurement errors (Stolper and Walter, 2017). To illustrate, determining whether financial literacy's positive effect on sound financial decision-making is causal or whether being involved in certain financial activities increases financial literacy is challenging.

The literature provides several examples of potential endogeneity owing to a reverse causation channel. Disney, Gathergood, and Weber (2015) examine the relationship between financial literacy and the decision to seek credit counseling, suggesting that financial literacy may evolve endogenously with the reception of credit counseling. Similarly, Bucher-Koenen and Lusardi (2011) find that financially literate individuals are more likely to enroll in retirement savings plans. However, they also acknowledge the possibility of reverse causality, wherein retirement planning could impact financial literacy, as individuals who have engaged in retirement planning acquire some level of financial literacy through their participation in savings plans. Likewise, Hilgert, Hogarth, and Beverly (2003) find that most individuals cite personal experience as the primary source of their financial learning, suggesting that some element of reverse causality is likely.

Additionally, financial literacy is likely endogenous owing to omitting essential predictors that can simultaneously affect financial literacy and financial outcomes (Bucher-Koenen and Lusardi, 2011). The omission of underlying factors that contribute to higher financial literacy levels and improved financial outcomes in a regression equation leads to their reflection in the error term, instead appearing among the explanatory variables, resulting in biased estimators and hindering reliable inferences (Stolper and Walter, 2017).

The literature provides numerous cases of such elusive factors likely to influence financial literacy and financial behavior. Meier and Sprenger (2010) demonstrate a positive association between voluntary participation in financial education programs and future orientation. Similarly, Hastings and Mitchell (2020) find a link between patience exhibited in experiments and a higher likelihood of saving additional funds for retirement. Further, Bucher-Koenen and Lusardi (2011) suggest an omitted variable bias owing to missing information on individuals' ability or motivation to manage financial matters.

Finally, endogeneity may also arise from measurement errors regarding the financial literacy variables. Thus, respondents might be sensitive to framing (i.e., how questions are asked) and some correct financial literacy answers could be attributable to guessing rather than skill (Lusardi and Mitchell, 2017; Van Rooij et al., 2011b).

Several empirical methodologies address endogeneity and estimate unbiased results. Research dealing with endogeneity concerning financial literacy's influence on financial outcomes typically employ an instrumental variable (IV) approach, which is usually applied with a two-stage least squares (2SLS) model (Klapper, Lusardi, and Panos, 2013; Lyons et al., 2020), or use the lagged values of the endogenous independent variable that measure the independent variable's value at a previous point in time (Blalock, 2017; Chhatwani and Mishra, 2021; Klapper et al., 2012).

2.3. FINANCIAL LITERACY'S INFLUENCE ON FINANCIAL RESILIENCE

As established in Section 2.2.3., ample empirical evidence documents that financially literate individuals are more likely to engage in healthy financial behaviors and achieve better financial outcomes. The findings in Table 5 indicate the various channels through which financial literacy can potentially improve financial resilience, particularly during financial upheaval. Accordingly, a growing body of literature investigates financial literacy's role in enabling individuals to better handle economic shocks, demonstrating that financial literacy is a crucial predictor of financial resilience (Andreou et al., 2023; Chhatwani and Mishra, 2021; Lusardi et al., 2020, among others).

Table 6 summarizes some of the empirical evidence of representative studies examining the relationship between financial literacy and financial resilience by providing details on the analyzed countries, data collection period, applied methodology, and key findings. The overview compilation is limited to studies conducting empirical analyses using quantitative methods and lists them chronologically from their publication date. The remainder of this section focuses on the key findings, similarities, and differences between the studies and emergent research gaps.

Table 6. Overview of empirical studies and their findings on financial literacy's influence on financial resilience

Publication	Data and sample	Methodology	Findings
Lusardi et al. (2011)	*Country:* U.S. *Period and sample size:* 2009; n=1,931	*Method*: Probit regression (probit) *Endogeneity:* n. a.	*Findings:* Financial knowledge positively affects the ability to cope with shocks.
Anderloni et al. (2012)	*Country:* Italy *Period and sample size*: 2009; n=3,102	*Method:* Linear regression (OLS) *Endogeneity:* n. a.	*Findings:* Higher levels of debt servicing and impulsive individuals who are impatient and short-sighted are more likely to be financially fragile. Higher educational and financial literacy levels are positively related to financial resilience.
Klapper et al. (2012); Klapper,	*Country:* Russia *Period and sample size:* 2008-2009; n=2,148	*Method*: Probit (random effects), logistic regression with fixed effects, ordered probit,	*Findings:* During the 2009 financial crisis, increasing financial literacy was linked to a decreased likelihood of adverse income shocks,

Publication	Data and sample	Methodology	Findings
Lusardi, and Panos (2013)		generalized least squares (random and fixed effects *Endogeneity*: Instrumental variable (IV) probit; number of newspapers and universities as instruments; lagged values of the independent variables	greater availability of unspent income, and higher spending capacity.
Babiarz and Robb (2014)	*Country: U.S.* *Period and sample size:* 2009; n=25,765	*Method:* Probit *Endogeneity:* n. a.	*Findings:* Higher objective and subjective financial literacy are positively related to financial resilience.
Bucher-Koenen and Ziegelmeyer (2014)	*Country*: Germany *Period and sample size:* 2009; n=2,012	*Method: P*robit *Endogeneity:* n. a.	*Findings:* Households with lower financial literacy are more likely to realize losses when selling their assets in response to the financial market crisis.
Woodyard et al. (2017)	*Country:* U.S. *Period:* 2012; n=25,509	*Method:* Logit *Endogeneity:* n. a.	*Findings:* Higher levels of both objective and subjective financial literacy are positively related to financial resilience. However, overconfidence results in adverse cash and credit behavior.
Hasler et al. (2018)	*Country:* U.S. *Period and sample size:* 2015*;* n=16,174	*Method:* OLS *Endogeneity:* n. a.	*Findings: F*inancial literacy reduces the likelihood of being financially fragile.
Hasler and Lusardi (2019)	*Country:* U.S. *Period and sample size:* 2015*;* n=16,174	*Method:* OLS *Endogeneity*: n. a.	*Findings:* Family size and debt burden negatively impact financial resilience of middle-income households, while financial literacy positively influences middle-income households' financial resilience.
Wiersma et al. (2020)	*Country:* The Netherlands *Period and sample size:* 2015, 2016; n=1,716	*Method: P*robit and ordered probit *Endogeneity*: n. a.	*Findings:* Higher levels of objective financial literacy, probability numeracy, and those who correctly assess their financial literacy skills are associated with higher financial resilience levels. Those who are overconfident or underconfident are more

Publication	Data and sample	Methodology	Findings
			likely to be financially fragile.
Lyons et al. (2020)	*Country:* Bangladesh, India, Kenya, Nigeria, Pakistan, Tanzania, and Uganda *Period and sample size:* 2017; n=72,858	*Method:* Probit *Endogeneity:* Two-stage least squares (2SLS) IV regression; numeracy and language comprehension as instruments.	*Findings:* Higher financial literacy is linked to more saving; better risk management behaviors, such as having life and health insurance; and better emergency preparedness.
Despard et al. (2020)	*Country:* U.S. *Period and sample size:* 2009 (n=28,146), 2012 (n=25,509), 2015 (n=27,564), 2018 (n=27,091)	*Method:* Probit *Endogeneity*: n. a.	*Findings:* Objective financial literacy has a weaker association with having an emergency fund than identified in prior studies. Subjective financial literacy, financial confidence, and savings account ownership are stronger and more stable predictors of financial resilience.
Lusardi, Mitchell, and Oggero (2020)	*Country:* U.S. *Period and sample size:* 2012, 2015; n=10,706	*Method:* OLS *Endogeneity:* n. a.	*Findings:* Financial literacy is a key factor in enhancing financial resilience.
Clark et al. (2020)	*Country:* U.S. *Period and sample size:* 2020; n=2,889	*Method:* Logit *Endogeneity*: n. a.	*Findings:* The more financially literate are more financially resilient.
Chhatwani and Mishra (2021)	*Country:* U.S. *Period and sample size:* 2018, 2020; n=1,952	*Method:* Logit *Endogeneity:* Lagged values of the independent variable.	*Findings:* The more financially literate are less likely to be financially fragile. The association is moderated by financial confidence and wealth; thus, financially literate individuals with high financial confidence and greater wealth were less financially fragile during COVID-19.
Singh and Malik (2022)	*Country:* India *Period and sample size*: 2018; n=11,234	*Method:* Fractional probit *Endogeneity:* n. a.	*Findings:* Higher financial literacy, better money management skills, and lower impulsivity in financial behavior are negatively associated with financial fragility.
Clark and Mitchell (2022)	*Country:* U.S. *Period and sample size:* 2020-2021; n=2,486	*Method:* OLS, probit *Endogeneity*: n. a.	*Findings:* The more financially literate were less likely to be financially fragile in 2020, though the effect attenuated one year

Publication	Data and sample	Methodology	Findings
			into the pandemic and was insignificant in 2021.
Erdem and Rojahn (2022)	*Country:* France, Germany, Italy, Spain *Period and sample size:* 2017, 2020; n=4,781	*Method:* Logit, partial proportional odds regression, and conditional random forest analysis *Endogeneity:* 2SLS IV regression; language and mathematical skills at the age of ten as instruments; lagged values of the explanatory variable.	*Findings:* Financial literacy increased financial resilience and ranked in the midfield in terms of variable importance during the COVID-19 pandemic.
Bialowolski et al. (2022)	*Country:* Austria, Germany, Sweden, Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, Czechia, Poland *Period and sample size:* 2004–2015; n=13,718 (first analysis), n=12,802 (second analysis)	*Method: M*ultivariate Cox proportional hazards model with time-varying covariates *Endogeneity*: n. a.	*Findings:* Financial literacy plays a protective role for financial resilience. Its role is not symmetrical and protects more against the loss of financial resilience than it contributes to the gain of financial resilience. Among individuals aged 65–74, the association between financial literacy and financial resilience is weaker than among adults in the middle-age (50–64) and among the oldest (75+).
Sconti (2022)	*Country:* Italy *Period and sample size:* 2016; n=1,035	*Method:* OLS, probit and ordered probit *Endogeneity*: n. a.	*Findings:* Financially literate households are more likely to be financially resilient. When an advanced financial literacy measure is applied, the positive effect on financial resilience is stronger than for basic financial literacy.
Nguyen et al. (2022)	*Country:* Vietnam *Period and sample size:* 2021; n=839	*Method:* Bayesian mindsponge framework analytics *Endogeneity*: n. a.	*Findings:* Individuals with better financial literacy and investment skills were less likely to be financially fragile during the peak of the COVID-19 crisis.
Cziriak (2022)	*Country:* Germany *Period and sample size:* 2020-2021; n=1,875	*Method: L*inear probability model and probit *Endogeneity*: n. a.	*Findings:* Financial literacy is associated with lower financial fragility in times of crisis and mitigates the negative consequences of income losses on the ability to cope with emergency expenses.

Publication	**Data and sample**	**Methodology**	**Findings**
Andreou et al. (2023)	*Country:* Cyprus *Period and sample size:* 2021; n=840	*Method:* Logit *Endogeneity*: n. a.	*Findings:* Being financially literate, educated in economic matters, and alert to recent financial and economic trends lessens the probability of being financially fragile.
Angrisani et al. (2023)	*Country:* U.S. *Period and sample size:* 2012, 2018; n=1,197	*Method:* OLS *Endogeneity*: n. a.	*Findings:* Financial literacy positively influences financial resilience, satisfaction with one's own financial situation, and planning for retirement.
Hamid, Loke, and Chin (2023)	*Country:* Malaysia *Period and sample size:* 2018; n=3,395	*Method:* Ordered logit *Endogeneity*: n. a.	*Findings:* Greater financial literacy and financial inclusion (i.e., having more bank accounts and holding more financial products) are associated with the probability of being financially resilient.
Hasler et al. (2023)	*Country:* U.S. *Period and sample size:* 2021; n=3,035	*Method:* Weighted linear regression *Endogeneity*: n. a.	*Findings:* The more financially literate are more likely to be financially resilient, plan for retirement, and feel unconstrained by debt.
Lusardi et al. (2020); Lusardi, Oggero, and Yakoboski (2017); Yakoboski, Lusardi, and Hasler (2018), (2019), (2020a); Yakoboski et al. (2020b), (2021), (2022), (2023)	*Country:* U.S. *Period and sample size:* 2016 (n=1,043), 2018 (n=1,012), 2019 (n=1,008), 2020 (n=1,008), 2021 (n=3,035), 2022 (n=3,582), 2023 (n=3,503)	*Method:* OLS *Endogeneity*: n. a.	*Findings:* The more financially literate are less likely to be financially fragile, more likely to have precautionary savings, more likely to save and plan for retirement, more likely to have non-retirement financial investments, more likely to be current on credit card and loan payments, and less likely to be debt constrained.

Note. This table provides an overview of important research contributions in the area of financial literacy and financial resilience.

[Source: Own representation]

Regarding the analyzed period, Lusardi et al. (2011) were among the first to examine financial literacy's influence on households' ability to cope with shocks. Although several researchers have investigated financial literacy and its implications on financial resilience thereafter, scholarly work in this domain during times of crises is still limited. Bucher-Koenen and Ziegelmeyer (2014), Klapper et al. (2012, 2013), and Lusardi et al. (2011) are among the few to document how financial literacy mitigated adverse financial consequences for households in the 2007/2008 financial crisis' aftermath, based on data collected during the crisis. Similarly, research based on datasets obtained in the early stages of or during the COVID-19 pandemic is still limited in scope, though it is gradually increasing. Chhatwani and Mishra (2021), Clark et al. (2020), Clark and Mitchell (2022), Hasler et al. (2023), and Yakoboski et al. (2020a, 2020b, 2021, 2022, 2023) investigate financial literacy's impact on financial resilience during COVID-19 in the U.S. context, while Andreou et al. (2023), Cziriak (2022), and Erdem and Rojahn (2022) are among the few to do so in the European context.

As Table 6 does not purport to provide a complete overview of financial literacy and financial resilience research, a comparison across various countries wherein empirical analyses have been conducted relies on the specific studies chosen for inclusion. However, such studies tend to focus predominantly on the U.S. (Angrisani et al., 2023; Babiarz and Robb, 2014; Chhatwani and Mishra, 2021; Clark et al., 2020; Clark and Mitchell, 2022; Despard et al., 2020; Hasler and Lusardi, 2019; Hasler et al., 2018, 2023; Lusardi et al., 2011, 2017, 2020; Woodyard et al., 2017; Yakoboski et al., 2018, 2019, 2020a, 2020b, 2021, 2022, 2023).

Few studies have analyzed European countries, such as Italy (Anderloni et al., 2012), Germany (Bucher-Koenen and Ziegelmeyer, 2014), and the Netherlands (Wiersma et al., 2020). However, only since 2022 has there been a growing body of research focusing on European countries, such as those conducted by Andreou et al. (2023), Cziriak (2022), and Sconti (2022). Nevertheless, cross-country analyses in Europe are rather limited, with Bialowolski et al. (2022) and Erdem and Rojahn (2022), to the best of the author's knowledge, being the only authors to recently empirically analyze financial literacy's influence on financial resilience across European countries.

Regarding applied empirical methodology, most studies use either multivariate probit or logit regression. Others apply multiple linear regression (OLS), arguing that although financial literacy is a choice variable, wherein case linear regression results may be misstated, OLS estimates provide a lower bound on financial literacy's full effect (Lusardi et al., 2020).

Few studies combine several methods and expand their quantitative analysis beyond the traditional logit or probit regression via random and fixed effects probit, random and fixed effects generalized least squares, ordered probit, or ordered logit (Erdem and Rojahn, 2022; Klapper et al., 2012, 2013; Sconti, 2022). In this context, machine learning techniques complement traditional regression models, as they are superior in variable importance determination (Levantesi and Zacchia, 2021). However, studies employing machine learning methods to examine the relationship between financial literacy and financial resilience are scarce. In this context, Erdem and Rojahn (2022) are the first to extend their empirical methodology with a tree-based machine learning method via a conditional random forest analysis, while Nguyen et al. (2022) are among the first to implement a Bayesian mindsponge framework analysis, which is a combination of the mindsponge mechanism and Bayesian inference. Thus, scope exists for further exploration and application of machine learning methods in explaining financial resilience.

Furthermore, only some studies consider the potential influence of endogeneity on the regression outcomes by employing either an instrumental variable (IV) regression via a two-stage least squares (2SLS) model or using time-lagged values of the independent variable (Chhatwani and Mishra, 2021; Erdem and Rojahn, 2022; Klapper et al., 2012, 2013; Lyons et al., 2020). However, like in the case of Clark et al. (2020), some scholars do not account for endogeneity but recognize that financial literacy can be endogenous and advise that their results represent a lower bound of financial literacy's effects on financial resilience and should be interpreted cautiously.

Regarding the empirical findings, the studies persistently disclose a positive relationship between financial literacy and financial resilience. For example, the P-Fin Index, which is an annual barometer of financial literacy and indicator of financial well-being (i.e., financial resilience) that has been used from 2017 until now, continuously finds that more financially literate individuals are less likely to be financially fragile (Lusardi et al., 2017; Yakoboski et al., 2018, 2019, 2020b, 2021, 2022, 2023).

However, the literature review raises questions regarding the strength and determinants of the relationship between financial literacy and financial resilience. Clark and Mitchell (2022) reveal that those who are more financially literate were less likely to be financially fragile in 2020. However, the effect attenuated one year into the pandemic and was insignificant in 2021, suggesting that the relationship between financial literacy and financial resilience may vary over time and may be influenced by changing economic conditions and external factors. Similarly, Erdem and Rojahn (2022) disclose that during the COVID-19 pandemic, financial literacy increased financial resilience but rather ranks in the midfield in terms of variable importance. In this context, Bialowolski et al. (2022) find that the association between financial literacy and financial resilience among individuals aged 65–74 is weaker than among adults in middle age (50–64) and the oldest (75+). Furthermore, Despard et al. (2020) discover that objective financial literacy has a weaker association with being financially resilient than identified in prior studies and that subjective financial literacy is a robust and more stable predictor of financial resilience.

2.4. DEVELOPMENT OF RESEARCH QUESTIONS AND HYPOTHESES

In an environment of financial stress, such as the COVID-19 pandemic, the challenge of making sound financial decisions and being financially resilient is amplified (Yakoboski et al., 2023). The findings from Table 5 and Table 6 demonstrate that financial literacy is a driver of sound financial behavior and fosters financial resilience, illustrating that financial literacy is relevant at the global level and affects all countries and economies, irrespective of the level of economic development (Lusardi and Messy, 2023). It is not that increased financial literacy in itself is a cure for poor financial resilience. Resources, such as income, matter, as do access and opportunity in the financial system. However, the ability to make sound financial decisions also matters, especially during challenging times, such as the recently experienced COVID-19 pandemic, which required individuals to grasp both short- and long-term consequences and react accordingly (Yakoboski et al., 2023). Consequently, quantifying the variable importance of financial literacy in predicting financial resilience is essential.

Table 6 indicates that empirical research investigating financial literacy's influence on financial resilience is predominantly performed in the U.S. and has been rather limited in Europe. Furthermore, analyses based on datasets obtained during the COVID-19 pandemic are limited in scope.

Moreover, most empirical studies dealing with financial literacy's influence on financial resilience depend on a single classification technique, such as via logit or probit models. Furthermore, endogeneity concerns are not sufficiently addressed in extant research analyzing financial literacy's influence on financial resilience, though empirical evidence documents endogeneity bias in studies investigating the connections between measured financial literacy and financial behavior, as discussed in Section 2.2.4, and advise that if not appropriately controlled for, estimates should be considered with caution.

Further, recent research findings reveal mixed evidence on the strength of financial literacy's relationship with financial resilience.

This thesis aims to address the research gaps identified above using data from seven European countries collected in 2020 to (i) determine financial literacy's impact on financial resilience and (ii) assess financial literacy's variable importance in explaining financial resilience. Multiple classification techniques, including logistic regression, multinomial logistic regression, partial proportional odds regression, and conditional random forest analysis, are applied while controlling for endogeneity via an instrumental variable regression to provide novel empirical evidence on financial literacy's relationship with financial resilience and the variable importance of financial literacy in explaining financial resilience, during periods of crisis. Thus, the following two hypotheses are proposed:

H1: The probability of being financially resilient increased with an individual's financial literacy level during the COVID-19 pandemic in European households.

H2: Financial literacy was an important predictor of financial resilience during the COVID-19 pandemic in European households.

Global financial resilience and financial literacy levels, as presented in Table 1 and Table 4, respectively, and recent studies document major differences within European countries (Demertzis et al., 2020; Demirgüç-Kunt et al., 2022; Mcknight and Rucci, 2020; S&P, 2014), suggesting heterogeneity in financial literacy's influence on financial resilience across European countries.

By conducting empirical analyses at the country level and comparing the strength of the association between financial literacy and financial resilience among Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain, this study aims to provide novel insights into potential variations within the European context regarding financial literacy's influence and importance on financial resilience. Consequently, the third and fourth hypotheses are as follows:

H3: The impact of an individual's financial literacy level on their probability of being financially resilient during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

H4: The importance of financial literacy in explaining financial resilience during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

III – EMPIRICAL ANALYSIS

III - EMPIRICAL ANALYSIS

3.1 SAMPLE AND DATA

3.1.1. Sample selection

The analysis of financial literacy's influence on financial resilience in Europe conducted in this thesis covers the years 2017 and 2020, encompassing the COVID-19 crisis' outbreak, which occurred in 2020. The data are obtained from SHARE, a cross-national panel study that has gathered data from up to 140,000 individuals aged 50 and older across 27 European countries and Israel. SHARE covers a wide range of topics related to the well-being of older adults, encompassing socioeconomic factors and physical and mental health conditions. The SHARE COVID-19 survey was introduced during SHARE's eighth wave of data collection in 2020. Due to the COVID-19 pandemic, fieldwork had to be suspended in all participating countries. To resume data collection, SHARE transitioned to interviews administered via telephone and created a reduced questionnaire, the COVID-19 survey, that did not include all the questions from previous SHARE waves but focused on gathering data related to the health and socioeconomic impact of COVID-19 on European individuals aged 50 and older (Scherpenzeel et al., 2020). It also assessed their financial resilience since the outbreak of the COVID-19 pandemic. SHARE's Wave 7 took place in 2017 and was released in April 2019. In contrast, the SHARE COVID-19 survey was conducted in June 2020 and released in December 2020.

Hence, data collected in 2020 from the SHARE COVID-19 survey is used for the dependent variable, while the data for the independent variable and most control variables originate from 2017. This is because these variables are either not obtainable in the SHARE COVID-19 survey or are highly improbable to have experienced significant changes over time (e.g., educational level). Each variable is marked with an index indicating the data collection period, where t-1 (t) corresponds to data gathered from Wave 7 (SHARE COVID-19 survey).

The analysis focuses on the individual-level data obtained from respondents residing in the eurozone countries covered by SHARE. By examining respondents from eurozone economies, macroeconomic factors, such as interest rates or exchange rates, which may influence the economic impact of COVID-19 and, consequently, individual financial resilience, can be controlled for. Furthermore, European governments focused on mitigating the COVID-19 pandemic's economic impact by providing financial assistance to businesses and employees, such as wage subsidies and tax payment deferrals (Bergsen et al., 2020). Additionally, the European Central Bank (ECB) injected liquidity into the financial system and introduced a €750 billion recovery fund comprising of grants and loans to support governments (Bergsen, 2020; Camous and Claeys, 2020).

However, differences in demographics, economic structure, and political stability among the countries in the eurozone have contributed to differences in the COVID-19 virus' spread. Likewise, the type and effectiveness of government support measures have differed across the eurozone countries. Hence, COVID-19 has had unequal impacts across Europe, resulting in asymmetric effects (Bergsen, 2020; Bergsen et al., 2020). These varying impacts and other factors like pension systems and cultural differences underscore the need to account for country-specific effects. To address this, in alignment with prior research on the influence of financial literacy in an international context (Thomas and Spataro, 2018), country dummy variables are introduced to capture the effects at the country level.

Table 7 details the sample selection process, which comprises 36,179 individuals from eurozone countries who were participants of the initial Wave 7 and were re-interviewed in the SHARE COVID-19 survey. In the first step, owing to the incomplete data for the dependent variable, the proxy for financial resilience, 11,650 observations are excluded from the sample size. In the second step, incomplete or missing data on the dependent variable, financial literacy, and additional control variables led to the removal of 13,358 observations. Finally, in a third step, 707 observations belonging to the countries Greece, Luxembourg, and Portugal were omitted from the sample to prevent over-specification by introducing country dummy variables for countries with insufficient observations on the dependent variable's individual outcome categories (Peduzzi, Concato, Kemper, Holford, and Feinstein, 1996). Details regarding the determination of the minimum number of observations per outcome category are provided in Section

4.1.1. Overall, these modifications led to a final sample size of n=10,464 comprising respondents from the seven eurozone countries Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

Table 7. Sample selection process

COVID-19 survey and Wave 7	Observations	% of baseline sample
Initial eurozone sample:	36,179	100.00%
less missing data on explanatory variable	-11,650	-32.20%
less missing data on dependent and control variables	-13,358	-36.92%
less countries with insufficient sample size for regression:	-707	-1.95%
Greece (n=389)		
Lux (n=264)		
Portugal (n=54)		
Final sample	10,464	28.92%
Thereof allocable to the following countries:		
Belgium	2,034	19.44%
Estonia	2,254	21.54%
France	1,113	10.64%
Germany	1,433	13.69%
Italy	1,600	15.29%
Slovenia	1,396	13.34%
Spain	634	6.06%

Note. This table provides an overview of the sample selection process and the final sample portioned by the countries.

[Source: Own representation]

3.1.2. Dependent variable

To capture respondents' financial resilience (FR_t), the following question from the SHARE COVID-19 survey is used: "Thinking of your household's total monthly income since the outbreak of COVID-19, would you say that your household is able to make ends meet with: 1) great difficulty, 2) some difficulty, 3) fairly easily, or 4) easily?" Respondents who answer with "Easily" or "Fairly easily" ("With great difficulty" or "With some difficulty"), are categorized as financially resilient (fragile). In line with prior research, the financial resilience variable is coded binary (Demertzis et al., 2020; Lusardi et al., 2011, 2020; Sconti, 2022, among others). Consequently, the dependent variable is assigned a value of one for financially resilient individuals and zero otherwise. Table 8 summarizes the descriptive statistics for the dependent variable. In the sample, 71% of the respondents were financially resilient, with a standard deviation of 0.46.

Table 8. Descriptive statistics of the dependent variable

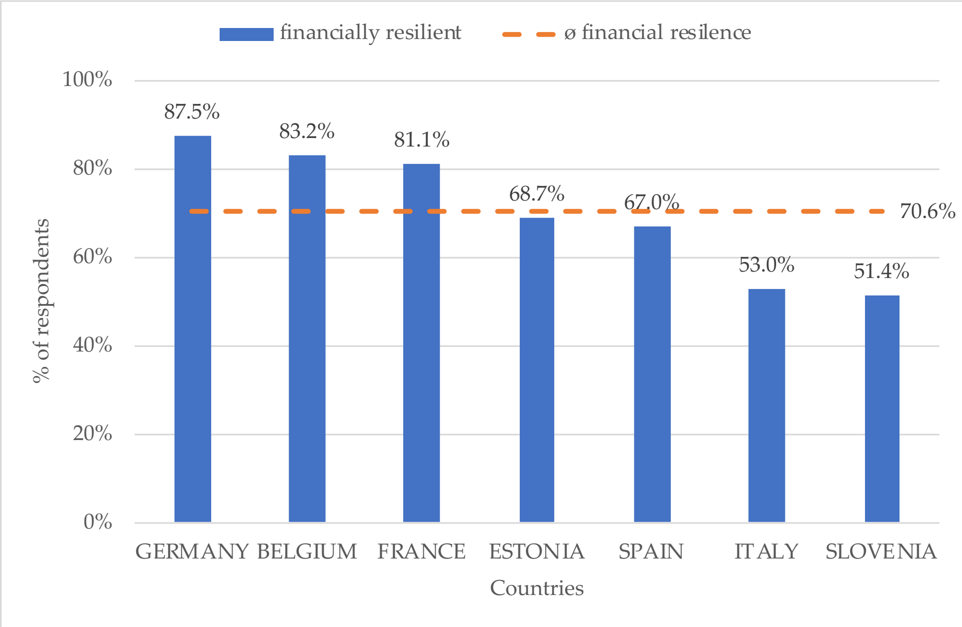
Dependent variable	Mean	Median	Std. dev.	Min.	Max.
FR_t	0.7060	1	0.4556	0	1

Note. This table displays the descriptive statistics for the dependent variable.

[Source: Own representation]

When the respondents' financial resilience is broken down at the country level, distinct disparities emerge (Figure 5). Respondents from Belgium (83%), France (81%), and Germany (88%) are the least financially fragile. This is followed by Estonia (69%) and Spain (67%), whose individuals are in the average position being close to the total sample mean of 71%. Italy (53%) and Slovenia (51%) display the lowest financial resilience levels, with nearly half of respondents being financially fragile. This aligns with studies conducted prior to the COVID-19 pandemic, with the least financially fragile households originating from Benelux, the Nordic countries, Germany, and France, and decreasing financial resilience levels for Southern and Eastern European countries (Demertzis et al., 2020; Mcknight and Rucci, 2020).

Figure 5. Financial resilience at the country level



Note. This figure provides an overview of the financial resilience levels for the country samples. [Source: Own representation]

3.1.3. Explanatory variable

In line with prior studies (Jappelli and Padula, 2013; Thomas and Spataro, 2018), respondents' financial literacy (FL_{t-1}) is measured using the indicator provided by SHARE's Wave 7. Details regarding the four questions used to create the financial literacy index are outlined in APPENDIX 3. The responses are combined into a summary indicator that spans from zero to five, with higher values indicating greater financial literacy levels. To evaluate the internal consistency of the financial literacy score, Cronbach's alpha is calculated using the responses to the four questions, assigning a value of one for a correct response and zero otherwise. An alpha value of 0.73 demonstrates an acceptable level of consistency among the items (Streiner, 2003). Table 9 summarizes the descriptive statistics for the explanatory variable. The mean financial literacy score in the sample is 3.42, with a median of 3.00 and a standard deviation of 1.03.

Table 9. Descriptive statistics of the explanatory variable

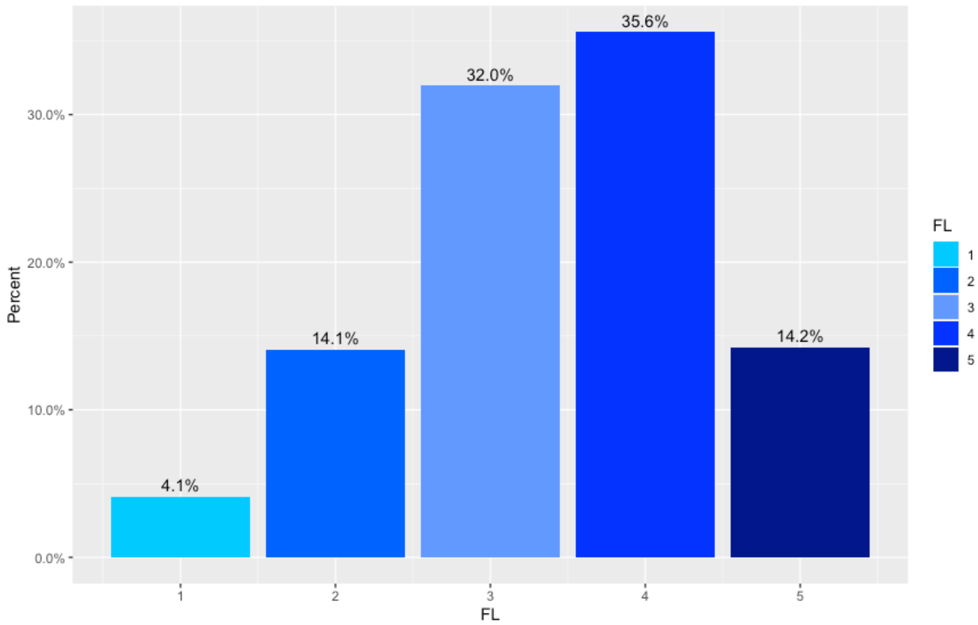
Explanatory variable	Mean	Median	Std. dev.	Min.	Max.
FL_{t-1}	3.4175	3	1.0284	1	5

Note. This table displays the descriptive statistics for the explanatory variable.

[Source: Own representation]

As presented in Figure 6, which illustrates the samples' financial literacy apportioned by the respective scores, most respondents have a financial literacy score of three (32%) and four (36%). Respondents are considered financially literate when they correctly reply to at least three of the four questions (i.e., have a financial literacy score greater than or equal to four) (Klapper and Lusardi, 2020). Hence, half of the respondents (50%) achieved this threshold. By contrast, 4% of the individuals could not answer any of the four financial literacy questions correctly, while 14% of the respondents could answer only one question correctly.

Figure 6. Total sample's financial literacy apportioned by score

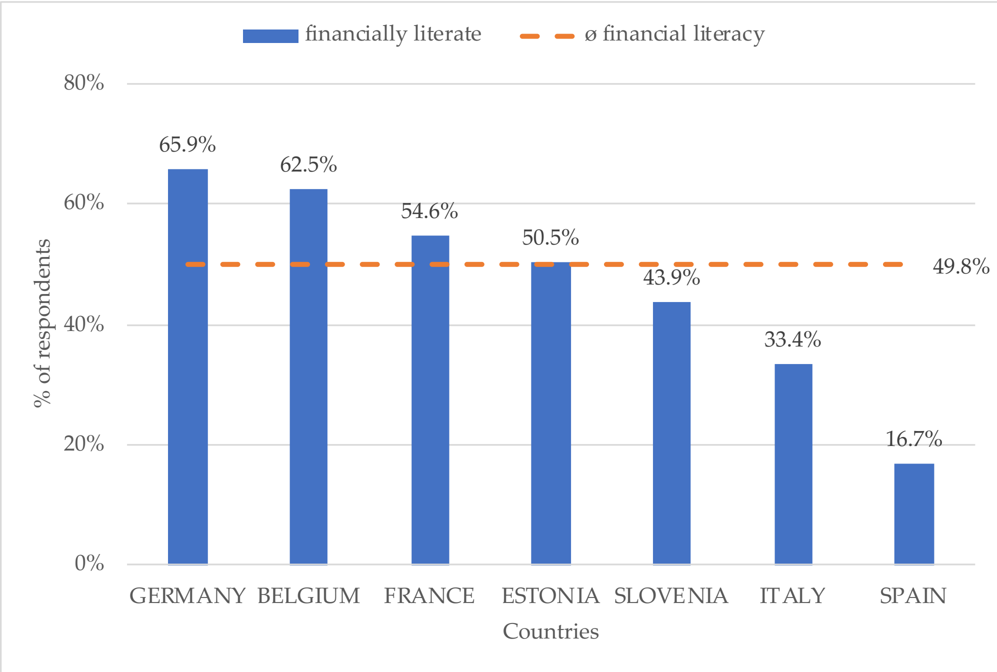


Note. This figure provides an overview of the financial literacy scores of the total sample.

[Source: Own representation]

Notable differences in financial literacy scores emerge at the country level (Figure 7). Germany and Belgium have the most financially literate individuals in the sample, with 66% and 63%, respectively, while in France (55%) and Estonia (51%), half of the respondents are financially literate. In Slovenia and Italy, 44% and 33% of respondents are financially literate. Finally, Spain ranks last, with merely 17% of respondents being financially literate.

Figure 7. Financial literacy at the country level



Note. This figure provides an overview of the financial literacy levels for the country samples. [Source: Own representation]

3.1.4. Control variables

To analyze financial literacy's influence on financial resilience and determine the drivers of financial resilience, a set of control variables, the selection of which is based on previous research as elaborated in Section 2.1.3., is included and described in detail in the following:

- AGE_{t-1} represents the age of the respondent during the interview.
- CH_{t-1} quantifies the respondents' number of children.
- $EDU\text{-}MED_{t-1}$ and $EDU\text{-}HIGH_{t-1}$ capture the individual's educational level. Following Bucher-Koenen and Lusardi (2011) and Fornero and Monticone (2011), the individual's highest school certificate or degree based on the International Standard Classification of Education (ISCED) is considered. The United Nations Education, Scientific, and Cultural Organization (UNESCO) has developed ISCED levels to enable comparisons across nations (UNESCO, 2012). The educational level in the sample is categorized into low, medium, and high education groups. Thereafter, two dummy variables are created to represent respondents with medium education ($EDU\text{-}MED_{t-1}$) and high education ($EDU\text{-}HIGH_{t-1}$), while low education is the reference category. $EDU\text{-}MED_{t-1}$ denotes individuals with at least upper secondary education, while $EDU\text{-}HIGH_{t-1}$ represents those with education at the first stage of tertiary level, and zero otherwise.
- $EMPL_t$ is a dummy variable denoted by one if, during the SHARE COVID-19 survey, the respondent was employed and zero otherwise. The employment status of individuals is determined based on the SHARE COVID-19 survey to consider the COVID-19 pandemic's potential effects.
- $FEMALE_{t-1}$ is a dummy variable denoted by one or zero if the respondent is a woman or man, respectively.
- $IN\text{-}MED_t$ and $IN\text{-}HIGH_t$ represent the monthly relative income level of the individual's household after accounting for taxes and contributions. This household income is grouped into terciles within each country. $IN\text{-}MED_t$ ($IN\text{-}HIGH_t$) corresponds to observations classified into the second (third) tercile of the individual's domicile and zero otherwise. The data used to construct $IN\text{-}MED_t$ and $IN\text{-}HIGH_t$ are from SHARE's COVID-19 survey to capture potential recent changes owing to the impact of the COVID-19 shock.

- P-FIH$_{t-1}$ states the years of experienced financial hardship of a respondent.
- PLAN$_{t-1}$ represents the preferred period for saving or spending planning. This score ranges from one to five and increases with a longer time horizon.
- RET$_{t-1}$ provides information about respondents' retirement status and is denoted by one if the respondent is retired and zero otherwise.
- BELGIUM$_{t-1}$, ESTONIA$_{t-1}$, FRANCE$_{t-1}$, GERMANY$_{t-1}$, SLOVENIA$_{t-1}$, and SPAIN$_{t-1}$ are dummy variables that account for country-specific factors, while observations from Italy serve as the reference category. Italy is selected as the reference category for two reasons. First, Italy is a negative outlier among highly developed economies considering adults' level of financial competencies (Di Salvatore, Franceschi, Neri, and Zanichelli, 2018; Klapper et al., 2017; Levantesi and Zacchia, 2021). Moreover, this aligns with the data used in this thesis, wherein, together with Spain, respondents from Italy have considerably low financial literacy levels. Second, Italy became the initial European epicenter of the coronavirus during the pandemic (O'Donnell, Shannon, and Sheehan, 2021), as it was hit particularly early and hard by the crisis, compared to other European countries (Bergsen et al., 2020). Thus, owing to the survey period and the low financial proficiency level in Italy, positive coefficients for the dummy variables ESTONIA$_{t-1}$, BELGIUM$_{t-1}$, FRANCE$_{t-1}$, and GERMANY$_{t-1}$ can be expected.

Table 10 provides the descriptive statistics for the control variables used in this empirical analysis. The average age of a respondent (AGE$_{t-1}$) in the sample is 70 years and ranges from 50 to 101 years. On average, the number of children (CH$_{t-1}$) a respondent has is two and varies from zero to thirteen. Regarding the educational level in the sample, 40% of the individuals have a medium educational level (EDU-MED$_{t-1}$), and 26% have a high educational level (EDU-HIGH$_{t-1}$). At the time of the COVID-19 outbreak, 19% of respondents were employed or self-employed (EMPL$_{t}$). The sample comprises 62% women (FEMALE$_{t-1}$). Respondents' overall monthly household income before the pandemic comprised 39% medium income (IN-MED$_{t}$) and 29% high income (IN-HIGH$_{t}$).

Table 10. Summary statistics of the control variables

Variable	Mean	Median	Std. dev.	Min.	Max.
Individual-level variables					
AGE_{t-1}	70.4543	70	9.4877	50	101
CH_{t-1}	2.0497	2	1.2966	0	13
$EDU\text{-}MED_{t-1}$	0.3962	0	0.4891	0	1
$EDU\text{-}HIGH_{t-1}$	0.2550	0	0.4359	0	1
$EMPL_{t}$	0.1892	0	0.3917	0	1
$FEMALE_{t-1}$	0.6238	1	0.4845	0	1
$IN\text{-}MED_{t}$	0.3895	0	0.4877	0	1
$IN\text{-}HIGH_{t}$	0.2909	0	0.4542	0	1
$P\text{-}FIH_{t-1}$	3.0869	0	7.8361	0	92
$PLAN_{t-1}$	2.1341	2	1.1927	1	5
RET_{t-1}	0.5545	1	0.4970	0	1
Country-level variables					
$BELGIUM_{t-1}$	0.1944	0	0.3957	0	1
$ESTONIA_{t-1}$	0.2154	0	0.4111	0	1
$FRANCE_{t-1}$	0.1064	0	0.3083	0	1
$GERMANY_{t-1}$	0.1369	0	0.3438	0	1
$SLOVENIA_{t-1}$	0.1334	0	0.3400	0	1
$SPAIN_{t-1}$	0.0606	0	0.2386	0	1

Note. This table presents summary statistics for the variables utilized in the regression, as outlined in Eq. (1) and Eq. (2). Definitions for all variables can be found in APPENDIX 4. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey).

[Source: Own representation]

The average duration of financial hardship ($P\text{-}FIH_{t-1}$) experienced by respondents is three years, spanning from zero to ninety-two years. The preferred period when planning on saving and spending ($PLAN_{t-1}$) ranges from one to five and has a mean of 2.13. Hence, on average, the respondents in the sample favor a short-term over a long-term oriented planning horizon. With 55%, more than half of the respondents in the sample are retired (RET_{t-1}). The sample provides 19% data from Belgium ($BELGIUM_{t-1}$), 22% from Estonia ($ESTONIA_{t-1}$), 11% from France ($FRANCE_{t-1}$), 14% from Germany ($GERMANY_{t-1}$), 13% from Slovenia

($SLOVENIA_{t-1}$), and 6% from Spain ($SPAIN_{t-1}$). Italy, the reference category, is represented by 15% of the sample (not presented in Table 10).

The analyses are performed to test for the hypotheses established in Section 2.4. while controlling for variables as detailed above. $FR_{ti,t}$ is modeled as a function of financial literacy and the control variables and can be summarized for the total sample and samples at the country level by the model given in Equation 1 and Equation 2, respectively:

Equation 1. Model for the total sample

$$\begin{aligned} FR_{i,t} = f(&FL_{i,t-1}, AGE_{i,t-1}, CH_{i,t-1}, EDU\text{-}MED_{i,t-1}, EDU\text{-}HIGH_{i,t-1}, \\ &EMPL_{i,t}, FEMALE_{i,t-1}, IN\text{-}MED_{i,t}, IN\text{-}HIGH_{i,t}, P\text{-}FIH_{i,t-1}, PLAN_{i,t-1}, \\ &RET_{i,t-1}, BELGIUM_{i,t-1}, ESTONIA_{i,t-1}, FRANCE_{i,t-1}, GERMANY_{i,t-1}, \\ &SLOVENIA_{i,t-1}, SPAIN_{i,t-1}). \end{aligned}$$

Equation 2. Model for the country-level sample

$$\begin{aligned} FR_{i,t} = f(&FL_{i,t-1}, AGE_{i,t-1}, CH_{i,t-1}, EDU\text{-}MED_{i,t-1}, EDU\text{-}HIGH_{i,t-1}, \\ &EMPL_{i,t}, FEMALE_{i,t-1}, IN\text{-}MED_{i,t}, IN\text{-}HIGH_{i,t}, P\text{-}FIH_{i,t-1}, PLAN_{i,t-1}, \\ &RET_{i,t-1}). \end{aligned}$$

3.2. RESEARCH METHODOLOGY

3.2.1. Variable importance

The variable importance of the selected predictor variables is assessed to analyze financial literacy's influence on financial resilience and quantify the importance of various features in predicting financial resilience. Variable importance assesses an independent variable's contribution in predicting a dependent variable relative to other independent variables. Hence, the variable importance assesses the extent to which features contribute to improving the population-level predictive power of the best possible outcome predictor based on all available features (Williamson, Gilbert, Carone, and Simon, 2021). This is also referred to as independent variable relative importance (Grömping, 2007; Johnson and LeBreton, 2004).

Depending on whether the analysis is predictive or explanatory, different methods can be used to obtain variable importance (Coleman, 2022; Gehrke, 2019). The identification of variables sufficient for an effective prediction of the response variable, as is this thesis' aim, is optimally served by a conditional perspective, while the determination of variable importance for explanatory purposes is better provided by the marginal perspective (Grömping, 2015).

However, depending on the applied technique, variable importance may vary (Bolón-Canedo et al., 2013; Dietterich, 1998; Luebke and Rojahn, 2016; Williamson et al., 2021). Therefore, this thesis employs different classification techniques to analyze feature importance in explaining financial resilience. As the dependent variable, FR_t is binary coded, this thesis follows the literature outlined in Section 2.3 and applies a traditional logistic regression. Although most studies in Table 6 use probit regression instead, their results differ only slightly from logistic regressions (Gehrke, 2019). Details regarding the logistic regression analysis are provided in Section 3.2.2. To ensure that the findings are not biased due to endogeneity, an instrumental variable approach is used, which is described in detail in Section 3.2.3.

To assess the findings' robustness, three alternative methods, defined as robustness checks, are employed (see Section 3.2.4). The first robustness check allows for a different definition of financial resilience and is a multinomial logistic regression, followed by a partial proportional odds regression, which serves as a second robustness check. Finally, a conditional random forest model is employed as a third robustness check.

All analyses are performed on the total sample size and on samples at the country level to examine whether variable importance in determining financial resilience varies within countries. The empirical analyses are performed with the open-source statistical software "R" (R Core Team, 2023).

3.2.2. Logistic regression

Considering the binary nature of the dependent variable $FR_{t,}$ the predictive analysis begins with a conventional logistic regression model, where all predictor variables are used simultaneously in estimation and prediction. The regression coefficients, which are estimated by the maximum likelihood method, measure the partial contribution of each independent variable to changes in the dependent variable. They are interpreted as odds ratios and are associated with the reference group (Gehrke, 2022). As the odds ratio per se is difficult to interpret and no direct interpretation of the coefficients is possible, except for the coefficient signs, the marginal effect of a variable is used. The average marginal effect (AME) reflects the impact of a one-unit change in an independent variable on the dependent variable, holding all other variables constant (Best and Wolf, 2012; Gehrke, 2022).

Various metrics can be employed when considering variable importance measures in logistic regression, including the absolute value of the z-statistic, the p-value, or standardized coefficients. The assessment of variable importance using the standardized coefficient metric can be subject to controversy. Some researchers argue that the utilization of the standardized coefficient, which involves division by the regressor variance, does not adequately represent the influence on response variability since it introduces an artificial element (Bring, 1996; Grömping, 2015). Using p-values as a selection criterion is standard practice as they measure the precision with which a regressor's coefficient is estimated. The z-statistic is calculated by dividing the coefficient of the independent variable by its standard deviation. Consequently, each variable is considered conditionally on all other variables in the model in the z-statistic, and a large absolute z-value, determined as a ranking within the model, signifies evidence against the null hypothesis (Gehrke, 2022; Grömping, 2015; James, Witten, Hastie, and Tibshirani, 2013). For the logistic regression, the absolute value of the z-statistic is used to assess variable importance.

Logistic regression is subject to several application requirements that are reviewed first to ensure that the regression coefficients, z-values, standard errors, and significance levels are reported correctly. In addition to sufficient sample size, logistic regression is subject to influential observations, nonlinear correlation, and multicollinearity, which can be tested through regression diagnostics (Field, Miles, and Field, 2012; Gehrke, 2022; Hosmer, Lemeshow, and Sturdivant, 2013; Menard, 2010). A description of the respective test procedures is detailed below:

- *Sample size.* To enable reliable maximum likelihood estimation, the individual outcome categories of the dependent variable must be represented in the sample to a sufficient extent, as multivariable analyses can produce problematic results if excessively few outcome events are available relative to the number of independent variables used in the model. Specifically, the regression coefficients' accuracy and precision are of concern, resulting in misleading associations. Therefore, general guidelines have been proposed for the minimum number of events per variable (EPV) required in multivariate analysis (Gehrke, 2022; Hosmer et al., 2013; Peduzzi et al., 1996). Numerous approaches to determine the necessary EPV conclude the rule of thumb that for each parameter of the regression, there should be a minimum of ten observations per category of the dependent variable (Gehrke, 2022; Hosmer et al., 2013; Moons et al., 2014; Pavlou, Ambler, Seaman, De Iorio, and Omar, 2016; Peduzzi et al., 1996, among others).
- *Outliers.* Influential observations that significantly impact the parameter estimates are considered outliers. They can be identified by a visual check of the "Residuals versus Leverage" plot, with leverage referring to the extent to which the coefficients in the regression model would change if a particular observation is removed from the dataset and residuals denoting the standardized difference between a predicted and actual value of the observation; as potential outliers stand apart from the other observations (Gehrke, 2022). Furthermore, outliers can be recognized if their absolute standardized residuals are greater than three (Pardoe, 2020; Yan and Su,

2009) or if their Cook's distance has any value above one (Field, 2013; Heiberger and Holland, 2015).

- *Linearity assumption*. Logistic regression assumes a linear relationship between the continuous predictor variables and the logit of the outcome variable. This can be assessed by visually inspecting the scatter plot between each metric predictor and the logit values (Gehrke, 2022). Another approach to detect a possible nonlinear relationship is the Box-Tidwell transformation (Box and Tidwell, 1962; Fox, 2015), which adds a term in the form of $x \times \ln(x)$ to the model, where x equates to the metric predictor variables. The null hypothesis states that the coefficient for this term is zero. Hence, when rejected, this identifies a nonlinear relationship between the logit of the outcome variable and the respective predictor (Gehrke, 2022). As suggested by Tabachnick and Fidell (2018), the p-values of the Box-Tidwell transformation are adjusted using the Bonferroni correction. Hence, the underlying alpha level is determined by dividing 0.05 by the sum of the predictors in the model and a constant.
- *Multicollinearity*. Multicollinearity arises when a linear intercorrelation exists between explanatory variables within a multiple regression model. In the presence of multicollinearity, the estimates are less precise and the standard errors of the regression coefficients are biased because they are highly correlated. The occurrence of multicollinearity is tested via the calculation of generalized variance inflation factors (GVIFs) because the explanatory variables used in this thesis are scaled differently. To ensure the comparability of GVIF values across dimensions, they are fitted by GVIF^(1/(2*Df)), as recommended by Fox and Monette (1992), where Df is the number of degrees of freedom. For GVIFs exceeding a value of two, multicollinearity is likely to be present (Pebsworth, MacIntosh, Morgan, and Huffman, 2012; Vega, Koike, and Suzuki, 2010).

3.2.3. Mitigating endogeneity

As specified in Section 2.2.4., research regarding the influence of financial literacy on financial resilience has predominantly relied on non-experimental data, and under such circumstances, endogeneity concerns can emerge. Thus, identifying a positive impact of financial literacy on financial resilience might originate from reverse causality, i.e., individuals who face financial challenges may seek resources and education to better understand their finances, which, in turn, enhances their financial literacy levels. Furthermore, financial literacy is likely to be endogenous owing to omitted variables that affect both financial literacy and financial resilience (Bucher-Koenen and Lusardi, 2011). Consequently, the logit coefficients would be biased and inconsistent in the presence of endogenous variables.

To account for the endogeneity concern, this thesis employs an instrumental variable regression that is widely used when examining financial literacy's effect on financial behavior (e.g., Bucher-Koenen and Lusardi, 2011; Grohmann, 2018; Stolper and Walter, 2017).

The instrumental variable approach is based on including instrumental variables in the regression and is usually applied with a two-stage least squares (2SLS) model. The 2SLS estimation eliminates the portion of the variance in the independent variable that is correlated with the error term. In the first stage, a linear probability model of the endogenous variable correlating with the residuals is performed on the instruments and all other control variables. In the second stage, the predicted values from the first regression are used to predict the dependent variable. Consequently, the independent variable's variance, which does not correlate with the error term, is used to predict the dependent variable (Gehrke, 2022; Hackl, 2008).

This thesis employs Newey's two-step endogenous probit estimator (Newey, 1987) for the instrumental variable regression. From the 2SLS method, the following three requirements, which strong instrumental variables must fulfill, can be derived:

- *Relevance criterion.* The instrument's relevance lies in its correlation with the endogenous independent variable. Hence, the instrument must be explicitly selected for the research question and should be based on preliminary theoretical considerations or empirical investigations regarding why the variable is a plausible instrument.

- *Exclusion restriction*. Exogeneity of the instrument. The instrument must be exogenous such that its effect on the dependent variable is only indirect via the endogenous independent variable, i.e., *only through criterion* (Gehrke, 2022; Stock and Watson, 2019).
- *Independence criterion.* The instrumental variable must be unrelated to the omitted variables (Angrist and Pischke, 2014).

Following previous studies, this thesis uses individuals' language and mathematical skills at the age of ten as instrumental variables (Jappelli and Padula, 2013; Lyons et al., 2020; Thomas and Spataro, 2018). These instrumental variables often correlate strongly with financial literacy while usually showing little to no correlation with the regression's error term, which tests financial literacy's influence on financial behavior (Thomas and Spataro, 2018). Respondents are asked to rank their performance in reading and writing and math compared to that of other children in their class at the age of ten. The scores range from zero to five, with higher values indicating higher initial financial literacy language (IFL-LAN$_{t-1}$) and initial financial literacy math (IFL-MAT$_{t-1}$) levels, respectively.

Table 11 reports the descriptive statistics for the instrumental variables. The respondents' mean initial financial literacy language score is 3.36, and their mean initial financial literacy math score is 3.26. Thus, on average, the individuals in the sample grade their initial financial literacy levels about the same as other children in their class. To test whether the instruments are strong, F-tests can be used when estimating a 2SLS model. According to Stock and Yogo (2005), instruments are considered weak when they fall below the critical F-test value of ten.

Table 11. Descriptive statistics of the instrumental variables

Instrumental variable	Mean	Median	Std. dev.	Min.	Max.
IFL-LAN$_{t-1}$	3.3574	3	0.9274	0	5
IFL-MAT$_{t-1}$	3.2586	3	0.9619	0	5

Note. This table displays the descriptive statistics for the instrumental variables.

[Source: Own representation]

Moreover, the lagged values of the endogenous independent variable may be used as an instrument (Blalock, 2017; Chhatwani and Mishra, 2021; Klapper et al., 2012), as it can be potentially difficult to find a suitable instrumental variable in theory and obtain the required data in practice. A lagged variable represents the value of the independent variable at a previous point in time. Although lagged variables may not be exogenous and, therefore, are not instrumental variables in the narrow sense, the research results reveal that using the endogenous variable's lagged values can mitigate endogeneity problems (Chhatwani and Mishra, 2021; Klapper et al., 2012). As this thesis uses the lagged values of the independent variable FL_{t-1} and current values of the dependent variable FR_t owing to data availability constraints, endogeneity concerns are addressed through two approaches.

3.2.4. Robustness checks

As a first robustness check, a multinomial logistic regression, an extension of the logistic regression, is applied. Multinomial logistic regression is conducted when the dependent variable is nominal, i.e., it has no intrinsic ordering and has more than two levels (Hosmer et al., 2013). The dependent variable that is derived from SHARE (i.e., FR_t) provides the following four outcome categories: "With great difficulty" (Y=1), "With some difficulty" (Y=2), "Fairly easily" (Y=3), and "Easily" (Y=4). Hence, the dependent variable, financial resilience, is converted into a four-outcome variable for the multinomial logistic regression instead of binary coding. As presented in Table 12, with a mean of 2.95, the respondents, on average, were "Fairly easily" able to make ends meet with their household's total monthly income since the COVID-19 outbreak.

Table 12. Descriptive statistics of the four-outcome dependent variable

Dependent variable	Mean	Median	Std. dev.	Min.	Max.
FR_t	2.9454	3	0.8942	1	4

Note. This table displays the descriptive statistics for the four-outcome coded dependent variable. [Source: Own representation]

Like binary logistic regression, multinomial logistic regression uses maximum likelihood estimation and estimates a separate binary logistic regression model for each dummy variable, which results in Y-1, i.e., three binary logistic regression models. Each model conveys the effect of predictors on the probability of success in that category compared to the reference outcome category (Hosmer et al., 2013).

Multinomial logistic regression is subject to the data satisfying the Independence of Irrelevant Alternatives (IIA) assumption, which states that the characteristics of a one-choice alternative do not impact the relative probabilities of selecting other alternatives (Fullerton, 2009; Vijverberg, 2011). A diagnostic developed by Hausman and McFadden (1984), the Hausman-McFadden test, can be used to test the IIA assumption. The test proceeds by omitting one of the alternatives and then re-estimates the model. Thus, the parameters are estimated once for the complete set of alternatives and then for a subset of alternatives and are subsequently compared. Under the IIA assumption, both estimates should be similar (Hosmer et al., 2013). Furthermore, multinomial logistic regression is subject to no multicollinearity (Osborne, 2008).

Concerning the variable importance assessment, this thesis proceeds analogously to the logistic regression and uses the absolute value of the z-statistic.

For the second robustness check, the financial resilience variable remains a four-outcome variable but is treated as ordinal instead of nominal. A typical approach for dependent variables with multiple ordered levels is the proportional odds regression, a standard ordinal logistic regression (Soon, 2010). The proportional odds model assumes that the parallel lines assumption holds for all outcome categories, i.e., the explanatory variable has the same coefficient for all outcome categories (Williams, 2006). After fitting the proportional odds model, the Brant test, a formal test used to determine which explanatory variables violate the parallel lines assumption (Brant, 1990), reveals that several predictors violate the assumption. When the parallel lines assumption is not fulfilled by all explanatory variables, the proportional odds model is inappropriate. Therefore, this thesis uses the partial proportional odds regression, an extension of the proportional odds model, as a second robustness check.

In the partial proportional odds model, the independent variables that violate the proportional odds assumption can vary across the logit equations (Fullerton, 2009; Peterson and Harrell, 1990; Williams, 2006). Hence, the parallel lines assumption is partially relaxed for explanatory variables that violate it.

Regarding variable importance, identically to the logistic and multinomial logistic regression, the absolute value of the z-statistic is used as a measure.

For the third robustness check, a conditional random forest analysis is performed for several reasons. First, conditional random forests do not necessitate the prior specification of a model to establish the connections between explanatory and dependent variables. Instead, they use a recursive algorithm to learn those relationships' form (Breiman, 2001). The recursive algorithm selects the explanatory variables in single steps, considering the strength of their relationship to the dependent variable (Gehrke, 2022). Hence, conditional random regression forests are based on conditional inference trees, wherein the splitting process is guided by significance tests (Hothorn, Hornik, and Zeileis, 2006). Thus, one of the notable advantages of conditional random forests lies in their ability to assess each explanatory variable's impact individually and in multivariate interactions with other predictors. This capability can help identify relevant variables even within high-dimensional settings characterized by complex interrelationships (Strobl, Boulesteix, Kneib, Augustin, and Zeileis, 2008).

Second, conditional random forests intrinsically offer insights into feature importance (Grömping, 2009) and are considered one of the machine-learning techniques for which variable importance is best researched (Grömping, 2015).

Third, in contrast to random forests, conditional random forests provide unbiased results regardless of the scale levels of the variables involved (Strobl et al., 2008; Strobl, Boulesteix, Zeileis, and Hothorn, 2007). In random forests, variable selection can be biased as variable importance measures are affected by the number of categories and the scale of measurement of the predictor variables. Therefore, if continuous predictor variables are combined with categorical ones, or when categorical predictors vary in their number of categories, variable selection with random forest variable importance measures is unreliable. However, conditional inference trees, used to construct the classification trees in conditional random forests, conduct the variable selection by minimizing the p-value of a conditional inference independence test, resulting in unbiased variable selection (Strobl et al., 2007). As this thesis focuses on variable importance, it is essential that the value and interpretation of the variable importance measure accurately reflect the importance of the variable and remain unaffected by any other characteristics.

Before model calibration, the dataset is randomly split into two segments, a 70% training dataset and a 30% testing dataset (Buntine and Niblett, 1992), wherein each model is calibrated using the training dataset and assessed for accuracy using the testing dataset. The number of trees in the forest should be selected depending on the number of predictors. Thus, when numerous predictor variables exist, the number of trees should be ample to allow each variable to occur in sufficient trees (Gehrke, 2022). Hence, owing to the large number of explanatory variables in this analysis, the number of trees for the conditional random forest analysis is set to 5,000.

In conditional random forests, variable importance can be assessed either by the principle of impurity reduction (i.e., the Gini importance) or by the permutation accuracy importance (i.e., the mean decrease in accuracy). The Gini importance measure can be biased when explanatory variables’ number of categories or scales of measurement vary (Strobl et al., 2007). Thus, permutation accuracy importance, termed "mean decrease in accuracy" in the following, is preferable to impurity reduction because it provides more reliable predictions (Breiman and Cutler, 2003).

The concept of mean decrease in accuracy is that by randomly permuting the predictor variable, its original association with the outcome variable Y is broken. When the permuted variable and remaining unpermuted predictor variables are used to predict the response, the prediction accuracy (i.e., the number of correctly classified observations) decreases substantively if the original variable is associated with the response. Thus, to determine the decrease in prediction accuracy, one predictor variable is permuted at a time, and the out-of-bag (OOB) error rate after permutation is calculated. The higher the OOB error rate after permutation, the more important the explanatory variable. Therefore, an appropriate variable importance measure is the difference in prediction accuracy before and after permuting (Grömping, 2015; Strobl et al., 2007). Thus, this thesis uses the mean decrease in accuracy for the conditional random forest analysis to measure variable importance.

IV – RESULTS AND DISCUSSION

IV - RESULTS AND DISCUSSION

4.1. BASIC REGRESSION FINDINGS

4.1.1. Regression diagnostics

The regression diagnostics for the logistic regression models, as defined in Equation 1 and Equation 2, are performed and summarized in Table 13.

Table 13. Test of model assumptions for logistic regression

Model Assumption	Testing method	Results
Sample size	- Minimum EPV of ten	- Total sample: EPV=171 - Samples at the country level: EPVs ranging from 15 to 63
Outliers	- Visual verification of the "Residuals versus Leverage" plot - Absolute standardized residuals < 3 - Cook's distance < 1	- Plots exhibit no evident outliers. - Absolute standardized residuals < 3 - Cook's distance < 1
Linearity	- Visual inspection of the scatter plots between each metric predictor and the logit values of the outcome variable - Box-Tidwell transformation	- Plots do not provide any evidence for a nonlinear relationship. - Box-Tidwell procedure with applied Bonferroni-correction does not provide any evidence for a nonlinear relationship.
Multicollinearity	- Test of generalized variance inflation factors (GVIF)	- GVIFs do not indicate multicollinearity because all values are below the critical value of two.

Note. This table provides an overview of the regression diagnostic results for the logistic regression models according to Eq. (1) and Eq. (2).

[Source: Own representation]

Beginning with the sample size, the requirement of a minimum of ten observations per category of the outcome variable is certainly fulfilled for the total sample with an EPV of 171. After breaking down the total sample into samples per country and determining the EPV, all models per country presented in this thesis fulfill the criterion of a minimum of ten events per variable, with EPVs ranging from 15 to 63.

The EPV is calculated by determining the minimum frequencies of the individual outcome categories of the dependent variable divided by the number of parameters in the model, as presented in Table 14.

Table 14. EPV determination

Sample	Total observations	Observations per category of the dependent variable		Number of parameters in the model	EPV
Total sample:	10,464	0 = 3,076	1 = 7,388	18	171
Samples at the country level					
Belgium	2,034	0 = 342	1 = 1,692	12	29
Estonia	2,254	0 = 705	1 = 1,549	12	59
France	1,113	0 = 210	1 = 903	12	18
Germany	1,433	0 = 179	1 = 1,254	12	15
Italy	1,600	0 = 752	1 = 848	12	63
Slovenia	1,396	0 = 679	1 = 717	12	57
Spain	634	0 = 209	1 = 425	12	17
Removed countries from sample owing to insufficient EPV					
Greece	389	0 = 58	1 = 331	12	5
Luxembourg	264	0 = 30	1 = 234	12	3
Portugal	54	0 = 19	1 = 35	12	2

Note. This table provides an overview on the minimum number of events per variable (EPV) required for the multivariate analysis for the total sample and samples at the country level.

[Source: Own representation]

As three countries, Greece, Luxembourg, and Portugal, do not fulfill the minimum of ten observations per category of the dependent variable (i.e., they have EPVs smaller than ten), they are excluded from the sample during the sample selection process, as specified in Table 7.

Continuing with Table 13, regarding outliers, a visual check of the "Residuals versus Leverage" plots presents no apparent outliers, as none of the points are close to having both high residual and leverage. Furthermore, the values for the absolute standardized residuals, which are smaller than three, and the values for the Cook's distance that are smaller than one, reveal that no influential observations are present in the sample.

Non-linearity is not a concern in the data because the visual inspection of the scatter plots between each metric predictor and the logit values of the outcome variable do not provide any evidence for a nonlinear relationship. Linearity is further tested using the Box-Tidwell transformation combined with a Bonferroni correction to all terms in the model. All variables follow a linear relationship.

Regarding multicollinearity, all reported GVIF values range between 1.02 and 1.50 for the total sample model and between 1.01 and 1.63 for the country-level models. As the values are below the critical threshold of two, the regression results remain unaffected by multicollinearity among the explanatory variables.

4.1.2. Logistic regression results

The results of the logistic regressions based on Equation 1 are presented in Table 15. Column (1) of Table 15 reports the regression coefficients, while column (2) presents the average marginal effects. The average marginal effect represents the change in the probability of financial resilience resulting from a one-unit change in each continuous independent variable or a discrete change from zero to one for a binary variable, while keeping all other regressors constant at their mean values. The findings of the logistic regressions are based on robust standard errors (i.e., sandwich estimators).

The accuracy, obtained from a confusion matrix constructed using the cut-off value of 0.5, which is commonly used in the literature (Backhaus, Erichson, Plinke, and Weiber, 2018), suggests good discrimination of the utilized model with 76.8% of the observations being correctly classified (Hosmer et al., 2013). However, the True Positive Rate (TPR) of 90.6% and True Negative Rate (TNR) of 43.9% indicate that the model performs excellently in correctly identifying the positive class instances (i.e., FR=1) but does not perform well in correctly identifying the negative class instances (i.e., FR=0). This is attributable to the prevalent class imbalance in the data set, with 70.6% of the respondents being financially resilient. Thus, the negative class is the minority class (see Table 14 for an overview of the observations per category of the dependent variable).

Moreover, the Area Under the Receiver Operating Characteristic (ROC) curve (i.e., AUC), which measures performance independent of the specific cut-off value selected for classification (Fawcett, 2006), suggests strong discrimination of the utilized model with a value of 0.8 (Hosmer et al., 2013).

The ROC curve allows for the determination of the optimal cut-off value, which is 0.7 and higher than the commonly used value of 0.5. When a confusion matrix is created with an optimal cut-off value of 0.7, the TNR distinctly improves to 72.5% (not reported in Table 15), while the TPR decreases to 73.5%, and overall model accuracy remains almost unchanged at 73.2%. Thus, the accuracy suggests good discrimination of the utilized model after adjusting the cut-off, which helps improve the TNR, but usually entails a trade-off between the TPR and TNR owing to the inherent relationship between sensitivity (TPR) and specificity (TNR) (Chu, 1999).

Finally, the Pseudo-R^2, adjusted Pseudo-R^2, and Nagelkerke-R^2 measures indicate sufficient goodness of regression with values ranging from 0.21 to 0.23 (Rohrlack, 2009). Furthermore, a significantly negative intercept suggests a low unconditional probability of financial resilience within the dataset.

The regression results of the controlling variables largely correspond with previous findings from the literature, as discussed in Section 2.1.3. FL_{t-1} has a significantly positive effect on FR_t. This aligns with the expectations of this analysis and underscores the role of financial literacy in promoting financial resilience and alleviating the adverse financial impacts of the COVID-19 pandemic.

Table 15. Logistic regression results for the total sample

Variable	(1) Coefficient	(2) Average marginal effect	(3) Rank
Intercept	-4.2275 ***		
(z-value)	(-15.353)		
FL_{t-1}	0.1739 ***	0.0314 ***	10
(z-value)	(6.511)	(6.524)	
AGE_{t-1}	0.0346 ***	0.0063 ***	6
(z-value)	(9.957)	(9.998)	
CH_{t-1}	-0.0374 *	-0.0067 *	17
(z-value)	(-1.928)	(-1.927)	
$EDU\text{-}MED_{t-1}$	0.1470 **	0.0263 **	16
(z-value)	(2.359)	(2.376)	
$EDU\text{-}HIGH_{t-1}$	0.4188 ***	0.0715 ***	11
(z-value)	(5.166)	(5.500)	
$EMPL_{t}$	-0.0918	-0.0168	18
(z-value)	(-1.103)	(-1.087)	
$FEMALE_{t-1}$	0.1318 **	0.0240 **	15
(z-value)	(2.450)	(2.428)	
$IN\text{-}MED_{t}$	1.1402 ***	0.1919 ***	2
(z-value)	(19.940)	(21.093)	
$IN\text{-}HIGH_{t}$	2.2691 ***	0.3163 ***	1
(z-value)	(27.774)	(36.408)	
$P\text{-}FIH_{t-1}$	-0.0303 ***	-0.0055 ***	7
(z-value)	(-8.667)	(-8.588)	
$PLAN_{t-1}$	0.1047 ***	0.0189 ***	13
(z-value)	(4.613)	(4.613)	
RET_{t-1}	0.2616 ***	0.0476 ***	14
(z-value)	(3.810)	(3.786)	
$BELGIUM_{t-1}$	1.4939 ***	0.2077 ***	4
(z-value)	(16.846)	(22.336)	
$ESTONIA_{t-1}$	0.5734 ***	0.0945 ***	9
(z-value)	(6.691)	(7.377)	
$FRANCE_{t-1}$	1.5416 ***	0.1949 ***	5
(z-value)	(14.984)	(22.719)	
$GERMANY_{t-1}$	1.9244 ***	0.2317 ***	3
(z-value)	(17.760)	(28.061)	
$SLOVENIA_{t-1}$	-0.4416 ***	-0.0863 ***	12
(z-value)	(-4.956)	(-4.624)	
$SPAIN_{t-1}$	0.8392 ***	0.1223 ***	8
(z-value)	(7.400)	(9.535)	
Number of obs.	10,464		
Pseudo McFadden-R^2	0.2106		
Adj. pseudo McFadden-R^2	0.2076		
Nagelkerke-R^2	0.2251		
Area under curve (AUC)	0.8022		
Accuracy	0.7683		
TPR	0.9055		
TNR	0.4386		

Note. Columns (1) and (2) of this table report the results of the logistic regression estimates for Eq. (1). The coefficients' z-values have been computed using robust standard errors (sandwich estimators). The standard errors for marginal effects have been corrected for heteroskedasticity. Column (3) indicates the variable importance ranking of the predictors of financial resilience, measured by the absolute z-value. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

AGE_{t-1} significantly positively influences FR_t, revealing that the older are less likely to be financially fragile. For CH_{t-1}, a significantly negative impact on FR_t is reported, indicating that a household with more children is at a higher risk of being financially fragile. As expected, $EDU\text{-}MED_{t-1}$ and $EDU\text{-}HIGH_{t-1}$ are both significantly positive, demonstrating that medium and high educational levels increase the ability to cope with financial shocks compared to low educational levels. $EMPL_t$ has a negative but non-significant effect on FR_t. $FEMALE_{t-1}$ significantly positively affects FR_t, indicating that women are more likely to be financially resilient than men during the COVID-19 crisis. This is an essential addition to existing findings, which are mixed regarding gender's effect on financial resilience.

Both $IN\text{-}MED_t$ and $IN\text{-}HIGH_t$ have a significantly positive effect on FR_t. The marginal effects reveal that when an individual is in a high income level, their probability of being financially resilient increases by 0.32 percentage points compared to a low income level. Furthermore, respondents with a high income level are 0.12 percentage points more likely to be financially resilient than individuals with a medium income level. This validates that income is crucial in dealing with unexpected financial shocks.

Adding to the sparse literature on the influence of an extended period of financial hardship on financial resilience, $P\text{-}FIH_{t-1}$ has a significantly negative effect on FR_t. Thus, increased periods of financial hardship precipitate financial fragility. $PLAN_{t-1}$ has a significantly positive effect on FR_t, revealing that individuals with a long-term oriented financial planning horizon regarding saving and spending are more likely to be financially resilient.

Contrary to numerous previous findings, RET_{t-1} shows a significantly positive effect on FR_t (Hasler and Lusardi, 2019; Wiersma et al., 2020, among others). Following Erdem and Rojahn (2022), who use a similar sample and period and also report positive estimates for retired individuals, RET_{t-1} exhibits a positive impact, which could be attributable to retired individuals being less prone to an unexpected income loss or unemployment risk during the COVID-19 crisis due to their stable pension income.

Finally, the country dummies, $BELGIUM_{t-1}$, $ESTONIA_{t-1}$, $FRANCE_{t-1}$, $GERMANY_{t-1}$, and $SPAIN_{t-1}$, significantly positively affect FR_t compared to $ITALY_{t-1}$. This largely aligns with research conducted prior to the COVID-19 pandemic, which indicates that households from Benelux, the Nordic countries, Germany and France are more financially resilient than households from Southern and Eastern European countries (Demertzis et al., 2020). By contrast, $SLOVENIA_{t-1}$ has a significantly negative effect on FR_t compared to $ITALY_{t-1}$. Consistent with findings from Demertzis et al. (2020), this could be attributable to Slovenia's above-average percentage of financially fragile households, which is also reflected in the data used for this analysis because households from Slovenia are the least financially resilient.

Examining the variable importance for financial resilience from the logistic regression, column (3) from Table 15 reveals that the most important variables in predicting financial resilience are $IN\text{-}HIGH_t$ and $IN\text{-}MED_t$, followed by the country dummies $GERMANY_{t-1}$, $BELGIUM_{t-1}$, and $FRANCE_{t-1}$. FL_{t-1} ranks in the midfield, being the 10^{th} most important feature out of 18 explanatory variables.

The results of the logistic regression models for the country-level analysis, based on Equation 2, are displayed in two tables in alphabetical order. Table 16 presents the results for Belgium, Estonia, France, and Germany, while Table 17 includes the results for Italy, Slovenia, and Spain.

Table 16. Logistic regression results for Belgium, Estonia, France, and Germany

	(1) Belgium		(2) Estonia		(3) France		(4) Germany	
Variable	Coefficient	Average marginal effect	Coefficient	Average marginal effect	Coefficient	Average marginal effect	Coefficient	Average marginal effect
Intercept	-2.7359 ***		-5.0248 ***		-1.6237		-3.6364 ***	
(z-value)	(-3.710)		(-8.624)		(-1.552)		(-3.056)	
FL_{t-1}	0.2502 ***	0.0266 ***	0.1156 **	0.0237 **	0.0177	0.0022	0.1394	0.0092
(z-value)	(3.384)	(3.398)	(2.283)	(2.285)	(0.192)	(0.192)	(1.447)	(1.443)
AGE_{t-1}	0.0344 ***	0.0036 ***	0.0552 ***	0.0113 ***	0.0251 *	0.0031 *	0.0481 ***	0.0032 ***
(z-value)	(3.633)	(3.631)	(7.411)	(7.482)	(1.727)	(1.743)	(2.848)	(2.883)
CH_{t-1}	-0.1172 **	-0.0124 ***	0.1994 ***	0.0408 ***	-0.0093	-0.0011	-0.0611	-0.0040
(z-value)	(-2.559)	(-2.593)	(4.503)	(4.547)	(-0.154)	(-0.154)	(-0.963)	(-0.956)
$EDU\text{-}MED_{t-1}$	0.0345	0.0036	0.0350	0.0072	-0.0724	-0.0090	0.3596	0.0243
(z-value)	(0.206)	(0.207)	(0.277)	(0.277)	(-0.362)	(-0.359)	(1.378)	(1.343)
$EDU\text{-}HIGH_{t-1}$	-0.0481	-0.0051	0.2876 *	0.0570 *	0.1272	0.0154	0.7559 **	0.0458 **
(z-value)	(-0.276)	(-0.275)	(1.838)	(1.901)	(0.496)	(0.504)	(2.328)	(2.535)
$EMPL_t$	-0.0011	-0.0001	0.4519 ***	0.0883 ***	0.0286	0.0035	-0.6802 ***	-0.0522 **
(z-value)	(-0.005)	(-0.005)	(2.581)	(2.712)	(0.096)	(0.097)	(-2.770)	(-2.341)
$FEMALE_{t-1}$	0.0014	0.0002	0.1345	0.0279	0.0453	0.0056	0.4998 ***	0.0337 **
(z-value)	(0.010)	(0.010)	(1.192)	(1.177)	(0.249)	(0.248)	(2.613)	(2.544)
$IN\text{-}MED_t$	1.4963 ***	0.1468 ***	0.6819 ***	0.1349 ***	1.4233 ***	0.1642 ***	1.7049 ***	0.1054 ***
(z-value)	(10.324)	(10.329)	(6.067)	(6.291)	(7.465)	(7.649)	(8.034)	(7.488)
$IN\text{-}HIGH_t$	2.5234 ***	0.1967 ***	1.7501 ***	0.2911 ***	2.3196 ***	0.2097 ***	2.0062 ***	0.0989 ***
(z-value)	(10.161)	(13.521)	(9.852)	(12.903)	(7.426)	(10.432)	(6.726)	(7.658)
$P\text{-}FIH_{t-1}$	-0.0375 ***	-0.0040 ***	-0.0092 *	-0.0019	-0.0413 ***	-0.0051 ***	-0.0602 ***	-0.0040 ***
(z-value)	(-4.639)	(-4.410)	(-1.646)	(-1.644)	(-3.638)	(-3.586)	(-6.338)	(-5.839)
$PLAN_{t-1}$	0.1164 **	0.0124 **	0.0724	0.0148	0.1726 **	0.0213 **	0.3252 ***	0.0215 ***
(z-value)	(2.224)	(2.232)	(1.368)	(1.367)	(2.436)	(2.460)	(3.552)	(3.565)
RET_{t-1}	0.2885	0.0314	-0.0244	-0.0050	0.3264	0.0396	0.0515	0.0034
(z-value)	(1.597)	(1.557)	(-0.149)	(-0.149)	(1.427)	(1.450)	(0.176)	(0.175)
Number of obs.	2,034		2,254		1,113		1,433	
Pseudo McFadden-R^2	0.1732		0.1002		0.1560		0.2409	

	(1) Belgium	(2) Estonia	(3) France	(4) Germany
Adj. pseudo McFadden-R^2	0.1590	0.0909	0.1318	0.2168
Nagelkerke-R^2	0.2437	0.1646	0.2260	0.3136
Area under curve (AUC)	0.7909	0.7110	0.7743	0.8362
Accuracy	0.8397	0.7134	0.8266	0.8876
TPR	0.9764	0.9193	0.9812	0.9809
TNR	0.1637	0.2610	0.1619	0.2346

Note. This table reports the results of the logistic regression estimates for Eq. (2). The z-values of the coefficients have been computed using robust standard errors (sandwich estimators). The standard errors for marginal effects have been corrected for heteroskedasticity. Column (1) reports the results for Belgium, column (2) for Estonia, column (3) for France, and column (4) for Germany. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

Table 17. Logistic regression results for Italy, Slovenia, and Spain

	(1) Italy		(2) Slovenia		(3) Spain	
Variable	Coefficient	Average marginal effect	Coefficient	Average marginal effect	Coefficient	Average marginal effect
Intercept	-3.8025 ***		-4.0492 ***		-2.8697 ***	
(z-value)	(-6.124)		(-5.850)		(-3.247)	
FL_{t-1}	0.3350 ***	0.0833 ***	0.1587 **	0.0396 **	0.0626	0.0132
(z-value)	(5.300)	(5.296)	(2.294)	(2.295)	(0.552)	(0.552)
AGE_{t-1}	0.0266 ***	0.0066 ***	0.0274 ***	0.0068 ***	0.0335 ***	0.0071 ***
(z-value)	(3.512)	(3.515)	(3.433)	(3.432)	(3.127)	(3.144)
CH_{t-1}	-0.1702 ***	-0.0423 ***	-0.0861	-0.0215	-0.1297 **	-0.0274 **
(z-value)	(-3.265)	(-3.261)	(-1.340)	(-1.340)	(-2.096)	(-2.096)
$EDU\text{-}MED_{t-1}$	0.3147 **	0.0774 **	0.4599 ***	0.1142 ***	0.0788	0.0164
(z-value)	(2.116)	(2.146)	(3.137)	(3.162)	(0.241)	(0.244)
$EDU\text{-}HIGH_{t-1}$	1.0999 ***	0.2453 ***	1.1614 ***	0.2681 ***	0.6603 *	0.1233 **
(z-value)	(3.547)	(4.310)	(5.305)	(6.081)	(1.721)	(1.992)
$EMPL_t$	-0.6110 ***	-0.1514 ***	-0.2243	-0.0560	-1.0542 ***	-0.2487 ***
(z-value)	(-3.161)	(-3.231)	(-0.742)	(-0.743)	(-2.945)	(-2.841)
$FEMALE_{t-1}$	0.1616	0.0402	0.2996 **	0.0747 **	0.0036	0.0008
(z-value)	(1.286)	(1.286)	(2.134)	(2.140)	(0.018)	(0.018)
$IN\text{-}MED_t$	1.3621 ***	0.3196 ***	0.6599 ***	0.1619 ***	1.0966 ***	0.2179 ***
(z-value)	(9.252)	(10.079)	(4.352)	(4.459)	(5.084)	(5.424)
$IN\text{-}HIGH_t$	2.5082 ***	0.5228 ***	2.0081 ***	0.4467 ***	1.9070 ***	0.3340 ***
(z-value)	(14.072)	(18.996)	(11.019)	(13.570)	(6.404)	(8.165)
$P\text{-}FIH_{t-1}$	-0.0397 ***	-0.0099 ***	-0.0263 **	-0.0066 **	-0.0126	-0.0027
(z-value)	(-4.313)	(-4.299)	(-2.022)	(-2.021)	(-1.047)	(-1.045)
$PLAN_{t-1}$	-0.0738	-0.0183	0.1457 **	0.0363 **	0.2510 ***	0.0529 ***
(z-value)	(-1.428)	(-1.429)	(2.550)	(2.551)	(2.674)	(2.676)
RET_{t-1}	0.5829 ***	0.1430 ***	0.0839	0.0209	0.2838	0.0581
(z-value)	(4.035)	(4.123)	(0.432)	(0.432)	(1.164)	(1.205)
Number of obs.	1,600		1,396		634	
Pseudo McFadden-R^2	0.2352		0.1823		0.1233	
Adj. pseudo McFadden-R^2	0.2235		0.1689		0.0910	

	(1) Italy	(2) Slovenia	(3) Spain
Nagelkerke-R^2	0.3707	0.2977	0.2014
Area under curve (AUC)	0.8102	0.7745	0.7346
Accuracy	0.7362	0.7135	0.7145
True positive rate	0.7677	0.6722	0.8894
True negative rate	0.7008	0.7570	0.3589

Note. This table reports the results of the logistic regression estimates for Eq. (2). The z-values of the coefficients have been computed using robust standard errors (sandwich estimators). The standard errors for marginal effects have been corrected for heteroskedasticity. Column (1) reports the results for Italy, column (2) for Slovenia, and column (3) for Spain. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

The Pseudo-R^2, adjusted Pseudo-R^2, and Nagelkerke-R^2 values largely suggest a satisfactory model fit. The models for Estonia and Spain are rather moderately fitted with comparatively low Pseudo-R^2 values. However, the chi-square values of the likelihood ratio tests are significant at the 1% level ($\chi2 = 280.64$, p-value= < 2.2e-16 and $\chi2 = 99.12$, p-value= 8.3e-16 respectively, not reported in Table 16 and Table 17), indicating that the full models provide a better fit than the null models with no independent variables in predicting financial resilience. Furthermore, the AUC values and accuracies for all models suggest acceptable to excellent discrimination (Hosmer et al., 2013).

However, again, class imbalance is present in all samples at the country level, with TNRs ranging from 16.2% to 35.9%, except for Italy and Slovenia (70.1% and 75.5%, respectively), where the categories of the dependent variable are relatively equally distributed (see Table 14). When confusion matrices are generated with the optimal cut-off values, determined via the ROC-curves, that range from 0.59 to 0.81 for the class-imbalance affected countries, the TNRs considerably improve, ranging from 46.0% to 69.6% (not reported in Table 16 and Table 17), while the TPRs slightly decrease, and the accuracies remain above 70% for all countries.

Considering the regression results of the controlling variables, distinct differences between the countries emerge. FL_{t-1} significantly positively influences FR_t in the countries Belgium, Estonia, Italy, and Slovenia, whereas in France, Germany, and Spain, FL_{t-1} is positive but has no significant effect.

AGE_{t-1} is significantly positive in all countries, while CH_{t-1} is significantly negative in Belgium, Italy, and Spain and significantly positive in Estonia. Hence, Estonia is the only country wherein, contrary to previous findings, households with more children are not at higher risk of being financially fragile but are more likely to be financially resilient. Education (i.e., $EDU\text{-}MED_{t-1}$ and $EDU\text{-}HIGH_{t-1}$) does not influence FR_t in Belgium and France, while it is significantly positive for all remaining countries under review. In Germany, Italy, and Spain, $EMPL_t$ has a significantly negative effect on FR_t. However, in Estonia, it is significantly positive, which aligns with prior findings, according to which the unemployed face a greater risk of encountering financial challenges (Wiersma et al., 2020). $FEMALE_{t-1}$ significantly positively affects FR_t in Germany and Slovenia, while it is non-significant in the remaining countries. Both $IN\text{-}MED_t$ and $IN\text{-}HIGH_t$ have a significantly positive effect on FR_t in every country under review.

Furthermore, P-FIH_{t-1} has a significantly negative effect on FR_t in all countries except for Spain, where the effect is negative but insignificant. $PLAN_{t-1}$ has a significantly positive effect on FR_t in all countries, excluding Estonia and Italy. Finally, RET_{t-1} exhibits a significantly positive effect on FR_t in Italy, while it is non-significant for the remaining countries.

Table 18 reports the variable importance results from the logistic regression models at the country level ranked by importance in descending order.

In line with the findings from the logistic regression on the total sample, the most important variables in explaining financial resilience are IN-$HIGH_t$ and IN-MED_t for each country.

For the remaining explanatory variables, the variations are distinct between the countries as with FL_{t-1}, which ranks in the midfield in the countries Belgium, Estonia, and Slovenia, is among the most important predictors of financial resilience in Italy, and is among the least important in France, Germany, and Spain.

A review of the findings from the logistic regressions at the country level reveals that, analogous to the results from the total sample, IN-MED_t and IN-$HIGH_t$ are the most important predictors of financial resilience. However, for the remaining explanatory variables, including FL_{t-1}, feature importance in explaining financial resilience differs widely.

Table 18. Variable importance for financial resilience from logistic regressions at the country level

Rank	(1) Belgium	(2) Estonia	(3) France	(4) Germany	(5) Italy	(6) Slovenia	(7) Spain
1	$IN\text{-}MED_t$	$IN\text{-}HIGH_t$	$IN\text{-}MED_t$	$IN\text{-}MED_t$	$IN\text{-}HIGH_t$	$IN\text{-}HIGH_t$	$IN\text{-}HIGH_t$
2	$IN\text{-}HIGH_t$	AGE_{t-1}	$IN\text{-}HIGH_t$	$IN\text{-}HIGH_t$	$IN\text{-}MED_t$	$EDU\text{-}HIGH_{t-1}$	$IN\text{-}MED_t$
3	$P\text{-}FIH_{t-1}$	$IN\text{-}MED_t$	$P\text{-}FIH_{t-1}$	$P\text{-}FIH_{t-1}$	FL_{t-1}	$IN\text{-}MED_t$	AGE_{t-1}
4	AGE_{t-1}	CH_{t-1}	$PLAN_{t-1}$	$PLAN_{t-1}$	$P\text{-}FIH_{t-1}$	AGE_{t-1}	$EMPL_t$
5	FL_{t-1}	$EMPL_t$	AGE_{t-1}	AGE_{t-1}	RET_{t-1}	$EDU\text{-}MED_{t-1}$	$PLAN_{t-1}$
6	CH_{t-1}	FL_{t-1}	RET_{t-1}	$EMPL_t$	$EDU\text{-}HIGH_{t-1}$	$PLAN_{t-1}$	CH_{t-1}
7	$PLAN_{t-1}$	$EDU\text{-}HIGH_{t-1}$	$EDU\text{-}HIGH_{t-1}$	$FEMALE_{t-1}$	AGE_{t-1}	FL_{t-1}	$EDU\text{-}HIGH_{t-1}$
8	RET_{t-1}	$P\text{-}FIH_{t-1}$	$EDU\text{-}MED_{t-1}$	$EDU\text{-}HIGH_{t-1}$	CH_{t-1}	$FEMALE_{t-1}$	RET_{t-1}
9	$EDU\text{-}HIGH_{t-1}$	$PLAN_{t-1}$	$FEMALE_{t-1}$	FL_{t-1}	$EMPL_t$	$P\text{-}FIH_{t-1}$	$P\text{-}FIH_{t-1}$
10	$EDU\text{-}MED_{t-1}$	$FEMALE_{t-1}$	FL_{t-1}	$EDU\text{-}MED_{t-1}$	$EDU\text{-}MED_{t-1}$	CH_{t-1}	FL_{t-1}
11	$FEMALE_{t-1}$	$EDU\text{-}MED_{t-1}$	CH_{t-1}	CH_{t-1}	$PLAN_{t-1}$	$EMPL_t$	$EDU\text{-}MED_{t-1}$
12	$EMPL_t$	RET_{t-1}	$EMPL_t$	RET_{t-1}	$FEMALE_{t-1}$	RET_{t-1}	$FEMALE_{t-1}$

Note. This table reports the variable importance for financial resilience from the logistic regression, measured by the absolute z-value, for the variables applied according to Eq. (2), in descending order. Column (1) reports the results for Belgium, column (2) for Estonia, column (3) for France, column (4) for Germany, column (5) for Italy, column (6) for Slovenia, and column (7) for Spain. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

4.1.3. Instrumental variable regression results

For the instrumental variable regression, Newey's two-step endogenous probit estimator (Newey, 1987) from the R package "ivprobit" (Zaghdoudi, 2018) is used. The results of the first-stage regression, which tests the relationship between the instrumental variables, i.e., IFL-LAN$_{t-1}$ and IFL-MAT$_{t-1}$, and endogenous independent variable FL$_{t-1}$, are presented in Table 19.

Table 19. First-stage IV regression results for the total sample

Variable	Coefficient
Intercept (Std. Error)	2.6381*** (0.0998)
IFL-LAN$_{t-1}$	0.0131 (0.0114)
IFL-MAT$_{t-1}$	0.1824*** (0.0112)
AGE$_{t-1}$	-0.0049*** (0.0013)
CH$_{t-1}$	-0.0121* (0.0068)
EDU-MED$_{t-1}$	0.3566*** (0.0244)
EDU-HIGH$_{t-1}$	0.5700*** (0.0277)
EMPL$_{t}$	0.0395 (0.0287)
FEMALE$_{t-1}$	-0.2118*** (0.0190)
IN-MED$_{t}$	0.1673*** (0.0221)
IN-HIGH$_{t}$	0.2994*** (0.0260)
P-FIH$_{t-1}$	0.0001 (0.0011)
PLAN$_{t-1}$	0.0237*** (0.0079)
RET$_{t-1}$	0.0483* (0.0253)
BELGIUM$_{t-1}$	0.2802*** (0.0326)
ESTONIA$_{t-1}$	0.0825** (0.0345)
FRANCE$_{t-1}$	0.2151*** (0.0379)
GERMANY$_{t-1}$	0.2943*** (0.0367)
SLOVENIA $_{t-1}$	0.0341 (0.0354)
SPAIN$_{t-1}$	-0.3555*** (0.0413)
Number of obs.	10,464
F-test for weak instruments	186.54

Note. This table presents the findings of the first-stage instrumental variable regression for the total sample, which are based on robust standard errors (sandwich estimators) presented in parentheses. The controlling variables AGE$_{t-1}$, CH$_{t-1}$, EDU-MED$_{t-1}$, EDU-HIGH$_{t-1}$, EMPL$_{t}$, FEMALE$_{t-1}$, IN-MED$_{t}$, IN-HIGH$_{t}$, P-FIH$_{t-1}$, PLAN$_{t-1}$, RET$_{t-1}$, BELGIUM$_{t-1}$, ESTONIA$_{t-1}$, FRANCE, GERMANY$_{t-1}$, SLOVENIA$_{t-1}$, and SPAIN$_{t-1}$ and the instrumental variables IFL-LAN$_{t-1}$ and IFL-MAT$_{t-1}$ are estimated on the financial literacy measure FL$_{t-1}$. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey).

Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

IFL-MAT$_{t-1}$ is significantly positive and is, thus, positively correlated with FL$_{t-1}$. However, IFL-LAN$_{t-1}$ shows no correlation with the endogenous variable FL$_{t-1}$ since it is positive but not significant. Hence, it does not fulfill the relevance criterion and is not considered a strong instrument (Ebbes, Papies, and Van Heerde, 2016). As recommended by Stock, Wright, and Yogo (2002), an incremental F-statistic for these instrumental variables is estimated to assess their strength because the reduced form in Newey's two-step endogenous probit estimator is also linear. The F-statistic for the total sample is 186.54 and comfortably surpasses the threshold value of ten for weak instruments (Stock and Yogo, 2005). Robust standard errors (i.e., sandwich estimators) are used for the first- and second-stage IV regressions.

Before the second-stage regression is run, an endogeneity test, i.e., the Wald statistic of exogeneity, is performed to confirm the endogeneity of the independent variable (i.e., FL$_{t-1}$). However, the p-value (0.4036) of the endogeneity test of the instrumented variables is not significant. Thus, FL$_{t-1}$ can be treated as exogenous, and endogeneity is not a concern for the influence of FL$_{t-1}$ on FR$_t$.

The findings are similar for the samples at the country level. The F-statistics range from 10.63 to 121.47 (not reported in Table 19) and exceed the threshold value of ten for weak instruments (Stock and Yogo, 2005). When the Wald statistic of exogeneity of the instrumented variables is performed, the p-values for all country-level samples are not significant at the 5% alpha level, revealing that also at the country level, the influence of FL$_{t-1}$ on FR$_t$ is not affected by endogeneity.

The findings from the two-step endogenous probit estimator largely align with those obtained from the logistic regression, although they exhibit only limited comparability. Generally, IV regressions are associated with lower efficiency than single regression models (Ebbes, Papies, and Van Heerde, 2016). As the null hypothesis of the Wald test of exogeneity cannot be rejected, the statistical inference relies on the one-step regressions (i.e., logistic regressions) and the instrumental variable regression results are not additionally reported.

4.2.1. Multinomial logistic regression

As a first robustness check, a multinomial logistic regression is performed using the R package "mlogit" (Croissant, 2020). The findings of the multinomial logistic regressions are based on robust standard errors (i.e., sandwich estimators) and are presented in Table 20.

The Pseudo-R^2, adjusted Pseudo-R^2, and Nagelkerke-R^2 measures indicate sufficient goodness of regression with values ranging from 0.18 to 0.36 (Rohrlack, 2009). The Hausman-McFadden test, which tests for the IIA assumption, yields a negative chi-square value with a non-significant p-value. Hausman and McFadden (1984) suggest that a negative outcome of the Hausman-McFadden test can be regarded as support for the null hypothesis. Thus, the data satisfy the IIA assumption. Furthermore, the GVIFs are below the critical threshold of two, indicating that multicollinearity among the explanatory variables is not present.

The multinomial logit model is set up as three baseline logit models with a single reference category (i.e., Y=2 vs. Y=1, Y=3 vs. Y=1, and Y=4 vs. Y=1). Thus, the multinomial logistic regression results are presented as comparisons with the baseline group (i.e., Y=1). Column (1) of Table 20 contrasts the Y=2 category with the baseline category Y=1. The coefficients' signs in column (1) indicate the likelihood of participants responding "With some difficulty," in contrast to the reference category (i.e., "With great difficulty"). Similarly, columns (2) and (3) contrast the Y=3 and Y=4 categories with the baseline category Y=1. Each column presents the results for the log odds estimates. Positive coefficients imply that higher predictor variable values decrease the probability that a respondent is in the Y=1 category than the current one. Conversely, negative coefficients imply that higher predictor values decrease the probability of being in the current Y category compared to the baseline category.

Table 20. Multinomial logistic regression results for the total sample

Variable	(1) Y=2 vs. Y=1	(2) Y=3 vs. Y=1	(3) Y=4 vs. Y=1	(4) Rank
Intercept (z-value)	-1.0091** (-2.292)	-4.0503*** (-8.986)	-8.3190*** (-16.272)	
FL_{t-1} (z-value)	0.1020** (2.186)	0.2406*** (5.156)	0.3007*** (5.876)	11
AGE_{t-1} (z-value)	0.0189*** (3.252)	0.0450*** (7.681)	0.0636*** (9.813)	7
CH_{t-1} (z-value)	-0.1084*** (-3.417)	-0.1134*** (-3.573)	-0.1567*** (-4.471)	13
$EDU\text{-}MED_{t-1}$ (z-value)	0.2812** (2.545)	0.3461*** (3.138)	0.4822*** (3.933)	14
$EDU\text{-}HIGH_{t-1}$ (z-value)	0.4962*** (2.733)	0.6719*** (3.784)	1.1377*** (6.166)	10
$EMPL_{t}$ (z-value)	-0.0617 (-0.415)	-0.1180 (-0.799)	-0.2188 (-1.381)	17
$FEMALE_{t-1}$ (z-value)	0.0360 (0.367)	0.1756* (1.790)	0.1335 (1.269)	18
$IN\text{-}MED_{t}$ (z-value)	0.8773*** (8.365)	1.6148*** (15.342)	2.5048*** (21.036)	2
$IN\text{-}HIGH_{t}$ (z-value)	1.3390*** (7.296)	2.8792*** (15.9929	4.6107*** (24.149)	1
$P\text{-}FIH_{t-1}$ (z-value)	-0.0146*** (-3.772)	-0.0366*** (-8.572)	-0.0569*** (-10.178)	6
$PLAN_{t-1}$ (z-value)	-0.0091 (-0.221)	0.0748* (1.841)	0.1415*** (3.257)	15
RET_{t-1} (z-value)	0.4651*** (4.028)	0.6286*** (5.407)	0.6399*** (4.962)	12
$BELGIUM_{t-1}$ (z-value)	0.4607*** (2.679)	1.2879*** (7.582)	3.3140*** (17.444)	3
$ESTONIA_{t-1}$ (z-value)	0.1729 (1.163)	0.6087*** (4.095)	1.1111*** (6.325)	9
$FRANCE_{t-1}$ (z-value)	0.5936*** (2.964)	1.5858*** (8.077)	3.2873*** (15.194)	5
$GERMANY_{t-1}$ (z-value)	0.5479** (2.416)	1.7122*** (7.746)	3.9435*** (16.548)	4
$SLOVENIA_{t-1}$ (z-value)	-0.2566* (-1.871)	-0.6744*** (-4.732)	-0.4688*** (-2.642)	16
$SPAIN_{t-1}$ (z-value)	0.4261** (2.230)	0.9120*** (4.761)	2.0808*** (9.477)	8
Number of obs.		10,464		
Pseudo McFadden-R^2		0.1764		
Adj. pseudo McFadden-R^2		0.1750		
Nagelkerke-R^2		0.3559		
Hausman-McFadden test $\chi 2$ (p-value)		-423.61 (1)		

Note. This table presents the results of the multinomial logistic regression model. The z-values are based on robust standard errors (sandwich estimators) and are reported in parentheses. Columns (1), (2), and (3) contrast the Y=2, Y=3, and Y=4 categories, respectively, with the Y=1 category. Y=1 (with great difficulty), Y=2 (with some difficulty), Y=3 (fairly easily), and Y=4 (easily) represent the dependent variable's (FR_t) outcome categories. Column (4) presents the variable importance ranking of the predictors of financial resilience, measured by the absolute z-value. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

Table 20 indicates that regarding signs and significance of the regression coefficients, the results from the multinomial logistic regression, based on Equation 1, largely align with those of the logistic regression reported in Table 15.

FL_{t-1} is significantly positive for all three models (i.e., Y=2 vs. Y=1, Y=3 vs. Y=1, and Y=4 vs. Y=1), revealing that as FL_{t-1} increases for a respondent, it has a positive effect on the choice of Y=2, Y=3, and Y=4 respectively, over the baseline outcome Y=1. That is, FL_{t-1} positively contributes to the FR_t level at the respective outcome level compared to the baseline level Y=1, considering that the other variables in the model are held constant. Thus, the results indicate that financial literacy positively impacts financial resilience.

The results of the remaining predictors coincide with those of the logistic regression. AGE_{t-1}, EDU-MED_{t-1}, EDU-$HIGH_{t-1}$, IN-MED_t, IN-$HIGH_t$, RET_{t-1}, and the country dummies $BELGIUM_{t-1}$, $FRANCE_{t-1}$, $GERMANY_{t-1}$, and $SPAIN_{t-1}$ are significantly positive across all three outcome categories, revealing that they positively influence the individual financial resilience level, e.g., Y=4 in column (3), in comparison to the baseline financial resilience level (i.e., Y=1). CH_{t-1}, P-FIH_{t-1}, and $SLOVENIA_{t-1}$ influence all outcome categories significantly negatively relative to the baseline category. Like the findings from the logistic regression, $EMPL_t$ has a negative but non-significant effect on FR_t across all outcome categories. $PLAN_{t-1}$ and $ESTONIA_{t-1}$ are significantly positive in columns (2) and (3), while they become non-significant for column (1). Likewise, $FEMALE_{t-1}$ is significantly positive only for the second column, indicating that gender's influence on financial resilience is strong for higher financial resilience levels.

Column (4) of Table 20 presents the predictors of financial resilience ranked by variable importance. To ensure comparability with the logistic regression results, the absolute z-values from column (3) are used as they represent variable importance for the highest vs. the lowest Y category.

The ranking largely corresponds to that of the logistic regression, with IN-$HIGH_t$ and IN-MED_t being the most important predictors of financial resilience, followed by $BELGIUM_{t-1}$, $GERMANY_{t-1}$, and $FRANCE_{t-1}$. FL_t ranks in the midfield, being the 11th most important variable of the 18 predictors.

The results of the multinomial logistic regression models for the country-level analysis, based on Equation 2, are displayed in two tables in alphabetical order. Table 21 presents the results for Belgium, Estonia, France, and Germany, while Table 22 includes the results for Italy, Slovenia, and Spain.

The Pseudo-R^2, adjusted Pseudo-R^2, and Nagelkerke-R^2 measures imply moderate to sufficient goodness of regression. The model for Estonia is somewhat moderately fitted compared to the other country models. However, the chi-square value of the likelihood ratio test is significant at the 1% level ($\chi2 = 401.27$, p-value $< 2.22e-16$, not reported in Table 21), indicating that the full model provides a better fit than the null model with no independent variables in predicting financial resilience.

The IIA assumption holds for all country-level models, with the Hausman-McFadden test resulting in non-significant p-values. Furthermore, the GVIF values are below the critical value of two and do not indicate multicollinearity.

Regarding signs and significance of the regression coefficients, the findings slightly differ from those of the logistic regression, as reported in Table 16 and Table 17, respectively. Table 21 and Table 22 reveal distinct differences between the countries.

FL_{t-1} is significantly positive in Belgium, Estonia, Germany, and Italy, while it has no significant effect on FR_t in France, Slovenia, and Spain. In Estonia and Italy, the effect is significant across the outcome categories Y=3 vs. Y=1 and Y=4 vs. Y=1, respectively, indicating that the influence of financial literacy in Estonia and Italy is strong for higher financial resilience levels.

Interestingly, FL_{t-1} has no significant effect on FR_t in Germany in the logistic regression but becomes significantly positive in the multinomial logistic regression across all outcome categories. By contrast, in the multinomial logistic regression, the effect of FL_{t-1} on FR_t becomes non-significant for Slovenia across all outcome categories, while it is significantly positive in the logistic regression.

The regression results of the controlling variables roughly align with those of the logistic regression. Overall, more predictors are significant in the multinomial logistic regression compared to the logistic regression results. This might be attributable to the dependent variable's breakdown into a four-outcome category variable, which enables uncovering significant effects that might diminish when FR_t is binary coded.

Table 21. Multinomial logistic regression results for Belgium, Estonia, France, and Germany

Variable	Belgium (1) Y=2 vs. Y=1	Belgium (2) Y=3 vs. Y=1	Belgium (3) Y=4 vs. Y=1	Estonia (4) Y=2 vs. Y=1	Estonia (5) Y=3 vs. Y=1	Estonia (6) Y=4 vs. Y=1	France (7) Y=2 vs. Y=1	France (8) Y=3 vs. Y=1	France (9) Y=4 vs. Y=1	Germany (10) Y=2 vs. Y=1	Germany (11) Y=3 vs. Y=1	Germany (12) Y=4 vs. Y=1
Intercept	-2.9340**	-4.7470***	-6.0612***	-0.8270	-5.0052***	-8.4909***	-3.1469	-3.8196**	-5.4462***	-3.1996	-5.6162**	-7.9858***
(z-value)	(-1.924)	(-3.203)	(-4.020)	(-0.750)	(-4.585)	(-6.776)	(-1.630)	(-2.048)	(-2.821)	(-1.287)	(-2.326)	(-3.257)
FL$_{t-1}$	0.3607**	0.5260***	0.5746***	0.0671	0.1720*	0.1663	0.1108	0.0614	0.1867	0.4728**	0.5407***	0.5075**
(z-value)	(2.389)	(3.601)	(3.887)	(0.678)	(1.786)	(1.541)	(0.585)	(0.334)	(0.990)	(2.340)	(2.773)	(2.572)
AGE$_{t-1}$	0.0405*	0.0636***	0.0724***	0.0198	0.0671***	0.0874***	0.0386	0.0569**	0.0575**	0.0642*	0.0930**	0.1160***
(z-value)	(1.926)	(3.125)	(3.517)	(1.331)	(4.611)	(5.404)	(1.387)	(2.123)	(2.088)	(1.656)	(2.482)	(3.071)
CH$_{t-1}$	-0.0994	-0.1800**	-0.2198**	-0.2087***	0.0220	0.0739	0.1114	0.0856	0.0668	0.0523	0.0078	-0.0378
(z-value)	(-1.120)	(-2.092)	(-2.517)	(-2.702)	(0.303)	(0.915)	(0.966)	(0.769)	(0.572)	(0.353)	(0.054)	(-0.257)
EDU-MED$_{t-1}$	-0.4828	-0.3628	-0.3494	0.2500	0.2097	0.3304	0.7118*	0.4364	0.6513	-0.6600	-0.2123	-0.1545
(z-value)	(-1.413)	(-1.106)	(-1.047)	(1.059)	(0.915)	(1.225)	(1.694)	(1.074)	(1.547)	(-1.103)	(-0.357)	(-0.254)
EDU-HIGH$_{t-1}$	-0.2233	-0.3690	-0.0881	0.6733*	0.7833**	1.1052***	0.5489	0.4009	0.8180	-0.5873	0.0771	0.4648
(z-value)	(-0.569)	(-0.970)	(-0.230)	(1.908)	(2.286)	(2.953)	(0.909)	(0.686)	(1.381)	(-0.800)	(0.107)	(0.635)
EMPL$_{t}$	1.2534***	1.0178**	1.0422**	0.0695	0.4775	0.5541	-0.0448	0.1472	-0.2070	0.6239	0.0749	-0.3574
(z-value)	(2.674)	(2.237)	(2.271)	(0.203)	(1.429)	(1.511)	(-0.076)	(0.257)	(-0.352)	(1.164)	(0.142)	(-0.666)
FEMALE$_{t-1}$	0.0512	0.1056	-0.0255	0.2921	0.3517	0.4531*	-0.0042	0.0051	0.0733	-0.1148	0.3292	0.4996
(z-value)	(0.165)	(0.352)	(-0.084)	(1.322)	(1.638)	(1.903)	(-0.011)	(0.014)	(0.190)	(-0.270)	(0.806)	(1.213)
IN-MED$_{t}$	0.5751	1.5935***	2.4276***	0.7006***	1.1660***	1.6616***	1.2323**	2.1824***	2.9712***	0.7249	1.7781***	3.0657***
(z-value)	(1.606)	(4.628)	(6.957)	(3.057)	(5.218)	(6.289)	(2.358)	(4.296)	(5.713)	(1.085)	(2.741)	(4.696)
IN-HIGH$_{t}$	0.2686	1.8404***	3.4369***	1.2265***	2.4797***	3.6522***	1.7435	2.9517***	4.7618***	-0.8183	-0.1870	2.5239***
(z-value)	(0.444)	(3.235)	(6.048)	(2.886)	(6.039)	(8.352)	(1.587)	(2.737)	(4.404)	(-1.190)	(-0.293)	(3.992)
P-FIH$_{t-1}$	-0.0052	-0.0298**	-0.0628***	-0.0053	-0.0132	-0.0143	-0.0226	-0.0555***	-0.0660***	-0.0346***	-0.0756***	-0.1097***
(z-value)	(-0.438)	(-2.476)	(-4.682)	(-0.571)	(-1.440)	(-1.266)	(-1.613)	(-3.718)	(-4.005)	(-2.705)	(-5.521)	(-6.993)
PLAN$_{t-1}$	0.0712	0.1658	0.1836	0.0312	0.0736	0.1757	0.4607**	0.5530***	0.5938***	-0.0145	0.2958**	0.3322**
(z-value)	(0.609)	(1.476)	(1.622)	(0.280)	(0.677)	(1.501)	(2.443)	(3.002)	(3.175)	(-0.078)	(1.658)	(1.849)
RET$_{t-1}$	0.6270*	0.6655*	0.9250**	0.2881	0.2766	-0.0334	-0.0352	0.2596	0.3520	-0.9014	-0.8017	-0.5534
(z-value)	(1.697)	(1.881)	(2.569)	(0.962)	(0.937)	(-0.099)	(-0.073)	(0.559)	(0.738)	(-1.478)	(-1.360)	(-0.925)

	Belgium	Estonia	France	Germany
Number of obs.	2,034	2,254	1,113	1,433
Pseudo McFadden-R^2	0.1194	0.0760	0.1258	0.1890
Adj. pseudo McFadden-R^2	0.1140	0.0715	0.1164	0.1807
Nagelkerke-R^2	0.2299	0.1631	0.2493	0.3173
Hausman-McFadden test $\chi 2$ (p-value)	9.73 (0.9984)	-6.56 (1)	-2.22 (1)	-62.02 (1)

Note. This table presents the findings of the multinomial logistic regression model for Eq. (2). The z-values are based on robust standard errors (sandwich estimators) and are reported in parentheses. Columns (1), (2), and (3) contrast the Y=2, Y=3, and Y=4 categories, respectively, with the Y=1 category for Belgium. Accordingly, columns (4), (5), and (6) present the results for Estonia; columns (7), (8), and (9) for France; and columns (10), (11), and (12) for Germany. Y=1 (with great difficulty), Y=2 (with some difficulty), Y=3 (fairly easily), and Y=4 (easily) represent the dependent variable's (FR_t) outcome categories. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

Table 22. Multinomial logistic regression results for Italy, Slovenia, and Spain

	Italy			Slovenia			Spain		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Y=2 vs. Y=1	Y=3 vs. Y=1	Y=4 vs. Y=1	Y=2 vs. Y=1	Y=3 vs. Y=1	Y=4 vs. Y=1	Y=2 vs. Y=1	Y=3 vs. Y=1	Y=4 vs. Y=1
Intercept	-1.2197	-3.9554***	-9.6372***	1.2799	-2.1244**	-7.2622***	-1.5263	-3.1063**	-7.1285***
(z-value)	(-1.518)	(-4.343)	(-7.327)	(1.281)	(-1.977)	(-4.979)	(-1.055)	(-2.150)	(-4.354)
FL_{t-1}	0.0585	0.3497***	0.5847***	-0.0634	0.0841	0.2025	0.2587	0.2422	0.3582
(z-value)	(0.641)	(3.542)	(4.421)	(-0.612)	(0.764)	(1.416)	(1.224)	(1.166)	(1.601)
AGE_{t-1}	0.0294***	0.0462***	0.0803***	-0.0159	0.0111	0.0376**	0.0342*	0.0526***	0.0852***
(z-value)	(2.698)	(3.874)	(5.183)	(-1.364)	(0.896)	(2.302)	(1.774)	(2.746)	(4.047)
CH_{t-1}	-0.0745	-0.2020***	-0.4481***	-0.0935	-0.1514	-0.2120*	-0.2490**	-0.2977***	-0.4365***
(z-value)	(-1.178)	(-2.747)	(-4.026)	(-1.088)	(-1.601)	(-1.676)	(-2.292)	(-2.788)	(-3.592)
EDU-MED_{t-1}	0.7218***	0.8776***	1.2444***	0.6150***	0.9065***	1.0926***	-1.7238***	-1.4097***	-0.8380
(z-value)	(2.671)	(3.161)	(3.738)	(2.985)	(4.112)	(3.138)	(-2.873)	(-2.581)	(-1.478)
EDU-$HIGH_{t-1}$	17.5800	18.1600	19.2870	1.1731**	1.8561***	2.8807***	-0.9553	-0.3848	0.3496
(z-value)	(0.007)	(0.007)	(0.008)	(2.101)	(3.336)	(4.677)	(-1.353)	(-0.587)	(0.514)
$EMPL_t$	-1.0519***	-1.5141***	-1.4765***	-0.0099	-0.4284	0.1218	-0.8393	-1.4342**	-2.1010***
(z-value)	(-3.561)	(-4.847)	(-3.798)	(-0.023)	(-0.893)	(0.208)	(-1.451)	(-2.540)	(-3.312)
$FEMALE_{t-1}$	-0.0853	0.1204	-0.1742	0.0271	0.3449	0.2744	0.2233	0.2761	-0.0408
(z-value)	(-0.441)	(0.583)	(-0.663)	(0.124)	(1.482)	(0.984)	(0.553)	(0.699)	(-0.097)
IN-MED_t	1.3821***	2.3823***	3.3734***	0.6309***	1.0168***	2.0559***	0.8431**	1.6256***	2.2201***
(z-value)	(6.433)	(10.2239	(6.899)	(3.004)	(4.511)	(4.704)	(2.077)	(4.023)	(4.732)
IN-$HIGH_t$	2.0704***	4.0078***	5.7441***	1.9276***	3.3746***	5.0885***	0.8496	2.1336***	3.5337***
(z-value)	(5.708)	(10.826)	(10.261)	(3.891)	(6.812)	(8.259)	(1.560)	(4.052)	(6.134)
P-FIH_{t-1}	-0.0211***	-0.0555***	-0.0638***	-0.0028	-0.0283*	-0.0302	-0.0359**	-0.0356**	-0.0396**
(z-value)	(-2.710)	(-5.003)	(-2.930)	(-0.243)	(-1.820)	(-1.083)	(-2.280)	(-2.388)	(-2.041)
$PLAN_{t-1}$	-0.2131***	-0.2469***	-0.2149*	0.0757	0.1901**	0.2655**	0.0791	0.2191	0.5169**
(z-value)	(-2.909)	(-3.084)	(-1.960)	(0.829)	(2.000)	(2.302)	(0.395)	(1.133)	(2.560)
RET_{t-1}	0.6758***	1.1613***	1.0532***	0.6580***	0.5655**	0.5256	1.5012**	1.6702**	1.4602**
(z-value)	(2.845)	(4.635)	(3.328)	(2.741)	(2.150)	(1.293)	(2.249)	(2.527)	(2.115)

	Italy	Slovenia	Spain
Number of obs.	1,600	1,396	634
Pseudo McFadden-R^2	0.1925	0.1479	0.1246
Adj. pseudo McFadden-R^2	0.1864	0.1411	0.1095
Nagelkerke-R^2	0.3783	0.3120	0.2694
Hausman-McFadden test $\chi2$ (p-value)	-65.60 (1)	6.92 (0.9999)	-25.37 (1)

Note. This table presents the findings of the multinomial logistic regression model for Eq. (2). The z-values are based on robust standard errors (sandwich estimators) and are reported in parentheses. Columns (1), (2), and (3) contrast the Y=2, Y=3, and Y=4 categories, respectively, with the Y=1 category for Italy. Accordingly, columns (4), (5), and (6) present the results for Slovenia, and columns (7), (8), and (9) for Spain. Y=1 (with great difficulty), Y=2 (with some difficulty), Y=3 (fairly easily), and Y=4 (easily) represent the dependent variable's (FR_t) outcome categories. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

The variable importance results of the multinomial logistic regression models for the respective country samples are reported in Table 23 and ranked by importance in descending order.

Consistent with the findings from the logistic regression, IN-HIGH$_t$ and IN-MED$_t$ are the most important variables in predicting financial resilience, except for Germany, where the most important variable is P-FIH$_{t-1}$, followed by the income variables. The remaining explanatory variables vary in importance between the countries and differ from the logistic regression results. For example, FL$_{t-1}$ ranks in the midfield in Estonia, France, Slovenia, and Spain, while it belongs to the more important predictors of financial resilience in Belgium, Germany, and Italy.

In summary, the findings from the multinomial logistic regression reveal that, although IN-MED$_t$ and IN-HIGH$_t$ remain the most important predictors of financial resilience, noticeable differences in variable importance emerge among the various methods at the country level.

Table 23. Variable importance for financial resilience from multinomial logistic regressions at the country level

Rank	(1) Belgium	(2) Estonia	(3) France	(4) Germany	(5) Italy	(6) Slovenia	(7) Spain
1	IN-MED$_t$	IN-HIGH$_t$	IN-MED$_t$	P-FIH$_{t-1}$	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	IN-HIGH$_t$	IN-MED$_t$	IN-HIGH$_t$	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$
3	P-FIH$_{t-1}$	AGE$_{t-1}$	P-FIH$_{t-1}$	IN-HIGH$_t$	AGE$_{t-1}$	EDU-HIGH$_{t-1}$	AGE$_{t-1}$
4	FL$_{t-1}$	EDU-HIGH$_{t-1}$	PLAN$_{t-1}$	AGE$_{t-1}$	FL$_{t-1}$	EDU-MED$_{t-1}$	CH$_{t-1}$
5	AGE$_{t-1}$	FEMALE$_{t-1}$	AGE$_{t-1}$	FL$_{t-1}$	CH$_{t-1}$	PLAN$_{t-1}$	EMPL$_t$
6	RET$_{t-1}$	FL$_{t-1}$	EDU-MED$_{t-1}$	PLAN$_{t-1}$	EMPL$_t$	AGE$_{t-1}$	PLAN$_{t-1}$
7	CH$_{t-1}$	EMPL$_t$	EDU-HIGH$_{t-1}$	FEMALE$_{t-1}$	EDU-MED$_{t-1}$	CH$_{t-1}$	RET$_{t-1}$
8	EMPL$_t$	PLAN$_{t-1}$	FL$_{t-1}$	RET$_{t-1}$	RET$_{t-1}$	FL$_{t-1}$	P-FIH$_{t-1}$
9	PLAN$_{t-1}$	P-FIH$_{t-1}$	RET$_{t-1}$	EMPL$_t$	P-FIH$_{t-1}$	RET$_{t-1}$	FL$_{t-1}$
10	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$	CH$_{t-1}$	EDU-HIGH$_{t-1}$	PLAN$_{t-1}$	P-FIH$_{t-1}$	EDU-MED$_{t-1}$
11	EDU-HIGH$_{t-1}$	CH$_{t-1}$	EMPL$_t$	CH$_{t-1}$	FEMALE$_{t-1}$	FEMALE$_{t-1}$	EDU-HIGH$_{t-1}$
12	FEMALE$_{t-1}$	RET$_{t-1}$	FEMALE$_{t-1}$	EDU-MED$_{t-1}$	EDU-HIGH$_{t-1}$	EMPL$_t$	FEMALE$_{t-1}$

Note. This table presents the variable importance for financial resilience from the multinomial logistic regression, measured by the absolute z-value, for the variables applied according to Eq. (2), in descending order. Column (1) reports the results for Belgium, column (2) for Estonia, column (3) for France, column (4) for Germany, column (5) for Italy, column (6) for Slovenia, and column (7) for Spain. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

4.2.2. Partial proportional odds

The second robustness check is a partial proportional odds regression, performed using the R package "VGAM" (Yee, 2015; Yee and Wild, 1996). After fitting a standard ordered logit model, the Brant test (Brant, 1990) reveals violations of the parallel lines assumption by several predictors. Consequently, a partial proportional odds model is used to allow predictors that violate the assumption to vary across the slopes (Soon, 2010). Table 24 presents the findings of the partial proportional odds regression based on Equation 1, along with robust standard errors (i.e., sandwich estimators).

The Pseudo-R^2, adjusted Pseudo-R^2, and Nagelkerke-R^2 measures indicate sufficient goodness of regression with values ranging from 0.18 to 0.36 (Rohrlack, 2009). Furthermore, the non-significant chi-square value of the Hosmer–Lemeshow test (Hosmer and Lemeshow, 2000), which examines whether the observed proportions of events are like the predicted probabilities of occurrence in ten subgroups of the data set, indicates a good data fit.

Column (1) of Table 24 contrasts the Y=1 category with the Y=2, Y=3, and Y=4 categories. The coefficient's signs indicate the likelihood that an individual dealt "With great difficulty" compared to the other three categories of financial resilience. Correspondingly, the Y=1 and Y=2 categories (Y=1, Y=2, and Y=3 categories) are contrasted with the Y=3 and Y=4 categories (Y=4 category) in column (2) (column (3)). Each of these columns present the results for the log odds estimates. The coefficients that are absent in columns (2) and (3) correspond to those found in column (1) because these are those wherein the parallel lines assumption holds. The seven variables in columns (2) and (3), that is, CH_{t-1}, RET_{t-1}, $BELGIUM_{t-1}$, $FRANCE_{t-1}$, $GERMANY_{t-1}$, $SLOVENIA_{t-1}$, and $SPAIN_{t-1}$, are those that violate the parallel lines assumption. Thus, those variables' coefficients vary across the outcome categories.

When interpreting the results from Table 24, the current category and the categories coded lower of each column are treated as the base group for comparison. Thus, positive coefficients suggest that higher values of a predictor variable increase the likelihood of an individual belonging to a higher Y category than the current one. Conversely, negative coefficients suggest that higher values of a predictor increase the likelihood of falling into the current or lower Y category.

Regarding the regression coefficients' signs and significance, the findings align with those of the logistic regression, as reported in Table 15, and largely correspond to the results from the multinomial logistic regression, as reported in Table 20.

FL_{t-1} has a significantly positive influence on FR_t across all outcome categories. Thus, respondents with higher financial literacy levels are more likely to be financially resilient.

RET_{t-1} is significantly positive in columns (1) and (2), while it turns non-significant in column (3). The same applies to the country dummy $SLOVENIA_{t-1}$, which is significantly negative in the first and second columns and non-significant in the third. This indicates that the influence of RET_{t-1} and $SLOVENIA_{t-1}$ on financial resilience is essential for individuals with lower financial resilience levels. The results of the remaining explanatory variables correspond to those of the logistic and multinomial logistic regression regarding signs and significance.

The variable importance results from the partial proportional odds regression largely match those of the logistic and multinomial logistic regression. The absolute z-values from column (1) are taken as a basis to enable comparison with the logistic and multinomial logistic regression results because they represent feature importance for the lowest vs. the remaining three categories of Y, including the highest.

$IN\text{-}HIGH_t$ and $IN\text{-}MED_t$ are the most important variables, followed by AGE_{t-1}, $P\text{-}FIH_{t-1}$, and $EDU\text{-}HIGH_{t-1}$. Thereafter, the country dummies $BELGIUM_{t-1}$ and $GERMANY_{t-1}$ follow. The absolute z-values of $BELGIUM_{t-1}$, $FRANCE_{t-1}$, $GERMANY_{t-1}$, and $SPAIN_{t-1}$ rise among the various outcome categories, emphasizing that country-specific factors are crucial in strengthening financial resilience. FL_{t-1} again ranks in the midfield, being the 10^{th} most important variable out of 18.

Table 24. Partial proportional odds regression results for the total sample

Variable	(1) *Y=1 vs. Y=2-4* *Y>1*	(2) *Y=1-2 vs. Y=3-4* *Y>2*	(3) *Y=1-3 vs. Y=4* *Y>3*	(4) Rank
Intercept (z-value)	-1.6575 *** (-7.532)	-3.8969 *** (-18.277)	-6.4330 *** (-28.919)	
FL_{t-1} (z-value)	0.1404 *** (6.766)			10
AGE_{t-1} (z-value)	0.0313 *** (11.830)			3
CH_{t-1} (z-value)	-0.1097 *** (-3.763)	-0.0353 * (-1.901)	-0.0469 ** (-2.407)	15
$EDU\text{-}MED_{t-1}$ (z-value)	0.1988 *** (3.962)			14
$EDU\text{-}HIGH_{t-1}$ (z-value)	0.5274 *** (8.773)			5
$EMPL_{t}$ (z-value)	-0.0873 (-1.377)			18
$FEMALE_{t-1}$ (z-value)	0.0733 * (1.788)			17
$IN\text{-}MED_{t}$ (z-value)	1.1713 *** (24.740)			2
$IN\text{-}HIGH_{t}$ (z-value)	2.2691 *** (37.570)			1
$P\text{-}FIH_{t-1}$ (z-value)	-0.0281 *** (-11.508)			4
$PLAN_{t-1}$ (z-value)	0.0876 *** (5.123)			12
RET_{t-1} (z-value)	0.5212 *** (5.647)	0.2977 *** (4.822)	0.0715 (1.116)	11
$BELGIUM_{t-1}$ (z-value)	1.2747 *** (8.725)	1.4661 *** (17.306)	2.2260 *** (26.279)	6
$ESTONIA_{t-1}$ (z-value)	0.5555 *** (7.855)			8
$FRANCE_{t-1}$ (z-value)	1.3665 *** (7.814)	1.5025 *** (15.277)	1.9586 *** (20.506)	9
$GERMANY_{t-1}$ (z-value)	1.7259 *** (8.697)	1.9302 *** (18.332)	2.5100 *** (26.738)	7
$SLOVENIA_{t-1}$ (z-value)	-0.3651 *** (-3.202)	-0.4348 *** (-5.184)	-0.0240 (-0.222)	16
$SPAIN_{t-1}$ (z-value)	0.7553 *** (4.480)	0.8476 *** (7.913)	1.3308 *** (11.234)	13
Number of obs.		10,464		
Pseudo McFadden-R^2		0.1751		
Adj. pseudo McFadden-R^2		0.1738		
Nagelkerke-R^2		0.3539		
Hosmer and Lemeshow test $\chi2$ (p-value)		33.20 (0.1564)		

Note. This table presents the results of the cumulative partial proportional odds model. The z-values are based on robust standard errors (sandwich estimators) and are reported in parentheses. Columns (1), (2), and (3) contrast the Y=1, Y=1-2, and Y=1-3 categories, respectively, with the Y=2-4, Y=3-4, and Y=4 categories. Y=1 (with great difficulty), Y=2 (with some difficulty), Y=3 (fairly easily), and Y=4 (easily) represent the dependent variable's (FR_t) outcome categories. Column (4) presents the variable importance ranking of the predictors of financial resilience, measured by the absolute z-value. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

The results of the partial proportional odds regression models for the country-level analysis, based on Equation 2, are displayed in two tables in alphabetical order. Table 25 presents the results for Belgium, Estonia, France, and Germany, while Table 26 includes the results for Italy, Slovenia, and Spain.

The Pseudo-R^2, adjusted Pseudo-R^2, and Nagelkerke-R^2 measures imply moderate to sufficient goodness of regression. The model for Estonia is relatively moderately fitted compared to the other country models. However, the chi-square values of the Hosmer-Lemeshow test are non-significant for all country-level models, including Estonia, indicating a good data fit.

The findings largely correspond to those of the multinomial logistic regression, as reported in Table 21 and Table 22. Regarding regression coefficients' signs and significance, distinct differences emerge between the countries. FL_{t-1} is significantly positive in Belgium, Estonia, Germany, Italy, and Slovenia, while it has no significant effect on FR_t in France and Spain.

In Germany, FL_{t-1} is significantly positive for the Y>1 and Y>2 outcome categories and is not significant for the Y>3 category, revealing that financial literacy in Germany is key in protecting individuals from financial fragility. Additionally, it has no significant influence on improving financial resilience when already financially resilient. This aligns with recent findings from Bialowolski et al. (2022), who reveal that for European countries, including Germany, financial literacy's impact on financial resilience is not symmetrical because it protects more against the loss of financial resilience than it contributes to the gain of financial resilience.

Table 25. Partial proportional odds regression results for Belgium, Estonia, France, and Germany

Variable	Belgium			Estonia			France			Germany		
	(1) *Y=1 vs. Y=2-4* *Y>1*	(2) *Y=1-2 vs. Y=3-4* *Y>2*	(3) *Y=1-3 vs. Y=4* *Y>3*	(4) *Y=1 vs. Y=2-4* *Y>1*	(5) *Y=1-2 vs. Y=3-4* *Y>2*	(6) *Y=1-3 vs. Y=4* *Y>3*	(7) *Y=1 vs. Y=2-4* *Y>1*	(8) *Y=1-2 vs. Y=3-4* *Y>2*	(9) *Y=1-3 vs. Y=4* *Y>3*	(10) *Y=1 vs. Y=2-4* *Y>1*	(11) *Y=1-2 vs. Y=3-4* *Y>2*	(12) *Y=1-3 vs. Y=4* *Y>3*
Intercept	-0.4886	-1.9700***	-3.5786***	-1.9125***	-4.4652***	-6.9231***	-0.0931	-1.4284**	-3.4559***	-1.7411**	-2.7639***	-4.0723***
(z-value)	(-0.769)	(-3.674)	(-6.745)	(-3.815)	(-9.042)	(-13.580)	(-0.131)	(-2.165)	(-5.205)	(-1.960)	(-3.699)	(-5.514)
FL_{t-1}	0.3713***	0.2303***	0.1291**	0.0781*			0.0851			0.5149***	0.1586*	0.0100
(z-value)	(2.960)	(3.473)	(2.319)	(1.839)			(1.394)			(2.934)	(1.748)	(0.145)
AGE_{t-1}	0.0256***			0.0477***			0.0183**			0.0370***		
(z-value)	(3.924)			(7.821)			(2.083)			(3.756)		
CH_{t-1}	-0.0844***			-0.0215	0.1870***	0.1251***	-0.0087			-0.0593		
(z-value)	(-2.685)			(-0.319)	(4.664)	(2.880)	(-0.202)			(-1.368)		
EDU-MED_{t-1}	0.0086			0.0870			0.1024			0.1042		
(z-value)	(0.074)			(0.795)			(0.699)			(0.535)		
EDU-$HIGH_{t-1}$	0.1487			0.3505***			0.3203*			0.4856**		
(z-value)	(1.260)			(2.681)			(1.886)			(2.231)		
$EMPL_t$	0.4608	-0.0321	0.1103	0.4462***			-0.1214			-0.4565***		
(z-value)	(1.165)	(-0.171)	(0.704)	(3.064)			(-0.637)			(-2.776)		
$FEMALE_{t-1}$	-0.0552			0.1782*			0.0411			0.3256***		
(z-value)	(-0.585)			(1.919)			(0.335)			(2.761)		
IN-MED_t	1.3053***			0.7152***			1.2823***			1.5686***		
(z-value)	(11.991)			(7.133)			(8.808)			(11.525)		
IN-$HIGH_t$	2.2138***			1.7300***			2.3442***			0.9596*	1.8484***	2.8635***
(z-value)	(15.436)			(12.758)			(12.373)			(1.772)	(6.627)	(14.903)
P-FIH_{t-1}	-0.0364***			-0.0080*			-0.0350***			-0.0548***		
(z-value)	(-6.455)			(-1.673)			(-4.589)			(-7.965)		
$PLAN_{t-1}$	0.0706**			0.0979**			0.5522***	0.1735**	0.0917*	0.3337*	0.3279***	0.0938*
(z-value)	(1.989)			(2.265)			(3.09)	(2.549)	(1.689)	(1.929)	(4.170)	(1.783)
RET_{t-1}	0.3191**			-0.0395			0.1874			0.1686		
(z-value)	(2.460)			(-0.281)			(1.218)			(0.925)		

	Belgium	Estonia	France	Germany
Number of obs.	2,034	2,254	1,113	1,433
Pseudo McFadden-R^2	0.1128	0.0717	0.1174	0.1827
Adj. pseudo McFadden-R^2	0.1074	0.0671	0.1079	0.1744
Nagelkerke-R^2	0.2187	0.1545	0.2347	0.3086
Hosmer and Lemeshow test $\chi 2$ (p-value)	23.42 (0.6090)	34.76 (0.1169)	36.45 (0.0836)	24.44 (0.5510)

Note. This table presents the results of the partial proportional odds model for Eq. (2). The z-values are based on robust standard errors (sandwich estimators) and are reported in parentheses. Columns (1), (2), and (3) contrast the Y=1, Y=1-2, and Y=1-3 categories, respectively, with the Y=2-4, Y=3-4, and Y=4 categories, for Belgium. Accordingly, columns (4), (5), and (6) present the results for Estonia; columns (7), (8), and (9) for France; and columns (10), (11), and (12) for Germany. Y=1 (with great difficulty), Y=2 (with some difficulty), Y=3 (fairly easily), and Y=4 (easily) represent the dependent variable's (FR_t) outcome categories. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

Table 26. Partial proportional odds regression results for Italy, Slovenia, and Spain

Variable	Italy			Slovenia			Spain		
	(1) *Y=1 vs. Y=2-4 Y>1*	(2) *Y=1-2 vs. Y=3-4 Y>2*	(3) *Y=1-3 vs. Y=4 Y>3*	(4) *Y=1 vs. Y=2-4 Y>1*	(5) *Y=1-2 vs. Y=3-4 Y>2*	(6) *Y=1-3 vs. Y=4 Y>3*	(7) *Y=1 vs. Y=2-4 Y>1*	(8) *Y=1-2 vs. Y=3-4 Y>2*	(9) *Y=1-3 vs. Y=4 Y>3*
Intercept	-1.6305***	-4.0252***	-6.9620***	-0.1531	-4.5169***	-6.3422***	-0.9712	-3.1096***	-5.3023***
(z-value)	(-3.365)	(-8.157)	(-13.287)	(-0.196)	(-6.895)	(-7.547)	(-1.440)	(-4.596)	(-7.581)
FL_{t-1}	0.2798***			0.1301**			0.1028		
(z-value)	(5.391)			(2.193)			(1.160)		
AGE_{t-1}	0.0319***			0.0036	0.0315***	0.0227**	0.0366***		
(z-value)	(5.225)			(0.365)	(4.029)	(2.148)	(4.407)		
CH_{t-1}	-0.1640***			-0.0819			-0.1588***		
(z-value)	(-3.965)			(-1.542)			(-3.081)		
EDU-MED_{t-1}	0.4408***			0.5369***			-1.1195**	0.0094	0.5225*
(z-value)	(3.495)			(4.185)			(-2.532)	(0.028)	(1.690)
EDU-$HIGH_{t-1}$	1.3598***			1.4022***			0.7860***		
(z-value)	(6.523)			(7.670)			(2.736)		
$EMPL_t$	-1.0689***	-0.6143***	-0.0799	0.0817			-1.0777***		
(z-value)	(-4.532)	(-3.393)	(-0.318)	(0.336)			(-3.480)		
$FEMALE_{t-1}$	0.0407			0.2096*			-0.0824		
(z-value)	(0.392)			(1.824)			(-0.485)		
IN-MED_t	1.4918***			0.7768***			1.0305***		
(z-value)	(11.605)			(5.797)			(5.473)		
IN-$HIGH_t$	2.6312***			2.0620***			1.9324***		
(z-value)	(17.090)			(12.833)			(8.571)		
P-FIH_{t-1}	-0.0311***			-0.0162*			-0.0173*		
(z-value)	(-5.082)			(-1.835)			(-1.853)		
$PLAN_{t-1}$	-0.1034**			0.1438***			0.3098***		
(z-value)	(-2.373)			(3.023)			(3.968)		
RET_{t-1}	0.8267***	0.5578***	0.1793	0.2583			0.1942		
(z-value)	(3.962)	(3.959)	(0.894)	(1.590)			(0.967)		

	Italy	Slovenia	Spain
Number of obs.	1,600	1,396	634
Pseudo McFadden-R^2	0.1843	0.1394	0.1076
Adj. pseudo McFadden-R^2	0.1782	0.1326	0.0926
Nagelkerke-R^2	0.3656	0.2971	0.2376
Hosmer and Lemeshow test $\chi 2$ (p-value)	25.46 (0.4930)	25.62 (0.4842)	18.94 (0.8388)

Note. This table presents the results of the partial proportional odds model for Eq. (2). The z-values are based on robust standard errors (sandwich estimators) and are reported in parentheses. Columns (1), (2), and (3) contrast the Y=1, Y=1-2, and Y=1-3 categories, respectively, with the Y=2-4, Y=3-4, and Y=4 categories, for Italy. Accordingly, columns (4), (5), and (6) present the results for Slovenia, and columns (7), (8), and (9) for Spain. Y=1 (with great difficulty), Y=2 (with some difficulty), Y=3 (fairly easily), and Y=4 (easily) represent the dependent variable's (FR_t) outcome categories. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

[Source: Own representation]

The variable importance results of the partial proportional odds regression models for the respective country samples are reported in Table 27 and ranked by importance in descending order.

In line with the logistic and multinomial logistic regression's findings, IN-HIGH$_t$ and IN-MED$_t$ are the most important variables in explaining financial resilience, except for Germany, where IN-MED$_t$ and P-FIH$_{t-1}$ are the most important variables.

FL$_{t-1}$ ranks in the midfield in Estonia, France, and Slovenia, while it belongs to the more important predictors of financial resilience in Belgium, Germany, and Italy and is among the least important in Spain.

Table 27. Variable importance for financial resilience from partial proportional odds regressions at the country level

Rank	(1) Belgium	(2) Estonia	(3) France	(4) Germany	(5) Italy	(6) Slovenia	(7) Spain
1	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$	IN-MED$_t$	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	IN-MED$_t$	AGE$_{t-1}$	IN-MED$_t$	P-FIH$_{t-1}$	IN-MED$_t$	EDU-HIGH$_{t-1}$	IN-MED$_t$
3	P-FIH$_{t-1}$	IN-MED$_t$	P-FIH$_{t-1}$	AGE$_{t-1}$	EDU-HIGH$_{t-1}$	IN-MED$_t$	AGE$_{t-1}$
4	AGE$_{t-1}$	EMPL$_t$	PLAN$_{t-1}$	FL$_{t-1}$	FL$_{t-1}$	EDU-MED$_{t-1}$	PLAN$_{t-1}$
5	FL$_{t-1}$	EDU-HIGH$_{t-1}$	AGE$_{t-1}$	EMPL$_t$	AGE$_{t-1}$	PLAN$_{t-1}$	EMPL$_t$
6	CH$_{t-1}$	PLAN$_{t-1}$	EDU-HIGH$_{t-1}$	FEMALE $_{t-1}$	P-FIH$_{t-1}$	FL$_{t-1}$	CH$_{t-1}$
7	RET$_{t-1}$	FEMALE $_{t-1}$	FL$_{t-1}$	EDU-HIGH$_{t-1}$	EMPL$_t$	P-FIH$_{t-1}$	EDU-HIGH$_{t-1}$
8	PLAN$_{t-1}$	FL$_{t-1}$	RET$_{t-1}$	PLAN$_{t-1}$	CH$_{t-1}$	FEMALE $_{t-1}$	EDU-MED$_{t-1}$
9	EDU-HIGH$_{t-1}$	P-FIH$_{t-1}$	EDU-MED$_{t-1}$	IN-HIGH$_t$	RET$_{t-1}$	RET$_{t-1}$	P-FIH$_{t-1}$
10	EMPL$_t$	EDU-MED$_{t-1}$	EMPL$_t$	CH$_{t-1}$	EDU-MED$_{t-1}$	CH$_{t-1}$	FL$_{t-1}$
11	FEMALE$_{t-1}$	CH$_{t-1}$	FEMALE $_{t-1}$	RET$_{t-1}$	PLAN$_{t-1}$	AGE$_{t-1}$	RET$_{t-1}$
12	EDU-MED$_{t-1}$	RET$_{t-1}$	CH$_{t-1}$	EDU-MED$_{t-1}$	FEMALE $_{t-1}$	EMPL$_t$	FEMALE $_{t-1}$

Note. This table presents the variable importance for financial resilience from the partial proportional odds model, measured by the absolute z-value, for the variables applied according to Eq. (2), in descending order. Column (1) reports the results for Belgium, column (2) for Estonia, column (3) for France, column (4) for Germany, column (5) for Italy, column (6) for Slovenia, and column (7) for Spain. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

4.2.3. Conditional random forest

A conditional random forest analysis is performed as a third and final robustness check, using the R package “party” (Hothorn, Bühlmann, Dudoit, Molinaro, and Van Der Laan, 2006; Strobl et al., 2008, 2007). A conditional random forest is selected over a random forest to ensure unbiased results concerning scale levels, as discussed in Section 3.2.4. The dataset is split into a training and a test set, according to the common splitting rule of 70%/30% (e.g., Buntine and Niblett, 1992). Therefore, the training and test sets comprise 7,372 and 3,092 observations, respectively. Three randomly selected predictors are tested to divide the sample at each split. The allocation of observations is determined through a majority vote among 5,000 classification trees, with subsamples being drawn without replacement.

When the conditional random forest results are generalized to the test dataset, sufficient goodness of regression is obtained, with an accuracy of 75.7%, as reported in Table 28. Overall, the conditional random forest’s accuracy is slightly lower than the logistic regression’s accuracy, demonstrating that multiple tree estimation, such as conditional random forest, does not, per se, outperform classical stochastic models (Breiman, 2001).

However, the TNR of 93.4% is distinctly higher than that of the logistic regression, while the TPR is comparably low with only 32.8%. One possible explanation for these inverse results, compared to the logistic regression, might be that conditional random forests are generally better able to handle the class imbalance of the dependent variable than logistic regression. By considering the class distribution within each tree and adjusting the splitting criteria accordingly, classification errors for majority class is reduced, which may lower TPR (Fernández-Delgado, Cernadas, Barro, and Amorim, 2014). However, as the low TPR indicates that the model may not perform well in correctly identifying the positive class instances, an AUC-based permutation variable importance measure, as described by Janitza, Strobl, and Boulesteix (2013), is used in addition to the mean decrease in accuracy measure.

The AUC-based permutation variable importance measure, termed "mean decrease in AUC" in the following, is an alternative permutation variable importance measure based on the area under the curve (i.e., AUC) that is more robust toward class imbalance than the regular permutation accuracy importance measure (i.e., mean decrease in accuracy). The mean decrease in AUC outperforms the mean decrease in accuracy measure for unbalanced data settings, replacing the error rate with the AUC. However, for balanced class data, the performance of both measures is similar (Calle, Urrea, Boulesteix, and Malats, 2011; Janitza et al., 2013).

Columns (1) and (2) of Table 28 report the conditional random forest analysis results ranked by mean decrease in accuracy and mean decrease in AUC, in descending order. The findings roughly correspond to those of the logistic, multinomial logistic, and partial proportional odds regressions, as reported in Table 15, Table 20, and Table 24, respectively. Table 28 reveals slight deviations in the results between the two applied variable importance measures.

The variables IN-HIGH$_t$ and IN-MED$_t$ contribute the most to prediction accuracy, followed by the country dummies GERMANY$_{t-1}$ and BELGIUM$_{t-1}$. Surprisingly, SLOVENIA$_{t-1}$ gains importance in the conditional random forest analysis and is the third most important variable in predicting financial resilience for the mean decrease in accuracy measure, while in the logistic regression, it ranks in the midfield, and for the multinomial logistic and partial proportional odds regression, it is among the least important variables. However, for the mean decrease in AUC measure, SLOVENIA$_{t-1}$ is the sixth most important variable in explaining financial resilience and, thus, ranks in the midfield.

Furthermore, SPAIN$_{t-1}$ is a less important predictor of financial resilience for both measures compared to the logistic, multinomial logistic, and partial proportional odds regression.

Differences between the two variable importance measures further emerge for P-FIH$_{t-1}$, which is less important according to the mean decrease in accuracy (12th rank), and in the midfield according to the mean decrease in AUC (9th rank).

The ranking of the remaining variables is similar between the two measures. Such as for FL$_{t-1}$, which ranks in the midfield for both measures, being the 8th most important variable out of 18.

Overall, the variable importance results based on the mean decrease in AUC more closely correspond to those of the logistic, multinomial logistic, and partial proportional odds regressions.

Table 28. Variable importance for financial resilience from conditional random forests for the total sample

Rank	(1) Mean decrease in accuracy		(2) Mean decrease in AUC	
Panel A: Variable importance using the training dataset				
1	IN-HIGH$_t$	0.0436	IN-HIGH$_t$	0.0720
2	IN-MED$_t$	0.0181	IN-MED$_t$	0.0286
3	SLOVENIA$_{t-1}$	0.0169	GERMANY$_{t-1}$	0.0271
4	GERMANY$_{t-1}$	0.0113	BELGIUM$_{t-1}$	0.0230
5	BELGIUM$_{t-1}$	0.0113	EDU-HIGH$_{t-1}$	0.0227
6	EDU-HIGH$_{t-1}$	0.0082	SLOVENIA$_{t-1}$	0.0207
7	FRANCE$_{t-1}$	0.0082	FRANCE$_{t-1}$	0.0130
8	FL$_{t-1}$	0.0065	FL$_{t-1}$	0.0099
9	AGE$_{t-1}$	0.0053	P-FIH$_{t-1}$	0.0090
10	ESTONIA$_{t-1}$	0.0048	AGE$_{t-1}$	0.0078
11	RET$_{t-1}$	0.0044	ESTONIA$_{t-1}$	0.0074
12	P-FIH$_{t-1}$	0.0044	PLAN$_{t-1}$	0.0067
13	EDU-MED$_{t-1}$	0.0030	RET$_{t-1}$	0.0064
14	PLAN$_{t-1}$	0.0028	EDU-MED$_{t-1}$	0.0049
15	EMPL$_t$	0.0018	EMPL$_t$	0.0039
16	SPAIN$_{t-1}$	0.0016	SPAIN$_{t-1}$	0.0019
17	CH$_{t-1}$	0.0012	CH$_{t-1}$	0.0017
18	FEMALE$_{t-1}$	0.0001	FEMALE$_{t-1}$	0.0005
Panel B: Prediction accuracy using the test dataset				
Accuracy		0.7565		
TPR		0.3279		
TNR		0.9344		

Note. Columns (1) and (2) of Panel A report the variable importance for financial resilience, based on the mean decrease in accuracy and AUC, respectively, for the variables applied according to Eq. (1), in descending order. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Panel B presents the prediction accuracy using the test dataset, which constitutes 30% of the observations in the sample. Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

Table 29 reports the findings from the conditional random forest analysis at the country level. The accuracies of all models indicate sufficient goodness of regression.

However, the TPRs are considerably low, with values ranging from 9.2% to 20.5%, except for Italy and Slovenia (68.8% and 72.4%, respectively), where the classes of the dependent variable are relatively equally distributed (Table 14). As the TPR values demonstrate that class imbalance is even more prominent for the samples at the country level and research documents that the mean decrease in AUC outperforms the mean decrease in accuracy for class imbalanced data (Calle et al., 2011; Janitza et al., 2013), the mean decrease in AUC is used as a variable importance measure for the country level analyses. Thus, Table 29 reports the findings from the conditional random forest analysis at the country level, ranked by mean decrease in AUC, in descending order.

In line with the logistic, multinomial logistic, and partial proportional odds regression findings, the most important variables in predicting financial resilience are IN-HIGH$_t$ and IN-MED$_t$, except for Germany, where, together with the income variables, P-FIH$_{t-1}$ evolves as one of the most important variables.

The remaining explanatory variables vary in their importance among the countries. Such as FL$_{t-1}$, which ranks in the midfield for Estonia, Germany, and Slovenia, belongs to the relatively important predictors of financial resilience for Belgium, Italy, and Spain, while it is among the least important in France.

When mean decrease in accuracy is additionally applied as a variable importance measure, the country-level findings slightly differ for those countries with prevalent class imbalances (i.e., Belgium, Estonia, France, Germany, and Spain), whereas for the countries with balanced class samples (i.e., Italy and Slovenia) the findings largely correspond with those of the mean decrease in AUC (not reported in Table 29).

Table 29. Variable importance for financial resilience from conditional random forests at the country level

Rank	(1) Belgium	(2) Estonia	(3) France	(4) Germany	(5) Italy	(6) Slovenia	(7) Spain
Panel A: Variable importance using the training dataset							
1	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$	P-FIH$_{t-1}$	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$	EDU-HIGH$_{t-1}$	AGE$_{t-1}$
3	P-FIH$_{t-1}$	AGE$_{t-1}$	P-FIH$_{t-1}$	IN-HIGH$_t$	FL$_{t-1}$	IN-MED$_t$	IN-MED$_t$
4	FL$_{t-1}$	CH$_{t-1}$	RET$_{t-1}$	PLAN$_{t-1}$	P-FIH$_{t-1}$	EDU-MED$_{t-1}$	FL$_{t-1}$
5	EDU-HIGH$_{t-1}$	EMPL$_t$	EDU-HIGH$_{t-1}$	AGE$_{t-1}$	EDU-HIGH$_{t-1}$	PLAN$_{t-1}$	RET$_{t-1}$
6	PLAN$_{t-1}$	P-FIH$_{t-1}$	CH$_{t-1}$	FL$_{t-1}$	RET$_{t-1}$	FL$_{t-1}$	P-FIH$_{t-1}$
7	AGE$_{t-1}$	FL$_{t-1}$	PLAN$_{t-1}$	RET$_{t-1}$	CH$_{t-1}$	AGE$_{t-1}$	CH$_{t-1}$
8	RET$_{t-1}$	RET$_{t-1}$	EDU-MED$_{t-1}$	EMPL$_t$	AGE$_{t-1}$	P-FIH$_{t-1}$	EDU-MED$_{t-1}$
9	CH$_{t-1}$	EDU-HIGH$_{t-1}$	EMPL$_t$	EDU-HIGH$_{t-1}$	EDU-MED$_{t-1}$	EMPL$_t$	EDU-HIGH$_{t-1}$
10	EMPL$_t$	PLAN$_{t-1}$	FL$_{t-1}$	EDU-MED$_{t-1}$	PLAN$_{t-1}$	FEMALE$_{t-1}$	FEMALE$_{t-1}$
11	FEMALE$_{t-1}$	FEMALE$_{t-1}$	AGE$_{t-1}$	FEMALE$_{t-1}$	EMPL$_t$	CH$_{t-1}$	EMPL$_t$
12	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$	FEMALE$_{t-1}$	CH$_{t-1}$	FEMALE$_{t-1}$	RET$_{t-1}$	PLAN$_{t-1}$
Panel B: Prediction accuracy using the test dataset							
Accuracy	0.8336	0.6909	0.8157	0.8891	0.7193	0.6888	0.6802
TPR	0.101	0.2046	0.0923	0.1177	0.6875	0.7238	0.1231
TNR	0.9904	0.9158	0.9925	0.9922	0.7500	0.6540	0.9546

Note. Panel A presents the variable importance for financial resilience, based on the mean decrease in AUC, for the variables applied according to Eq. (2), in descending order. t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Column (1) reports the results for Belgium, column (2) for Estonia, column (3) for France, column (4) for Germany, column (5) for Italy, column (6) for Slovenia, and column (7) for Spain. Panel B presents the prediction accuracy using the test dataset, which constitutes 30% of the observations in the sample. Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

4.3. SUMMARY AND INTERPRETATION OF EMPIRICAL FINDINGS

4.3.1 Overview of regression results

To test H1 and H3, the regression results from the logistic, multinomial logistic, and partial proportional odds regression for the total sample and samples at the country level are summarized in the following. As the conditional random forest analysis does not provide individual coefficients that can be interpreted, it is not considered for evaluating the first and third hypotheses.

For the total sample, the findings from the robustness checks largely correspond to those of the logistic regression. In line with the expectations of this analysis, FL_{t-1} has a significantly positive effect on FR_t among all applied methods. Accordingly, the analysis fails to reject H1.

H1: The probability of being financially resilient increased with an individual's financial literacy level during the COVID-19 pandemic in European households.

While the regression results of most controlling variables correspond with previous findings from the literature, as discussed in Section 2.1.3., some findings are noteworthy.

$FEMALE_{t-1}$ significantly positively affects FR_t among all applied methods, indicating women's greater likelihood to be financially resilient than men during the COVID-19 crisis in Europe. However, in the multinomial logistic regression, it is only significantly positive for the Y=3 vs. Y=1 outcome category. This contributes to existing findings, which have been mixed regarding gender's effect on financial resilience.

Further, contrary to numerous previous findings, RET_{t-1} exhibits a significantly positive effect on FR_t among all applied methods, indicating that pensioners were less susceptible to financial fragility during COVID-19.

Considering the country-level regression findings to test for H3, the results from the robustness checks largely correspond to those of the logistic regression for the country-level samples.

Regarding financial literacy's impact on financial resilience, the findings consistently reveal that FL_{t-1} positively influences FR_t. However, its statistical significance varies across the countries. Consequently, the analysis fails to reject H3.

H3: The impact of an individual's financial literacy level on their probability of being financially resilient during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

FL_{t-1} has a significantly positive effect on FR_t among all applied methods in Belgium, Estonia, and Italy, whereas, in France and Spain, FL_{t-1} positively impacts FR_t but the effect is not statistically significant. Interestingly, the regression results are mixed in Germany and Slovenia. In Germany, the relation between FL_{t-1} and FR_t is positive but not significant in the logistic regression, while in the multinomial and partial proportional odds regression, it becomes significantly positive. In the partial proportional odds regression, the association is significantly positive for the Y>1 and Y>2 outcome categories, while it is not significant for the Y>3 category, indicating that in Germany, financial literacy helps protect individuals from financial fragility but has no significant influence on improving financial resilience when already financially resilient. In Slovenia, FL_{t-1} significantly positively influences FR_t in the logistic and partial proportional odds regression, while the relation becomes insignificant in the multinomial logistic regression.

Overall, the findings from the multiple regressions reveal that although financial literacy positively influences financial resilience, differences between the countries emerge in terms of statistical significance. In the case of Germany and Slovenia, variations arise even within the methods.

Considering the controlling variables' regression results, as expected, distinct differences emerge among the countries. Noteworthily, $FEMALE_{t-1}$ has a significantly positive effect on FR_t only in Estonia, Germany, and Slovenia, revealing that the gender effect in the total sample originates from these countries.

4.3.2 Comparison of variable importance and discussion of research results

To test H2, the variable importance of financial resilience resulting from the different employed techniques are compared and listed in descending order in Table 30. Relative variable importance for the logistic, multinomial logistic and partial proportional odds regression is based on absolute z-values. By contrast, for the conditional random forest analysis, variable importance is based on the mean decrease in AUC to account for the prevalent class imbalance in the sample. Overall, the findings from the three robustness checks largely correspond to those of the logistic regression.

Table 30. Variable importance ranking comparison for the total sample

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$	IN-MED$_t$
3	GERMANY$_{t-1}$	BELGIUM $_{t-1}$	AGE$_{t-1}$	GERMANY$_{t-1}$
4	BELGIUM$_{t-1}$	GERMANY $_{t-1}$	P-FIH$_{t-1}$	BELGIUM $_{t-1}$
5	FRANCE$_{t-1}$	FRANCE$_{t-1}$	EDU-HIGH$_{t-1}$	EDU-HIGH $_{t-1}$
6	AGE$_{t-1}$	P-FIH$_{t-1}$	BELGIUM$_{t-1}$	SLOVENIA $_{t-1}$
7	P-FIH$_{t-1}$	AGE$_{t-1}$	GERMANY$_{t-1}$	FRANCE $_{t-1}$
8	SPAIN$_{t-1}$	SPAIN $_{t-1}$	ESTONIA$_{t-1}$	FL $_{t-1}$
9	ESTONIA$_{t-1}$	ESTONIA $_{t-1}$	FRANCE$_{t-1}$	P-FIH$_{t-1}$
10	FL$_{t-1}$	EDU-HIGH$_{t-1}$	FL$_{t-1}$	AGE $_{t-1}$
11	EDU-HIGH$_{t-1}$	FL$_{t-1}$	RET$_{t-1}$	ESTONIA $_{t-1}$
12	SLOVENIA$_{t-1}$	RET$_{t-1}$	PLAN$_{t-1}$	PLAN$_{t-1}$
13	PLAN$_{t-1}$	CH$_{t-1}$	SPAIN$_{t-1}$	RET$_{t-1}$
14	RET$_{t-1}$	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$
15	FEMALE$_{t-1}$	PLAN$_{t-1}$	CH$_{t-1}$	EMPL $_t$
16	EDU-MED$_{t-1}$	SLOVENIA $_{t-1}$	SLOVENIA$_{t-1}$	SPAIN$_{t-1}$
17	CH$_{t-1}$	EMPL$_t$	FEMALE$_{t-1}$	CH $_{t-1}$
18	EMPL$_t$	FEMALE$_{t-1}$	EMPL$_t$	FEMALE $_{t-1}$

Note. This table presents the variable importance for financial resilience, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (1). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

The income variables IN-HIGH$_t$ and IN-MED$_t$ are the most important variables in explaining FR$_t$, followed by GERMANY$_{t-1}$ and BELGIUM$_{t-1}$, which account for country-specific factors. In the partial proportional odds regression, AGE$_{t-1}$, P-FIH$_{t-1}$, and EDU-HIGH$_{t-1}$ precede the country dummies BELGIUM$_{t-1}$ and GERMANY$_{t-1}$.

Furthermore, SLOVENIA$_{t-1}$ is more important in the conditional random forest analysis, while it has distinctly less importance in the other methods. Likewise, the country dummy SPAIN$_{t-1}$ continuously ranks in the midfield for all methods except for the conditional random forest, wherein its importance decreases substantially, ranking the 16th most important variable out of 18. These findings support the literature's indication that the relative importance of variables can vary between different empirical methods (Bolón-Canedo et al., 2013; Dietterich, 1998; Luebke and Rojahn, 2016; Williamson et al., 2021).

The focal variable in this study, FL$_{t-1}$, consistently ranks in the midfield among all applied methods, indicating that, although not among the most important, it is an important predictor of FR$_t$. Consequently, the analysis fails to reject H2.

H2: Financial literacy was an important predictor of financial resilience during the COVID-19 pandemic in European households.

One explanation for FL$_{t-1}$ variable importance ranking in the midfield may lie in the operationalization of financial literacy. The financial literacy measure used in this thesis, as reported in SHARE, assesses objective financial literacy based on questions that can be assigned to basic financial literacy and, therefore, inherently delimits the scope of knowledge that it evaluates. Sconti (2022) reveals that financial literacy's effect on financial resilience is stronger when a more comprehensive financial literacy indicator that measures advanced financial literacy is used, compared to the standard measure of financial literacy, which reflects basic financial knowledge. Thus, utilizing a financial literacy measure that mirrors advanced financial literacy might lead to more differentiated results. Advanced financial literacy is determined by a set of questions covering topics such as stocks, bonds, risk diversification, stock market, and the relationship between bond prices and interest rates (Ouachani et al., 2021; Van Rooij et al., 2011b), as discussed in Section 2.2.1. However, data on advanced financial literacy are not provided by SHARE; thus, alternative data sources are needed to implement this approach.

In the context of financial literacy's operationalization, a further explanation for financial literacy's importance on financial resilience ranking in the midfield may be provided by the findings of Despard et al. (2020), who document that objective financial literacy has a weaker association with financial resilience compared to subjective financial literacy and financial confidence, which are stronger and more robust predictors of financial resilience. This emphasizes the important distinction between financial knowledge and financial literacy, as the latter refers to the ability to understand and have the confidence to apply financial information (Huston, 2010), as discussed in Section 2.2.1. Thus, adding a subjective financial literacy measure in the analysis that mirrors perceived financial literacy and allows one to determine financial confidence might lead to more differentiated results. However, again, data availability is an issue because SHARE does not provide a subjective financial literacy measure, and alternative data sources are needed to implement this approach.

Another reason for financial literacy's importance ranking in the midfield might be the relatively high income level of the sample. Angrisani et al. (2023) find that the link between financial literacy and financial resilience is substantially larger for low-income individuals than for high-income individuals. Thus, financial literacy is more beneficial for low-income individuals regarding its influence on financial resilience. However, the countries under review in this thesis (Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain) are all high-income economies according to the World Bank income group classifications from 2023 (World Bank, 2023). Within those countries, on average, only one-third of the respondents are from low-income households (see Table 10), though the income group is determined concerning the individual's domicile income tercile (i.e., a high-income country's tercile). Thus, extending the analysis to low-income economies might lead to more diverse results.

To test H4, the variable importance of financial resilience resulting from the different techniques employed at the country level are presented in descending order from Table 31 to Table 37. Overall, the findings from the three robustness checks largely correspond to those of the logistic regression of the respective countries, and disparities in variable importance among the countries emerge. This aligns with this thesis' expectations, as diverse degrees of financial resilience and financial literacy are surveyed within European countries, as reported in Table 1 and Table 4, respectively, and prior research analyzing financial literacy's influence on financial resilience documents considerable heterogeneity within European countries (e.g., Demertzis et al., 2020; Demirgüç-Kunt et al., 2022; Mcknight and Rucci, 2020).

In Belgium, France, and Germany (Table 31, Table 33, and Table 34, respectively), the income variables IN-HIGH$_t$ and IN-MED$_t$ are the most important variables in explaining FR$_t$, followed by P-FIH$_{t-1}$, which is respondents' period of experienced financial difficulties, measured in years. In Estonia and Spain, as reported in Table 32 and Table 37, the most important variables of FR$_t$ are IN-HIGH$_t$, IN-MED$_t$, and AGE$_{t-1}$. Italy (Table 35) is the only country wherein, together with the income variables IN-HIGH$_t$ and IN-MED$_t$, FL$_{t-1}$ is among the top three predictors of FR$_t$. In Slovenia (Table 36), in addition to the income variables IN-HIGH$_t$ and IN-MED$_t$, respondents' educational levels (i.e., EDU-HIGH$_{t-1}$ and EDU-MED$_{t-1}$) are among the most important predictors of FR$_t$. Overall, in all the examined countries, income is crucial in developing financial resilience.

The findings reveal variations across the countries regarding financial literacy's importance in predicting financial resilience. Consequently, the analysis fails to reject H4.

H4: The importance of financial literacy in explaining financial resilience during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

FL$_{t-1}$ is among the most important predictors of FR$_t$ throughout all applied methods in Italy. One explanation for this could be that Italy was hit harder by the COVID-19 crisis than the other countries under review (Bergsen et al., 2020). Under such circumstances, financial literacy's protective characteristic on financial resilience may have been amplified. This coincides with the findings from Bialowolski et al. (2022), who reveal that financial literacy's impact on financial resilience is not symmetrical since it protects more against the loss of financial resilience than it contributes to the gain of financial resilience.

By contrast, in Spain, FL$_{t-1}$ is among the least important variables in explaining FR$_t$, though its importance significantly increases in the conditional random forest, where it ranks the fourth most important variable of 12. Why financial literacy plays a less important role in predicting financial resilience in Spain remains unclear; however, one justification for this finding could be attributable to the low variance in the financial literacy scores within Spain because it had the least financially literate respondents in the sample (17%), as depicted in Figure 7.

For the remaining countries, FL_{t-1} ranges in the upper midfield (Belgium and Germany) and midfield (Estonia, France, and Slovenia).

Overall, the findings from the country-level analysis reveal that the respondents' monthly household income remains the most important determinant of financial resilience and that FL_{t-1} is an important factor in strengthening financial resilience. However, noticeable differences in variable importance between the different countries arise, attributing more and less importance to FL_{t-1} and the remaining predictors in explaining financial resilience, indicating that certain drivers of financial resilience are country-specific.

Table 31. Variable importance ranking comparison for Belgium

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	IN-MED$_t$	IN-MED$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	IN-HIGH$_t$	IN-HIGH$_t$	IN-MED$_t$	IN-MED$_t$
3	P-FIH$_{t-1}$	P-FIH$_{t-1}$	P-FIH$_{t-1}$	P-FIH$_{t-1}$
4	AGE$_{t-1}$	FL$_{t-1}$	AGE$_{t-1}$	FL$_{t-1}$
5	FL$_{t-1}$	AGE$_{t-1}$	FL$_{t-1}$	EDU-HIGH$_{t-1}$
6	CH$_{t-1}$	RET$_{t-1}$	CH$_{t-1}$	PLAN$_{t-1}$
7	PLAN$_{t-1}$	CH$_{t-1}$	RET$_{t-1}$	AGE$_{t-1}$
8	RET$_{t-1}$	EMPL$_t$	PLAN$_{t-1}$	RET$_{t-1}$
9	EDU-HIGH$_{t-1}$	PLAN$_{t-1}$	EDU-HIGH$_{t-1}$	CH$_{t-1}$
10	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$	EMPL$_t$	EMPL$_t$
11	FEMALE$_{t-1}$	EDU-HIGH$_{t-1}$	FEMALE$_{t-1}$	FEMALE$_{t-1}$
12	EMPL$_t$	FEMALE$_{t-1}$	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$

Note. This table presents the variable importance for financial resilience in Belgium, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. [Source: Own representation]

Table 32. Variable importance ranking comparison for Estonia

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	AGE$_{t-1}$	IN-MED$_t$	AGE$_{t-1}$	IN-MED$_t$
3	IN-MED$_t$	AGE$_{t-1}$	IN-MED$_t$	AGE$_{t-1}$
4	CH$_{t-1}$	EDU-HIGH$_{t-1}$	EMPL$_t$	CH$_{t-1}$
5	EMPL$_t$	FEMALE$_{t-1}$	EDU-HIGH$_{t-1}$	EMPL$_t$
6	FL$_{t-1}$	FL$_{t-1}$	PLAN$_{t-1}$	P-FIH$_{t-1}$
7	EDU-HIGH$_{t-1}$	EMPL$_t$	FEMALE $_{t-1}$	FL$_{t-1}$
8	P-FIH$_{t-1}$	PLAN$_{t-1}$	FL$_{t-1}$	RET$_{t-1}$
9	PLAN$_{t-1}$	P-FIH$_{t-1}$	P-FIH$_{t-1}$	EDU-HIGH$_{t-1}$
10	FEMALE$_{t-1}$	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$	PLAN$_{t-1}$
11	EDU-MED$_{t-1}$	CH$_{t-1}$	CH$_{t-1}$	FEMALE$_{t-1}$
12	RET$_{t-1}$	RET$_{t-1}$	RET$_{t-1}$	EDU-MED$_{t-1}$

Note. This table presents the variable importance for financial resilience in Estonia, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. [Source: Own representation]

Table 33. Variable importance ranking comparison for France

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	IN-MED$_t$	IN-MED$_t$	IN-HIGH$_t$	IN-HIGH$_t$
2	IN-HIGH$_t$	IN-HIGH$_t$	IN-MED$_t$	IN-MED$_t$
3	P-FIH$_{t-1}$	P-FIH$_{t-1}$	P-FIH$_{t-1}$	P-FIH$_{t-1}$
4	PLAN$_{t-1}$	PLAN$_{t-1}$	PLAN$_{t-1}$	RET$_{t-1}$
5	AGE$_{t-1}$	AGE$_{t-1}$	AGE$_{t-1}$	EDU-HIGH$_{t-1}$
6	RET$_{t-1}$	EDU-MED$_{t-1}$	EDU-HIGH$_{t-1}$	CH$_{t-1}$
7	EDU-HIGH$_{t-1}$	EDU-HIGH$_{t-1}$	FL$_{t-1}$	PLAN$_{t-1}$
8	EDU-MED$_{t-1}$	FL$_{t-1}$	RET$_{t-1}$	EDU-MED$_{t-1}$
9	FEMALE$_{t-1}$	RET$_{t-1}$	EDU-MED$_{t-1}$	EMPL$_t$
10	FL$_{t-1}$	CH$_{t-1}$	EMPL$_t$	FL$_{t-1}$
11	CH$_{t-1}$	EMPL$_t$	FEMALE $_{t-1}$	AGE$_{t-1}$
12	EMPL$_t$	FEMALE$_{t-1}$	CH$_{t-1}$	FEMALE$_{t-1}$

Note. This table presents the variable importance for financial resilience in France, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. [Source: Own representation]

Table 34. Variable importance ranking comparison for Germany

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	IN-MED$_t$	P-FIH$_{t-1}$	IN-MED$_t$	P-FIH$_{t-1}$
2	IN-HIGH$_t$	IN-MED$_t$	P-FIH$_{t-1}$	IN-MED$_t$
3	P-FIH$_{t-1}$	IN-HIGH$_t$	AGE$_{t-1}$	IN-HIGH$_t$
4	PLAN$_{t-1}$	AGE$_{t-1}$	FL$_{t-1}$	PLAN$_{t-1}$
5	AGE$_{t-1}$	FL$_{t-1}$	EMPL$_t$	AGE$_{t-1}$
6	EMPL$_t$	PLAN$_{t-1}$	FEMALE $_{t-1}$	FL$_{t-1}$
7	FEMALE$_{t-1}$	FEMALE$_{t-1}$	EDU-HIGH$_{t-1}$	RET$_{t-1}$
8	EDU-HIGH$_{t-1}$	RET$_{t-1}$	PLAN$_{t-1}$	EMPL$_t$
9	FL$_{t-1}$	EMPL$_t$	IN-HIGH$_t$	EDU-HIGH$_{t-1}$
10	EDU-MED$_{t-1}$	EDU-HIGH$_{t-1}$	CH$_{t-1}$	EDU-MED$_{t-1}$
11	CH$_{t-1}$	CH$_{t-1}$	RET$_{t-1}$	FEMALE$_{t-1}$
12	RET$_{t-1}$	EDU-MED$_{t-1}$	EDU-MED$_{t-1}$	CH$_{t-1}$

Note. This table presents the variable importance for financial resilience in Germany, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. [Source: Own representation]

Table 35. Variable importance ranking comparison for Italy

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	$IN\text{-}HIGH_{t}$	$IN\text{-}HIGH_{t}$	$IN\text{-}HIGH_{t}$	$IN\text{-}HIGH_{t}$
2	$IN\text{-}MED_{t}$	$IN\text{-}MED_{t}$	$IN\text{-}MED_{t}$	$IN\text{-}MED_{t}$
3	FL_{t-1}	AGE_{t-1}	$EDU\text{-}HIGH_{t-1}$	FL_{t-1}
4	$P\text{-}FIH_{t-1}$	FL_{t-1}	FL_{t-1}	$P\text{-}FIH_{t-1}$
5	RET_{t-1}	CH_{t-1}	AGE_{t-1}	$EDU\text{-}HIGH_{t-1}$
6	$EDU\text{-}HIGH_{t-1}$	$EMPL_{t}$	$P\text{-}FIH_{t-1}$	RET_{t-1}
7	AGE_{t-1}	$EDU\text{-}MED_{t-1}$	$EMPL_{t}$	CH_{t-1}
8	CH_{t-1}	RET_{t-1}	CH_{t-1}	AGE_{t-1}
9	$EMPL_{t}$	$P\text{-}FIH_{t-1}$	RET_{t-1}	$EDU\text{-}MED_{t-1}$
10	$EDU\text{-}MED_{t-1}$	$PLAN_{t-1}$	$EDU\text{-}MED_{t-1}$	$PLAN_{t-1}$
11	$PLAN_{t-1}$	$FEMALE_{t-1}$	$PLAN_{t-1}$	$EMPL_{t}$
12	$FEMALE_{t-1}$	$EDU\text{-}HIGH_{t-1}$	$FEMALE_{t-1}$	$FEMALE_{t-1}$

Note. This table presents the variable importance for financial resilience in Italy, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. [Source: Own representation]

Table 36. Variable importance ranking comparison for Slovenia

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	$IN\text{-}HIGH_{t}$	$IN\text{-}HIGH_{t}$	$IN\text{-}HIGH_{t}$	$IN\text{-}HIGH_{t}$
2	$EDU\text{-}HIGH_{t-1}$	$IN\text{-}MED_{t}$	$EDU\text{-}HIGH_{t-1}$	$EDU\text{-}HIGH_{t-1}$
3	$IN\text{-}MED_{t}$	$EDU\text{-}HIGH_{t-1}$	$IN\text{-}MED_{t}$	$IN\text{-}MED_{t}$
4	AGE_{t-1}	$EDU\text{-}MED_{t-1}$	$EDU\text{-}MED_{t-1}$	$EDU\text{-}MED_{t-1}$
5	$EDU\text{-}MED_{t-1}$	$PLAN_{t-1}$	$PLAN_{t-1}$	$PLAN_{t-1}$
6	$PLAN_{t-1}$	AGE_{t-1}	FL_{t-1}	FL_{t-1}
7	FL_{t-1}	CH_{t-1}	$P\text{-}FIH_{t-1}$	AGE_{t-1}
8	$FEMALE_{t-1}$	FL_{t-1}	$FEMALE_{t-1}$	$P\text{-}FIH_{t-1}$
9	$P\text{-}FIH_{t-1}$	RET_{t-1}	RET_{t-1}	$EMPL_{t}$
10	CH_{t-1}	$P\text{-}FIH_{t-1}$	CH_{t-1}	$FEMALE_{t-1}$
11	$EMPL_{t}$	$FEMALE_{t-1}$	AGE_{t-1}	CH_{t-1}
12	RET_{t-1}	$EMPL_{t}$	$EMPL_{t}$	RET_{t-1}

Note. This table presents the variable importance for financial resilience in Slovenia, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4. [Source: Own representation]

Table 37. Variable importance ranking comparison for Spain

Rank	(1) Logistic regression	(2) Multinomial logistic regression	(3) Partial proportional odds regression	(4) Conditional random forest
1	IN-HIGH_{t}	IN-HIGH_{t}	IN-HIGH_{t}	IN-HIGH_{t}
2	IN-MED_{t}	IN-MED_{t}	IN-MED_{t}	AGE_{t-1}
3	AGE_{t-1}	AGE_{t-1}	AGE_{t-1}	IN-MED_{t}
4	EMPL_{t}	CH_{t-1}	PLAN_{t-1}	FL_{t-1}
5	PLAN_{t-1}	EMPL_{t}	EMPL_{t}	RET_{t-1}
6	CH_{t-1}	PLAN_{t-1}	CH_{t-1}	P-FIH_{t-1}
7	EDU-HIGH_{t-1}	RET_{t-1}	EDU-HIGH_{t-1}	CH_{t-1}
8	RET_{t-1}	P-FIH_{t-1}	EDU-MED_{t-1}	EDU-MED_{t-1}
9	P-FIH_{t-1}	FL_{t-1}	P-FIH_{t-1}	EDU-HIGH_{t-1}
10	FL_{t-1}	EDU-MED_{t-1}	FL_{t-1}	FEMALE_{t-1}
11	EDU-MED_{t-1}	EDU-HIGH_{t-1}	RET_{t-1}	EMPL_{t}
12	FEMALE_{t-1}	FEMALE_{t-1}	FEMALE_{t-1}	PLAN_{t-1}

Note. This table presents the variable importance for financial resilience in Spain, sorted in descending order. In columns (1), (2), and (3), variable importance is assessed based on the absolute z-values, while in column (4), it is determined by the mean decrease in AUC for the variables applied according to Eq. (2). t-1 (t) denotes data gathered from Wave 7 (SHARE COVID-19 survey). Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

V – CONCLUSION

V - CONCLUSION

5.1. SUMMARY

Despite the growing body of literature investigating financial literacy's role in enabling individuals to increase their financial resilience, this thesis identified specific areas wherein research gaps can be addressed, and light can be shed on the mixed findings of recent literature.

First, this thesis addresses the mixed evidence provided by recent research regarding the strength of financial literacy's relationship with financial resilience by investigating financial literacy's impact and variable importance in predicting financial resilience. By examining whether financial literacy is an important determinant of financial resilience, this study provides a deeper understanding of financial literacy's role in mitigating financial distress' impact during economic crises.

Second, considering the scarce evidence on the links between financial literacy and financial resilience during the COVID-19 crisis in the European context, this thesis analyzes financial literacy's impact and relative importance on financial resilience during the COVID-19 pandemic using the novel SHARE COVID-19 survey dataset, which covers 2017 and 2020, a crucial period representing individuals' economic and financial situation following the initial wave of the COVID-19 pandemic. Thus, adults aged 50 and older from the seven European economies of Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain are investigated.

Third, this thesis employs multiple classification techniques to assess feature importance, including logistic regression, multinomial logistic regression, partial proportional odds regression, and conditional random forest analysis. The integration of both methodological approaches, techniques that yield individual coefficients for the variables under investigation and machine learning methodologies that excel in assessing variable importance, serve as a valuable complement because it enables the quantification of the relationship between independent and dependent variables, as well as the determination of their importance (Gehrke, 2022; Levantesi and Zacchia, 2021). Moreover, as previous studies have raised concerns regarding a potential endogeneity bias when analyzing financial literacy's role on financial outcomes (Stolper and Walter, 2017), as described in Section 2.2.4, endogeneity is addressed by applying an instrumental variable approach and utilizing time-lagged values of the independent variable.

Fourth, this thesis aims to provide novel insights into potential heterogeneity within the European context regarding financial literacy's impact and importance on financial resilience and additionally conducts country-level empirical analyses, providing a cross-country comparison of the strength of the association between financial literacy and financial resilience.

Considering the aforementioned research objectives and contributions, within the analyses of this dissertation, the following research hypotheses were tested:

H1: The probability of being financially resilient increased with an individual's financial literacy level during the COVID-19 pandemic in European households.

H2: Financial literacy was an important predictor of financial resilience during the COVID-19 pandemic in European households.

H3: The impact of an individual's financial literacy level on their probability of being financially resilient during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

H4: The importance of financial literacy in explaining financial resilience during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.

Table 38 provides an overview of the key findings pertaining to the research hypotheses. Panel A presents the results of financial literacy's impact on financial resilience for the total sample. While controlling for an extensive set of additional explanatory variables derived from related empirical studies, as described in Section 2.1.3., the logistic regression results for the total sample demonstrate that financial literacy significantly increases financial resilience. The findings remain robust when an alternative definition of financial resilience is used, and a multinomial logistic regression and partial proportional odds regression are applied. Moreover, a 2SLS instrumental variables regression is conducted to address potential endogeneity concerns, which indicates that the logistic regression results are not biased by endogeneity.

Table 38. Summary of empirical findings pertaining to the research hypotheses

<table>
<tr><th colspan="4">Research hypotheses</th><th>Results support hypothesis</th></tr>
<tr><td colspan="5">H1: The probability of being financially resilient increased with an individual's financial literacy level during the COVID-19 pandemic in European households.
Panel A: Regression results of FL_{t-1} for the total sample</td></tr>
<tr><td>Logistic regression</td><td>Multinomial logistic regression</td><td colspan="2">Partial proportional odds regression</td><td></td></tr>
<tr><td>significantly positive</td><td>significantly positive</td><td colspan="2">significantly positive</td><td>Yes</td></tr>
<tr><td colspan="5">H2: Financial literacy was an important predictor of financial resilience during the COVID-19 pandemic in European households.
Panel B: Variable importance of FL_{t-1} out of 18 variables</td></tr>
<tr><td>Logistic regression</td><td>Multinomial logistic regression</td><td>Partial proportional odds regression</td><td>Conditional random forest</td><td></td></tr>
<tr><td>10</td><td>11</td><td>10</td><td>8</td><td>Yes</td></tr>
<tr><td colspan="5">H3: The impact of an individual's financial literacy level on their probability of being financially resilient during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.
Panel C: Regression results of FL_{t-1} for the samples at the country level</td></tr>
<tr><td></td><td>Logistic regression</td><td>Multinomial logistic regression</td><td>Partial proportional odds regression</td><td></td></tr>
<tr><td>Belgium</td><td>significantly positive</td><td>significantly positive</td><td>significantly positive</td><td rowspan="6">Yes</td></tr>
<tr><td>Estonia</td><td>significantly positive</td><td>significantly positive (for outcome category Y=3 vs. Y=1)</td><td>significantly positive</td></tr>
<tr><td>France</td><td>not significant</td><td>not significant</td><td>not significant</td></tr>
<tr><td>Germany</td><td>not significant</td><td>significantly positive</td><td>significantly positive (for outcome category Y>1; Y>2)</td></tr>
<tr><td>Italy</td><td>significantly positive</td><td>significantly positive (for outcome category Y=3 vs. Y=1; Y=4 vs. Y=1)</td><td>significantly positive</td></tr>
<tr><td>Slovenia</td><td>significantly positive</td><td>not significant</td><td>significantly positive</td></tr>
</table>

Research hypotheses					**Results support hypothesis**
Spain	not significant	not significant	not significant		
H4: The importance of financial literacy in explaining financial resilience during the COVID-19 pandemic differed across Belgium, Estonia, France, Germany, Italy, Slovenia, and Spain.					
Panel D: Variable importance of FL_{t-1} out of 12 variables					
	Logistic regression	Multinomial logistic regression	Partial proportional odds regression	Conditional random forest	
Belgium	5	4	5	4	Yes
Estonia	6	6	8	7	
France	10	8	7	10	
Germany	9	5	4	6	
Italy	3	4	4	3	
Slovenia	7	8	6	6	
Spain	10	9	10	4	

Note. This table summarizes the findings regarding H1, H2, H3, and H4. Panels A and C report the findings regarding H1 and H3 for the total sample and samples at the country level, respectively, while Panels B and D disclose the findings regarding H2 and H4 for the total sample and samples at the country level, respectively. The variable importance for the logistic, multinomial logistic, and partial proportional odds regression in Panels B and D are based on the absolute z-values, while for the conditional random forest, it is based on the mean decrease in AUC. The values in Panel B (D) depict the rank of FL_{t-1} in relation to 18 (12) predictor variables for the total sample (country-level samples). t-1 (t) denotes data gathered from Wave 7. Definitions for all variables can be found in APPENDIX 4.

[Source: Own representation]

Panel C provides the findings of the country-level analysis, which are also not biased by endogeneity and consistently reveal that the direction of financial literacy's influence on financial resilience is positive. However, its statistical significance varies across countries. Financial literacy's positive impact on financial resilience is particularly strong in Belgium, Estonia, and Italy as the association is significantly positive among the logistic regression, multinomial logistic regression, and partial proportional odds regression.

In Germany and Slovenia, the multiple methods yield mixed findings regarding the statistical significance. In Germany, financial literacy is significantly linked to greater financial resilience in the multinomial logistic regression and partial proportional odds regression, while it is not statistically significant in the logistic regression. The partial proportional odds regression results indicate that in Germany, financial literacy helps protect individuals from financial fragility but has no significant influence on improving financial resilience among those that are already financially resilient. In Slovenia, the association is significantly positive in the logistic and partial proportional odds regression and insignificant in the multinomial logistic regression.

By contrast, in France and Spain, financial literacy's impact on financial resilience is positive but neither significant for the logistic regression nor for the robustness checks.

Panels B and D provide an overview of the key findings that assess financial literacy's importance in predicting financial resilience. Relative variable importance for the logistic regression, multinomial logistic regression, and partial proportional odds regression is based on absolute z-values, while for the conditional random forest analysis, it is based on the mean decrease in AUC to account for the prevalent class imbalance in the sample.

For the total sample, the most important predictors of financial resilience according to the four classification techniques employed are individuals' income and domicile (i.e., $BELGIUM_{t-1}$ and $GERMANY_{t-1}$). Panel B indicates that financial literacy is an important predictor of financial resilience, though it is not among the most important, ranking in the midfield in terms of variable importance throughout the logistic regression and robustness checks.

The findings from the country-level analysis reveal that respondents' monthly household income remains the most important predictor of financial resilience. Regarding financial literacy's importance in predicting financial resilience, Panel D uncovers considerable variation across the countries, attributing more and less importance to financial literacy.

In Italy, financial literacy is among the most important variables in predicting financial resilience, while for the remaining countries, its importance ranges in the upper midfield (Belgium and Germany) and midfield (Estonia, France, and Slovenia). Spain is the only country where financial literacy is among the least important variables in predicting financial resilience, except for the conditional random forest, wherein it gains substantial importance and ranks among the most important variables, demonstrating that the relative importance of variables can vary between different classification methods (Bolón-Canedo, Sánchez-Maroño, and Alonso-Betanzos, 2013; Dietterich, 1998; Luebke and Rojahn, 2016).

In summary, this study's findings demonstrate that financial literacy was an important predictor of financial resilience during the COVID-19 pandemic in Europe. Importantly, these results are robust and unaffected by endogeneity. Furthermore, the cross-country analysis reveals heterogeneity in financial literacy's importance for financial resilience.

In conclusion, by focusing on financial literacy's variable importance and utilizing a multiple-method approach, this dissertation's findings contribute to a growing body of literature that investigates financial literacy's role in enabling individuals to better handle economic shocks in crisis periods.

5.2. LIMITATIONS

As with most empirical research, this study is not without limitations. Any objections would likely be primarily aimed at the sample data used, dependent variable's appropriateness, and independent variable's measurement approach.

First, the results are based on a specific sample comprising individuals aged 50 years and older and are restricted to seven high-income European countries. While the findings align with previous research that include younger age groups (Lusardi et al., 2011; Wiersma et al., 2020) and cover a broader range of European countries (Bialowolski et al., 2022; Cziriak, 2022; Demertzis et al., 2020), their generalizability remains a subject for further investigation. Future research can broaden the scope by expanding the coverage of countries using alternative data gathered during the COVID-19 pandemic.

Second, a class imbalance is present within the dataset, particularly in the samples for Belgium, Estonia, France, Germany, and Spain. The distribution of individuals classified as financially resilient and financially fragile is not equally balanced, with financially resilient respondents being the majority class. This unequal distribution may affect the findings' generalizability, as financially fragile individuals are underrepresented.

To mitigate the potential bias caused by class imbalance and improve the analysis' accuracy, this study ensures that the minimum EPV criterion within the samples is fulfilled (Table 14). Thereby, a sufficient number of events from the minority class (i.e., financially fragile individuals) relative to the number of predictor variables is maintained. Additionally, the mean decrease in AUC, a variable importance measure robust to class imbalance, is utilized in the conditional random forest analysis.

Third, this thesis uses the SHARE financial literacy indicator, which assesses objective financial literacy, reflects individuals' basic financial literacy, is among the commonly used indicators of financial literacy in the literature, and is considered a good proxy for financial literacy being related to the Big Three financial literacy questions (Section 2.2.1). However, determining whether financial literacy's importance in predicting financial resilience would change if other measures of financial literacy were added to the analysis, such as indicators of advanced financial literacy or subjective financial literacy, would be interesting. However, data regarding advanced financial literacy and subjective financial literacy is not provided by SHARE. Consequently, alternative data sources are needed to implement this approach.

Fourth, while resilience is a multidimensional concept (Salignac et al., 2019) and no single measure captures all aspects of financial resilience, as discussed in Section 2.1.1., different results might be obtained when using other measures of financial resilience. However, again, this approach necessitates the use of alternative data sources.

Finally, this research is limited to analyzing financial literacy's impact and importance on financial resilience. While the findings reveal that financial literacy has emerged as an important variable in explaining financial resilience, the available data do not permit examining the channels through which financial literacy impacts financial resilience.

5.3. OUTLOOK AND IMPLICATIONS FOR RESEARCH

This thesis focuses on the impact and importance of financial literacy on financial resilience. Overall, this dissertation's findings guide both individuals and institutions in identifying the most important factors that enhance financial resilience during COVID-19. Understanding what drives individuals' financial resilience during the COVID-19 pandemic allows for the development of targeted interventions and policies to enhance individuals' financial well-being and can offer lessons for improving a country's socioeconomic sustainability when faced with an impending crisis.

While financial literacy is not among the most important variables, it is one of the few predictors of financial resilience that can be actively shaped. Furthermore, the findings for Germany reveal that financial literacy's impact in improving financial resilience is particularly strong for financially fragile individuals. Thus, to enhance the preparedness level for future crises, it is crucial to shape a more resilient society by formulating policies that improve financial literacy and offering tailored interventions for different population groups.

Fostering financial education may be one means to increase financial literacy and, reportedly, has important intergenerational spillover effects (Frisancho, 2023). However, research findings concerning financial education's effectiveness are mixed. Fernandes et al. (2014) criticize that financial education, akin to other forms of education, deteriorates over time. By contrast, in a recent and more extensive analysis, Kaiser et al. (2022) find no evidence to support a rapid decay in the realized treatment effects and disclose that financial education's effect on financial literacy is large and economically significant.

Adopting a holistic approach when designing financial education programs is essential to better fulfill the needs of a heterogeneous population (Clark, 2023). Thus, policymakers should recognize financial literacy's varying impact on different countries and individuals and consider tailoring financial education programs to target specific groups. Specifically, interventions should be designed to address the needs of financially vulnerable populations, such as low-income households, and also target individuals lacking financial confidence and offer guidance through financial counseling or coaching to develop financial resilience instead of merely providing information regarding the need to do so (Despard et al., 2020).

Furthermore, a mix of policy measures encompassing financial education, choice architecture, regulatory frameworks (Fernandes et al., 2014), and nudging strategies (García and Vila, 2020) can potentially increase financial literacy and, consequently, financial resilience.

Choice architecture refers to designing decision-making environments to influence individuals' choices. By utilizing defaults or framing, i.e., making beneficial choices the default option or structuring choices in a manner that encourages positive outcomes, choice architecture can guide individuals toward better financial decisions (Thorp, Liu, Agnew, Bateman, and Eckert, 2023). One example of choice architecture is automatic enrollment in a savings plan, whereby the saving choice becomes the default option, i.e., saving a predefined percentage of an individual's monthly earnings, from which one can later opt out if they wish to (Gale and Levine, 2013; Ly, Mažar, Zhao, and Soman, 2013; Thaler and Sunstein, 2008). Such an approach is a cost-effective strategy (Zhao, 2018) and, reportedly, significantly increases retirement plan participation rates because it takes advantage of an individual's tendency to stick with the default option (Prast and Soest, 2016; Thaler and Benartzi, 2004).

Nudging involves subtly guiding individuals toward desirable choices without limiting their freedom of choice. Nudges can be used to encourage positive financial behaviors and improve financial literacy. Examples include personalized messages or reminders encouraging savings, responsible borrowing, or budgeting (García and Vila, 2020). To illustrate, Karlan, McConnell, Mullainathan, and Zinman (2016) document evidence that reminder messages from banks increase commitment attainment for clients who recently opened commitment savings accounts. Specifically, messages that mention both savings goals and financial incentives are particularly effective. Furthermore, García and Vila (2018) find that nudging from employers promotes long-term savings among their staff and that the nudging mechanism's positive impact is greater among individuals with the lowest savings (i.e., the financially fragile).

Thus, with financial education enhancing financial knowledge and confidence, choice architecture shaping decision-making environments, nudging guiding individuals toward better financial behaviors, and regulation establishing fair practices and trust, policymakers can create a comprehensive approach to improve financial literacy, ultimately enhancing financial resilience.

In addition to the abovementioned policy implications, this study's results provide recommendations for future research. This study captures respondents' financial resilience at one point in time (during the first wave of the COVID-19 pandemic in 2020). A recent study from Clark and Mitchell (2022) reveals that financial literacy's positive impact on financial resilience attenuates one year into the pandemic, suggesting that the relationship between financial literacy and financial resilience may vary over time and may be influenced by changing economic conditions and external factors. Thus, repeating the SHARE survey in future years and investigating such longitudinal data would enable an analysis of the ways whereby financial literacy impacts individuals' financial resilience over time and whether its importance alters.

Finally, research on financial literacy and financial resilience might benefit from the application of a Bayesian hierarchical modeling approach. While logistic regression estimates financial literacy's average influence on financial resilience, Bayesian hierarchical modeling enables examinations of the individual-specific influence. By providing posterior distributions for each individual-specific parameter instead of computing only point estimates, Bayesian hierarchical modeling enables the assessment of an independent variable's influence on a dependent variable at the individual level rather than the average influence (Allenby and Rossi, 2006; Hansen, Perry, and Reese, 2004).

Bayesian methods have been applied in assessing individual financial literacy levels by utilizing Bayesian item response theory models (Tabak, Silva, Horta, Silva, and Tabak, 2023) or analyzing financial literacy's influence on household finances, employing a Bayesian two-part latent variable modeling approach (Feng, Lu, Song, and Ma, 2019).

However, to the best of the author's knowledge, thus far, no study has utilized Bayesian hierarchical modeling approaches in the context of financial literacy and financial resilience. By employing this individualized methodology, additional insights on financial literacy's relationship with financial resilience can be provided because it allows the consideration of heterogeneity in the relationships between financial literacy and financial resilience, thus capturing the unique characteristics of different individuals.

VI – BIBLIOGRAPHICAL REFERENCES

VI - BIBLIOGRAPHICAL REFERENCES

Abbott-Chapman, J., Denholm, C., and Wyld, C. (2008). Social support as a factor inhibiting teenage risk-taking: Views of students, parents and professionals. *Journal of Youth Studies*, *11*(6), 611–627. https://doi.org/10.1080/13676260802191938

Adger, W. N. (2000). Social and ecological resilience: Are they related? *Progress in Human Geography*, *24*(3), 347–364. https://doi.org/10.1191/030913200701540465

Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., and Evanoff, D. D. (2015). Financial literacy and financial planning: Evidence from India. *Journal of Housing Economics*, *27*, 4–21. https://doi.org/10.1016/j.jhe.2015.02.003

Agnew, J. R., and Szykman, L. R. (2005). Asset allocation and information overload: The influence of information display, asset choice, and investor experience. *Journal of Behavioral Finance*, *6*(2), 57–70. https://doi.org/10.1207/s15427579jpfm0602_2

Al-Tamimi, H. A. H., and Bin Kalli, A. A. (2009). Financial literacy and investment decisions of UAE investors. *Journal of Risk Finance*, *10*(5), 500–516. https://doi.org/10.1108/15265940911001402

Alessie, R. J. M., Van Rooij, M., and Lusardi, A. (2011). Financial literacy and retirement preparation in the Netherlands. *Journal of Pension Economics & Finance*, *10*(4), 527–545. https://doi.org/10.1017/S1474747211000461

Ali, L., Khan, M. K. N., and Ahmad, H. (2020). Education of the head and financial vulnerability of households: Evidence from a household's survey data in Pakistan. *Social Indicators Research*, *147*(2), 439–463. https://doi.org/10.1007/s11205-019-02164-2

Allenby, G. M., and Rossi, P. E. (2006). Hierarchical bayes models. In R. Grover and M. Vriens (Eds.), *The handbook of marketing research: Uses, misuses, and future advances* (pp. 418–440). Thousand Oaks, CA: Sage Publications.

Allgood, S., and Walstad, W. B. (2013). Financial literacy and credit card behaviors:

A cross-sectional analysis by age. *Numeracy*, *6*(2), 1–26. https://doi.org/10.5038/1936-4660.6.2.3

Allgood, S., and Walstad, W. B. (2016). The effects of perceived and actual financial literacy on financial behaviors. *Economic Inquiry*, *54*(1), 675–697. https://doi.org/10.1111/ecin.12255

Almenberg, J., and Dreber, A. (2015). Gender, stock market participation and financial literacy. *Economics Letters*, *137*, 140–142. https://doi.org/10.1016/j.econlet.2015.10.009

Amari, M., and Jarboui, A. (2017). Financial literacy in Tunisia: Its determinants and its implications on investment behavior. *Research in International Business and Finance*, *39*, 568–577. https://doi.org/10.1016/j.ribaf.2016.09.018

Ampudia, M., Van Vlokhoven, H., and Żochowski, D. (2016). Financial fragility of euro area households. *Journal of Financial Stability*, *27*, 250–262. https://doi.org/10.1016/j.jfs.2016.02.003

Anderloni, L., Bacchiocchi, E., and Vandone, D. (2012). Household financial vulnerability: An empirical analysis. *Research in Economics*, *66*(3), 284–296. https://doi.org/10.1016/j.rie.2012.03.001

Anderloni, L., and Vandone, D. (2008). Households over-indebtedness in the economic literature. In *Universit'a degli Studi di Milano Working Paper* (No. 2008–46).

Anderson, A., Baker, F., and Robinson, D. T. (2017). Precautionary savings, retirement planning and misperceptions of financial literacy. *Journal of Financial Economics*, *126*(2), 383–398. https://doi.org/10.1016/j.jfineco.2017.07.008

Andreou, P. C., Anyfantaki, S., and Atkinson, A. (2023). Financial literacy for financial resilience: Evidence from Cyprus during the pandemic period. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4316433

Angrisani, M., Burke, J., Lusardi, A., and Mottola, G. (2023). The evolution of financial literacy over time and its predictive power for financial outcomes: Evidence from longitudinal data. *Journal of Pension Economics and Finance*, 1–18. https://doi.org/10.1017/s1474747222000154

Angrist, J. D., and Pischke, J.-S. (2014). *Mastering metrics: The path from cause to effect*.

Princeton and Oxford: Princeton University Press.

Antonakis, J., Bendahan, S., Jacquart, P., and Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly*, *21*(6), 1086–1120. https://doi.org/10.1016/j.leaqua.2010.10.010

Aren, S., and Dinç Aydemir, S. (2014). A literature review on financial literacy. *Finansal Araştırmalar ve Çalışmalar Dergisi*, *6*(11), 33–50. https://doi.org/10.14784/jfrs.2014117326

Arrondel, L., Debbich, M., and Savignac, F. (2014). Financial literacy and financial planning in France. *Numeracy*, *6*(2), 2–20. https://ssrn.com/abstract=2374363

Babiarz, P., and Robb, C. A. (2014). Financial literacy and emergency saving. *Journal of Family and Economic Issues*, *35*(1), 40–50. https://doi.org/10.1007/s10834-013-9369-9

Backhaus, K., Erichson, B., Plinke, W., and Weiber, R. (2018). *Multivariate Analysemethoden – Eine anwendungsorientierte Einführung [Multivariate analysis methods – An application-oriented introduction]* (15th ed.). Berlin/Heidelberg: Springer Gabler.

Balloch, A., Nicolae, A., and Philip, D. (2015). Stock market literacy, trust, and participation. *Review of Finance*, *19*(5), 1925–1963. https://doi.org/10.1093/rof/rfu040

Bayrakdaroğlu, A., and Şan, F. B. (2014). Financial literacy training as a strategic management tool among small – medium sized businesses operating in Turkey. *Procedia - Social and Behavioral Sciences*, *150*, 148–155. https://doi.org/10.1016/j.sbspro.2014.09.019

Bazarbash, M. (2019). *Fintech in financial inclusion: Machine learning applications in assessing credit risk* (No. 19/109). International Monetary Fund.

Behrman, J. R., Mitchell, O. S., Soo, C. K., and Bravo, D. (2012). How financial literacy affects household wealth accumulation. *American Economic Review*, *102*(3), 300–304. https://doi.org/10.1257/aer.102.3.300

Bellofatto, A., D'Hondt, C., and De Winne, R. (2018). Subjective financial literacy and retail investors' behavior. *Journal of Banking and Finance*, *92*, 168–181. https://doi.org/10.1016/j.jbankfin.2018.05.004

Bergmann, M., Scherpenzeel, A., and Börsch-Supan, A. (2019). *SHARE Wave 7 methodology: Panel innovations and life histories*. Share project. https://share-eric.eu/fileadmin/user_upload/Methodology_Volumes/SHARE_Methodenband_A4_WEB_Wave7MFRB.pdf

Bergsen, P. (2020). A new political economy for Europe post-COVID-19. *European View*, *19*(2), 131–137. https://doi.org/10.1177/1781685820968301

Bergsen, P., Billon-Galland, A., Kundnani, H., Ntousas, V., and Raines, T. (2020). *Europe after coronavirus: The EU and a new political economy*. London: Chatham House, the Royal Institute of International Affairs.

Bernheim, D. (1998). Financial illiteracy, education and retirement saving. In *Olivia, S., Mitchell and Sylvester, Schieber (Eds), Living with Defined Contribution Pensions* (pp. 38–68). University of Pennsylvania Press. https://repository.upenn.edu/cgi/viewcontent.cgi?article=1601&context=prc_papers

Best, H., and Wolf, C. (2012). Modellvergleich und Ergebnisinterpretation in Logit- und Probit-Regressionen [Model comparison and result interpretation in logit and probit regressions]. *Kölner Zeitschrift Für Soziologie Und Sozialpsychologie*, *64*(2), 377–395. https://doi.org/10.1007/s11577-012-0167-4

Bhargava, V., and Lown, J. M. (2006). Preparedness for financial emergencies: Evidence from the survey of consumer finances. *Journal of Financial Counseling and Planning*, *17*(2), 17–26. https://ssrn.com/abstract=2232126

Bi, L., and Montalto, C. (2004). Emergency funds and alternative forms of saving. *Financial Services Review*, *13*(2), 93–110.

Bialowolski, P., Cwynar, A., and Weziak-Bialowolska, D. (2022). The role of financial literacy for financial resilience in middle-age and older adulthood. *International Journal of Bank Marketing*, *40*(7), 1718–1748. https://doi.org/10.1108/IJBM-10-2021-0453

Bianchi, M. (2018). Financial literacy and portfolio dynamics. *Journal of Finance*, *73*(2), 831–859. https://doi.org/10.1111/jofi.12605

Bilias, Y., Georgarakos, D., and Haliassos, M. (2010). Portfolio inertia and stock market fluctuations. *Journal of Money, Credit and Banking*, *42*(4), 715–742.

https://doi.org/10.1111/j.1538-4616.2010.00304.x

Blalock, H. M. (2017). Causal inferences, closed populations, and measures of association. In *Causal models in the social sciences* (pp. 81–94). New York: Routledge.

Bolón-Canedo, V., Sánchez-Maroño, N., and Alonso-Betanzos, A. (2013). A review of feature selection methods on synthetic data. *Knowledge and Information Systems*, *34*(3), 483–519. https://doi.org/10.1007/s10115-012-0487-8

Bonanno, G. A. (2005). Clarifying and extending the construct of adult resilience. *Amercian Psychologist*, *60*(3), 265–267. https://doi.org/10.1037/0003-066X.60.3.265b

Börsch-Supan, A., Brandt, M., Hunkler, C., Kneip, T., Korbmacher, J., Malter, F., … Zuber, S. (2013). Data resource profile: The survey of health, ageing and retirement in Europe (SHARE). *International Journal of Epidemiology*, *42*(4), 992–1001. https://doi.org/10.1093/ije/dyt088

Box, G. E. P., and Tidwell, P. W. (1962). Transformation of the independent variables. *Technometrics*, *4*(4), 531–550.

Bracke, P., Datta, A., and Jung, C. (2019). *Machine learning explainability in finance: An application to default risk analysis* (No. 816). London: Bank of England. https://doi.org/10.2139/ssrn.3435104

Brant, R. (1990). Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics*, *46*(4), 1171–1178. https://doi.org/10.2307/2532457

Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science*, *16*(3), 199–215. https://doi.org/10.1214/ss/1009213726

Breiman, L., and Cutler, A. (2003). Setting up, using, and understanding random forests V4. 0. *University of California, Department of Statistics*.

Briguglio, L., Cordina, G., Farrugia, N., and Vella, S. (2014). Economic vulnerability and resilience: Concepts and measurements. In *Measuring Vulnerability in Developing Countries* (pp. 47–65). New York: Routledge.

Brown, S., and Taylor, K. (2008). Household debt and financial assets: Evidence from Germany, Great Britain and the USA. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *171*(3), 615–643.

https://doi.org/10.1111/j.1467-985X.2007.00531.x

Browning, M., and Crossley, T. F. (2001). The life-cycle model of consumption and saving. *Journal of Economic Perspectives*, *15*(28), 3–22. https://doi.org/10.1257/jep.15.3.3.

Brunetti, M., Giarda, E., and Torricelli, C. (2016). Is financial fragility a matter of illiquidity? An appraisal for Italian households. *Review of Income and Wealth*, *62*(4), 628–649. https://doi.org/10.1111/roiw.12189

Bucher-Koenen, T., and Lusardi, A. (2011). Financial literacy and retirement planning in Germany. *Journal of Pension Economics and Finance*, *10*(4), 565–584. https://doi.org/10.2139/ssrn.1810479

Bucher-Koenen, T., and Ziegelmeyer, M. (2011). *Who lost the most? Financial literacy, cognitive abilities, and the financial crisis* (No. 1299). Frankfurt am Main. https://doi.org/10.2139/ssrn.1761512

Bucher-Koenen, T., and Ziegelmeyer, M. (2014). Once burned, twice shy? Financial literacy and wealth losses during the financial crisis. *Review of Finance*, *18*(6), 2215–2246. https://doi.org/10.1093/rof/rft052

Buikstra, E., Ross, H., King, C. A., Baker, P. G., Hegney, D., McLachlan, K., and Rogers-Clark, C. (2010). The components of resilience—Perceptions of an Australian rural community. *Journal of Community Psychology*, *38*(8), 975–991. https://doi.org/10.1002/jcop.20409

Buntine, W., and Niblett, T. (1992). A further comparison of splitting rules for decision-tree induction. *Machine Learning*, *8*(1), 75–85. https://doi.org/10.1023/A:1022686419106

Burke, M. A., and Manz, M. (2014). Economic literacy and inflation expectations: Evidence from a laboratory experiment. *Journal of Money, Credit and Banking*, *46*(7), 1421–1456. https://doi.org/10.1111/jmcb.12144

Calle, M. L., Urrea, V., Boulesteix, A.-L., and Malats, N. (2011). AUC-RF: A new strategy for genomic profiling with random forest. *Human Heredity*, *72*(2), 121–132. https://doi.org/10.1159/000330778

Calvet, L. E., Campbell, J. Y., and Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy*, *115*(5), 707–747. https://doi.org/10.1086/524204

Calvet, L. E., Campbell, J. Y., and Sodini, P. (2009). Measuring the financial sophistication of households. *American Economic Review*, *99*(2), 393–398. https://doi.org/10.1257/aer.99.2.393

Camous, A., and Claeys, G. (2020). The evolution of European economic institutions during the COVID-19 crisis. *European Policy Analysis*, *6*(2), 328–341. https://doi.org/10.1002/epa2.1100

Chan, S., and Stevens, A. H. (2008). What you don't know can't help you: Pension knowledge and retirement decision-making. *The Review of Economics and Statistics*, *90*(2), 253–266. https://doi.org/10.1162/rest.90.2.253

Chhatwani, M., and Mishra, S. K. (2021). Does financial literacy reduce financial fragility during COVID-19? The moderation effect of psychological, economic and social factors. *International Journal of Bank Marketing*, *39*(7), 1114–1133. https://doi.org/10.1108/IJBM-11-2020-0536

Chieffe, N., and Rakes, G. K. (1999). An integrated model for financial planning. *Financial Services Review*, *8*(4), 261–268. https://doi.org/10.1016/s1057-0810(00)00044-5

Christelis, D., Jappelli, T., Paccagnella, O., and Weber, G. (2009). Income, wealth and financial fragility in Europe. *Journal of European Social Policy*, *19*(4), 359–376. https://doi.org/10.1177/1350506809341516

Christelis, D., Jappelli, T., and Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, *54*(1), 18–38. https://doi.org/10.1016/j.euroecorev.2009.04.001

Chu, K. (1999). An introduction to sensitivity, specificity, predictive values and likelihood ratios. *Emergency Medicine*, *11*(3), 175–181. https://doi.org/10.1046/j.1442-2026.1999.00041.x

Chua, S. M., and Chin, P. N. (2022). What drives working adults to be better prepared for their retirements? *Managerial Finance*, *48*(9–10), 1317–1333. https://doi.org/10.1108/MF-07-2021-0327

Clark, R. L. (2023). Effectiveness of employer-provided financial education programs. *Journal of Financial Literacy and Wellbeing*, *1*(1), 154–168. https://doi.org/10.1017/flw.2023.1

Clark, R. L., Lusardi, A., and Mitchell, O. S. (2017). Financial knowledge and 401 (k) investment performance: A case study. *Journal of Pension Economics &*

Finance, *16*(3), 324–347. https://doi.org/10.1017/S1474747215000384

Clark, R. L., Lusardi, A., and Mitchell, O. S. (2020). Financial fragility during the COVID-19 pandemic. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3723940

Clark, R. L., and Mitchell, O. S. (2022). Americans' financial resilience during the pandemic. *Financial Planning Review*, *5*(2–3), 1–15. https://doi.org/10.1002/cfp2.1140

Cole, S., Sampson, T., and Zia, B. (2011). Prices or knowledge? What drives demand for financial services in emerging markets? *Journal of Finance*, *66*(6), 1933–1967. https://doi.org/10.1111/j.1540-6261.2011.01696.x

Coleman, C. D. (2022). The importance of variable importance. *ArXiv Preprint ArXiv:2212.03289.*, 1–32. https://www.farmmanagement.pro/the-importance-of-variable-rate-irrigation/

Conger, R. D., and Conger, K. J. (2002). Resilience in Midwestern families: Selected findings from the first decade of a prospective, longitudinal study. *Journal of Marriage and Family*, *64*(2), 361–373. https://doi.org/10.1111/j.1741-3737.2002.00361.x

Connolly, C. (2012). Measuring financial exclusion in Australia. *Centre for Social Impact for National Australia Bank*. https://apo.org.au/sites/default/files/resource-files/2012-05/apo-nid29635.pdf

Croissant, Y. (2020). Mlogit: Random utility models in r. *Journal of Statistical Software*, *95*(11), 1–41. https://doi.org/10.18637/jss.v095.i11

Cull, R., Ehrbeck, T., and Holle, N. (2014). *Financial inclusion and development: Recent impact evidence*. The World Bank. https://www.cgap.org/sites/default/files/FocusNote-Financial-Inclusion-and-Development-April-2014.pdf

Cumming, F., and Hubert, P. (2021). The distribution of households' indebtedness and the transmission of monetary policy. *The Review of Economics and Statistics*, 1–36. https://doi.org/10.1162/rest_a_01094

Cziriak, M. (2022). Households' financial fragility during the COVID-19 pandemic in Germany. *ZEW Discussion Papers, No. 22-070*. https://doi.org/10.1136/ip.8.suppl_2.ii32

Daud, S. N. M., Marzuki, A., Ahmad, N., and Kefeli, Z. (2019). Financial vulnerability and its determinants: Survey evidence from Malaysian households. *Emerging Markets Finance and Trade*, *55*(9), 1991–2003. https://doi.org/10.1080/1540496X.2018.1511421

De Bassa Scheresberg, C. (2013). Financial literacy and financial behavior among young adults: Evidence and implications. *Numeracy*, *6*(2), 1–21. https://doi.org/10.5038/1936-4660.6.2.5

Deevy, M., Streeter, J. L., Hasler, A., and Lusardi, A. (2021). *Financial Resilience in America*. Global Financial Literacy Excellence Center. https://gflec.org/wp-content/uploads/2021/08/Financial-Resilience-in-America-Report-August-2021.pdf

Del Río, A., and Young, G. (2005). The impact of unsecured debt on financial distress among British households. *Bank of England Working Paper Series* (No. 262). https://doi.org/10.2139/ssrn.824147

Demertzis, M., Domínguez-Jiménez, M., and Lusardi, A. (2020). The financial fragility of European households in the time of COVID-19. *ECONIS - Online Catalogue of the ZBW*, *15*(July), 1–16. https://www.bruegel.org/wp-content/uploads/2020/07/PC-15-2020-final.pdf

Demirgüç-Kunt, A., Klapper, L. F., Singer, D., and Ansar, S. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank. https://www.worldbank.org/en/publication/globalfindex

Demirgüç-Kunt, A., Klapper, L. F., Singer, D., and Van Oudheusden, P. (2015). *The Global Findex Database 2014: Measuring financial inclusion around the world* (No. 7255). https://ssrn.com/abstract=2594973

Despard, M. R., Friedline, T., and Martin-West, S. (2020). Why do households lack emergency savings? The role of financial capability. *Journal of Family and Economic Issues*, *41*(3), 542–557. https://doi.org/10.1007/s10834-020-09679-8

Deuflhard, F., Georgarakos, D., and Inderst, R. (2017). Financial literacy and savings account returns. *Journal of the European Economic Association*, *17*(1), 131–164. https://doi.org/10.1093/jeea/jvy003

DFID. (2011). Defining disaster resilience: A DFID approach paper. *UKaid department for international development*. https://www.fsnnetwork.org/sites/default/files/dfid_defining_disaster_resilience.pdf

Di Salvatore, A., Franceschi, F., Neri, A., and Zanichelli, F. (2018). Measuring the financial literacy of the adult population: The experience of Banca D'Italia. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3212627

Dietterich, T. G. (1998). Approximate statistical tests for comparing supervised classification learning algorithms. *Neural Computation*, *10*(7), 1895–1923. https://doi.org/10.1162/089976698300017197

Disney, R., and Gathergood, J. (2013). Financial literacy and consumer credit portfolios. *Journal of Banking & Finance*, *37*(7), 2246–2254. https://doi.org/10.1016/j.jbankfin.2013.01.013

Disney, R., Gathergood, J., and Weber, J. (2015). Credit counseling: A substitute for consumer financial literacy? *Journal of Pension Economics & Finance*, *14*(4), 466–491. https://doi.org/10.1017/S1474747215000219

Dixon, M. F., Halperin, I., and Bilokon, P. (2020). *Machine learning in Finance* (Vol. 1170). Cham: Springer.

Donnellan, M. B., Conger, K. J., McAdams, K. K., and Neppl, T. K. (2009). Personal characteristics and resilience to economic hardship and its consequences: Conceptual issues and empirical illustrations. *Journal of Personality*, *77*(6), 1645–1676. https://doi.org/10.1111/j.1467-6494.2009.00596.x

Ebbes, P., Papies, D., and Van Heerde, H. J. (2016). Dealing with endogeneity: A nontechnical guide for marketing researchers. In *Handbook of market research*. Cham: Springer. https://doi.org/10.1007/978-3-319-05542-8

Emmons, W. R., and Noeth, B. J. (2013). Economic vulnerability and financial fragility. *Federal Reserve Bank of St. Louis Review*, *95*(5), 361–388. https://doi.org/10.20955/r.95.361-388

Ensel, W. M., and Lin, N. (1991). The life stress paradigm and psychological distress. *Journal of Health and Social Behavior*, *32*(4), 321–341. https://doi.org/10.2307/2137101

Erdem, D., and Rojahn, J. (2022). The influence of financial literacy on financial resilience – New evidence from Europe during the COVID-19 crisis.

Managerial Finance, *48*(9–10), 1453–1471. https://doi.org/10.1108/MF-09-2021-0442

Faruqui, U. (2008). *Indebtedness and the household financial health: An examination of the Canadian debt service ratio distribution* (No. 2008, 46). Bank of Canada. https://www.bankofcanada.ca/2008/12/working-paper-2008-46/

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, *27*(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

Feng, L., and Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, *9*(3), 305–351. https://doi.org/10.1007/s10679-005-2262-0

Feng, X., Lu, B., Song, X., and Ma, S. (2019). Financial literacy and household finances: A Bayesian two-part latent variable modeling approach. *Journal of Empirical Finance*, *51*, 119–137. https://doi.org/10.1016/j.jempfin.2019.02.002

Fernandes, D., Lynch, J. G. J., and Netemeyer, R. G. (2014). Financial literacy, financial education, and downstream financial behaviors. *Management Science*, *60*(8), 1861–1883. https://doi.org/10.1287/mnsc.2013.1849

Fernández-Delgado, M., Cernadas, E., Barro, S., and Amorim, D. (2014). Do we need hundreds of classifiers to solve real world classification problems? *Journal of Machine Learning Research*, *15*(1), 3133–3181. https://doi.org/10.1080/13216597.1999.9751892

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Thousand Oaks, CA: Sage Publications.

Field, A., Miles, J., and Field, Z. (2012). *Discovering statistics using R*. Thousand Oaks, CA: Sage Publications.

Fornero, E., and Monticone, C. (2011). Financial literacy and pension plan participation in Italy. *Journal of Pension Economics and Finance*, *10*(4), 547–564. https://doi.org/10.1017/S1474747211000473

Fox, J. (2015). *Applied regression analysis and generalized linear models*. Thousand Oaks, CA: Sage Publications.

Fox, J., and Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, *87*(417), 178–183.

https://doi.org/10.1080/01621459.1992.10475190

French, D., and McKillop, D. (2016). Financial literacy and over-indebtedness in low-income households. *International Review of Financial Analysis*, *48*, 1–11. https://doi.org/10.1016/j.irfa.2016.08.004

Frisancho, V. (2023). Spillover effects of financial education : The impact of school-based programs on parents. *Journal of Financial Literacy and Wellbeing*, *1*(1), 138–153. https://doi.org/10.1017/flw.2023.2

Fullerton, A. S. (2009). A conceptual framework for ordered logistic regression models. *Sociological Methods and Research*, *38*(2), 306–347. https://doi.org/10.1177/0049124109346162

Gale, W. G., and Levine, R. (2013). Financial literacy: What works? How could it be more effective? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2316933

García, J. M., and Vila, J. (2018). Nudging long-term saving : The Ahorra + program. *Journal of Behavioral Economics for Policy*, *2*(2), 49–53.

García, J. M., and Vila, J. (2020). Financial literacy is not enough: The role of nudging toward adequate long-term saving behavior. *Journal of Business Research*, *112*, 472–477. https://doi.org/10.1016/j.jbusres.2020.01.061

Gathergood, J., and Weber, J. (2017). Financial literacy, present bias and alternative mortgage products. *Journal of Banking and Finance*, *78*, 58–83. https://doi.org/10.1016/j.jbankfin.2017.01.022

Gehrke, M. (2019). *Angewandte empirische Methoden in Finance & Accounting: Umsetzung mit R [Applied empirical methods in finance & accounting: Implementation with R]*. Walter de Gruyter GmbH & Co KG. https://doi.org/10.1515/9783110586251

Gehrke, M. (2022). *Angewandte empirische Methoden in Finance & Accounting: Umsetzung mit R [Applied empirical methods in finance & accounting: Implementation with R]*. Walter de Gruyter GmbH & Co KG. https://doi.org/10.1515/9783110767261

Genesove, D., and Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics*, *116*(4), 1233–1260. https://doi.org/10.1162/003355301753265561

Goetzmann, W. N., and Kumar, A. (2008). Equity portfolio diversification. *Review of Finance*, *12*(3), 433–463. https://doi.org/10.1093/rof/rfn005

Goyal, K., Kumar, S., Rao, P., Colombage, S., and Sharma, A. (2021). Financial distress and COVID-19: Evidence from working individuals in India. *Qualitative Research in Financial Markets*, *13*(4), 503–528. https://doi.org/10.1108/QRFM-08-2020-0159

Grinblatt, M., and Keloharju, M. (2001). How distance, language, and culture influence stockholdings and trades. *Journal of Finance*, *56*(3), 1053–1073. https://doi.org/10.1111/0022-1082.00355

Grohmann, A. (2018). Financial literacy and financial behavior: Evidence from the emerging Asian middle class. *Pacific Basin Finance Journal*, *48*, 129–143. https://doi.org/10.1016/j.pacfin.2018.01.007

Grömping, U. (2007). Estimators of relative importance in linear regression based on variance decomposition. *The American Statistician*, *61*(2), 139–147. https://doi.org/10.1198/000313007X188252

Grömping, U. (2009). Variable importance assessment in regression: Linear regression versus random forest. *The American Statistician*, *63*(4), 308–319. https://doi.org/10.1198/tast.2009.08199

Grömping, U. (2015). Variable importance in regression models. *Wiley Interdisciplinary Reviews: Computational Statistics*, *7*(2), 137–152. https://doi.org/10.1002/wics.1346

Gros, D. (2020). The great lockdown: Was it worth it? *Centre for European Policy Studies*. https://www.ceps.eu/ceps-publications/the-great-lockdown/

Guiso, L., and Jappelli, T. (2009). *Financial literacy and portfolio diversification* (No. 212). Naples. http://www.csef.it/wp/wp212.pdf

Guiso, L., and Viviano, E. (2015). How much can financial literacy help? *Review of Finance*, *19*(4), 1347–1382. https://doi.org/10.1093/rof/rfu033

Hackl, P. (2008). *Einführung in die Ökonometrie [Introduction to econometrics]* (Vol. 7118). Pearson Deutschland GmbH.

Hallegatte, S. (2014). *Economic resilience: Definition and measurement* (No. 6852). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2432352

Hamid, F. S., Loke, Y. J., and Chin, P. N. (2023). Determinants of financial resilience:

Insights from an emerging economy. *Journal of Social and Economic Development*. https://doi.org/10.1007/s40847-023-00239-y

Hansen, M. H., Perry, L. T., and Reese, C. S. (2004). A bayesian operationalization of the resource-based view. *Strategic Management Journal*, *25*(13), 1279–1295. https://doi.org/10.1002/smj.432

Hansen, T., Slagsvold, B., and Moum, T. (2008). Financial satisfaction in old age: A satisfaction paradox or a result of accumulated wealth? *Social Indicators Research*, *89*(2), 323–347. https://doi.org/10.1007/s11205-007-9234-z

Hasler, A., and Lusardi, A. (2019). *Financial fragility among middle-income households: Evidence beyond asset building* (No. 2019–1). Washington. https://www.pgpf.org/sites/default/files/US-2050-Financial-Fragility-Among-Middle-Income-Households-Evidence-Beyond-Asset-Building.pdf

Hasler, A., Lusardi, A., and Oggero, N. (2018). Financial fragility in the US: Evidence and implications. In *Global Financial Literacy Excellence Center*. https://gflec.org/wp-content/uploads/2018/04/Financial-Fragility-Research-Paper-04-16-2018-Final.pdf?x38887

Hasler, A., Lusardi, A., Yagnik, N., and Yakoboski, P. (2023). Resilience and wellbeing in the midst of the COVID-19 pandemic: The role of financial literacy. *Journal of Accounting and Public Policy*, *42*(2), 107079. https://doi.org/10.1016/j.jaccpubpol.2023.107079

Hastings, J. S., Madrian, B. C., and Skimmyhorn, W. L. (2013). Financial literacy, financial education, and economic outcomes. *Annual Review of Economics*, *5*(1), 347–373. https://doi.org/10.1146/annurev-economics-082312-125807

Hastings, J. S., and Mitchell, O. S. (2020). How financial literacy and impatience shape retirement wealth and investment behaviors. *Journal of Pension Economics & Finance*, *19*(1), 1–20. https://doi.org/10.1017/S1474747218000227

Hauff, J. C., Carlander, A., Gärling, T., and Nicolini, G. (2020). Retirement financial behaviour: How important is being financially literate? *Journal of Consumer Policy*, *43*, 543–564. https://doi.org/10.1007/s10603-019-09444-x

Hausman, J., and McFadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica: Journal of the Econometric Society*, *52*(5), 1219–1240. https://doi.org/10.2307/1910997

Heiberger, R. M., and Holland, B. (2015). *Statistical Analysis and Data Display An Intermediate Course with Examples in R*. Springer.

Hilgert, M. A., Hogarth, J. M., and Beverly, S. G. (2003). Household financial management: The connection between knowledge and behavior. *Federal Reserve Bulletin*, *89*(7), 309–322.

Hoffmann, A. O. I., and McNair, S. J. (2019). How does consumers' financial vulnerability relate to positive and negative financial outcomes? The mediating role of Individual psychological characteristics. *Journal of Consumer Affairs*, *53*(4), 1630–1673. https://doi.org/10.1111/joca.12233

Hoffmann, A. O. I., Post, T., and Pennings, J. M. E. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, *37*(1), 60–74. https://doi.org/10.1016/j.jbankfin.2012.08.007

Hosmer, D. W., and Lemeshow, S. (2000). *Applied Logistic Regression* (2nd ed.). New York: John Wiley & Sons.

Hosmer, D. W., Lemeshow, S., and Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398). New York: John Wiley & Sons.

Hothorn, T., Bühlmann, P., Dudoit, S., Molinaro, A., and Van Der Laan, M. J. (2006). Survival ensembles. *Biostatistics*, *7*(3), 355–373. https://doi.org/10.1093/biostatistics/kxj011

Hothorn, T., Hornik, K., and Zeileis, A. (2006). Unbiased recursive partitioning: A conditional interference framework. *Journal of Computational and Graphical Statistics*, *15*(3), 651–674. https://doi.org/10.1198/106186006X133933

Huffman, D., Maurer, R., and Mitchell, O. S. (2019). Time discounting and economic decision-making in the older population. *Journal of the Economics of Ageing*, *14*, 100121. https://doi.org/10.1016/j.jeoa.2017.05.001

Hung, A., Parker, A. M., and Yoong, J. (2009). Defining and measuring financial literacy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1498674

Huston, S. J. (2010). Measuring Financial Literacy. *Journal of Consumer Affairs*, *44*(2), 296–316. https://doi.org/10.1111/j.1745-6606.2010.01170.x

Hwang, H., and Park, H. I. (2022). The relationships of financial literacy with both financial behavior and financial well-being: Meta-analyses based on the selective literature review. *Journal of Consumer Affairs*, *57*(1), 222–244. https://doi.org/10.1111/joca.12497

International Monetary Fund. (2023). World Economic Outlook Database: April 2023. Retrieved April 10, 2023, from https://www.imf.org/en/Publications/WEO/weo-database/2023/April/weo-report?c=512,914,612,171,614,311,213,911,314,193,122,912,313,419,513,316,913,124,339,638,514,218,963,616,223,516,918,748,618,624,522,622,156,626,628,228,924,233,632,636,634,238,662,960,42

Jacobs, D., Perera, D., and Williams, T. (2014). Inflation and the cost of living. *RBA Bulletin*, 33–46.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An Introduction to Statistical Learning with Applications in R*. New York: Springer.

Janitza, S., Strobl, C., and Boulesteix, A. L. (2013). An AUC-based permutation variable importance measure for random forests. *BMC Bioinformatics*, *14*(119), 1–11. https://doi.org/10.1186/1471-2105-14-119

Jappelli, T., and Padula, M. (2013). Investment in financial literacy and saving decisions. *Journal of Banking and Finance*, *37*(8), 2779–2792. https://doi.org/10.1016/j.jbankfin.2013.03.019

Jappelli, T., Pagano, M., and Di Maggio, M. (2013). Households' indebtedness and financial fragility. *Journal of Financial Management, Markets and Institutions*, *1*(1), 23–46. https://doi.org/10.12831/73631

Johnson, D., and Widdows, R. (1985). Emergency fund levels of households. In *The Proceedings of the American Council on Consumer Interests 31st Annual Conference*, *Vol. 235*, p. 241.

Johnson, J. W., and LeBreton, J. M. (2004). History and use of relative importance indices in organizational research. *Organizational Research Methods*, *7*(3), 238–257. https://doi.org/10.1177/1094428104266510

Kaiser, T., Lusardi, A., Menkhoff, L., and Urban, C. (2022). Financial education affects financial knowledge and downstream behaviors. *Journal of Financial Economics*, *145*(2), 255–272. https://doi.org/10.1016/j.jfineco.2021.09.022

Kalmi, P., and Ruuskanen, O.-P. (2018). Financial literacy and retirement planning in Finland. *Journal of Pension Economics & Finance*, *17*(3), 335–362. https://doi.org/10.1017/S1474747217000270

Karlan, D., McConnell, M., Mullainathan, S., and Zinman, J. (2016). Getting to the top of mind: How reminders increase saving. *Management Science*, *62*(12), 3393–3411. https://doi.org/10.1287/mnsc.2015.2296

Kass-Hanna, J., Lyons, A. C., and Liu, F. (2022). Building financial resilience through financial and digital literacy in South Asia and Sub-Saharan Africa. *Emerging Markets Review*, *51*(Part A). https://doi.org/10.1016/j.ememar.2021.100846

Kim-Cohen, J., and Turkewitz, R. (2012). Resilience and measured gene–environment interactions. *Development and Psychopathology*, *24*(4), 1297–1306. https://doi.org/10.1017/S0954579412000715

Kimball, M. S., and Shumway, T. (2010). Investor sophistication and the home bias, diversification, and employer stock puzzles. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1572866

Klapper, L. F., and Lusardi, A. (2020). Financial literacy and financial resilience: Evidence from around the world. *Financial Management*, *49*(3), 589–614. https://doi.org/10.1111/fima.12283

Klapper, L. F., Lusardi, A., and Panos, G. A. (2012). *Financial literacy and the financial crisis* (No. 17930). Cambridge. http://www.nber.org/papers/w17930

Klapper, L. F., Lusardi, A., and Panos, G. A. (2013). Financial literacy and its consequences: Evidence from Russia during the financial crisis. *Journal of Banking and Finance*, *37*(10), 3904–3923. https://doi.org/10.1016/j.jbankfin.2013.07.014

Klapper, L. F., Lusardi, A., and Van Oudheusden, P. (2017). Insights from the Standard & Poor's Ratings Services Global Financial Literacy Survey. *Financial Literacy around the World*, 1–27. http://www.openfininc.org/wp-content/uploads/2016/04/2015-Finlit_paper_17_F3_SINGLES.pdf

Kunovskaya, I. A., Cude, B. J., and Alexeev, N. (2014). Evaluation of a financial literacy test using classical test theory and item response theory. *Journal of Family and Economic Issues*, *35*(4), 516–531. https://doi.org/10.1007/s10834-013-9386-8

Lepore, S. J., and Revenson, T. A. (2014). Resilience and posttraumatic growth:

Recovery, resistance, and reconfiguration. In L. G. Galhoun and R. G. Tedeschi (Eds.), *Handbook of posttraumatic growth* (pp. 24–46). New York: Psychology Press.

Letkiewicz, J. C., and Fox, J. J. (2014). Conscientiousness, financial literacy, and asset accumulation of young adults. *Journal of Consumer Affairs*, *48*(2), 274–300. https://doi.org/10.1111/joca.12040

Levantesi, S., and Zacchia, G. (2021). Machine learning and financial literacy: An exploration of factors influencing financial knowledge in Italy. *Journal of Risk and Financial Management*, *14*(3), 120. https://doi.org/10.3390/jrfm14030120

Liao, L., Xiao, J. J., Zhang, W., and Zhou, C. (2017). Financial literacy and risky asset holdings: Evidence from China. *Accounting and Finance*, *57*(5), 1383–1415. https://doi.org/10.1111/acfi.12329

Loschiavo, D., and Graziano, M. (2022). Liquidity-poor households in the midst of the COVID-19 pandemic. *Review of Income and Wealth*, *68*(2), 541–562. https://doi.org/10.1111/roiw.12581

Luebke, K., and Rojahn, J. (2016). Firm-specific determinants on dividend changes: Insights from data mining. In *Wilhelm, A.F.X. and Kestler, H.A. (Eds), Analysis of Large and Complex Data. Studies in Classification, Data Analysis, and Knowledge Organization.* (pp. 335–344). Cham: Springer. https://doi.org/10.1007/978-3-319-25226-1_29

Lusardi, A. (2011). *Americans' financial capability* (No. 17103). Cambridge. http://www.nber.org/papers/w17103

Lusardi, A. (2012). Numeracy, financial literacy, and financial decision-making. In *NBER Working Paper Series* (No. 17821). http://www.nber.org/papers/w17821

Lusardi, A. (2019). Financial literacy and the need for financial education: Evidence and implications. *Swiss Journal of Economics and Statistics*, *155*(1), 1–8. https://doi.org/10.1186/s41937-019-0027-5

Lusardi, A., and De Bassa Scheresberg, C. (2013). *Financial literacy and high-cost borrowing in the United States*. National Bureau of Economic Research. https://doi.org/10.3386/w18969

Lusardi, A., Hasler, A., and Yakoboski, P. J. (2020). Building up financial literacy and financial resilience. *Mind and Society*, *49*, 589–614. https://doi.org/10.1007/s11299-020-00246-0

Lusardi, A., and Messy, F.-A. (2023). The importance of financial literacy and its impact on financial wellbeing. *Journal of Financial Literacy and Wellbeing*, *1*(1), 1–11. https://doi.org/10.1017/flw.2023.8

Lusardi, A., and Mitchell, O. S. (2006). *Financial literacy and planning: Implications for retirement well-being* (No. WP2006–01). Philadelphia. https://doi.org/10.1093/acprof:oso/9780199696819.003.0002

Lusardi, A., and Mitchell, O. S. (2007a). Baby Boomer retirement security: The roles of planning, financial literacy, and housing wealth. *Journal of Monetary Economics*, *54*(1), 205–224. https://doi.org/10.1016/j.jmoneco.2006.12.001

Lusardi, A., and Mitchell, O. S. (2007b). *Financial literacy and retirement planning: New evidence from the Rand American life panel* (No. WP 2007-157). Michigan.

Lusardi, A., and Mitchell, O. S. (2007c). *Financial literacy and retirement preparedness: Evidence and implications for financial education programs* (No. 2007/15). Frankfurt am Main.

Lusardi, A., and Mitchell, O. S. (2008). Planning and financial literacy: How do women fare? *American Economic Review: Papers & Proceedings*, *98*(2), 413–417. http://www.aeaweb.org/articles.php?doi=10.1257/aer.98.2.413

Lusardi, A., and Mitchell, O. S. (2011a). Financial literacy and planning: Implication for retirement wellbeing. In *NBER Working Paper Series* (No. 17078). http://www.nber.org/papers/w17078

Lusardi, A., and Mitchell, O. S. (2011b). Financial literacy and retirement planning in the United States. *Journal of Pension Economics and Finance*, *10*(4), 509–525. https://doi.org/10.2139/ssrn.1810550

Lusardi, A., and Mitchell, O. S. (2011c). Financial literacy around the world: An overview. *Journal of Pension Economics and Finance*, *10*(4), 497–508. https://doi.org/10.1017/S1474747211000448

Lusardi, A., and Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, *52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5

Lusardi, A., and Mitchell, O. S. (2017). How ordinary consumers make complex economic decisions: Financial literacy and retirement readiness. *Quarterly Journal of Finance*, *7*(03), 1750008. https://doi.org/10.1142/S2010139217500082

Lusardi, A., Mitchell, O. S., and Curto, V. (2010). Financial literacy among the young: Evidence and implications for consumer policy. *Center for Financial Studies Working Paper* (No. 2010/09). Frankfurt am Main.

Lusardi, A., Mitchell, O. S., and Oggero, N. (2020). Debt and financial vulnerability on the verge of retirement. *Journal of Money, Credit and Banking*, *52*(5), 1005–1034. https://doi.org/10.1111/jmcb.12671

Lusardi, A., Oggero, N., and Yakoboski, P. J. (2017). *The TIAA Institute-GFLEC Personal Finance Index: A New Measure of Financial Literacy*. https://www.researchgate.net/publication/317286009

Lusardi, A., Schneider, D., and Tufano, P. (2011). Financially fragile households: Evidence and implications. *NBER Working Paper Series* (No. 17072). Cambridge. https://doi.org/10.1353/eca.2011.0002

Lusardi, A., and Tufano, P. (2009). Debt literacy, financial experiences, and overindebtedness. *NBER Working Paper Series* (No. 14808). Cambridge. http://www.nber.org/papers/w14808

Lusardi, A., and Tufano, P. (2015). Debt literacy, financial experiences, and overindebtedness. *Journal of Pension Economics & Finance*, *14*(4), 332–368. https://doi.org/10.1017/S1474747215000232

Ly, K., Mažar, N., Zhao, M., and Soman, D. (2013). *A practitioner's guide to nudging* (No. 2609347).

Lyons, A. C., Kass-Hanna, J., Liu, F., Greenlee, A. J., and Zeng, L. (2020). *Building financial resilience through financial and digital literacy in South Asia and Sub-Saharan Africa* (No. 1098). Tokyo. https://www.adb.org/publications/building-financial-resilience-through-financial-digital- literacy-south-asia-saharan-africa

Masten, A. S. (2001). Ordinary magic: Resilience processes in development. *American Psychologist*, *56*(3), 227.

Mcknight, A., and Rucci, M. (2020). The financial resilience of households: 22 country study with new estimates, breakdowns by household characteristics and a review of policy options. *Centre for Analysis of Social*

Exclusion, London School of Economics, (May), 3–56. http://sticerd.lse.ac.uk/case

Meier, S., and Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, *2*(1), 193–210. https://doi.org/10.1257/app.2.1.193

Menard, S. (2010). *Logistic regression: From introductory to advanced concepts and applications*. Los Angeles: Sage Publications.

Midões, C. (2020). Who can live without two months of income? *Covid Economics: Vetted and Real-Time Papers*, Centre for Economic Policy Research, pp. 157–169. https://cepr.org/system/files/publication-files/101370-covid_economics_issue_18.pdf#page=162

Midões, C., and Seré, M. (2022). Living with reduced income: An analysis of household financial vulnerability under COVID-19. *Social Indicators Research*, *161*(1), 125–149. https://doi.org/10.1007/s11205-021-02811-7

Mitchell, O. S., Clark, R. L., and Lusardi, A. (2022). Income trajectories in later life: Longitudinal evidence from the Health and Retirement Study. *Journal of the Economics of Ageing*, *22*, 1–57. https://doi.org/10.1016/j.jeoa.2022.100371

Mitchell, O. S., and Lusardi, A. (2022). Financial literacy and financial behavior at older ages. *Pension Research Council Working Paper* (No. 2022–01). Philadelphia. https://doi.org/10.1016/j.pacfin.2020.101481

Moons, K. G. M., de Groot, J. A. H., Bouwmeester, W., Vergouwe, Y., Mallett, S., Altman, D. G., … Collins, G. S. (2014). Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies: The CHARMS Checklist. *PLoS Medicine*, *11*(10), 1–12. https://doi.org/10.1371/journal.pmed.1001744

Moore, D. (2003). *Survey of financial literacy in Washington State: Knowledge, behavior, attitudes, and experiences,* (No. 03–39). https://doi.org/10.13140/2.1.4729.4722

Morrow, B. H. (2008). *Community resilience: A social justice perspective*. CARRI Research Report Oak Ridge, TN. https://doi.org/10.13140/RG.2.1.1278.9604

Mottola, G. R. (2013). In our best interest: Women, financial literacy, and credit card behavior. *Numeracy*, *6*(2), 4. https://doi.org/10.5038/1936-4660.6.2.4

Müller, S., and Weber, M. (2010). Financial literacy and mutual fund investments: Who buys actively managed funds? *Schmalenbach Business Review*, *62*, 126–153. https://doi.org/10.1007/BF03396802

Mundi, H. S., and Vashisht, S. (2023). Cognitive abilities and financial resilience: Evidence from an emerging market. *International Journal of Bank Marketing*. https://doi.org/10.1108/IJBM-05-2022-0216

Newey, W. K. (1987). Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, *36*(3), 231–250. https://doi.org/10.1016/0304-4076(87)90001-7

Nguyen, M.-H., Khuc, Q. V., La, V.-P., Le, T.-T., Nguyen, Q.-L., Jin, R., … Vuong, Q.-H. (2022). Mindsponge-based reasoning of households' financial resilience during the COVID-19 crisis. *Journal of Risk and Financial Management*, *15*(11), 1–18. https://doi.org/10.3390/jrfm15110542

Nicolosi, G., Peng, L., and Zhu, N. (2009). Do individual investors learn from their trading experience? *Journal of Financial Markets*, *12*(2), 317–336. https://doi.org/10.1016/j.finmar.2008.07.001

Noctor, M., Stoney, S., and Stradling, R. (1992). Financial literacy: A discussion of concepts and competences of financial literacy and opportunities for its introduction into young people's learning. *National Foundation for Educational Research*.

Norris, F. (2010). Behavioral science perspectives on resilience. *CARRI Research Report 10*. https://merid.org/wp-content/uploads/2019/09/Behavioral-Science-Perspectives-on-Resilience.pdf

O'Connor, G. E., Newmeyer, C. E., Wong, N. Y. C., Bayuk, J. B., Cook, L. A., Komarova, Y., … Warmath, D. (2019). Conceptualizing the multiple dimensions of consumer financial vulnerability. *Journal of Business Research*, *100*, 421–430. https://doi.org/10.1016/j.jbusres.2018.12.033

O'Donnell, N., Shannon, D., and Sheehan, B. (2021). Immune or at-risk? Stock markets and the significance of the COVID-19 pandemic. *Journal of Behavioral and Experimental Finance*, *30*, 100477. https://doi.org/10.1016/j.jbef.2021.100477

OECD. (2014). PISA 2012 Results: Students and money: Financial literacy skills for the 21st Century. In *Pisa*. OECD Publishing. http://www.oecd-ilibrary.org/%5Cnjsessionid=1fwyo5fg5eknb.x-oecd-live-02content/book/9789264208094-en

OECD. (2020). *OECD/INFE 2020 International Survey of Adult Financial Literacy*. www.oecd.org/financial/education/launchoftheoecdinfeglobalfinancialliteracysurveyreport.htm

OECD. (2022). *The Impact of the COVID-19 Pandemic on Financial Consumers in Asia*. https://www.oecd.org/financial/education/the-impact-of-the-covid-19-pandemic-on-financial-consumers-in-asia.htm

Orthner, D. K., Jones-Sanpei, H., and Williamson, S. (2004). The resilience and strengths of low-income families. *Family Relations*, *53*(2), 159–167. https://doi.org/10.1111/j.0022-2445.2004.00006.x

Osborne, J. W. (2008). *Best practices in quantitative methods*. Thousand Oaks, CA: Sage Publications.

Ouachani, S., Belhassine, O., and Kammoun, A. (2021). Measuring financial literacy: A literature review. *Managerial Finance*, *47*(2), 266–281. https://doi.org/10.1108/MF-04-2019-0175

PACFL. (2008). Annual report to the President. *US Treasury*. https://www.treasury.gov/about/organizational-structure/offices/Domestic-Finance/Documents/PACFL_Draft-AR-0109.pdf

Pant, R., Barker, K., and Zobel, C. W. (2014). Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. *Reliability Engineering & System Safety*, *125*, 92–102. https://doi.org/10.1016/j.ress.2013.09.007

Pardoe, I. (2020). *Applied regression modeling*. New York: John Wiley & Sons.

Pavlou, M., Ambler, G., Seaman, S., De Iorio, M., and Omar, R. Z. (2016). Review and evaluation of penalised regression methods for risk prediction in low-dimensional data with few events. *Statistics in Medicine*, *35*(7), 1159–1177. https://doi.org/10.1002/sim.6782

Pebsworth, P. A., MacIntosh, A. J. J., Morgan, H. R., and Huffman, M. A. (2012). Factors Influencing the ranging behavior of Chacma baboons (Papio hamadryas ursinus) living in a human-modified habitat. *International*

Journal of Primatology, *33*(4), 872–887. https://doi.org/10.1007/s10764-012-9620-5

Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., and Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology*, *49*(12), 1373–1379. https://doi.org/10.1016/j.amepre.2003.12.002

Peterson, B., and Harrell, F. E. (1990). Partial proportional odds models for ordinal response variables. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *39*(2), 205–217. https://doi.org/10.2307/2347760

Porto, N., and Xiao, J. J. (2016). Financial literacy, overconfidence and financial advice seeking. *Journal of Financial Service Professionals*, *70*(4), 78–88. https://ssrn.com/abstract=4051786

Prast, H., and Soest, A. Van. (2016). Financial literacy and preparation for retirement. *Intereconomics*, *51*(3), 113–118. https://doi.org/10.1007/s10272-016-0588-9

R Core Team. (2023). *R: A language and environment for statistical computing. R Foundation for Statistical Computing.* Vienna, Austria. https://www.r-project.org/

Rieger, M. O. (2020). How to measure financial literacy? *Journal of Risk and Financial Management*, *13*(12), 324. https://doi.org/10.3390/jrfm13120324

Robb, C., and Woodyard, A. (2011). Financial knowledge and best practice behavior. *Journal of Financial Counseling and Planning*, *22*(1), 60–70. https://ssrn.com/abstract=2061308

Rohrlack, C. (2009). Logistische und Ordinale Regression [Logistic and ordinal regression]. In *Albers, S. , Klapper, D., Konradt, U. , Walter, A. & Wolf,J. (Hrsg.), Methodik der empirischen Forschung* (3rd ed., pp. 267–282). Wiesbaden: Gabler Verlag.

Room, T., and Merikull, J. (2017). *The financial fragility of Estonian households: Evidence from stress tests on the HFCS microdata* (No. 2017–4). https://doi.org/10.23656/25045520/42017/0142

S&P. (2014). Standard & Poor’s Ratings Services Global Financial Literacy Survey. https://gflec.org/initiatives/sp-global-finlit-survey/

Salignac, F., Marjolin, A., Reeve, R., and Muir, K. (2019). Conceptualizing and measuring financial resilience: A multidimensional framework. *Social Indicators Research*, *145*(1), 17–38. https://doi.org/10.1007/s11205-019-02100-4

Scherpenzeel, A., Axt, K., Bergmann, M., Douhou, S., Oepen, A., Sand, G., … Börsch-Supan, A. (2020). Collecting survey data among the 50+ population during the COVID-19 pandemic: The survey of health, ageing and retirement in Europe. *Survey Research Methods*, *14*(2), 217–221. https://doi.org/10.18148/srm/2020.v14i2.7738

Sconti, A. (2022). Having trouble making ends meet? Financial literacy makes the difference. *Italian Economic Journal*. https://doi.org/10.1007/s40797-022-00212-4

Seccombe, K. (2002). "Beating the odds" versus "changing the odds": Poverty, resilience, and family policy. *Journal of Marriage and Family*, *64*(2), 384–394. https://doi.org/10.1111/j.1741-3737.2002.00384.x

Sekita, S. (2011). Financial literacy and retirement planning in Japan. *Journal of Pension Economics & Finance*, *10*(4), 637–656. https://doi.org/10.1017/S1474747211000527

Serido, J., Shim, S., and Tang, C. (2013). A developmental model of financial capability: A framework for promoting a successful transition to adulthood. *International Journal of Behavioral Development*, *37*(4), 287–297. https://doi.org/10.1177/0165025413479476

Seru, A., Shumway, T., and Stoffman, N. (2010). Learning by trading. *The Review of Financial Studies*, *23*(2), 705–739. https://doi.org/10.1093/rfs/hhp060

Singh, K. N., and Malik, S. (2022). An empirical analysis on household financial vulnerability in India: Exploring the role of financial knowledge, impulsivity and money management skills. *Managerial Finance*, *48*(9–10), 1391–1412. https://doi.org/10.1108/MF-08-2021-0386

Sivaramakrishnan, S., Srivastava, M., and Rastogi, A. (2017). Attitudinal factors, financial literacy, and stock market participation. *International Journal of Bank Marketing*, *35*(5), 818–841. https://doi.org/10.1108/IJBM-01-2016-0012

Smythe, K. D. (1968). An approach to determining "safe" levels for family credit commitments. *The Journal of Consumer Affairs*, *2*(2), 167–181.

Soon, J. J. (2010). The determinants of students' return intentions: A partial proportional odds model. *Journal of Choice Modelling*, *3*(2), 89–112. https://doi.org/10.1016/S1755-5345(13)70037-X

Southwick, S. M., Bonanno, G. A., Masten, A. S., Panter-Brick, C., and Yehuda, R. (2014). Resilience definitions, theory, and challenges: Interdisciplinary perspectives. *European Journal of Psychotraumatology*, *5*(1), 25338. https://doi.org/10.3402/ejpt.v5.25338

Stango, V., and Zinman, J. (2009). Exponential growth bias and household finance. *Journal of Finance*, *64*(6), 2807–2849. https://doi.org/10.1111/j.1540-6261.2009.01518.x

Steccolini, I., and Jones, M. (2014). UK municipalities' financial resilience in the face of austerity: Facing crises and looking ahead. *EGPA Annual Conference, PSG XII Public Sector Financial Management*. Speyer: Nottingham Trent University.

Stock, J. H., and Watson, M. W. (2019). *Introduction to Econometrics*. London: Pearson.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics*, *20*(4), 518–529. https://doi.org/10.1198/073500102288618658

Stock, J. H., and Yogo, M. (2005). Testing for weak instruments in linear IV regression. In *Andrews DWK Identification and Inference for Econometric Models. New York: Cambridge* (pp. 80–108).

Stolper, O. A., and Walter, A. (2017). Financial literacy, financial advice, and financial behavior. *Journal of Business Economics*, *87*(5), 581–643. https://doi.org/10.1007/s11573-017-0853-9

Streiner, D. L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment*, *80*(1), 99–103. https://doi.org/10.1207/S15327752JPA8001_18

Strobl, C., Boulesteix, A. L., Kneib, T., Augustin, T., and Zeileis, A. (2008). Conditional variable importance for random forests. *BMC Bioinformatics*, *9*(307), 1–11. https://doi.org/10.1186/1471-2105-9-307

Strobl, C., Boulesteix, A. L., Zeileis, A., and Hothorn, T. (2007). Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics*, *8*(25). https://doi.org/10.1186/1471-2105-8-25

Tabachnick, B. G., and Fidell, L. S. (2018). *Using Multivariate Statistics, 7th Edn London*. London: Pearson.

Tabak, B. M., Silva, E. B., Horta, R., Silva, T. C., and Tabak, G. C. (2023). Modeling financial literacy using multilevel item response theory and the COVID-19 pandemic. *Available at SSRN 4368359*. https://doi.org/10.2139/ssrn.4368359

Tahir, M. S., Shahid, A. U., and Richards, D. W. (2022). The role of impulsivity and financial satisfaction in a moderated mediation model of consumer financial resilience and life satisfaction. *International Journal of Bank Marketing*, *40*(4), 773–790. https://doi.org/10.1108/IJBM-09-2021-0407

Taylor, M. (2011). Measuring financial capability and its determinants using survey data. *Social Indicators Research*, *102*, 297–314. https://doi.org/10.1007/s11205-010-9681-9

Thaler, R. H., and Benartzi, S. (2004). Save more tomorrow: Using behavioral economics to increase employee saving. *Journal of Political Economy*, *112*(S1), S164–S187. https://doi.org/10.1086/380085

Thaler, R. H., and Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth and happiness. *Amsterdam Law Forum; HeinOnline: Online*, 306. https://heinonline.org/HOL/LandingPage?handle=hein.journals/amslawf1&div=49&id=&page=

Thomas, A., and Spataro, L. (2018). Financial literacy, human capital and stock market participation in Europe. *Journal of Family and Economic Issues*, *39*(4), 532–550. https://doi.org/10.1007/s10834-018-9576-5

Thorp, S., Liu, J., Agnew, J., Bateman, H., and Eckert, C. (2023). Feeling comfortable with a mortgage : The impact of framing , financial literacy and advice. *Journal of Financial Literacy and Wellbeing*, *1*(1), 47–78. https://doi.org/10.1017/flw.2023.3

Tomyn, A. J., and Cummins, R. A. (2011). Subjective wellbeing and homeostatically protected mood: Theory validation with adolescents. *Journal of Happiness Studies*, *12*, 897–914. https://doi.org/10.1007/s10902-010-9235-5

UNESCO Institute for Statistics. (2012). International standard classification of education: ISCED 2011. *Montreal: UNESCO Institute for Statistics*. https://doi.org/10.1007/BF02207511

United Nations Statistics Division. (n.d.). Standard country or area codes for statistical use (M49). https://unstats.un.org/unsd/methodology/m49/

Van Ooijen, R., and Van Rooij, M. (2016). Mortgage risks, debt literacy and financial advice. *Journal of Banking and Finance*, *72*, 201–217. https://doi.org/10.1016/j.jbankfin.2016.05.001

Van Rooij, M., Lusardi, A., and Alessie, R. J. M. (2007). Financial literacy and stock market participation. *CFS Working Paper* (No. 2007/27). Frankfurt am Main.
https://www.econstor.eu/bitstream/10419/25528/1/559752334.PDF

Van Rooij, M., Lusardi, A., and Alessie, R. J. M. (2011a). Financial literacy and retirement planning in the Netherlands. *Journal of Economic Psychology*, *32*(4), 593–608. https://doi.org/10.1016/j.joep.2011.02.004

Van Rooij, M., Lusardi, A., and Alessie, R. J. M. (2011b). Financial literacy and stock market participation. *Journal of Financial Economics*, *101*(2), 449–472. https://doi.org/10.1016/j.jfineco.2011.03.006

Van Rooij, M., Lusardi, A., and Alessie, R. J. M. (2012). Financial literacy, retirement planning and household wealth. *The Economic Journal*, *122*(560), 449–478. https://doi.org/10.1111/j.1468-0297.2012.02501.x

Vega, L. A., Koike, F., and Suzuki, M. (2010). Conservation study of Myrsine seguinii in Japan: Current distribution explained by past land use and prediction of distribution by land use-planning simulation. *Ecological Research*, *25*(6), 1091–1099. https://doi.org/10.1007/s11284-010-0734-y

Vijverberg, W. (2011). Testing for IIA with the Hausman-Mcfadden Test. In *SSRN Electronic Journal* (No. 5826). https://doi.org/10.2139/ssrn.1882845

Von Gaudecker, H. M. (2015). How does household portfolio diversification vary with financial literacy and financial advice? *Journal of Finance*, *70*(2), 489–507. https://doi.org/10.1111/jofi.12231

Von Stumm, S., O'Creevy, M. F., and Furnham, A. (2013). Financial capability, money attitudes and socioeconomic status: Risks for experiencing adverse financial events. *Personality and Individual Differences*, *54*(3), 344–349.

https://doi.org/10.1016/j.paid.2012.09.019

Wiersma, J., Alessie, R. J. M., Kalwij, A., Lusardi, A., and Van Rooij, M. (2020). Skating on thin ice: New evidence on financial fragility. *SSRN Electronic Journal*, (670). https://doi.org/10.2139/ssrn.3531017

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal*, *6*(1), 58–82. https://doi.org/10.1177/1536867x0600600104

Williamson, B. D., Gilbert, P. B., Carone, M., and Simon, N. (2021). Nonparametric variable importance assessment using machine learning techniques. *Biometrics*, *77*(1), 9–22. https://doi.org/10.1111/biom.13392

Woodyard, A. S., Robb, C., Babiarz, P., and Jung, J. (2017). Knowledge and practice: Implications for cash and credit management behaviors. *Family and Consumer Sciences Research Journal*, *45*(3), 300–314. https://doi.org/10.1111/fcsr.12202

World Bank. (2023). *The World Bank: Income group classification.* https://datahelpdesk.worldbank.org/knowledgebase/articles/378833-how-are-the-income-group-thresholds-determined

Worthington, A. C. (2003). *Emergency finance in Australian households: An empirical analysis of capacity and sources.* (No. 163). https://eprints.qut.edu.au/8800/

Xia, T., Wang, Z., and Li, K. (2014). Financial Literacy Overconfidence and Stock Market Participation. *Social Indicators Research*, *119*(3), 1233–1245. https://doi.org/10.1007/s11205-013-0555-9

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2018). *The 2018 TIAA Institute-GFLEC Personal Finance Index: The State of Financial Literacy Among U.S. Adults*. Council for Economic Education, New York. http://counciforeconed.org/resource/national-standards-for-financial-literacy/.

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2019). *Financial literacy in the United States and its link to financial wellness: The 2019 TIAA Institute-GFLEC Personal Finance Index*. Council for Economic Education, New York. http://councilforeconed.org/resource/national-standards-for-financial-literacy/.

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2020a). *Financial literacy and wellness* *among U.S. women: Insights on underrepresented minority women*. TIAA Institute. https://www.tiaainstitute.org/sites/default/files/presentations/2020-11/TIAA Institute-GFLEC_Womens P-Fin Index_November 2020.pdf

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2020b). *The 2020 TIAA Institute-GFLEC Personal Finance Index: Many do not know what they do and do not know*. TIAA Institute. http://councilforeconed.org/resource/national-standards-for-financial-literacy/.

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2021). *Financial well-being and literacy in the midst of a pandemic: The 2021 TIAA Institute-GFLEC Personal Finance Index*. TIAA Institute. https://www.tiaa.org/content/dam/tiaa/institute/pdf/executive-summary/2021-06/2021-p-fin-executive-summary-final.pdf

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2022). *How financial literacy varies among U.S. adults: The 2022 TIAA Institute-GFLEC Personal Finance Index*. TIAA Institute. http://councilforeconed.org/resource/

Yakoboski, P. J., Lusardi, A., and Hasler, A. (2023). *Financial well-being and literacy in a high-inflation environment: TIAA Institute-GFLEC Personal Finance Index*. TIAA Institute. https://www.tiaa.org/content/dam/tiaa/institute/pdf/insights-report/2023-04/tiaa_institute_gflec_2023_personal_finance_index_ti_yakoboski_april_2023.pdf

Yan, X., and Su, X. G. (2009). *Linear regression analysis: Theory and computing*. Singapore: World Scientific Publishing.

Yee, T. W. (2015). *Vector generalized linear and additive models: With an implementation in R.* New York: Springer.

Yee, T. W., and Wild, C. J. (1996). Vector generalized additive models. *Journal of Royal Statistical Society: Series B (Methodological)*, *58*(3), 481–493. https://doi.org/10.1111/j.2517-6161.1996.tb02095.x

Yeh, T. (2022). An empirical study on how financial literacy contributes to preparation for retirement. *Journal of Pension Economics & Finance*, *21*(2), 237–259. https://doi.org/10.1017/S1474747220000281

Yoong, J. (2011). Financial illiteracy and stock market participation: Evidence from the RAND American Life Panel. In A. Lusardi and O. S. Mitchell (Eds.), *Financial literacy: Implications for retirement security and the financial marketplace* (pp. 76–97). Oxford: Oxford University Press.

Zaghdoudi, T. (2018). ivprobit: An R package to estimate the instrumental variables probit model. *The Journal of Open Source Software*, *3*(22), 523. https://doi.org/10.21105/joss.00523

Zahedi, J., Salehi, M., and Moradi, M. (2022). Identifying and classifying the contributing factors to financial resilience. *Foresight*, *24*(2), 177–194. https://doi.org/10.1108/FS-10-2020-0102

Zhao, M. (2018). Choice architecture in consumer financial decisions. *Review of Behavioral Economics*, *5*(3–4), 417–437. https://doi.org/10.1561/105.00000088

VII – APPENDIX

VII - APPENDIX

APPENDIX 1: Financial resilience at the country level

Country	Financially resilient (%)	Region	Income group
Afghanistan	42	Southern Asia	Low
Albania	62	Southern Europe	Upper middle
Algeria	64	Northern Africa	Lower middle
Argentina	52	Latin America & Caribbean	Upper middle
Armenia	64	Western Asia	Upper middle
Australia	84	Oceania	High
Austria	86	Western Europe	High
Bangladesh	38	Southern Asia	Lower middle
Belgium	82	Western Europe	High
Benin	52	Sub-Saharan Africa	Lower middle
Bolivia	63	Latin America & Caribbean	Lower middle
Bosnia and Herzegovina	63	Southern Europe	Upper middle
Brazil	45	Latin America & Caribbean	Upper middle
Bulgaria	68	Eastern Europe	Upper middle
Burkina Faso	51	Sub-Saharan Africa	Low
Cambodia	59	South-eastern Asia	Lower middle
Cameroon	49	Sub-Saharan Africa	Lower middle
Canada	82	Northern America	High
Chile	57	Latin America & Caribbean	High
China	84	East Asia	Upper middle
Colombia	44	Latin America & Caribbean	Upper middle
Congo, Rep.	42	Sub-Saharan Africa	Lower middle
Costa Rica	47	Latin America & Caribbean	Upper middle
Côte d'Ivoire	49	Sub-Saharan Africa	Lower middle
Croatia	61	Southern Europe	High
Cyprus	65	Western Asia	High
Czech Republic	84	Eastern Europe	High
Denmark	89	Northern Europe	High
Dominican Republic	49	Latin America & Caribbean	Upper middle
Ecuador	54	Latin America & Caribbean	Upper middle
Egypt, Arab Rep.	43	Northern Africa	Lower middle
El Salvador	45	Latin America & Caribbean	Lower middle
Estonia	86	Northern Europe	High
Finland	89	Northern Europe	High
France	78	Western Europe	High
Gabon	49	Sub-Saharan Africa	Upper middle
Georgia	49	Western Asia	Upper middle
Germany	79	Western Europe	High
Ghana	49	Sub-Saharan Africa	Lower middle
Greece	70	Southern Europe	High
Guinea	37	Sub-Saharan Africa	Low

Country	Financially resilient (%)	Region	Income group
Honduras	43	Latin America & Caribbean	Lower middle
Hong Kong SAR, China	88	Eastern Asia	High
Hungary	75	Eastern Europe	High
Iceland	88	Northern Europe	High
India	31	Southern Asia	Lower middle
Indonesia	56	South-eastern Asia	Lower middle
Iran, Islamic Rep.	71	Southern Asia	Lower middle
Iraq	50	Western Asia	Upper middle
Ireland	80	Northern Europe	High
Israel	77	Western Asia	High
Italy	78	Southern Europe	High
Jamaica	53	Latin America & Caribbean	Upper middle
Japan	80	Eastern Asia	High
Jordan	51	Western Asia	Upper middle
Kazakhstan	48	Central Asia	Upper middle
Kenya	47	Sub-Saharan Africa	Lower middle
Korea, Rep.	81	Eastern Asia	High
Kosovo	72	Southern Europe	Upper middle
Kyrgyz Republic	63	Central Asia	Lower middle
Lao PDR	33	South-eastern Asia	Lower middle
Latvia	79	Northern Europe	High
Lebanon	58	Western Asia	Lower middle
Liberia	40	Sub-Saharan Africa	Low
Lithuania	63	Northern Europe	High
Malawi	46	Sub-Saharan Africa	Low
Malaysia	61	South-eastern Asia	Upper middle
Mali	32	Sub-Saharan Africa	Low
Malta	81	Southern Europe	High
Mauritius	63	Sub-Saharan Africa	Upper middle
Moldova	65	Eastern Europe	Upper middle
Mongolia	68	Eastern Asia	Lower middle
Morocco	49	Northern Africa	Lower middle
Mozambique	41	Sub-Saharan Africa	Low
Myanmar	72	South-eastern Asia	Lower middle
Namibia	35	Sub-Saharan Africa	Upper middle
Nepal	55	Southern Asia	Lower middle
Netherlands	77	Western Europe	High
New Zealand	85	Oceania	High
Nicaragua	57	Latin America & Caribbean	Lower middle
Nigeria	36	Sub-Saharan Africa	Lower middle
North Macedonia	58	Southern Europe	Upper middle
Norway	89	Northern Europe	High
Pakistan	30	Southern Asia	Lower middle
Panama	37	Latin America & Caribbean	High
Paraguay	44	Latin America & Caribbean	Upper middle
Peru	58	Latin America & Caribbean	Upper middle
Philippines	50	South-eastern Asia	Lower middle
Poland	82	Eastern Europe	High
Portugal	69	Southern Europe	High

Country	Financially resilient (%)	Region	Income group
Romania	61	Eastern Europe	High
Russian Federation	74	Eastern Europe	Upper middle
Saudi Arabia	82	Western Asia	High
Senegal	40	Sub-Saharan Africa	Lower middle
Serbia	62	Southern Europe	Upper middle
Sierra Leone	36	Sub-Saharan Africa	Low
Singapore	76	South-eastern Asia	High
Slovak Republic	84	Eastern Europe	High
Slovenia	78	Southern Europe	High
South Africa	40	Sub-Saharan Africa	Upper middle
South Sudan	16	Northern Africa	Low
Spain	78	Southern Europe	High
Sri Lanka	48	Southern Asia	Lower middle
Sweden	94	Northern Europe	High
Switzerland	73	Western Europe	High
Taiwan, China	88	Eastern Asia	High
Tajikistan	59	Central Asia	Lower middle
Tanzania	48	Sub-Saharan Africa	Lower middle
Thailand	61	South-eastern Asia	Upper middle
Togo	51	Sub-Saharan Africa	Low
Tunisia	58	Northern Africa	Lower middle
Türkiye	41	Western Asia	Upper middle
Uganda	49	Sub-Saharan Africa	Low
Ukraine	75	Eastern Europe	Lower middle
United Arab Emirates	59	Western Asia	High
United Kingdom	86	Northern Europe	High
United States	76	Northern America	High
Uruguay	54	Latin America & Caribbean	High
Uzbekistan	63	Central Asia	Lower middle
Venezuela, RB	45	Latin America & Caribbean	Lower middle
West Bank and Gaza	60	Western Asia	Lower middle
Zambia	21	Sub-Saharan Africa	Low
Zimbabwe	32	Sub-Saharan Africa	Lower middle

Note. This table provides an overview of financial resilience levels worldwide at the country level based on data from the Global Findex 2021 Survey.

[Source: Own representation]

APPENDIX 2: Financial literacy at the country level

Country	Financially literate (%)	Region	Income group
Afghanistan	14	Southern Asia	Low
Albania	14	Southern Europe	Upper middle
Algeria	33	Northern Africa	Lower middle
Angola	15	Sub-Saharan Africa	Lower middle
Argentina	28	Latin America & Caribbean	Upper middle
Armenia	18	Western Asia	Upper middle
Australia	64	Oceania	High
Austria	53	Western Europe	High
Azerbaijan	36	Western Asia	Upper middle
Bahrain	40	Western Asia	High
Bangladesh	19	Southern Asia	Lower middle
Belarus	38	Eastern Europe	Upper middle
Belgium	55	Western Europe	High
Belize	33	Latin America & Caribbean	Upper middle
Benin	37	Sub-Saharan Africa	Lower middle
Bhutan	54	Southern Asia	Lower middle
Bolivia	24	Latin America & Caribbean	Lower middle
Bosnia and Herzegovina	27	Southern Europe	Upper middle
Botswana	52	Sub-Saharan Africa	Upper middle
Brazil	35	Latin America & Caribbean	Upper middle
Bulgaria	35	Eastern Europe	Upper middle
Burkina Faso	33	Sub-Saharan Africa	Low
Burundi	24	Sub-Saharan Africa	Low
Cambodia	18	South-eastern Asia	Lower middle
Cameroon	38	Sub-Saharan Africa	Lower middle
Canada	68	Northern America	High
Chad	26	Sub-Saharan Africa	Low
Chile	41	Latin America & Caribbean	High
China	28	Eastern Asia	Upper middle
Colombia	32	Latin America & Caribbean	Upper middle
Congo, Dem. Rep.	32	Sub-Saharan Africa	Low
Congo, Rep.	31	Sub-Saharan Africa	Lower middle
Costa Rica	35	Latin America & Caribbean	Upper middle
Croatia	44	Southern Europe	High
Cyprus	35	Western Asia	High
Czech Republic	58	Eastern Europe	High
Côte d'Ivoire	35	Sub-Saharan Africa	Lower middle
Denmark	71	Northern Europe	High
Dominican Republic	35	Latin America & Caribbean	Upper middle
Ecuador	30	Latin America & Caribbean	Upper middle
Egypt, Arab Rep.	27	Northern Africa	Lower middle
El Salvador	21	Latin America & Caribbean	Lower middle
Estonia	54	Northern Europe	High
Ethiopia	32	Sub-Saharan Africa	Low
Finland	63	Northern Europe	High
France	52	Western Europe	High
Gabon	35	Sub-Saharan Africa	Upper middle
Georgia	30	Western Asia	Upper middle

Country	Financially literate (%)	Region	Income group
Germany	66	Western Europe	High
Ghana	32	Sub-Saharan Africa	Lower middle
Greece	45	Southern Europe	High
Guatemala	26	Latin America & Caribbean	Upper middle
Guinea	30	Sub-Saharan Africa	Low
Haiti	18	Latin America & Caribbean	Lower middle
Honduras	23	Latin America & Caribbean	Lower middle
Hong Kong SAR, China	43	Eastern Asia	High
Hungary	54	Eastern Europe	High
Indonesia	32	South-eastern Asia	Lower middle
Iran, Islamic Rep.	20	Southern Asia	Lower middle
Iraq	27	Western Asia	Upper middle
Ireland	55	Northern Europe	High
Israel	68	Western Asia	High
Italy	37	Southern Europe	High
Jamaica	33	Latin America & Caribbean	Upper middle
Japan	43	Eastern Asia	High
Jordan	24	Western Asia	Upper middle
Kazakhstan	40	Central Asia	Upper middle
Kenya	38	Sub-Saharan Africa	Lower middle
Korea, Rep.	33	Eastern Asia	High
Kosovo	20	Southern Europe	Upper middle
Kuwait	44	Western Asia	High
Kyrgyz Rep.	19	Central Asia	Lower middle
Latvia	48	Northern Europe	High
Lebanon	44	Western Asia	Lower middle
Lithuania	39	Northern Europe	High
Luxembourg	53	Western Europe	High
North Macedonia	21	Southern Europe	Upper middle
Madagascar	38	Sub-Saharan Africa	Low
Malawi	35	Sub-Saharan Africa	Low
Malaysia	36	South-eastern Asia	Upper middle
Mali	33	Sub-Saharan Africa	Low
Malta	44	Southern Europe	High
Mauritania	33	Sub-Saharan Africa	Lower middle
Mauritius	39	Sub-Saharan Africa	Upper middle
Mexico	32	Latin America & Caribbean	Upper middle
Moldova	27	Eastern Europe	Upper middle
Mongolia	41	Eastern Asia	Lower middle
Montenegro	48	Southern Europe	Upper middle
Myanmar	52	South-eastern Asia	Lower middle
Namibia	27	Sub-Saharan Africa	Upper middle
Nepal	18	Southern Asia	Lower middle
Netherlands	66	Western Europe	High
New Zealand	61	Oceania	High
Nicaragua	20	Latin America & Caribbean	Lower middle
Niger	31	Sub-Saharan Africa	Low
Nigeria	26	Sub-Saharan Africa	Lower middle
Norway	71	Northern Europe	High

Country	Financially literate (%)	Region	Income group
Pakistan	26	Southern Asia	Lower middle
Panama	27	Latin America & Caribbean	High
Peru	28	Latin America & Caribbean	Upper middle
Philippines	25	South-eastern Asia	Lower middle
Poland	42	Eastern Europe	High
Portugal	26	Southern Europe	High
Puerto Rico	32	Latin America & Caribbean	High
Romania	22	Eastern Europe	High
Russian Federation	38	Eastern Europe	Upper middle
Rwanda	26	Sub-Saharan Africa	Low
Saudi Arabia	31	Western Asia	High
Senegal	40	Sub-Saharan Africa	Lower middle
Serbia	38	Southern Europe	Upper middle
Sierra Leone	21	Sub-Saharan Africa	Low
Singapore	59	South-eastern Asia	High
Slovak Republic	48	Eastern Europe	High
Slovenia	44	Southern Europe	High
Somalia	15	Sub-Saharan Africa	Low
South Africa	42	Sub-Saharan Africa	Upper middle
Spain	49	Southern Europe	High
Sri Lanka	35	Southern Asia	Lower middle
Sudan	21	Sub-Saharan Africa	Low
Sweden	71	Northern Europe	High
Switzerland	57	Western Europe	High
Taiwan, China	37	Eastern Asia	High
Tajikistan	17	Central Asia	Lower middle
Tanzania	40	Sub-Saharan Africa	Lower middle
Thailand	27	South-eastern Asia	Upper middle
Togo	38	Sub-Saharan Africa	Low
Tunisia	45	Northern Africa	Lower middle
Türkiye	24	Western Asia	Upper middle
Turkmenistan	41	Central Asia	Upper middle
Uganda	34	Sub-Saharan Africa	Low
Ukraine	40	Eastern Europe	Lower middle
United Arab Emirates	38	Western Asia	High
United Kingdom	67	Northern Europe	High
United States	57	Northern America	High
Uruguay	45	Latin America & Caribbean	High
Uzbekistan	21	Central Asia	Lower middle
Venezuela, RB	25	Latin America & Caribbean	Lower middle
Vietnam	24	South-eastern Asia	Lower middle
West Bank and Gaza	25	Western Asia	Lower middle
Yemen, Rep.	13	Western Asia	Low
Zambia	40	Sub-Saharan Africa	Low
Zimbabwe	41	Sub-Saharan Africa	Lower middle

Note. This table provides an overview of financial literacy levels worldwide at the country level based on data from the S&P Global FinLit Survey.

[Source: Own representation]

APPENDIX 3: Financial literacy index

The following questions from SHARE's Wave 7 are used to construct the financial literacy index:

"(1) If the chance of getting a disease is ten percent, how many people out of 1000 (one thousand) would be expected to get the disease? The possible answers are 100, 10, 90, 900 and another answer.

(2) In a sale, a shop is selling all items at half price. Before the sale, a sofa costs 300 euro. How much will it cost in the sale? The possible answers are 150, 600 and another answer.

(3) A second hand car dealer is selling a car for 6,000 euro. This is two-thirds of what it costs new. How much did the car cost new? The possible answers are 9,000, 4,000, 8,000, 12,000, 18,000 and another answer.

(4) Let us say you have 2000 euro in a savings account. The account earns ten per cent interest each year. How much would you have in the account at the end of two years? The possible answers are 2420, 2020, 2040, 2100, 2200, 2400 and another answer."

When an individual responds correctly to (1), they are subsequently asked (3), and if their response to (3) is also correct, they are asked (4). An accurate response to (1) results in a score of 3. Correctly answering (3) but not (4) leads to a score of 4, whereas a correct response to (4) yields a score of 5. If the individual answers (1) incorrectly, they are directed to (2). A correct answer to (2) awards a score of 2, but an incorrect response to (2) results in a score of 1.

APPENDIX 4: Variable definition

Variable	Definition	Source
Variables at the individual level		
FR_t	Indicator for financial resilience, assigned a value of one when respondents reply with "Easily" or "Fairly easily" to the following question: "Thinking of your household's total monthly income since the outbreak of Corona, would you say that your household is able to make ends meet with great difficulty, with some difficulty, fairly easily, or easily?" Otherwise, it is set to zero.	SHARE COVID-19 survey
FL_{t-1}	Assessment of financial literacy, scored on a scale from one to five, with higher scores denoting a greater level of financial literacy.	Wave 7
AGE_{t-1}	Corresponds to the age of the respondent.	Wave 7
CH_{t-1}	Represents the number of children the respondent has.	Wave 7
$EDU\text{-}MED_{t-1}$	A binary variable with a value of one if the individuals' educational credentials or degree, in line with the ISCED, equals at least upper secondary education; otherwise, it is zero.	Wave 7
$EDU\text{-}HIGH_{t-1}$	A binary variable with a value of one if the individuals' educational credentials or degree, in line with the ISCED, equals at least the first stage of tertiary education; otherwise, it is zero.	Wave 7
$EMPL_t$	A binary variable indicating whether the respondent is currently employed or self-employed, with a value of one; otherwise, it is zero.	SHARE COVID-19 survey
$FEMALE_{t-1}$	Binary variable that equals one if the respondent is a woman, and zero otherwise.	Wave 7
$IN\text{-}MED_t$	A binary variable that equals one if the respondent's household monthly income after taxes and contributions falls into the second tercile of their country of residence; otherwise, it is zero.	SHARE COVID-19 survey
$IN\text{-}HIGH_t$	A binary variable that equals one if the respondent's household monthly income after taxes and contributions falls into the third tercile of their country of residence; otherwise, it is zero.	SHARE COVID-19 survey
$P\text{-}FIH_{t-1}$	Duration of experienced financial difficulties, measured in years.	Wave 7
$PLAN_{t-1}$	The preferred time frame for saving and spending by respondents, rated on a scale from one to five. Higher values denote a more long-term planning horizon.	Wave 7

Variable	Definition	Source
RET_{t-1}	Binary variable set to one if the respondent is in retirement status; otherwise, it is zero.	Wave 7
Variables at the country level		
$BELGIUM_{t-1}$	Binary variable set to one if the respondent resides in Belgium; otherwise, it is zero.	Wave 7
$ESTONIA_{t-1}$	Binary variable set to one if the respondent resides in Estonia; otherwise, it is zero.	Wave 7
$FRANCE_{t-1}$	Binary variable set to one if the respondent resides in France; otherwise, it is zero.	Wave 7
$GERMANY_{t-1}$	Binary variable set to one if the respondent resides in Germany; otherwise, it is zero.	Wave 7
$SLOVENIA_{t-1}$	Binary variable set to one if the respondent resides in Slovenia; otherwise, it is zero.	Wave 7
$SPAIN_{t-1}$	Binary variable set to one if the respondent resides in Spain; otherwise, it is zero.	Wave 7
Variables used as instruments for assessing financial literacy		
$IFL\text{-}LAN_{t-1}$	Participants' self-assessment of their reading and writing skills at the age of ten compared to their classmates. Scores vary from zero to five, with higher values signifying greater initial financial literacy language proficiency.	Wave 7
$IFL\text{-}MAT_{t-1}$	Participants' self-assessment of their math skills at the age of ten compared to their classmates. Scores vary from zero to five, with higher values signifying greater initial financial literacy math proficiency.	Wave 7