CARINA RAMOS JESUS

COMPANY RESILIENCE IN THE EUROPEAN TOURISM INDUSTRY:
EVIDENCE FROM THE COVID-19 PANDEMIC

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UNIVERSIDADE DO ALGARVE
FACULDADE DE ECONOMIA

FARO, 2025

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PhD in Economic and Management Sciences

(Specialty in Management)

Work carried out under the guidance of:

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Statement of Work Authorship

I declare to be the author of this work, which is unique and unprecedented. Authors and works consulted are properly cited in the text and are included in the listing of references included.

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(Carina Ramos Jesus)

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To my mother, my unwavering pillar of strength, for she is the true embodiment of resilience in my life.

Mom, this thesis is a tribute to the strong, fearless woman you are, and to all that you have taught me about fighting for what truly matters. Now I know that no challenge is too great, and no dream is out of reach, as long as I'm willing to work hard enough for it.

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Looking at this project, now completed, I realize that I am, and will always remain, a lifelong student. I have learned that I should always be ready to be humbled by how much I still don't know, and to work even harder. There truly is no limit to how much I can continue to learn and grow. I am deeply inspired by the endless possibilities ahead. This journey has not been a culmination of my academic efforts, but rather the starting point for a lifetime of learning and growth. On a final note, these thoughts remind me of the wise words attributed to Albert Einstein, who beautifully captured the joy of curiosity:

"I have no special talent. I am only passionately curious."

ABSTRACT

What influences the ability of tourism companies to withstand and recover from disruptive events like pandemics or wars? How can these businesses strengthen their resilience? Why do some profitable companies collapse while others thrive in the face of adversity? The resilience of tourism firms to disruptive events is a critical but underexplored topic. This thesis addresses these critical questions by examining the determinants of company resilience, its dynamic mechanisms across resistance and recovery phases, and the distinct resilience drivers of profit-making and loss-making firms.

Through a systematic literature review and the application of a proposed resilience index, our research provides a unified framework for future research, advancing theoretical understanding of company resilience in the tourism industry and providing insights for managers and policymakers in this sector. Findings from our review highlight the dynamic, idiosyncratic, interdisciplinary and context-dependent nature of resilience, with clear evidence that human capital plays a pivotal role in the tourism industry's ability to remain resilient. Furthermore, the empirical studies identify the factors driving the resilience of these firms to COVID-19, suggesting that their effects differ across countries, resilience stages, and types of firms. The results further underscore the potential consequences of Eurozone membership in the resilience of tourism firms, providing valuable insights into future preparedness strategies and policies. Moreover, the results contribute to the resource-based view and dynamic capabilities perspective by demonstrating the impact of firm-level resources across crisis phases.

Together, these studies provide a comprehensive understanding of the resilience mechanisms of tourism firms, expanding the current understanding of how these firms can enhance their resilience, bridging theory and practice. Finally, this thesis provides actionable insights for academics, policymakers, and managers, discussing theoretical and practical implications, as well as future research directions, ultimately contributing to build a more sustainable and enduring tourism industry.

Keywords: Covid-19; Crisis Management; Dynamic Capabilities; Recovery; Resilience; Tourism.

RESUMO

O conceito de resiliência empresarial é de crucial importância para compreender como as empresas reagem e resistem a eventos disruptivos, particularmente numa era de crescente incerteza global, marcada por tensões geopolíticas, inflação e instabilidade financeira (International Monetary Fund, 2023). Tais crises dão origem a custos económicos e sociais significativos, o que insta a que compreendamos como melhorar a resiliência destas empresas, de modo a reduzir esses custos e prepará-las para futuras disrupções (Bertschek et al., 2019).

Este tema assume particular interesse na sequência de eventos altamente disruptivos para a economia mundial, como foi o caso da pandemia de COVID-19. Investigar este tópico no setor do turismo revela-se crucial por vários motivos. Em primeiro lugar, esta indústria é responsável por uma percentagem considerável do PIB e nível de emprego mundial (World Travel & Tourism Council, 2024). Em segundo lugar, o turismo é uma indústria particularmente vulnerável a eventos disruptivos (Chowdhury et al., 2019; Espiner & Becken, 2014; Prayag et al., 2020), o que reforça a necessidade de aumentar a resiliência das empresas deste setor. A recente pandemia ilustrou vividamente essa vulnerabilidade, causando reduções severas nos fluxos internacionais e no PIB do setor (World Tourism Organization, 2021). A recuperação tem sido mais lenta do que seria expectável. De facto, apenas quatro anos após o início da pandemia é que os níveis de turismo foram totalmente recuperados (UNWTO, 2024b, 2025). Estes desafios reafirmam a importância de identificar e compreender os processos e fatores que contribuem para a resiliência neste setor.

A estes desafios, acresce que o setor do turismo foi gravemente afetado em surtos anteriores de síndrome respiratória aguda grave (SARS), enquanto outros setores foram significativamente menos afetados (M.-H. Chen et al., 2007; Zeng et al., 2005). Alguns estudos demonstram que várias empresas do setor do turismo possuem níveis de resiliência insuficientes (Wieczorek-Kosmala, 2022), e que se consideram menos resilientes do que empresas de outros setores (Ntounis et al., 2022). Por fim, alguns estudos revelam também que as empresas de turismo reagem de forma diferente aos mesmos eventos disruptivos. Isto é evidenciado, por exemplo, no estudo do setor de alojamento de Pongtanalert e Assarut (2022), que detalha os diferentes mecanismos usados por pequenas empresas para sobreviver ao impacto da pandemia. Estando

particularmente dependente da mobilidade (Archanskaia et al., 2023), este setor é bastante suscetível a choques externos que afetem severamente a continuidade das suas operações (Bharwani & Mathews, 2012; Dimitrić et al., 2019; Dogru et al., 2023; Vivel-Búa et al., 2019). Além disso, as medidas de resposta à pandemia, como as medidas de confinamento, distanciamento social e restrições de mobilidade, impactaram significativamente o desempenho das empresas deste setor (S. Lee et al., 2024), motivo pelo qual este trabalho de investigação se debruça especificamente sobre este subsetor.

Contudo, importa frisar que a resiliência empresarial está muito para além de uma tendência recente: trata-se de um tópico de investigação intemporal e indispensável. A teoria demonstra que desenvolver resiliência é vital não apenas para a sobrevivência das empresas, mas também para a criação e manutenção de vantagens competitivas (Vogus & Sutcliffe, 2007). Esta conclusão reforça a necessidade de implementar estratégias de desenvolvimento da resiliência empresarial mesmo em períodos de aparente estabilidade.

Embora a resiliência no turismo continue pouco explorada, é cada vez mais reconhecida como um processo multidisciplinar e dinâmico (Amaral & Da Rocha, 2023; Brown et al., 2017; Hall et al., 2023; W. Liu et al., 2024; Wided, 2022). Os seus determinantes variam consoante o contexto, o tipo de disrupção e as características das empresas (Amaral & Da Rocha, 2023; Orchiston et al., 2016; Sobaih et al., 2021). Assim, as organizações adotam diferentes estratégias de resiliência ao longo de uma crise (A. V. Lee et al., 2013), consoante a sua capacidade de recolha de informação e adaptação vai evoluindo (S. X. Chen et al., 2022). Um estudo posterior conduzido por Amaral e Da Rocha (2023) ilustra bem o modo como as pequenas empresas familiares no setor do turismo recorrem a diversas estratégias, emoções e capacidades ao longo da progressão da pandemia. Coletivamente, estes estudos descrevem a resiliência como um processo dinâmico e idiossincrático, caracterizado por uma interação complexa de recursos, competências e estratégias que evoluem ao longo das diferentes fases da disrupção (Amaral & Da Rocha, 2023; Biggs et al., 2012, 2015; S. X. Chen et al., 2022; Hoang et al., 2021; Jawed et al., 2021; S. Lee et al., 2024; Usher et al., 2019).

No entanto, apesar do crescente interesse no tema da resiliência empresarial, a literatura existente tende a privilegiar o estudo da resiliência regional em detrimento das dinâmicas empresariais, tratando frequentemente a resiliência como um atributo estático, em vez de um processo dinâmico e idiossincrático. Deste modo, esta tese procura colmatar estas lacunas, explorando os determinantes, os mecanismos e as implicações da resiliência empresarial em empresas do setor do turismo.

Assim, os principais objetivos desta investigação são três. Primeiro, a atenção é direcionada para os determinantes da resiliência empresarial nas empresas do setor do turismo, com particular enfoque no papel crítico dos fatores ao nível da empresa. Segundo, é abordada a natureza dinâmica da resiliência, com modelos direcionados às suas fases principais: resistência e recuperação. Destaca-se particularmente a forma como as características de cada empresa influenciam a sua resiliência de forma distinta em cada uma destas fases. Por fim, esta tese explora em detalhe os fatores que influenciam a resiliência de empresas rentáveis e não rentáveis, identificando os mecanismos específicos que cada tipo de empresa pode utilizar a seu favor. Estes objetivos são repartidos por três artigos científicos distintos, mas interrelacionados, cada um contribuindo com perspetivas teóricas e práticas sobre a resiliência destas empresas.

O primeiro artigo visa desenvolver um referencial teórico unificado para estudar a resiliência empresarial. Aplicando este quadro ao setor do turismo, o estudo procura identificar os determinantes da resiliência empresarial evidenciados na literatura, por forma a identificar que características influenciam a resiliência das empresas que operam neste setor.

O segundo artigo explora a necessidade de métricas que possam ser utilizadas para medir a resiliência no setor do turismo, propondo uma adaptação de um índice de resiliência regional ao contexto empresarial. A aplicação desta métrica permite identificar, de modo empírico, os fatores que influenciaram a resiliência de empresas de alojamento à pandemia de COVID-19.

Dada a perspetiva estática da maioria dos estudos existentes, o terceiro artigo desta tese explora a natureza dinâmica da resiliência e as idiossincrasias entre empresas rentáveis e não rentáveis. Para tal, índice de resiliência proposto no segundo artigo é decomposto em índices de resistência e recuperação. Através da aplicação destes índices, o artigo procura identificar os papéis distintos das características empresariais ao longo das duas fases da resiliência, com o objetivo de identificar se a rentabilidade impacta a resiliência das empresas no setor do turismo e se o seu papel é distinto nas duas fases da resiliência.

Em conjunto, estes artigos oferecem uma perspetiva holística da resiliência no setor do turismo, colmatando importantes lacunas teóricas e práticas, com contribuições teóricas e práticas significativas. Ao identificar os fatores que impulsionam a resiliência, propor uma métrica de resiliência empresarial e explorar os mecanismos dinâmicos da resiliência, esta investigação abre caminho para um setor do turismo mais resiliente, capaz de enfrentar futuras disrupções e promover a sustentabilidade a longo prazo.

Palavras-chave: Covid-19; Capacidades Dinâmicas; Gestão de crises; Recuperação; Resiliência; Turismo.

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AUC	Area Under the Receiver Operating Characteristic Curve
CAP	Capital Intensity
COVID-19	Coronavirus Disease 2019
CR	Company Resilience
CSR	Corporate Social Responsibility
DOI	Digital Object Identifier
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
FCT	Fundação para a Ciência e a Tecnologia
GDP	Gross Domestic Product
GVA	Gross Value Added
HR	Human Resources
LEV	Leverage
LIQ	Liquidity
NEGCP	Negative Book Equity
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RBV	Resource-Based View
REDHC	Human Capital Reductions
REDSAL	Salary Reductions
ROA	Return on Assets
ROC	Receiver Operating Characteristic curve
SARS	Severe Acute Respiratory Syndrome
SAS	Statistical Analysis System
SIC	Standard Industrial Classification
SIZE	Firm size
SME	Small and Medium-sized Enterprises
UNWTO	United Nations World Tourism Organization
VIF	Variance Inflation Factor

CHAPTER 1 – GENERAL INTRODUCTION

1.1. Research background and overview

The concept of company resilience (CR) has never been more critical, in an era of increasing global uncertainty, marked by geopolitical tensions, inflation, and financial instability (International Monetary Fund, 2023). Crises carry significant economic and social costs, making it essential to understand how businesses can better navigate them and strengthen their resilience in preparation for future disruptions (Bertschek et al., 2019).

This is a particularly interesting theme in the wake of very dramatic events, such as the global COVID-19 pandemic or the recent war in Europe and the Middle East. Tourism provides a compelling lens through which to examine this topic, given its significant contribution to the global GDP and employment (World Travel & Tourism Council, 2024). Additionally, this is an industry with pronounced vulnerability to major disruptive events (Chowdhury et al., 2019; Espiner & Becken, 2014; Prayag et al., 2020). The recent pandemic vividly illustrated this weakness, leading to severe reductions in international flows and GDP (World Tourism Organization, 2021). Interestingly, the recovery had a slower pace than anticipated, with pre-pandemic tourism levels only fully recovered four years after the outbreak (UNWTO, 2024, 2025), which clearly emphasizes the urgency of identifying and understanding the mechanisms and factors that contribute to CR in this sector.

Company resilience is, however, more than a recent trend; it is a timeless and much needed research field, a long-term strategic imperative. In fact, existing research shows that developing resilience is not only vital for firm survival; it also plays a crucial role in developing and sustaining competitive advantage (Vogus & Sutcliffe, 2007), a conclusion that emphasizes the need to invest in resilience-building strategies even during periods of stability. This leads us to a brief introduction of the concept and its evolution, with an emphasis on its application to tourism businesses.

1.2. The concept of resilience

Derived from the Latin *resiliens*, the act of "bouncing back" (Iborra et al., 2020), the concept of resilience originated in ecology, where Holling (1973) defined resilience as the ability of a system to absorb the impact of disturbance and persist. Since then, the concept has been adopted in several studies within the field of economics and expanded across many research streams (Linnenluecke, 2017).

It has been established that resilience is beyond the scope of persistence (Folke, 2006; Weick et al., 1999), including two additional dimensions: adaptability, and transformability (Folke et al., 2010; Walker et al., 2004). While adaptability reflects the capacity to learn and adjust to external and internal stimuli (Folke et al., 2010), transformability refers to the ability to create new stability domains when existing ones become unsustainable (Walker et al., 2004). These dimensions align with the resource-based view (RBV) and dynamic capabilities (Ambrosini & Bowman, 2009; Wernerfelt, 1984), which emphasize the role of adaptability in sustaining competitive advantage in volatile business environments.

The evolution of the concept has been shaped by major disruptions, such as the Great Recession and COVID-19 (Hall et al., 2023), which prompted the study of how firms respond to and endure such challenges (Linnenluecke, 2017). In fact, Hall et al. (2023) underscore the fragmentation of existing CR frameworks and call for longitudinal studies to develop a more cohesive understanding of the topic.

While resilience in tourism remains underexplored, it is increasingly recognized as a multidisciplinary and dynamic process (Amaral & Da Rocha, 2023; Brown et al., 2017; Hall et al., 2023; W. Liu et al., 2024; Wided, 2022). Its determinants vary by context, disruption type and firm characteristics (Amaral & Da Rocha, 2023; Orchiston et al., 2016; Sobaih et al., 2021), requiring context-specific analyses. It follows that organizations respond through varied resilience strategies (A. V. Lee et al., 2013), based on the evolving sensemaking and adaptation stages experienced at different stages of a crisis (S. X. Chen et al., 2022). A later study by Amaral and Da Rocha (2023) further illustrates how small family firms in tourism employ a range of strategies, emotions and capabilities through the progression of the pandemic. Collectively, these studies emphasize resilience as a dynamic and context-dependent process, characterized by a complex interaction of resources, skills, and strategies that evolve through the different phases of disruption (Amaral & Da Rocha, 2023; Biggs et al., 2012, 2015; S. X. Chen et al., 2022; Hoang et al., 2021; Jawed et al., 2021; S. Lee et al., 2024; Usher et al., 2019).

In this sense, resilience can be divided into the resistance and recovery stages. Regional resilience studies often consider a system more resilient if it displays stronger resistance to shocks or recovers faster from them (Martin, 2012). In the tourism literature, Hall et al. (2023) identify resistance and recovery as core components of the existing resilience frameworks. Resistance is associated with the concept of persistence, in resilience theory (Folke et al., 2010), and robustness in complex adaptive systems theory (Martin & Sunley, 2015). Also described as the absorption stage (Wieczorek-Kosmala, 2022), it reflects a system's vulnerability to disturbance (Martin, 2012; Walker et al., 2004) and capacity to respond to it while maintaining stability (H. Liu et al., 2021; Martin & Sunley, 2015; Soroka et al., 2020). Conversely, recovery aligns with the adaptability and transformability dimensions (Walker et al., 2004), focusing on the speed and efficiency of return to pre-shock performance levels (Folke, 2006; Holling, 1973) or establishment of new stability domains (Brown et al., 2017).

Despite growing interest in CR, resilience studies tend to prioritize regional research over firm-level dynamics, often treating resilience as a static attribute rather than dynamic and context-dependent. This thesis addresses these gaps, by exploring the dynamic determinants, mechanisms and implications of CR in tourism firms.

1.3. Research aims and objectives

The main objectives of this research are threefold. First, attention is turned to the determinants of CR in tourism firms, focusing on the critical role of firm-specific factors. Second, the dynamic mechanisms of resilience are investigated, specifically addressing the resistance and recovery phases and highlighting how firm-level characteristics influence resilience differently across these stages. Finally, this thesis further investigates the drivers of resilience in profit-making and loss-making firms, uncovering the distinct mechanisms that these different types of firms have in their favor. These objectives are pursued across three distinct but interrelated studies, each contributing unique theoretical and practical insights into the resilience of tourism firms.

The first paper aims to develop a unified and cohesive theoretical framework to address company resilience in a business setting. By applying this framework to the tourism industry, the study aims to identify the determinants of company resilience evidenced in the literature, with the purpose of answering the research question of which firm-level characteristics are likely to impact the resilience of companies operating in this industry.

The second paper delves into the need for robust, practical metrics to measure resilience in the tourism industry, which limits the ability of managers to benchmark and improve resilience strategies effectively across firms. To address this gap, this paper adapts a sensitivity index from the regional resilience literature and applies it, using a similar metric of economic value creation that can be applied in a firm-level context. The application of this metric allows for the identification of factors that influenced the resilience of accommodation firms to COVID-19, further addressing the context-dependent nature of resilience by considering factors such as the location of headquarters and Eurozone membership.

The third and final paper of this thesis explores the dynamic nature of resilience, as well as the idiosyncrasies between profit-making firms and loss-making firms. To address this gap in the literature, this paper decomposes resilience into two main stages – resistance and recovery – each represented by its own index. The application of these indexes aims to identify the distinct roles of firm-level characteristics across the two stages of disruption, adopting a dynamic, rather than static perspective of resilience.

1.4. Relevance of the study

This research makes important theoretical and practical contributions to the literature on company resilience in the tourism industry, which we now briefly summarize.

The first study is a systematic literature review, advancing the theoretical understanding of company resilience by analyzing and synthesizing existing research about the resilience of firms in the tourism industry. While resilience has been studied broadly in organizational contexts (e.g. Bhamra et al., 2011; Iftikhar et al., 2021; Linnenluecke, 2017), tourism remains an underexplored domain despite its high vulnerabilities. More than synthesizing existing research, this study organizes it in a cohesive and unified framework, identifying the antecedents, characteristics and consequences of the resilience building process. Furthermore, this study identifies several determinants of resilience while emphasizing its dynamic and interdisciplinary nature, integrating insights from economics, sociology, and environmental theories to address the fragmented and static perspectives prevalent in earlier studies. Practically, it emphasizes the importance of human and social capital, innovation, and planning for building resilience, offering insights for both managers and policymakers. Finally, by highlighting how resilience evolves across different stages of disruption, this study sets a foundation for future longitudinal research, an approach to capture the evolving and dynamic nature of resilience.

The second study employs empirical methods to assess the resilience of tourism firms during COVID-19. This study bridges the gap in the literature regarding practical metrics for assessing resilience in tourism firms. By adapting a sensitivity index from the regional resilience literature, it provides a novel measure of firm-level resilience. Through the application of binary logistic regression models, this study identifies key factors influencing resilience during the COVID-19 pandemic, with significant variations across countries, uncovering potential challenges linked to a unified monetary policy. The study also uncovers some unexpected findings, such as the negative role played by profitability. This second study advances theoretical evidence in support of the resource-based view (Wernerfelt, 1984) and dynamic capabilities perspective (Ambrosini & Bowman, 2009) in crisis settings. Importantly, the results further highlight the context-dependent nature of resilience. From a practical standpoint, the study provides tourism managers with a valuable tool for self-assessment, enabling them to benchmark their resilience against industry peers and adopt best practices. It also offers insights into the role of governmental and monetary policies, something that can be applied by policymakers in future policy design.

Finally, the third study delves deeper into the role of profitability in CR, addressing the dynamic and longitudinal nature of resilience, emphasizing its heterogeneity across stages and types of firms. By decomposing resilience into resistance and recovery phases, this study demonstrates that most firm-level characteristics play distinct roles across the two stages, while also illustrating the distinct challenges faced by profit-makers and loss-makers. These findings further emphasize the idiosyncratic nature of resilience, highlighting the need for tailored resilience strategies that reflect firm-specific and contextual factors.

Collectively, these studies provide a comprehensive roadmap for resilience in the tourism sector, with significant theoretical and practical contributions. By identifying drivers of resilience, proposing a company resilience metric and exploring the dynamic mechanisms of resilience, this research paves the way for a more resilient tourism industry, capable of weathering future disruptions and fostering long-term sustainability.

1.5. Study design

Given the inherent complexity of the topic, this thesis employs quantitative methods to enhance the understanding of the research questions. Additionally, a systematic literature review is conducted to provide a comprehensive overview of the broader research field in which this thesis is situated.

The first paper collects, analyzes, and synthesizes existing research on company resilience in the tourism industry using a systematic literature approach. It begins with an exploratory literature review to map and identify relevant keywords and search strings, which are subsequently discussed and validated by a panel of experts in the field. After this stage, the approach outlined by Denyer and Tranfield (2009) is followed, while also considering the recommendations of Rojon et al. (2021). Following the application of the systematic literature protocol, thematic analysis is employed to uncover the main themes and subthemes within the literature. An inductive approach is applied, allowing key themes to emerge naturally from the data. The literature is subsequently categorized and clustered based on these themes, to integrate them into the framework and highlight the most prominent ones, emphasizing their relative importance in the existing literature. This approach can be read in detail in the second chapter of this thesis.

The second and third papers follow quantitative approaches. In these studies, we adapt a decomposed resilience index from the regional resilience literature, following the approach applied by Iacobucci and Perugini (2021) to assess the resilience of tourism destinations. To do so, we begin with the identification of all companies classified under the primary SIC code 7011, corresponding to accommodation services, from the Orbis database, supplied by Bureau Van Dijk. Their financial data is gathered for the period between 2019 and 2022, which is the period required to compute the resilience index. To compute such an index, the computation of the Gross Value Added (GVA) is required for each firm in the sample, which limits the sample in study to the countries where the majority of firms report the data that is required, namely those in Belgium, Bulgaria, Croatia, Poland, Portugal, Romania, Serbia, Slovenia, Spain, and Sweden. After the resilience index is computed, logistic regression models are employed to investigate the likelihood of resilience, resistance and recovery, respectively. This methodology is detailed in Chapters Three and Four. In both of these studies, data processing and analysis was conducted using Statistical Analysis System (SAS) Enterprise Guide, version 7.1.

By integrating these distinct research methods, this thesis follows a pragmatic approach, combining the strengths of each one to provide a holistic view of company resilience.

1.6. Outline of the thesis

This thesis is structured around three distinct yet complementary studies, each presented in a dedicated chapter. In this first chapter, we provide an in-depth overview of the research background, identify key research gaps, outline the research questions and objectives, emphasize the relevance of the research and describe its structure. The second, third and fourth chapters present the three studies and a discussion of the main results of each study, aligned with the research objectives. The fifth chapter concludes, by summarizing the main findings and contributions. This last chapter further discusses the theoretical and practical implications of this research, while addressing its limitations and providing future research recommendations.

Figure 1.1 presents the structure of this thesis. Together, these chapters follow a structured framework, from the presentation of the conceptual background to the discussion of the main findings, in a comprehensive summary of contributions, implications, limitations, and opportunities for future research.

Figure 1.1 – Thesis structure

CHAPTER 1 GENERAL INTRODUCTION	Presentation of the research background, main research gaps, research aims and objectives, relevance and structure.
CHAPTER 2 BUILDING COMPANY RESILIENCE: DETERMINANTS IN THE TOURISM INDUSTRY (PAPER 1)	Development of a unified and comprehensive conceptual framework for CR research. Identification of CR determinants to be observed in future longitudinal studies.
CHAPTER 3 BUILDING RESILIENCE IN TOURISM FIRMS: EVIDENCE FROM COVID-19 (PAPER 2)	Empirical investigation of the factors determining company resilience to COVID-19 within the accommodation sector, as well as the impact of location and Eurozone membership in the resilience of these firms.
CHAPTER 4 HOW PROFITABLE FIRMS FAIL: FIRM-LEVEL DETERMINANTS OF RESISTANCE AND RECOVERY (PAPER 3)	Empirical investigation of the role of profitability in the resilience of accommodation firms to COVID-19, with a distinction between profit-making and loss-making firms. Examination of CR determinants across the resistance and recovery phases, to investigate the dynamic nature of resilience and its effect on resilience determinants.
CHAPTER 5 GENERAL CONCLUSION	Synthesis of results, contributions, implications, limitations, and opportunities for future research.

Source: Own elaboration

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CHAPTER 2 – BUILDING COMPANY RESILIENCE: DETERMINANTS IN THE TOURISM INDUSTRY (PAPER ONE)[1]

Abstract

What characteristics enable a company in the tourism industry to withstand and recover from disruptive events such as a global pandemic or a war? How can these firms enhance their resilience? This paper presents a systematic literature review of peer-reviewed publications on company resilience within the tourism industry to address these critical questions. Despite the current significance of these topics, existing research is fragmented and unconsolidated. Our findings reveal a range of perspectives and factors that influence company resilience, with clear evidence that human capital plays a pivotal role in the tourism industry's ability to remain resilient. We also identify theoretical and practical implications, along with directions for future research.

Keywords: Company resilience; Determinants of resilience; Tourism industry; Human capital; Systematic literature review.

2.1. *Introduction*

Which firm-level characteristics facilitate the resilience of companies operating in the tourism industry? This is a particularly interesting question in the wake of a very disruptive event such as a global COVID-19 pandemic. Crises carry economic and social costs, so understanding how to improve company resilience (CR) is crucial to reduce such costs and prepare firms for future disruptions (Bertschek et al., 2019). Looking at this theme is relevant for three main reasons. First, this is a very relevant industry, responsible for 10.3% of the global GDP and 333 million jobs in 2019 (World Travel & Tourism Council, 2022). Second, the tourism sector is especially vulnerable to major disruptive events, such as war or a global pandemic. The COVID-19 pandemic is a clear example of this vulnerability. According to UNWTO (2021), international flows decreased by 73.9% in 2020 relative to 2019, resulting in a 50.4% decline in the tourism industry's

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share in global GDP and an estimated loss of 62 million jobs (World Travel & Tourism Council, 2022). Despite the ongoing recovery, international tourism remained below pre-pandemic levels in 2023 and has thus had a slower-than-anticipated rebound (UNWTO, 2024). The tourism industry was also severely harmed during previous outbreaks of SARS, while other sectors were less affected (M.-H. Chen et al., 2007; Zeng et al., 2005). Third, evidence suggests that tourism firms experience and manage losses differently during the same disruptive events. Kaczmarek et al. (2021) found that tourism firms in less individualistic countries and in those that implemented strict pandemic measures actually outperformed others. Conversely, Wieczorek-Kosmala (2022) notes that many firms lack the necessary resilience to withstand disruptive events, thus reinforcing the perception among tourism companies that they are less resilient than their counterparts in other industries (Ntounis et al., 2022).

This review makes significant contributions to both theory and practice. To explore the determinants of CR in the tourism industry, what is currently known about this subject must first be analysed. Existing studies have investigated the literature about resilience in a broad organizational context (e.g. Bhamra et al., 2011; Iftikhar et al., 2021; Linnenluecke, 2017), and there is also research looking at this theme through specific groups of companies, like family firms in diverse sectors (Yilmaz et al., 2024) and business networks in the food industry (Bondeli & Havenvid, 2022). However, evidence about the tourism industry remains quite scarce. In fact, the study by Hall et al. (2023) is among the few to look at this issue and concluded that there is a need for longitudinal research to better understand the topic, while also acknowledging that the existing research is fragmented and lacks a cohesive framework. Our study addresses this gap in the literature, as it sheds light on the determinants of CR and provides a clear understanding of the resources and skills that tourism firms must develop to build resilience.

As such, this is the first systematic literature review on this topic to highlight the state of the art and identify potential determinants of resilience that can be observed in future longitudinal studies. By reviewing existing studies, we identify which determinants are supported by the evidence to provide the basis for future investigation. Our review underscores the dynamic nature of resilience, rather than the static perspective that is present in the earlier studies. In fact, resilience presents itself in many forms through different stages of disruption, which suggests that it is context dependent and requires tailored strategies for different scenarios. Our findings highlight the need to address resilience from an interdisciplinary standpoint, drawing from economics, sociology and environmental theories. Finally, this paper emphasizes that the dynamic nature of CR requires future research to develop theoretical models that account for the longitudinal aspect of CR and the varying strategies employed by firms at different stages.

The results of our review also have important implications for practitioners and policymakers. In particular, our results show that resilience in the tourism industry is contingent on developing human and social capital, embracing innovation and investing in planning. At the same time, this research highlights the effectiveness of government support practices and suggests measures to better support firms in their efforts.

The remainder of this paper is structured as follows: the literature review is presented in Sections 2 and 3. Section 4 addresses the methodological aspects. Section 5 reports the findings, followed by a brief discussion in Section 6. Section 7 presents the conclusions.

2.2. Theoretical background

2.2.1. General concepts and a new framework for understanding CR

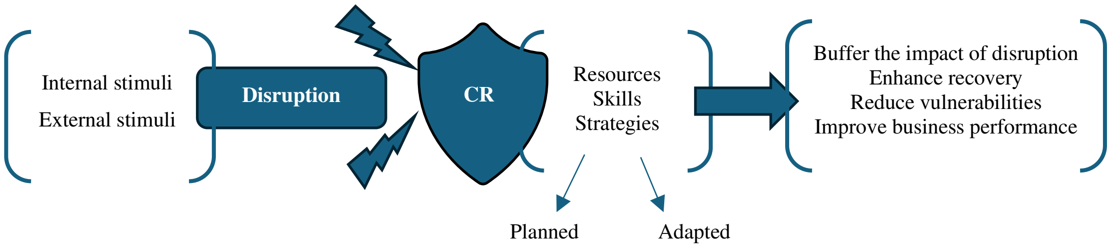
The term resilience originates from the Latin word *resiliens*, which describes the act of "jumping back, falling back or bouncing" (Iborra et al., 2020, p. 3). Resilience as a concept emerged from Holling's (1973) seminal work on ecological systems, which describes resilience as a measure of the capacity of these systems to absorb changes in the environment and persist. Many authors have adapted this definition to economics (see, e.g. Balugani et al., 2020; Bhamra et al., 2011; Biggs et al., 2012; Burnard & Bhamra, 2011; Clément & Rivera, 2017; Cochrane, 2010; Espiner & Becken, 2014; Fraccascia et al., 2017; Lin & Wen, 2021; Tsiapa & Batsiolas, 2019), and resilience has since been defined in different terms across several research streams (Linnenluecke, 2017).

However, resilience is not restricted to the ability to absorb the impact of disturbance and survive (Folke, 2006; Weick et al., 1999). Rather, it can be seen as a set of three complementary attributes: persistence, adaptability and transformability, where adaptability is the ability of the system to learn and respond to external and internal stimuli (Folke et al., 2010) and transformability is the ability to create a different stability domain when the existing one is no longer viable (Walker et al., 2004). The resource-based view of the firm and the dynamic capabilities literature emphasize the instrumental role of adaptability to the competitive advantage of firms (Ambrosini & Bowman, 2009; Wernerfelt, 1984). Given the unstable environment in which firms operate, they must evolve and adapt their resources to remain competitive (Ambrosini & Bowman, 2009). In fact, A. V. Lee et al. (2013) propose that resilience is a combination of planning and adaptive capacity and argue that adaptive resilience is a result of good leadership practices that promote an organizational culture of preparedness, thus enabling organizations to be dynamic in response to emergency.

The evolution of the concept of resilience was influenced by distinct disruptive events that motivated the study of how companies respond to and survive from such events (Linnenluecke, 2017), such as the Great Recession and, more recently, COVID-19. It is undeniable that COVID-19 has provided a significant boost to CR-related research (Hall et al., 2023), as we also show in our results. In this challenging context, for example, Marco-Lajara et al. (2022) show that corporate social responsibility (CSR) strategies implemented by rural hotels in response to COVID-19 had positive effects on their resilience levels which, in turn, increased their business performance after the pandemic. Amaral and Da Rocha (2023) followed, in real-time, the journey of a small family business during COVID-19. They report the emergence of different emotions, strategies, capabilities and dimensions of resilience in response to the evolution of the pandemic, thus providing evidence of the dynamic nature of the process of CR. S. X. Chen et al. (2022) found similar results in the adaptation of travel agencies to COVID-19. They highlighted the contrast that such a long-lasting and complex event provoked in adaptation efforts, demanding a unique balance from companies between prevention and continuity. More than a dynamic process, CR is highly idiosyncratic and requires different resources, skills and strategies from companies, even among very similar companies. A good example of this is the work of Pongtanalert and Assarut (2022), who detail the mechanisms that small accommodation firms used to survive the shock induced by COVID-19 by activating two types of social capital: bonding and bridging social capital. In this case, similar accommodation businesses achieved similar resilience outcomes by employing different strategies.

Based on these early studies, we develop a general framework of CR to guide us during the different steps of the systematic literature review. Figure 2.1 illustrates its main characteristics:

Figure 2.1 – Proposed conceptual framework



As can be seen, CR protects firms from the external (and internal) stimuli that cause disruptions to their operations by acting upon the two mains phases of the shock. In the first phase, the presence of CR buffers the impact of disruptions while, in the recovery phase, it helps firm recover better and faster. Ultimately, CR may help improve business performance in the post-disruption period, something that has already been highlighted in previous research (e.g. Chowdhury et al., 2019; Marco-Lajara et al., 2022; Melián-Alzola et al., 2020; Prayag et al., 2018; Sobaih et al., 2021). This suggests that some firms can adapt and develop domains of stability that are even stronger than those they operated in before the disruptive event. Building on this, the main aim of this systematic literature review was to identify the determinants of CR – that is, the set of resources, capabilities and strategies that allow these firms to develop their resilience capabilities.

2.2.2. Resilience in the tourism industry

A few conceptual discussions have addressed the issue of resilience in the context of the tourism industry (e.g. Cochrane, 2010; Espiner et al., 2017; Lew, 2014; Strickland-Munro et al., 2010). There are also a few case studies dealing with the resilience of tourism destinations or regions (Cochrane, 2010; Terhorst & Erkuş-Öztürk, 2019), tourism communities (Lew, 2014; Orchiston, 2013; Strickland-Munro et al., 2010) and tourism sub-systems (Becken, 2013). A few papers have also explored this topic in the context of niches, such as reef tourism (Biggs, 2011; Biggs et al., 2012), travel and leisure (Brown et al., 2018; Duarte Alonso et al., 2020; Kaczmarek et al., 2021) or ethnic tourism (Lin & Wen, 2021). Research on this topic is, however, at an early stage and has mostly been exploratory, while a unified framework of CR is still lacking (Hall et al., 2023; W. Liu et al., 2024; Usher et al., 2019). To address this, we review the existing literature to provide a clear picture of the skills, resources and tools that firms can use to support their resilience. This enables us to synthesize current knowledge about the characteristics that distinguish resilient companies from non-resilient ones, thus laying the foundation for future research into the determinants of resilience in a particularly vulnerable industry.

2.3. Methodology

This paper follows the systematic literature review approach outlined by Denyer and Tranfield (2009), while also considering the recommendations of Rojon et al. (2021). The first step is to identify the research question, which is the following: "What are the determinants of company resilience in the tourism industry?". Three databases (i.e. Web of Science, Scopus and EBSCOhost) were used to identify the relevant studies, following the recommendations of Kraus et al. (2020). An exploratory literature review was also conducted to map the relevant keywords and search strings. Importantly, the thesaurus is used to ensure that all common synonyms are included in the keywords, and these were discussed and validated with four experts in the field. Ultimately, the following search strings are employed:

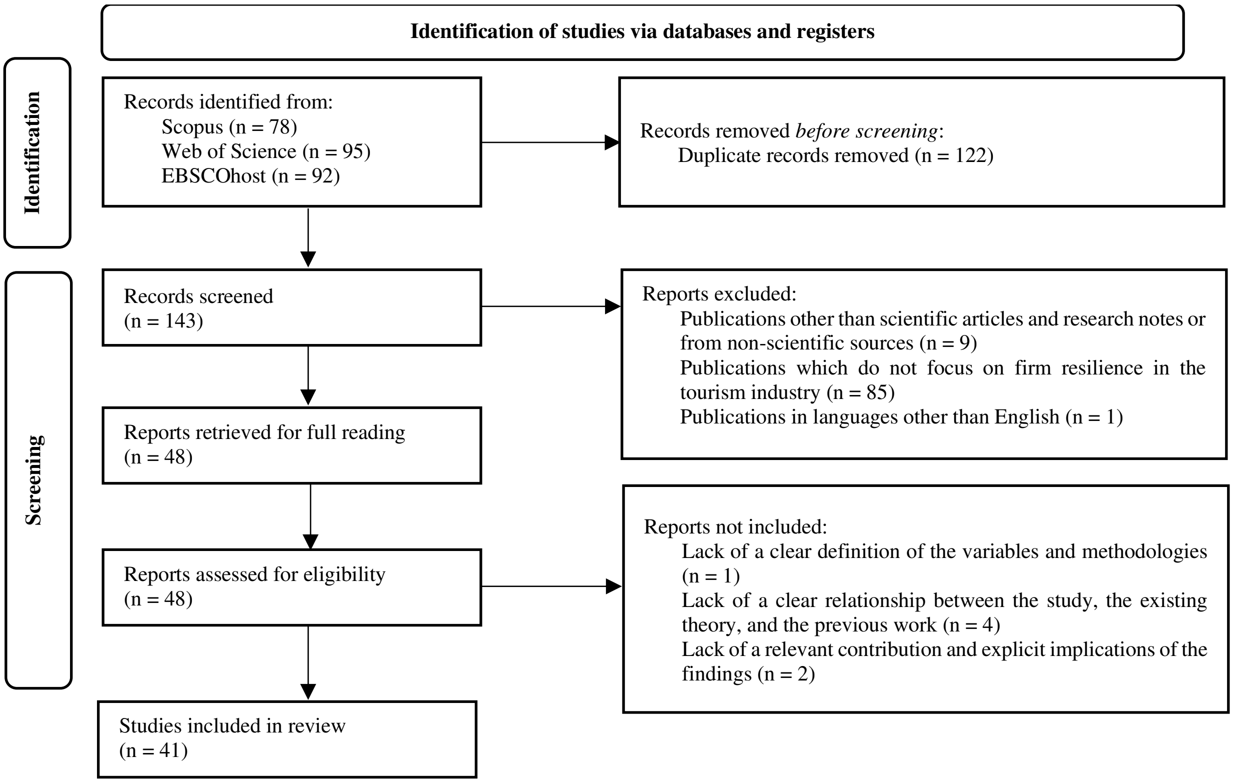
Table 2.1 – Search strings

(touris* OR travel OR hospitality OR hotel)	**AND**	"organizational resilien*"
		"business resilien*"
		"firm resilien*"
		"corporate resilien*"
		"enterprise resilien*"

Source: Own elaboration

Truncation is employed to ensure the inclusion of all possible terms derived from the word "tourism", as well as the terms derived from or used in alternative to "resilience". The search strings are applied to the title, abstract and keywords of the publications, which consist only of peer-reviewed journal articles. The screening was conducted on 23 November 2022, and no limitations are established regarding the time of publication, as well as journal ranking, scientific area or scope. Figure 2.2 summarizes the research procedure and criteria through an adapted PRISMA flowchart (Page et al., 2021).

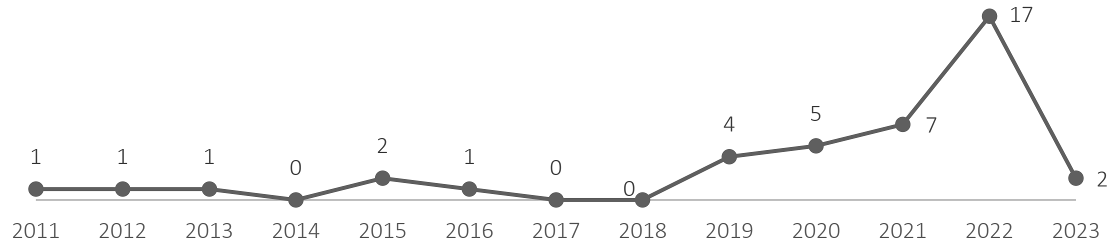
Figure 2.2 – The systematic literature review process



Source: Own elaboration, adapted from Page et al. (2021)

As can be seen, the search identifies 265 publications. Abstracts are analysed to determine inclusion in the study. Whenever abstracts are unclear or insufficient for a decision to be made, full texts are retrieved. After applying the exclusion criteria, 217 papers are removed from the sample. The remaining articles are then read in full, and the following inclusion criteria are employed: (a) the study must be explicit as to its objectives and assumptions; (b) a clear definition of the variables and methodologies must be provided; (c) there must be a clear relationship between the study, the existing theory and previous research; and (d) the study makes a relevant contribution to existing knowledge and provides explicit implications of its findings. We ultimately identify a final sample of 41 manuscripts, which were published between 2011 and 2023. Figure 2.3 reports the number of publications per year, showing that this topic has only recently captured a greater degree of academic interest.

Figure 2.3 – Publications per year



Source: Own elaboration

In fact, while the subject started being explored in 2011, the progression of relevant publications was relatively slow until 2020, when it became the first order of business. Resilience in tourism is thus not only a recent and timely research field, but it also appears to be expanding, with COVID-19 as a trigger (Hall et al., 2023).

After the final sample is determined, thematic analysis is used to identify the main themes and subthemes in the literature. Data analysis was inductive, with the main themes emerging from the literature regarding the types of characteristics that are determinants of CR. The literature was then categorized and clustered according to these main themes to identify the most prevalent ones, indicating their importance over others. The main findings are reported in the next section.

2.4. Findings

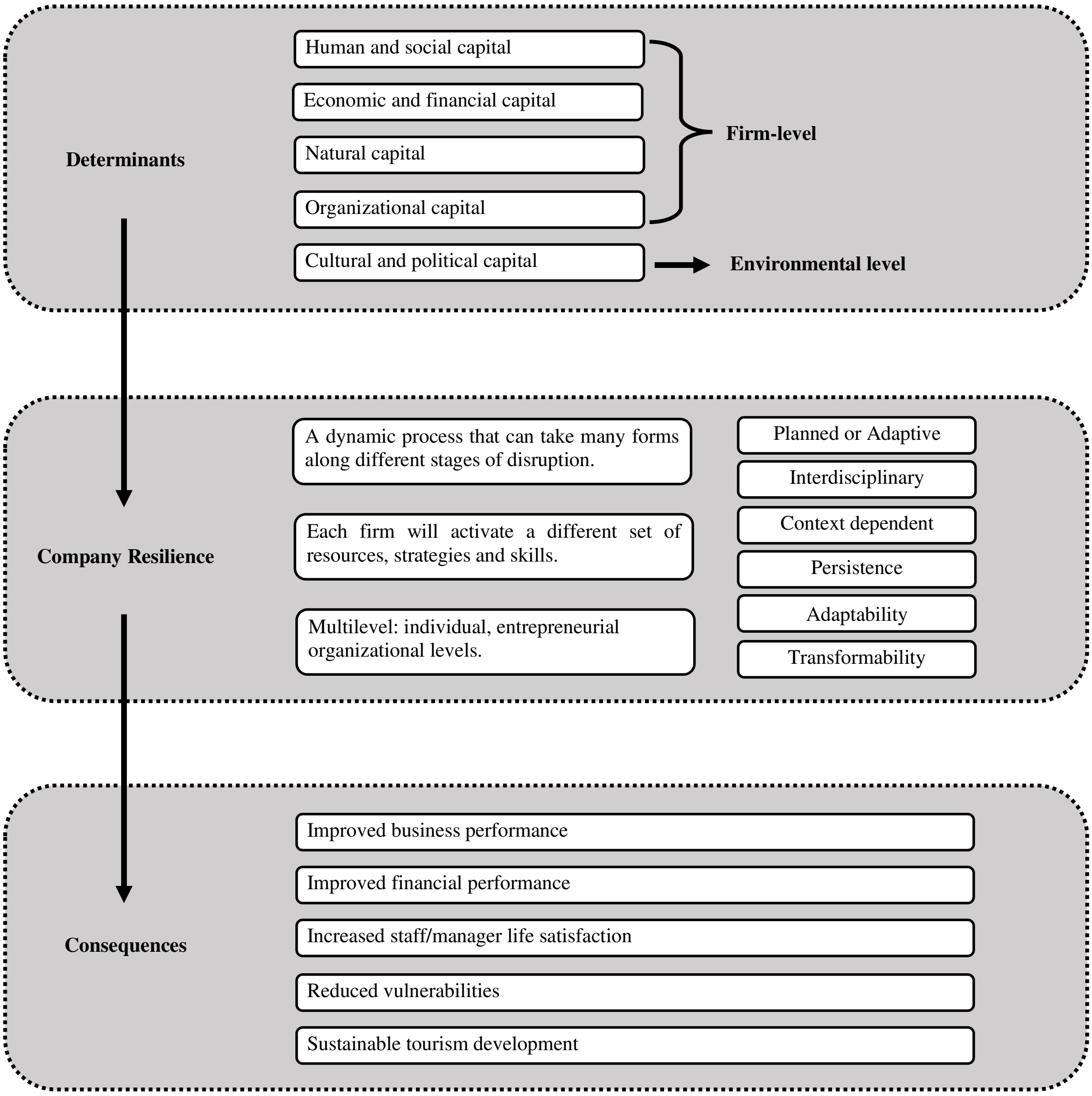
2.4.1. Resilience in the tourism industry

Figure 2.4 highlights the results of the thematic analysis, providing an overview of the resilience-building process, its determinants and positive outcomes. The results provide additional detail to our conceptual framework (see Figure 2.1), which outlines how CR acts as a protective mechanism against both internal and external disruptions, mitigating their impact during the initial shock phase and enhancing recovery in the aftermath. The comprehensive look at the characteristics of CR in the thematic analysis illustrates that CR is a dynamic and context-dependent process, involving a complex interplay of resources, skills and strategies that evolve throughout different stages of disruption. Our analysis further delves into these specific resources and strategies, ultimately identifying two levels of CR determinants — that is, firm-level and environmental determinants. We also identify the different types of capital that contribute to CR and lead to positive consequences that are a byproduct of this resilience-building process.

As illustrated in Figure 2.4, the evidence collected supports the idea that resilience is a dynamic process (Amaral & Da Rocha, 2023; Brown et al., 2017; Duarte Alonso et al., 2020; W. Liu et al., 2024; Wided, 2022). Factors that foster it are thus not homogeneous across industries, tourism sub-sectors and situations (Orchiston et al., 2016; Sobaih et al., 2021). It is also apparent that these determinants vary depending on the setting, business context and type of disruption (Amaral & Da Rocha, 2023; Biggs et al., 2012, 2015; Dahles & Susilowati, 2015; Usher et al., 2019), as they are complex and multifaceted (Biggs, 2011). Resilience strategies also evolve through the stages of a crisis (S. X. Chen et al., 2022; Dahles & Susilowati, 2015; Hoang et al., 2021; Jawed et al., 2021).

Previous literature has noted the scarcity of studies that measure resilience and develop assessment indicators that practitioners can use to improve CR (Liu et al., 2021; Yao & Fabbe-Costes, 2018). This is particularly true for the literature on tourism companies, which remains underdeveloped (Biggs et al., 2012; Chowdhury et al., 2019; Dahles & Susilowati, 2015; Orchiston et al., 2016; Prayag et al., 2020), particularly concerning given their vulnerability to disruptions (Espiner & Becken, 2014; Prayag et al., 2020). Companies in the tourism industry are often characterized by their small size and elementary hierarchies (Y. Jiang et al., 2019; Tanner et al., 2022), which can lead to lack of resources and expertise (Ates & Bititci, 2011; Burnard & Bhamra, 2011). However, this can also play in their favour, as they display higher flexibility and adaptability when abruptly faced with the need to change (Biggs, 2011; Orchiston, 2013; Tanner et al., 2022). Importantly, evidence suggests that tourism businesses can reduce these vulnerabilities by increasing their resilience (Doğantan & Akoğlan Kozak, 2019). Both planned and adaptive resilience are positively linked with the sustainability of the tourism industry (Sobaih et al., 2021). Notably, resilience is also found to have a positive impact on self-reported business performance (Chowdhury et al., 2019; Marco-Lajara et al., 2022; Melián-Alzola et al., 2020; Sobaih et al., 2021) and financial performance (Prayag et al., 2018), which is why firms in the tourism industry should improve their resilience.

Figure 2.4 – Results: Determinants and consequences of CR



Source: Own elaboration

While not all studies in the sample explored the determinants of CR, the results revealed important aspects that can help improve the understanding of how firms develop their ability to cope with disruption.

2.4.1.1. Human and social capital

Human capital is a key determinant of CR in the tourism industry (Biggs, 2011), and its relevance is common across several groups of enterprises (Biggs et al., 2015). Even considering that the determinants of resilience differ between formal and informal enterprises, both types of firms agree that commitment and hard work are key to weathering disruptive events (Biggs et al., 2012). The same is true for family-owned rural hotels (Engeset, 2020). However, reducing human capital was precisely one of the cost-cutting strategies adopted by travel agencies in their adaptation to COVID-19 (S. X. Chen et al., 2022) and several models disregard the role of human capital in fostering resilience and fail to consider its capacity to amplify the impact of other variables on organizational resilience (Núñez-Ríos et al., 2022).

2.4.1.2. Human resources

Hospitality firms must address human resource management as a priority when dealing with an uncertain environment; in providing their workforce with employment security, autonomy and training, they can improve employee satisfaction and motivation (Colmekcioglu et al., 2022), and these practices play an important part in the development of organizational resilience (Njunguna et al., 2021). These results are in line with the actions commonly employed by tourism companies in Vietnam in response to COVID-19 (Huynh et al., 2022). Investing in an organizational culture that nurtures individual well-being and resilience is a step towards organizational resilience in the tourism industry (Prayag et al., 2020), because CR is heavily dependent on the indispensable role of employees (Schwaiger et al., 2022).

2.4.1.3. Stakeholder relationships

Collaboration between distinct tourism subsectors can contribute to a more resilient tourism industry (Huynh et al., 2022; Melián-Alzola et al., 2020). In fact, collaboration, communication with stakeholders and past experience in dealing with disasters emerge as important enhancers of perceived resilience (Amaral & Da Rocha, 2023; S. X. Chen et al., 2022; Ghaderi et al., 2022; Orchiston et al., 2016; Usher et al., 2019), which is consistent with the findings of Becken (2013) on climate change resilience and Brown et al. (2017) on disaster resilience. However, while the benefits of maintaining long-lasting partnerships in the tourism industry are positively related to the resilience of these firms, there are also costs in maintaining such partnerships, something that negatively affects resilience (C. Williams et al., 2020).

2.4.1.4. Background experience

There is evidence that enterprise age is positively correlated with the intention to remain in the industry after a disruptive event (Biggs, 2011) and that the age of the company's owner increases the probability of that company being perceived as resilient (Neise et al., 2021; Verfürth et al., 2022). Past experience from previous SARS outbreaks guided the actions of travel agencies in the first phase of their response to COVID-19 (S. X. Chen et al., 2022). Yet, firm age and size were also found to be negatively associated with recovery speed, which means that older and bigger firms face a slower recovery process after disruption (Nguyen et al., 2022). A possible interpretation of this finding is that, while firms that have been in business for longer have the advantage of past experience in dealing with challenges, they also have deeply rooted habits and procedures that result in more rigid, less adaptable structures. In other words, experienced firms may have the resources, but they often lack the flexibility required to overcome disruptions successfully.

2.4.1.5. Social capital

A firm's social capital, staff adaptability and entrepreneurial mindset play an important role in building the resilience of small tourism businesses (Pongtanalert & Assarut, 2022; Tanner et al., 2022). Social capital can even help small firms overcome their lack of resources by fostering innovation and adaptability (Pongtanalert & Assarut, 2022). One of the predictors of social capital, measured through online ratings as an expression of consumer trust, is associated with higher resilience of restaurants during COVID-19 (Liu et al., 2022). Chowdhury et al. (2019) also found that relational capital can be used as a predictor for the adaptive resilience of tourism organizations, which is in line with previous results of Biggs et al. (2012) in the Thai reef tourism industry; this reinforces the need for companies to invest in their social capital. To build relational capital, firms must develop a network of key stakeholders and nurture these interfirm relationships through communication, mutual trust and respect (Chowdhury et al., 2019). Employee trust is crucial for firms' adaptation during crises, but it cannot be expected to emerge in the short-term – rather, it must be built in the long-term (Pongtanalert & Assarut, 2022).

2.4.1.6. Social impact

Tourism companies' social efforts can act as enablers of their stock price resilience to COVID-19 (Torres & Augusto, 2021). In fact, the evidence suggests that rural hotels' CSR strategies positively influence their resilience levels (Marco-Lajara et al., 2022), which is strengthened in the presence of a sustainability certificate. This is in line with the findings of Melián-Alzola et al. (2020), who suggested that hotels must develop a CSR plan that allows them not only to improve their own resilience, but also the resilience of the surrounding tourism ecosystem.

2.4.1.7. Innovation and technology

Orchiston et al. (2016) identify one of the dimensions of resilience as "collaboration and innovation", which defines the capacity of firms to work in a creative and collective manner to overcome the challenges of an ever-changing tourism environment. Innovation, through the diversification of both daily business operations and long-term strategy, has been addressed as a key determinant of the resilience of tourism firms (Dahles & Susilowati, 2015). Companies in the tourism industry must collaborate and develop new products that foster the interaction between tourism subsectors and thus their collective resilience (Melián-Alzola et al., 2020). Indeed, business owners perceive cooperation within the industry as a way to foster innovative ideas and leverage their expertise (Schwaiger et al., 2022); they see advantages in being affiliated with organizations both during and following disruptive events, given the benefits of that affiliation (Usher et al., 2019).

Tourism managers consider technology a necessary shift in the way of conducting business (S. X. Chen et al., 2022). COVID-19 triggered the acceleration of the digital transformation in the tourism industry (Huynh et al., 2022; Tanner et al., 2022). However, the claim for innovation extends beyond just technology. Embracing marketing innovation and online platforms is recommended for the recovery of hospitality firms (Colmekcioglu et al., 2022). These firms must also engage in learning processes that prepare them to face unexpected events (Ghaderi et al., 2022) and allow them to apply the knowledge gathered from past experience to prepare for future incidents (Y. Jiang et al., 2019). Learning processes are an important part of innovation, firms must strengthen their learning capabilities before delving into that realm (Núñez-Ríos et al., 2022).

2.4.1.8. Adaptability, flexibility, and diversification

Flexibility, adaptability and diversification play a pivotal role in the resilience of small tourism firms in developing countries (Dahles & Susilowati, 2015) and were also found to be important for family firms operating in ethnic tourism in Yunnan, China (Lin & Wen, 2021). Flexibility and diversification were crucial to firm survival during the COVID-19 lockdown, which compelled tourism firms to seek alternative ways of conducting business, including outside their main area of activity (Tanner et al., 2022). Adaptability is important for small hospitality firms, who had to adapt in order to survive the pandemic and diversify their sources of income (Duarte Alonso et al., 2020). Flexibility, expressed through firms' slack resources, is key to this process of adaptation, because environmental turbulence requires firms to respond rapidly to new circumstances and develop new strategies to survive (Y. Jiang et al., 2019). The inherent seasonality of the tourism business is also an obstacle that jeopardizes firm resilience in the industry (Ntounis et al., 2022), thus reinforcing the need for companies to develop a certain flexibility, not only to endure external and disruptive events, but also to better face the uncertainty of their business environment.

2.4.1.9. Planning

Planning plays an important role in the resilience of tourism firms when faced with a natural disaster, such as an earthquake (Orchiston, 2013). Companies must remain vigilant about their business environment to collect information that allows them to prepare for possible changes and adjust their strategies accordingly (Núñez-Ríos et al., 2022). Planning capabilities must become part of a company's culture, and this involves anticipating, preparing for and facing unexpected events (Orchiston et al., 2016). Despite evidence that planned resilience allows firms to recover faster from disruption (Nguyen et al., 2022), tourism businesses have demonstrated low levels of disaster preparedness and planning, which is particularly worrying for small enterprises (Orchiston, 2013). Findings that relate planned resilience to faster recovery are consistent with previous evidence that planning and professional advice help tourism firms recover more rapidly from a disruptive event like a contagious disease (Irvine & Anderson, 2004). Regardless of the importance of planning, there is evidence of a certain reluctance among managers to allocate the necessary financial resources to this type of activity (Ghaderi et al., 2022). Many companies operating in the tourism industry still have not developed and implemented a risk management strategy (Nguyen et al., 2022) or a formal emergency plan (Tanner et al., 2022; Usher et al., 2019), and are thus not prepared to face disruptions (Usher et al., 2019).

2.4.1.10. Economic capital

Liquidity and a flexible cost structure are crucial determinants of resilience of formal enterprises during disruptive events (Biggs et al., 2012). Unfortunately, there is evidence that some enterprises were already experiencing poor economic and financial conditions even before the COVID-19 pandemic hit them (Neise et al., 2021; Ntounis et al., 2022). Enduring the lockdown with a costly operating and fiscal structure was challenging for businesses that struggled with liquidity issues (Neise et al., 2021), and companies with previous poor financial performance are less likely to be perceived as resilient by their managers (Verfürth et al., 2022). In fact, lower leverage, lower valuation and high asset growth are key determinants of the resilience of travel and leisure firms (Kaczmarek et al., 2021), and firms that rely on loans are less likely to be perceived as resilient by their managers (Verfürth et al., 2022). In the same vein, Wieczorek-Kosmala (2022) presented evidence that profitability, liquidity and lower financial leverage improve the quality of firms' cash-driven resilience capabilities. These results are consistent with those of Carter et al. (2022), who suggested that larger firms, with higher liquidity and a higher book-to-market ratio, were more resilient to the impact of the COVID-19 pandemic in stock prices, while higher leverage penalized firms. In light of the emphasis on adaptability and flexibility, these results reinforce the idea of slack resources as fundamental for the resilience of firms operating in the tourism industry.

2.4.1.11. Government support

Government support is often listed as a critical factor influencing tourism companies' resilience to crisis (Biggs et al., 2015; S. X. Chen et al., 2022; Huynh et al., 2022; Kaczmarek et al., 2021; Verfürth et al., 2022). This type of support can play a crucial role in keeping tourism firms afloat during extended periods of crisis (Huynh et al., 2022; Ntounis et al., 2022), although its effect on CR is not significant in some cases (Neise et al., 2021; Verfürth et al., 2022) and, in other cases, the necessary proceedings are perceived as long and discouraging (Schwaiger et al., 2022), lack clarity or fail to address the needs of small tourism firms (Tanner et al., 2022). Some small firms reported disappointment with how government support was carried out during COVID-19, perceiving it as a standard, one-size-fits-all measure that ignored the idiosyncrasies of small tourism firms (Sobaih et al., 2021). Unfortunately, in many cases, cooperation within local tourism ecosystems was limited and government engagement was insufficient (Schwaiger et al., 2022). However, even without government support, firms can still formulate resilience strategies to survive disruptions (Amaral & Da Rocha, 2023). It remains important, however, for governments to develop capabilities to anticipate and prepare for this type of events, supporting firms in their recovery process (Amaral & Da Rocha, 2023), as government support is thought to boost manager's crisis planning skills (Ghaderi et al., 2022). Government support can appear not only through direct assistance, but also, importantly, through legislation that allows companies to be flexible and adapt in response to disruption (Biggs et al., 2015), such as the layoff mechanisms adopted during the recent pandemic. Another type of government support relevant for small companies operating in the tourism industry includes specialized training programmes in matters such as planning and operational management (Sobaih et al., 2021), which is important given these companies' particular fragilities.

2.4.1.12. Family-owned firms

Examining family business resilience to COVID-19 in the tourism industry, Lin and Wen (2021) found that the resilience of these companies was fostered through entrepreneurship, diversification, reorganization of resources and digital literacy. Strategies adopted by these firms alternated between those that can be described as bouncing back or bouncing forward, but in some cases the lines between the two are blurry (Engeset, 2020). Human capital, ownership and leadership are also important attributes of resilient family firms (Lin & Wen, 2021), and developing social capital is crucial to family firm resilience (Amaral & Da Rocha, 2023). Engeset (2020) provides evidence of the role played by human and social capital in enabling firm resilience of family-owned rural hotels through entrepreneurial thinking, hard work, complementarity, support, respect and commitment. For this reason, family firm resilience can be jeopardized when these are at risk. Human capital is of particular relevance for small family firms that rely mainly on the capacities of their managers and family members to overcome disruption (Lin & Wen, 2021). These findings also provide valuable insights into the reasons why owner-managed firms are less prone to being perceived as resilient than their non-owner-managed counterparts (Neise et al., 2021; Verfürth et al., 2022). The company owner's psychological well-being and satisfaction with life is a critical factor in small companies' resilience and their recovery to disruptive events (Pathak & Joshi, 2021; Tanner et al., 2022), and the latter is a strong predictor of both employee and organizational resilience (Prayag et al., 2020). Liquidity is also key for preparing small family firms to overcome disruption (Schwaiger et al., 2022), and there is evidence that small firms capable of maintaining healthy financials have a higher propensity for achieving sustainable tourism (Sobaih et al., 2021). Despite the difficulties experienced by small family firms, there is evidence in the literature that these businesses are actually highly resilient (Schwaiger et al., 2022).

2.5. Discussion

The results of this literature review reveal a trend of research on the topic of CR in the tourism industry, particularly after COVID-19, which posed a threat to firm survival and led to increased interest in the unexplored theme of CR. Very few literature reviews have looked at the particular theme of CR (for a general review, see Linnenluecke, 2017; for a review on family firms, see Yilmaz et al., 2024; for a review on creative industries, see Khlystova et al., 2022), and only Hall et al. (2023) considered the tourism industry, but with the aim of developing a research agenda for future investigation. As such, to the best of our knowledge, a thorough understanding of the determinants and antecedents of CR in the tourism industry is still lacking. This review responds to this need by consolidating the results of the existing literature on this topic and highlighting the determinants of CR in the tourism industry that can be used as a basis for following studies. Table 2.2 offers an overview of the key themes and subthemes identified from the literature analysis.

Table 2.2 – Determinants of CR

Theme		Sub-theme		Citation count
Firm-level	Human and social capital	Staff/Management commitment and hard work	3	61
		Staff/Management psychological capital, resilience, skills, and knowledge base	7	
		Staff/Management satisfaction and motivation	3	
		HR management practices	2	
		CSR practices	2	
		Past experience from previous events	3	
		Communication with stakeholders	2	
		Family/Community/Stakeholder support, network, and embeddedness	8	
		Ownership and family/cultural/heritage values	3	
		Lifestyle identity, satisfaction, and benefits	3	
		Relational capital	4	
		Entrepreneurial mindset, innovative capacity, and creativity	11	
		Adaptability, agility, and flexibility	9	
		Reputation/Online ratings	1	
	Economic and financial capital	Lower enterprise valuations	1	22
		Lower leverage	4	
		Lower operational costs and asset ownership	3	
		Solid prior financial situation/performance	4	
		Alternative sources of income	2	
		Access to financing	2	
		Financial slack/Liquidity	3	
		Chain operations/franchising	3	
	Natural capital	Location	4	4
	Organizational capital (organizational culture)	Capacity to diversify	7	41
		Intensive investment policies	1	
		Strategic planning	9	
		Risk management practices	2	
		Leadership	3	
		Dynamic capability processes and routines	5	
		Access to information	1	
		Positive/supportive organizational culture and investment in employee well-being	3	
		Business ownership	2	
		Business structure	1	
		Business age	2	
		Business size	5	
Environmental (Cultural and political capital)		Tourism demand and seasonality of demand	2	23
		Collaboration between subsectors	8	
		Government support	5	
		Strength of government policies and quick policy response capacity	1	
		Collectivistic national culture	1	
		Recurrence of disruptions	2	
		Tax loads	1	
		Regulatory environment and bureaucracy	3	

Source: Own elaboration.

As can be seen in Table 2.2, two primary themes emerge: firm-level determinants and environmental determinants. The literature in the sample predominantly focused on the firm level, which constitutes 84.8% of the citations. Within this domain, the significance of human capital stands out, accounting for 40.4% of the total citations. The same pattern has already been well-documented in the field of regional resilience, a more advanced area of study, where human capital has been identified as the most crucial factor for enhancing resilience (Crescenzi et al., 2016). The distinctive characteristics of the tourism industry further underscore the importance of human capital in this sector compared to others (Srhoj et al., 2024). For instance, the high level of specialization within tourism markets relies heavily on human capital to deliver unique and differentiated experiences (Biggs, 2011). Our findings also reveal that this impact is both direct and indirect, as human capital enhances the effectiveness of other variables influencing CR (Núñez-Ríos et al., 2022). It follows that individuals are clearly at the heart of CR in the tourism industry, because their skills, adaptability and agility are essential for developing resilience at the organization level, but also, through this indirect contribution, individuals shape the development of other critical CR factors. Furthermore, previous experience with disruptive events, as a component of human capital, has also been found to enhance CR (Ghaderi et al., 2022; Melián-Alzola et al., 2020; Neise et al., 2021). Interestingly, Tanner et al. (2022) noted that the experience gathered from dealing with previous disasters did not enhance the resilience of SMEs during COVID-19. These conflicting results may be due to the changing and unpredictable nature of disruptions: no two disasters are the same, with the pandemic being a clear example of a very novel and specific disruption. At the same time, there could be a non-linear relationship between experience and CR, depending on the similarity between the disruptive events. For example, in regions with high seismic or flooding risk, it is likely that the experience of dealing with such events plays an important role in CR, while other regions may experience lower or non-significant impacts. This is in line with the conclusions of Ghaderi et al. (2022) that the recurrence of the disaster influences managerial propensity for planning and preparedness.

This relationship between previous experience and CR is particularly relevant, because it links directly with the importance of planning and preparedness we find in the literature, thus suggesting that these processes have different impacts on CR depending on the nature of the disruption and regional context. Understanding these mechanisms is pivotal, because SMEs often face resource constraints and, to make effective use of existing resources, managers tend to avoid the allocation of resources to planning processes if they perceive that they do not contribute to CR. What, then, do SMEs do when planning is not an option, because they lack the skills or resources to do so? We recognize the unique challenges faced by small tourism firms, particularly regarding resource limitations. Small firms, which account for a great part of the tourism industry (Y. Jiang et al., 2019; Tanner et al., 2022), face many challenges due to their idiosyncrasies (Ates & Bititci, 2011; Burnard & Bhamra, 2011). In this case, our results evidence the critical role of flexibility, adaptability and the capacity to diversify. This requires adaptability at the individual level, but also at the organization level, with flexible hierarchies and cost structures.

Furthermore, the literature also reports mixed results regarding firm size. In fact, several arguments would support a positive link between firm size and resilience. Size is an important determinant of performance (D. A. Williams, 2014) and business risk (M.-H. Chen, 2013). Larger firms have more resources (Jawed et al., 2021; Situm, 2023) and benefit from economies of scale and increased bargaining power (Dimitrić et al., 2019). This availability of resources allows for better preparation through investment in resilience-building and resilience tools (Orchiston, 2013; Situm, 2023). However, our results point to a non-linear relationship between these two factors, which is consistent with findings on business performance (Serrasqueiro & Nunes, 2008), profitability (Nunes et al., 2010), the probability of failure and financial distress (Altman et al., 2010; Sehgal et al., 2021). In fact, larger firms may have the resources, but they often lack the flexibility that is key for overcoming disruptions. Their inflexibility burdens firm performance during economic downturns, because size often implies higher fixed costs and lower capacity to absorb a shortage in returns (Hua et al., 2013).

Table 2.2 shows that other firm-specific characteristics are important for CR in the tourism industry. In particular, the previous literature concludes that moderate leverage levels, lower operational cost structures, robust financials, access to internal and external funds, and diversified income sources increase resilience (Biggs et al., 2012; Dahles & Susilowati, 2015; Huynh et al., 2022; Kaczmarek et al., 2021; Neise et al., 2021; Orchiston, 2013; Schwaiger et al., 2022; Verfürth et al., 2022; Wieczorek-Kosmala, 2022). Another economic factor at play is the potential for firms to belong to a franchise or a chain. Indeed, businesses can benefit from this affiliation by gaining improved access to operational resources and financing (Biggs et al., 2012; Dahles & Susilowati, 2015; W. Liu et al., 2024; Neise et al., 2021; Schwaiger et al., 2022; Usher et al., 2019).

Importantly, organizational capital and organizational culture are also well documented determinants of CR. The implementation of strategic planning practices and the capacity to diversify seem to be of the utmost importance across several tourism subsectors (S. X. Chen et al., 2022; Dahles & Susilowati, 2015; Doğantan & Akoğlan Kozak, 2019; Ghaderi et al., 2022; Huynh et al., 2022; Lin & Wen, 2021; Melián-Alzola et al., 2020; Nguyen et al., 2022; Orchiston et al., 2016; Pongtanalert & Assarut, 2022; Sobaih et al., 2021; Tanner et al., 2022; Usher et al., 2019; Verfürth et al., 2022). Despite this, the extant literature indicates that tourism businesses often present low levels of disaster preparedness and lack planning and risk management processes (Nguyen et al., 2022), partly due a reluctance to allocate funds to this type of activity (Ghaderi et al., 2022). Other important attributes of organizational culture include investment policies (Kaczmarek et al., 2021), leadership (Doğantan & Akoğlan Kozak, 2019; Orchiston et al., 2016; Tanner et al., 2022), dynamic capabilities (Hussain & Malik, 2022; Melián-Alzola et al., 2020; Mohammad et al., 2022; Tanner et al., 2022; Wided, 2022), positive and supportive cultures (Prayag et al., 2020; Schwaiger et al., 2022; Tanner et al., 2022), business ownership (Lin & Wen, 2021; Neise et al., 2021) and business structure (Ghaderi et al., 2022).

Finally, Table 2.2 also shows that the resilience of tourism firms also depends on the business environment where these firms operate. In particular, firm location (W. Liu et al., 2024; Ntounis et al., 2022; Verfürth et al., 2022; Wieczorek-Kosmala, 2022), the characteristics of local tourism demand and disruptions (Ghaderi et al., 2022; Nguyen et al., 2022; Ntounis et al., 2022), government policies (Kaczmarek et al., 2021; Neise et al., 2021; Schwaiger et al., 2022; Tanner et al., 2022) and national culture (Kaczmarek et al., 2021) also affect resilience capacity, because they shape firms' preparedness, flexibility and ability to respond to disruptions.

In sum, by consolidating the results of the existing literature into a unified theoretical framework of CR that can be used as a basis for future studies, we identify several relationships that require further research within the scope of CR. We address these future research opportunities in the following section.

2.6. Conclusions and implications

Although recent events have indicated the importance of CR for tourism-related companies, research on this topic remains fragmented (Iacobucci & Perugini, 2021; Linnenluecke, 2017; saad et al., 2021; Yao & Fabbe-Costes, 2018). As such, a common framework of CR is still to be developed; we contribute to this task by identifying the antecedents and consequences of CR. This review adds to our knowledge by providing a clear picture of the tools that firms operating in the tourism sector have at their disposal to build their resilience capacity and how they benefit from doing so. Furthermore, this study highlights that the idiosyncrasies and challenges of the tourism industry are fertile ground for further development of research on CR. This is especially important given the industry's relevance to the global economy and its susceptibility to many different types of crises and adverse events (Espiner & Becken, 2014; Prayag et al., 2020).

Our results are very important for researchers. In fact, this review has shown that CR in the tourism industry is multifaceted and context-dependent, which supports the idea that resilience should be studied through an interdisciplinary lens, incorporating insights from various fields such as economics, sociology and environmental studies. Furthermore, we find that resilience is not a static trait that firms possess, but rather a dynamic process that evolves through different stages of disruption (Amaral & Da Rocha, 2023; Brown et al., 2017; Duarte Alonso et al., 2020; Liu et al., 2022; Wided, 2022), which is consistent with the theory of dynamic capabilities. The present results therefore clearly highlight that future theoretical models must incorporate the longitudinal aspect of CR and recognize that different strategies may be employed at various stages. At the same time, new theoretical advances should also embrace the concept that companies can actively adopt behaviours and develop competencies that foster resilience (Lengnick-Hall et al., 2011), rather than being constrained by the mere presence or absence of resilience as an attribute. This dynamic view also implies that resilience is not a one-size-fits-all concept. Attributes that are important determinants of resilience in a certain context can be proven irrelevant or even harmful to resilience in a different scenario (Amaral & Da Rocha, 2023; Biggs et al., 2012, 2015; Dahles & Susilowati, 2015; Usher et al., 2019). Given the context-dependent nature of resilience, future research should include context-sensitive variables tailored to specific tourism subsectors, geographic regions or types of disruptions to investigate the reasons for the different behaviours of CR determinants.

At a different level, our findings underscore the importance of human and social capital, innovation, adaptability, flexibility and planning in building CR. As a result, theoretical frameworks of CR must incorporate these determinants to provide a comprehensive understanding of resilience mechanisms in the tourism industry. Similarly, some authors have found a positive correlation between CR and business performance, both financial and operational. Organizational performance theory should thus investigate the role of resilience as a key factor influencing firm performance and sustainability in the tourism industry. Finally, there is a notable scarcity of studies measuring CR and developing comparable indicators. Future research should focus on creating robust metrics and tools that can be applied in real-world settings to compare and investigate resilience mechanisms, to address the issue of generalization and promote the comparison of results between companies and industries, so best practices can be identified.

The results of this review should also be of interest for policymakers, as there is evidence that government support plays a crucial role in enhancing CR. Unfortunately, the scarce literature currently available on the topic suggests that firms perceive such support to be a set of very bureaucratic and standardized processes (Schwaiger et al., 2022; Sobaih et al., 2021; Tanner et al., 2022). It follows that policymakers should design support mechanisms that are more flexible and tailored to the situations and needs of SMEs, which account for a significant portion of the industry, rather than adopting a one-size-fits-all approach. Such policies must enhance the flexibility and adaptability of firms by including measures such as layoff mechanisms during crises or incentives for innovation, collaboration and the digital transformation of the industry. The present results also provide evidence that strategic planning for crisis management and recovery can significantly improve CR, but companies often lack the skills or resources to implement such risk management strategies. Governments could help by providing specialized training, skills and resources to develop the risk management strategies of SMEs. Finally, the industry could benefit from policies that support the growth of human capital, such as a simplified process for skilled workers to apply for work permits or incentives to support skill development programmes.

Practitioners can also learn from our results, which clearly stress that managers must prioritize human resource practices that enhance individual resilience, while providing employment security, work-life balance, autonomy and continuous training. Training and skill development programmes are thus recommended, as well as avoiding staff turnover at all costs. Furthermore, practising job rotation amongst staff, as suggested by Chowdhury et al. (2019), should ensure that the necessary skills and knowledge are maintained and spread across the organization, avoiding overconcentration that may lead to the loss of human capital in disruptive circumstances. Similarly, building a positive organizational culture, where employees feel heard, and investing in individual well-being is also crucial. There is also evidence that establishing strong relationships with stakeholders and other firms in the tourism ecosystem can enhance CR through collaboration and networking. For this reason, industry managers need to invest in their relational capital and promote the dynamics of industry associations to build and maintain these relationships through effective communication and mutual trust. At a different level, our results suggest that maintaining liquidity and a flexible cost structure is vital; managers should focus on building financial resilience through an optimal use of leverage, ensuring alternative income sources and slack resources to weather disruptions. However, more research is required on this topic, since most of the existing research has focused on the looks at stock price resilience of listed firms, while ignoring the predominance of non-listed firms in this industry, which may lead to biased results.

This study is not without limitations. There is a degree of subjectivity inherent to the researchers' inclusion decisions and categorization of papers, which we addressed with an ex-ante defined and validated protocol, and by applying no limitations to the scope or ranking of the journals in the sample. While there was an effort to be thorough in the inclusion of publications, pertinent studies may have been unintentionally overlooked, particularly those published in journals not indexed in the databases selected. This is, however, an important criterion to ensure the baseline quality of the publications included in the sample and strengthen the quality of the systematic literature review.

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CHAPTER 3 – BUILDING RESILIENCE IN TOURISM FIRMS: EVIDENCE FROM COVID-19 (PAPER TWO)[2]

Abstract

What determines whether tourism companies can resist and overcome a disruptive event such as a pandemic or a war? This paper investigates this issue using a sensitivity index, and finds that reductions in human capital, bigger size, and higher past profitability diminish resilience, while higher leverage and capital intensity strengthen it. Our findings further suggest that these effects differ across countries and underscore the negative consequences of Eurozone membership. This paper broadens our understanding of how companies can improve their resilience, providing valuable insights for future preparedness strategies for tourism firms and policymakers.

Keywords: Covid-19; Crisis; Resilience; Firm-level; Tourism; Hospitality; Dynamic capabilities.

3.1. Introduction

What actions can tourism firms take to increase their resilience? What tools, skills, and resources are available to them to ensure survival when facing disruptive events? Investigating the factors contributing to company resilience (CR) in the tourism sector is particularly interesting in the aftermath of globally disruptive events, such as the COVID-19 pandemic, which impose significant economic and social costs (Bertschek et al., 2019). Moreover, it is appealing to investigate these issues focusing on the tourism sector given its considerable contribution to global GDP and employment (World Travel & Tourism Council, 2024) and its severe vulnerability to external events (Espiner & Becken, 2014; Prayag et al., 2020), factors that heighten the need for resilience in tourism-related firms. To that extent, the recent pandemic, which sharply reduced international flows and GDP (UNWTO, 2021b), has left the industry recovering at a slower pace than anticipated, with international tourism still below pre-pandemic levels (UNWTO, 2024).

[2] **This paper is submitted and currently under review in the International Journal of Hospitality Management and its structure follows this journal style.**

Furthermore, this sector's vulnerability to the previous severe acute respiratory syndrome (SARS) outbreaks also emphasizes the importance of studying CR within this industry (M.-H. Chen et al., 2007; Zeng et al., 2005). In effect, previous research shows that several tourism-related firms lack the resilience to withstand such disruptions (Wieczorek-Kosmala, 2022), with additional evidence suggesting that they perceive themselves as less resilient than their peers in other industries (Ntounis et al., 2022).

To address this gap in the literature, this paper employs binary logistic regression models and examines the resilience of hospitality firms to COVID-19, and how such resilience is influenced by specific firm characteristics. We find that reductions in human capital, firm size, and past profitability reduce the likelihood of resilience, while leverage and capital intensity increase it. Importantly, evidence suggests that these effects vary by country, with our findings indicating that companies based in Sweden stand in advantage when compared with the rest. We enhance the analysis by looking at Eurosystem membership, uncovering potential challenges linked to the unified monetary policy. We investigate how this affects CR and provide insights into the role played by this differentiation in monetary governance, offering deeper understanding of the interplay between policy frameworks and CR.

Our theoretical contributions are multi-faceted. First, we respond to the call for further exploration of the impact of firm-level characteristics in CR (S. Lee et al., 2024). Our results confirm the critical role of human capital and reveal an unexpected negative effect of profitability, possibly due to managerial complacency after several years of strong performance in the tourism industry. Second, our findings support the resource-based view proposed by Wernerfelt (1984) and the existence of dynamic capabilities as suggested by Ambrosini and Bowman (2009), by emphasizing the effect of firm-specific characteristics on CR in crisis contexts. Finally, the application of our sensitivity index as a measure of resilience within these theoretical frameworks also represents a valuable contribution in its own right.

This study also offers valuable insights for managers and policymakers looking to enhance the resilience of tourism firms. In fact, the application of our resilience index provides a practical tool for the self-assessment of these companies and, through it, managers can also identify the most resilient industry peers and best practices to implement. This paper also highlights the importance of monetary policy and Eurosystem membership for firm resilience, something that policymakers must consider when designing economic policies. Finally, the study also emphasizes human capital and profitability as critical to CR, urging managers to avoid complacency and overconfidence during profitable periods and exercise caution with layoffs or salary reductions as solutions to reduce costs.

This paper is structured as follows: section 3.2 presents the literature review, section 3.3 addresses methodological aspects, section 3.4 reports the findings, which are discussed in section 3.5. Section 3.6 concludes.

3.2. Literature review

3.2.1. Resilience in the tourism industry

The concept of resilience, initially defined in ecology by Holling (1973) as the ability of systems to absorb changes and persist, has evolved and is currently regarded as a set of three complementary attributes instead: persistence, adaptability and transformability (Folke et al., 2010; Walker et al., 2004). This is consistent with the resource-based view (RBV) (Barney, 2001) and the dynamic capabilities theory (Ambrosini & Bowman, 2009), according to which firms must evolve and adapt their resources to sustain competitive advantages under disruptive circumstances.

While CR research in tourism remains scant, it is recognized as a multidisciplinary (Hall et al., 2023) and dynamic process (Amaral & Da Rocha, 2023; Brown et al., 2017; W. Liu et al., 2024), with distinct determinants in different contexts and events (Amaral & Da Rocha, 2023; Orchiston et al., 2016; Sobaih et al., 2021).

Previous studies have demonstrated that resilience is highly context-dependent (Amaral & Da Rocha, 2023; Biggs et al., 2012, 2015; Dahles & Susilowati, 2015; S. Lee et al., 2024; Usher et al., 2019). Furthermore, the recent COVID-19 pandemic has turned the attention of scholars to the investigation of firm-level determinants of resilience, raising important questions that require further investigation. For instance, using profitability as a proxy of resilience, S. Lee et al. (2024) find that certain firm-specific factors contributed to enhance the resilience of hospitality firms during the COVID-19 pandemic. Importantly, the authors find that this effect is greater during such period than in the 2008 financial crisis, suggesting that CR determinants are contingent on factors from the business environment. Tascón et al. (2023) and Ramelli & Wagner (2020) reported similar results in what concerns the role of profitability and liquidity in the resilience of tourism firms to COVID-19, but contrasting results in terms of leverage and capital intensity. Conflicting results regarding leverage (H. J. Song et al., 2021), firm size (Nguyen et al., 2022) and profitability (H. J. Song et al., 2021) have also been reported in the literature, which prompts the need for further investigation.

3.2.2. Tourism: Testing resilience and competitive advantages in crisis contexts

Building on the literature review and drawing on the RBV, this study explores how tourism companies' internal resources drive their resilience in crisis contexts. Within this theoretical framework, CR relies on the unique set of resources and capabilities that help businesses secure their competitive advantage even in times of distress. Based on these theoretical insights, this paper identifies eight firm-level characteristics that can affect CR in the tourism industry. These include six financial characteristics (leverage, capital intensity, profitability, liquidity, solvency and size), two human capital proxies and firm location. We follow with a discussion of how each of these characteristics can impact the probability of resilience.

Tourism firms tend to rely heavily on fixed assets like properties, aircrafts, or ships (Dimitrić et al., 2019; Jawed et al., 2021; S. Lee et al., 2024; Vinod, 2020). Such operational structures lead to high capital requirements, which are typically met with high levels of debt (Vinod, 2020), facilitated by easy access to loans using collateral (Singal, 2015). These assets are often illiquid and not easily sold or repurposed (Alfaro et al., 2020; Singal, 2015) and they carry high fixed costs, like depreciation and maintenance, even during periods of low utilization (Colak et al., 2023; Dube et al., 2021; Santos et al., 2022), which can not be eliminated (Lai & Wong, 2020; Majumdar, 2021). For these reasons, a heavy reliance on fixed assets may reduce a firm's flexibility to adapt to environmental changes. Hence, we hypothesize a negative effect of capital intensity on CR.

H1: Higher capital intensity has a negative effect on the likelihood of resilience.

During economic challenges, high leverage increases firm vulnerability to financial distress, reducing the available cash-flow (González, 2013; Neise et al., 2021). In these downturns, heavily levered firms suffer market share losses and lower profitability compared to less leveraged counterparts (Opler & Titman, 1994), which may also limit their access to liquidity (Neise et al., 2021). In contrast, in such setting, companies with lower reliance on debt experience lower interest costs, higher cash-flows, and better market performance, which should lead to higher resilience during crises (Kaczmarek et al., 2021; Ramelli & Wagner, 2020; Verfürth et al., 2022). Therefore, we hypothesize that leverage negatively impacts CR.

H2: Higher leverage has a negative effect on the likelihood of resilience.

Financial constraints can significantly hinder a firm's ability to remain in business (Biggs et al., 2015; Musso & Schiavo, 2008). Liquidity is particularly important in the tourism sector due to its idiosyncrasies, such as seasonality and high capital intensity (Srhoj et al., 2024). Liquidity is even more critical during economic downturns, acting as a buffer to absorb shocks and sustain operations (Becerra-Vicario et al., 2020; Situm, 2023; H. J. Song et al., 2021; Srhoj et al., 2024; Vivel-Búa et al., 2019; Wieczorek-Kosmala, 2022). Indeed, during COVID-19, firms with limited cash reserves suffered more severely than their peers (Neise et al., 2021; Ramelli & Wagner, 2020), and the literature suggests that higher liquidity levels increase resilience (Carter et al., 2022; Martins & Cró, 2022; Safón et al., 2024; Wieczorek-Kosmala, 2022). Hence, we hypothesize that firms with higher liquidity levels are more likely to be resilient.

H3: Higher liquidity has a positive effect on the likelihood of resilience.

Higher solvency also plays an important role in firm survival, since it is associated with lower financial distress risk (Mselmi et al., 2017; Sehgal et al., 2021), higher profitability and credit scores (Dimitrić et al., 2019). These characteristics improve the access to financing, flexibility, and security in times of crisis. However, solvency issues are common amongst tourism firms, due to their high leverage, capital intensity, and investment requirements (Singal, 2015; Vinod, 2020). Companies with solvency issues are also often stereotyped (Luo et al., 2021), which impacts their access to funding. Therefore, evidence suggests that solvency issues may restrict the access to resources, weaken financial performance, and limit the ability to adapt to changing market conditions. For this reason, we hypothesize that solvency issues, represented by negative book equity, reduce the likelihood of being resilient.

H4: Solvency issues have a negative effect on the likelihood of resilience.

Profitability is usually associated with a firm's survival ability (Biggs et al., 2015; Gémar et al., 2019; Kaczmarek et al., 2021; Neise et al., 2021; Verfürth et al., 2022; Vivel-Búa et al., 2019), better liquidity (Wieczorek-Kosmala, 2022), outperformance (Hua et al., 2013), and lower probability of financial distress (Fernández-Gámez et al., 2016; Situm, 2023). All these factors help create the flexibility that firms need to endure disruption (Ramelli & Wagner, 2020), since profitable companies are capable of generating internal funds and obtaining external funding, ensuring the necessary liquidity to endure the impact of crises (Wieczorek-Kosmala, 2022). For this reason, we hypothesize that profitability positively impacts CR.

H5: Higher profitability has a positive effect on the likelihood of resilience.

Despite their higher asset dependency, tourism firms are often small (Eggers, 2020; Srhoj et al., 2024; Tanner et al., 2022). Such firms face the “liability of smallness” (Eggers, 2020) due to resource constraints, which results in higher likelihood of bankruptcy (Vivel-Búa et al., 2019; D. A. Williams, 2014). Hence, they are particularly vulnerable during crisis periods (Cucculelli & Peruzzi, 2020). However, small companies also exhibit operational flexibility and adaptability (Nguyen et al., 2022; Tanner et al., 2022) and navigate seasonality more effectively (Vivel-Búa et al., 2019). Together, these effects suggest a non-linear relationship between firm size and resilience (Situm, 2023). Hence, this paper hypothesizes that firm size is likely to affect the likelihood of tourism firms demonstrating resilience, although it does not specify the direction of this relationship.

H6: Firm size impacts the likelihood of resilience.

The important role of employees is highly evidenced in the resilience literature (Biggs et al., 2015). Human capital carries an increased importance in tourism (Srhoj et al., 2024), due to the high specialization of certain markets that rely heavily on it to provide differentiated touristic experiences (Biggs, 2011). Evidence also suggests that highly skilled employees are more flexible and agile in reacting to economic downturns, promoting innovation and value creation (N. Lee, 2014). For this reason, we hypothesize that human capital reductions negatively impact CR.

H7: Reductions in human capital have a negative effect on the likelihood of resilience.

Previous research highlights the context-dependent nature of resilience (Amaral and Da Rocha, 2023; Biggs et al., 2012, 2015; Dahles and Susilowati, 2015; Usher et al., 2019). Furthermore, location is key for hotel occupation, income and survival (Gémar et al., 2016). CR may be influenced by location-specific factors due to differing regulatory, economic, and financial conditions. For this reason, we hypothesize that firm location has an impact on the likelihood of resilience. However, the direction of this relationship is not specified.

H8: The location of the firm impacts the likelihood of resilience

While a common currency generally benefits member states' economies (Hegerty, 2020; Zimková et al., 2021), it also limits their ability to use monetary policy to manage macroeconomic fluctuations (Hegerty, 2020). This restriction can be detrimental during crises, as evidenced by the negative effects on economic growth in the Eurozone (Zimková et al., 2021). Hence, we hypothesize that there are differences between the resilience of companies located in Eurosystem member-states and those outside of it.

H9: The likelihood of resilience of firms within the Eurosystem is distinct and influenced by different factors than that of their non-Eurosystem counterparts.

In sum, through this research, we aim to answer the following research questions: Are companies more likely to fail because of governmental policies that they do not control? Can location serve as a competitive advantage during downturns? More importantly, do traditional competitive advantages like liquidity and profitability behave as expected under disruptive circumstances? To address these questions, we introduce a novel approach to CR, through the application of a sensitivity index adapted from the regional resilience literature.

3.3. Methodology

3.3.1. Data

This study starts by identifying all companies with a primary SIC code of 7011 (accommodation services) in the Orbis database provided by Bureau Van Dijk for the period between 2019 and 2022, that had their headquarters located in Belgium, Bulgaria, Croatia, Poland, Portugal, Romania, Serbia, Slovenia, Spain, and Sweden, since companies in these countries are the only ones to report the data we require for our empirical tests. To improve data reliability, observations with missing or null values required for computing variables of interest are deleted. This leads us to a final sample of 6.038 companies. Details about the sample are available on section 4.1.

3.3.2. The model

This study employs binary logistic regression models to investigate how the resilience of the sample firms to COVID-19 is influenced by certain specific characteristics, their country of origin and Eurozone membership. Equation (1) presents the general model:

$$ln\left(\frac{P_{(RESILIENT_i)}}{1-P_{(RESILIENT_i)}}\right) = \beta_1 + \beta_2 LEV_i + \beta_3 CAP_i + \beta_4 ROA_i + \beta_5 LIQ_i + \beta_6 SIZE_i + \beta_7 REDHC_i + \beta_8 REDSAL_i + \beta_9 NEGCP_i + \beta_{10} COUNTRY_i + \varepsilon_i \quad (1)$$

Three different specifications are, however, employed. The first considers the total sample and helps investigate the impact of firm-level characteristics and country of headquarters in the likelihood of a firm being resilient. The two alternative models divide the initial sample between companies that are headquartered in Eurozone and non-Eurozone member-states, respectively. These specifications help examine whether there are significant differences in the effect of firm-level characteristics on CR between these important subsamples.

3.3.2.1. Dependent variable

The dependent variable in Equation (1) is computed following Iacobucci and Perugini (2021). Specifically, for each firm, a resilience index is employed to measure CR, which is computed as per Equation 2:

$$R_i = \frac{\left(\frac{GVA_{i,t+1}}{GVA_{i,t-1}}\right)}{\left(\frac{GVA_{c,t+1}}{GVA_{c,t-1}}\right)} \quad (2)$$

Where $GVA_{i,t+1}$ ($GVA_{c,t+1}$) represents the gross value added (GVA) for firm i (country c) in the end of the period of interest (i.e., 2022) and $GVA_{i,t-1}$ ($GVA_{c,t-1}$) is the same but for the peak year (i.e., 2019). As can be seen, the index is built in relative terms, as the resilience of a given firm is compared to that of its industry's country average (Iacobucci & Perugini, 2021). As such, a value for R_i above (below) 1 indicates that the firm exhibits greater (lower) resilience compared to its peers within the same country.

3.3.2.2. Independent variables

Following our research questions, eight firm-level characteristics are used as independent variables. Six relate to financial characteristics; two proxies for human capital and the final one captures the location of the companies' headquarter. Table 3.1 summarizes the relevant information about these variables.

Table 3.1 – Independent variables

Variable	Variable description	References
Leverage (LEV)	Weight of the total debt on the total assets	(Carter et al., 2022; Crespí-Cladera et al., 2021; Kaczmarek et al., 2021; S. Lee et al., 2024; Singal, 2015; Situm, 2023; H. J. Song et al., 2021; Verfürth et al., 2022; Wieczorek-Kosmala, 2022)
Capital Intensity (CAP)	Weight of the total fixed assets on the total assets	(Jawed et al., 2021; S. Lee et al., 2024; Santos et al., 2022; Singal, 2015)
Profitability (ROA)	Ratio of net income to total assets	(Kaczmarek et al., 2021; S. Lee et al., 2024; Orchiston, 2013; Santos et al., 2022; Situm, 2023; H. J. Song et al., 2021; Wieczorek-Kosmala, 2022)
Liquidity (LIQ)	Ratio of current assets to current debt	(Carter et al., 2022; Crespí-Cladera et al., 2021; S. Lee et al., 2024; Wieczorek-Kosmala, 2022)
Firm size (SIZE)	Natural logarithm of total assets	(Carter et al., 2022; Dimitrić et al., 2019; S. Lee et al., 2024; Nguyen et al., 2022; Situm, 2023; H. J. Song et al., 2021)

Human Capital	**REDHC**	Dummy variable: 1 if the firm reduced the number of employees in 2020; 0 otherwise	(Biggs, 2011; Biggs et al., 2015, 2012; Lee, 2014; Njunguna et al., 2021; Srhoj et al., 2024)
	REDSAL	Dummy variable: 1 if the firm reduced the average staff expenditure per employee in 2020; 0 otherwise	
Solvency (NEGCP)		Dummy variable: 1 if the firm has negative shareholder equity in 2019; 0 otherwise	(Dimitrić et al., 2019; Luo et al., 2021; Schwaiger et al., 2022; Situm, 2023)
Location (COUNTRY)		Categorical variable defined as each country's ISO 3166-1 alpha-2 code	(Dimitrić et al., 2019; Kaczmarek et al., 2021; W. Liu et al., 2024; Ntounis et al., 2022; Situm, 2023)

Source: Own elaboration

3.3.2.3. Diagnostic tests

This study applies diagnostic tests to assess the models' performance and their goodness-of-fit. As recommended by Thompson et al. (2017), the presence of multicollinearity is analyzed through multiple diagnostics, namely the correlation matrix, variance inflation factor (VIF) values, eigenvalues, condition indices and linear regression models between independent variables. We additionally regress the dependent variable in each independent variable, individually, to analyze eventual sign, significance, or magnitude changes that could, nevertheless, indicate the presence of multicollinearity in our model.

3.4. Results

3.4.1. Sample characterization – resilience index

Table 3.2 summarizes the distribution of firms across countries. As evidenced, Spain accounts for nearly half of the sample (44.67%), while Belgium is the less represented country, with only 77 observations.

Table 3.2 – Sample characterization: Number of resilient and non-resilient companies

Country	Resilient	Non-Resilient	Total	% Resilient
BE	39	38	77	50.65
BG	51	58	109	46.79
ES	1312	1385	2697	48.65
HR	133	185	318	41.82
PL	202	183	385	52.47
PT	348	580	928	37.50
RO	338	243	581	58.18
RS	68	79	147	46.26
SE	492	180	672	73.21
SI	35	89	124	28.23
Total	**3018**	**3020**	**6038**	**49.98**

Source: Own elaboration

The last column indicates that 73.21% of Swedish companies are classified as resilient, while this proportion is only 28.23% in Slovenia. Table 3.2 further reveals that most firms from Belgium, Poland, Romania, and Sweden are categorized as resilient; Bulgaria, Spain, Croatia, Portugal, Serbia and Slovenia exhibit the opposite pattern. Importantly, nearly half of the firms in the sample are classified as resilient, illustrating an equitable distribution in terms of CR. Our index specification, based on relative measures of change rather than absolute ones, along with this equitable distribution, provides reassurance that this measure of resilience is not affected by eventual outliers, such as larger companies with significantly higher GVAs compared to their peers.

3.4.2. Descriptive statistics – independent variables

Descriptive statistics for the independent variables are presented in Table 3.3, covering the total sample and dividing the sample into resilient and non-resilient firms according to the resilience index.

Table 3.3 – Descriptive statistics – independent variables in the year of 2019

Variable	Sample	Mean	Std. Dev.	Minimum	Maximum	Median	Mann–Withney Test Chi-Square Test
LEV (%)	**Total**	53.25	37.14	0.10	559.68	51.01	<0.0001
	Non-Resilient	49.87	35.11	0.14	411.6	46.81	
	Resilient	56.63	38.78	0.10	559.68	55.97	
CAP (%)	**Total**	55.95	31.93	0	99.95	62.31	0.6900
	Non-Resilient	55.84	31.80	0	99.95	61.95	
	Resilient	56.05	32.06	0	99.91	62.70	
ROA (%)	**Total**	6.02	16.42	-174.97	149.36	3.57	<0.0001
	Non-Resilient	7.86	15.63	-174.97	149.36	4.61	
	Resilient	4.18	16.98	-173.12	101.1	2.69	
LIQ (%)	**Total**	340.54	1116.19	0.08	21675.22	118.96	0.0209
	Non-Resilient	347.48	1131.48	0.08	21294.44	123.91	
	Resilient	333.60	1100.82	0.08	21675.22	115.14	
SIZE	**Total**	14.54	1.83	6.05	22.56	14.72	<0.0001
	Non-Resilient	14.68	1.83	6.05	20.58	14.87	
	Resilient	14.40	1.82	6.14	22.56	14.54	
REDHC	**Total**	0.75	0.43	0	1	1	<0.0001
	Non-Resilient	0.80	0.40	0	1	1	
	Resilient	0.71	0.45	0	1	1	
REDSAL	**Total**	0.64	0.48	0	1	1	<0.0001
	Non-Resilient	0.68	0.47	0	1	1	
	Resilient	0.61	0.49	0	1	1	
NEGCP	**Total**	0.05	0.21	0	1	0	0.0090
	Non-Resilient	0.04	0.19	0	1	0	
	Resilient	0.05	0.22	0	1	0	

Source: Own elaboration

As can be seen, on average, debt accounts for 53.25% of total assets of the sample firms and fixed assets represent an average of 55.95% of total assets. Profitability ranges from -174.97% to 149.36%, with a mean of 6.02%. The average liquidity is 3.41 euros of current assets per euro of current debt, indicating good coverage of short-term debt by current assets. SIZE has a mean of 14.54, with a standard deviation of 1.83, and ranges from 6.05 to 22.56. Regarding human capital, 75.00% of companies reduced their workforce (REDHC) and 64.00% reduced their average staff expenditure per employee (REDSAL) in 2020. Finally, only 5.00% of the companies operated with negative book equity (NEGCP).

Table 3.3 also presents separate statistics for resilient and non-resilient companies. Unreported results from a Kolmogorov–Smirnov test indicate that the data is not normally distributed, a conclusion that holds for all the independent variables. Thus, this paper uses the Mann–Whitney non-parametric test to verify if there are significant differences in firm-level characteristics between the two groups of interest. As evidenced, there are statistically significant differences at the 5% level between resilient and non-resilient firms for all variables except capital intensity. In particular, resilient firms seem to operate with higher leverage and lower profitability and liquidity. Such companies are also smaller than their non-resilient counterparts. Importantly, for the binary variables in Table 3.3, this paper runs a Chi-Square test of independence. Results show that there are statistically significant differences between the proportion of resilient and non-resilient companies that reduce human capital and operate with negative book equity.

Table 3.4 presents the results of Spearman's rank correlation coefficients among variables, computed for the year of 2019.

The analysis shows that leverage is positively correlated with resilience, meaning that the more levered firms are more likely to be resilient. Conversely, profitability and liquidity are negatively associated with resilience, which contradicts our initial expectations. Additionally, firm size has a negative correlation with resilience. Reductions in human capital also negatively impact resilience, something that is in line with our initial expectations. Surprisingly, solvency issues are positively associated with resilience, indicating that financially vulnerable firms may still display resilience under certain conditions.

Table 3.4 – Correlation matrix

	RESILIENT	LEV	CAP	ROA	LIQ	SIZE	REDHC	REDSAL	NEGCP
RESILIENT	1								
LEV	0.100 ***	1							
CAP	0.005	0.008	1						
ROA	-0.136 ***	-0.242 ***	-0.278 ***	1					
LIQ	-0.030 **	-0.468 ***	-0.349 ***	0.246 ***	1				
SIZE	-0.095 ***	-0.157 ***	0.193 ***	-0.078 ***	0.003	1			
REDHC	-0.101 ***	-0.036 ***	-0.011	0.038 ***	-0.022 *	0.100 ***	1		
REDSAL	-0.068 ***	-0.030 **	0.024 *	0.005	0.015	0.011	-0.147 ***	1	
NEGCP	0.034 ***	0.338 ***	-0.023 *	-0.200 ***	-0.137 ***	-0.109 ***	-0.001	0.019	1

Note: *, **, and * are statistically significant at the 1%, 5%, and 10% level, respectively. Source: Own elaboration**

Finally, the correlation matrix shows no evidence of high and statistically significant correlation between variables (Allison, 1999), since all the correlation coefficients are below the common thresholds of 0.80 and 0.90 (Midi et al., 2010).

3.4.3. Regression results

3.4.3.1. Diagnostic tests

This paper first discusses the results of the diagnostic tests before proceeding to present the regression analysis. The Hosmer-Lemeshow test for the model encompassing the full sample yields a p-value of 0.78, suggesting a good model fit. The results obtained for the Eurosystem and non-Eurosystem specifications are lower, 0.22 and 0.23, respectively. Yet, these results also indicate a good fit from both specifications (Hosmer et al., 2013). Additionally, the area under the Receiver Operating Characteristic (ROC) curve shows that our base model can correctly distinguish between resilient and non-resilient firms approximately 66.50% of the time, which is close to the threshold for acceptable discrimination (Hosmer et al., 2013). The Eurosystem specification has a slightly lower AUC of 64.20%, while its non-Eurosystem alternative provides the highest discriminatory power, with an AUC of 69.40%.

We also test for multicollinearity issues by regressing each independent variable on all the other independent variables. All these models have low r-squared values, so we move on to the analysis of VIF values, which are all below the 2.50 threshold (Allison, 1999; Midi et al., 2010). Finally, we look at eigenvalues and condition indices, which further confirm the absence of serious multicollinearity in our data.

3.4.3.2. Estimation results

Table 3.5 presents the results of estimating Equation (1) with the different specifications mentioned in section 3.2. We start by discussing the evidence from estimating the model with the full sample. As can be seen, the estimated coefficient for leverage, capital intensity, profitability, size, human capital reduction and location are all statistically significant at normal levels. Conversely, there is no evidence to support that liquidity and solvency issues have a statistically significant impact on resilience when the other explanatory factors are accounted for.

Table 3.5 – Regression results

	(1) Total sample	**(2) Eurosystem member-states**	**(3) Non-Eurosystem member-states**
C	3.206***	1.229***	4.234***
LEV	0.264***	0.190	0.439***
CAP	0.250***	0.224**	0.339*
ROA	-1.836***	-2.884***	-1.038***
LIQ	0.000	0.001	-0.000
SIZE	-0.124***	-0.091***	-0.203***
REDHC	-0.587***	-0.506***	-0.677***
REDSAL	-0.249***	-0.200***	-0.317***
NEGCP	-0.139	0.022	-0.476*
COUNTRY – BE	-1.383***	0.177	-
COUNTRY – BG	-0.948***	-	-0.809***
COUNTRY – ES	-0.908***	0.581***	-
COUNTRY – HR	-1.923***	-	-2.148***
COUNTRY – PL	-0.882***	-	-0.784***
COUNTRY – PT	-1.481***	-	-
COUNTRY – RO	-0.564***	-	-0.580***
COUNTRY – RS	-1.432***	-	-1.421***
COUNTRY – SI	-2.234***	-0.721***	-

Notes: *, **, and * are statistically significant at the 1%, 5%, and 10% level, respectively. Reference category for COUNTRY is Sweden for models (1) and (3) and Portugal for model (2). Source: Own elaboration**

Some of these results warrant further discussion. Specifically, Table 3.5 indicates that higher profitability is linked to a lower likelihood of a firm being classified as resilient, which contradicts our initial expectations. Burnett and Johnston (2020), however, suggest that, following a period of economic stability, managers may become complacent, exhibiting short-sighted behavior and failing to anticipate potential threats, something that can help explain our empirical results. Our findings also suggest that firm size negatively affects the likelihood of firms being classified as resilient, something that is somewhat counterintuitive. Yet, similar findings have been reported by Nguyen et al. (2022) and Vivel-Búa et al. (2019), who argue that larger firms, all else being equal, possess less flexibility to adapt and reduce fixed costs in the short term. Lastly, when using Sweden as the reference category, all the estimated coefficients for the country dummy variables are negative and statistically significant. This suggests that, all else being equal, companies headquartered in other countries are less likely to demonstrate resilience than those of Sweden, a finding that is consistent with prior research highlighting the strong influence of contextual factors on resilience (Amaral and Da Rocha, 2023; Biggs et al., 2012, 2015; Dahles and Susilowati, 2015; Usher et al., 2019).

This paper now turns to the discussion of the results obtained with the two alternative specifications, also presented in Table 3.5. As shown, for companies located in countries within the Eurosystem, the estimated coefficient for capital intensity, profitability, size and human capital reduction are all statistically significant at conventional levels. Capital intensity positively impacts the resilience of firms, while profitability, size and human capital reductions have the opposite effect, something that is consistent with the findings presented for the base model. Additionally, all country dummy variables are significant at the 1% level, with the exception of Belgium. Importantly, the estimated coefficient for leverage is now not statistically significant at normal levels. This result suggests that firms headquartered within the Eurosystem do not benefit from the positive effect of leverage, which is in contrast to the conclusion we draw from the base model. Furthermore, there is no evidence to support that liquidity and solvency issues significantly impact the resilience of firms within the Eurozone, when all other firm characteristics are considered. Finally, these firms exhibit a lower baseline probability of resilience when compared to the base model, even before the effect of firm-level characteristics is considered, as demonstrated by comparing the constant terms from both models.

The results of the specification that only includes firms located outside of the Eurosystem are also presented in Table 3.5 and are somewhat different. The estimated coefficients for leverage and solvency issues are now statistically significant at conventional levels, as are those for capital intensity, profitability, size, and human capital reduction. Interestingly, the direction of all these relationships follows the findings reported for the base model. Yet, in terms of magnitude, all these coefficients have a more significant impact in this specification, except for profitability. This suggests that firms within the Eurozone benefit from a buffering effect, which does not happen outside the Eurozone. As with the previous specifications, the coefficient for liquidity is not statistically significant.

In a nutshell, the results portrayed in Table 3.5 show that only two of our determinants of resilience differ across the three model specifications employed in this study. In fact, our results suggest that leverage and solvency impact firms headquartered outside the Eurozone, but not firms headquartered within it. This result contradicts the general claim that financial distress reduces the likelihood of CR (Mselmi et al., 2017; Neise et al., 2021; Ramelli & Wagner, 2020; Situm, 2023; Verfürth et al., 2022), highlighting the buffering effect of Eurozone membership. Specifically, while non-Eurozone companies are penalized by their negative book equity, they benefit from a positive effect of leverage, a conclusion that does not hold for their Eurozone counterparts. This comparison of different specifications provides additional insight into how Eurosystem membership influences the resilience determinants of tourism firms. Overall, membership does not appear to significantly alter how the studied characteristics affect resilience. However, firms within the Eurozone benefit from a buffering effect, experiencing reduced impacts from these characteristics on their resilience. Despite this advantage, Eurozone firms face a disadvantage compared to their non-Eurozone counterparts, as they exhibit a lower baseline probability of resilience even before considering firm-level characteristics.

3.4.3.3. Robustness tests results

Several robustness tests are conducted, using different measures of resilience, size, and profitability. Specifically, for an alternative measure of resilience, we benchmark each firm to the sample average, instead of the country average. Furthermore, since the hotel industry often operates under franchising and management contracts, which do not translate into a firm's assets, we compute the logarithm of revenue (S. Lee & Xiao, 2011) as an alternative measure of size. Finally, this paper tests two alternative measures for profitability, by computing ROA from EBIT and EBITDA. Results from these robustness tests are consistent with those reported above. These are not reported here to save space but are available upon request.

3.5. Discussion

Understanding resilience in tourism is important due to the industry's vulnerabilities. Resilience offers a pathway to reduce such weaknesses (Doğantan & Akoğlan Kozak, 2019), improve post-disruption performance (Chowdhury et al., 2019; Marco-Lajara et al., 2022; Melián-Alzola et al., 2020; Prayag et al., 2018) and promote the sustainability of the tourism industry (Sobaih et al., 2021).

This study adds to the growing body of evidence that shows that human capital is crucial for the resilience of tourism firms. In fact, our results indicate that human capital reductions significantly decrease the probability of a firm being classified as resilient, confirming previous assertions that CR heavily depends on the critical role of employees (Biggs, 2011; Biggs et al., 2012; Njunguna et al., 2021; Pongtanalert and Assarut, 2022; Prayag et al., 2020; Schwaiger et al., 2022; Tanner et al., 2022). Notably, this conclusion does not depend on firm location, since it is common across all three model specifications considered in the analysis.

In general, solvency issues, represented by negative book equity, should be detrimental to CR. In practice, higher solvency – an indicator of a firm's ability to fulfil its obligations (Mselmi et al., 2017) – improves access to financing, flexibility, and security during crisis (Dimitrić et al., 2019). Consequently, companies with solvency issues are more susceptible to financial distress (Situm, 2023) and are often stereotyped as unprofitable and unlikely to survive in the long run (Luo et al., 2021). In the tourism industry, research shows that companies were particularly susceptible to financial distress situations, due to solvency issues, as a result of COVID-19 (Crespí-Cladera et al., 2021). Yet, our findings only partially corroborate these conclusions, and for the case of the non-Eurozone companies. As such, this paper's results suggest that Eurozone membership may offer firms a certain degree of protection or access to alternative financing sources, enabling them to secure the necessary funds to absorb revenue reductions and sustain their operations, even when operating with negative book equity.

This paper also finds that Sweden has the most resilient firms in the sample. This finding is in line with previous assertions that location plays a crucial role in hotel occupation, revenue and survival (Gémar et al., 2016) due to the competitive advantages it creates (Andres and Round, 2015). Sweden's unique approach to COVID-19, which relied on individual responsibility rather than strict lockdowns (Andersson and Jonung, 2024; Kavaliunas et al., 2020), may be the reason behind this paper's results. In fact, the country's approach likely allowed firms to maintain their client base and operations, by allowing citizens to travel freely (Andersson and Jonung, 2024), contributing to CR, as observed in the restaurant industry by Verfürth et al. (2022).

This study also identifies important benefits and drawbacks to Eurozone membership. First, we find that firms within the Eurosystem do not benefit from the positive effects of leverage and have a lower probability of being resilient. Second, our analysis reveals that all the determinants have more significant impacts on companies located outside the Eurozone, except for profitability. This suggests that firms within the Eurozone benefit from a buffering effect, something that does not happen outside of it. However, this can also be detrimental for CR, as it allows these firms to operate under distress without incentives for higher efficiency, which translates into lower baseline resilience levels.

The relationship between firm size and resilience is complex and multifaceted, especially in the tourism sector. Companies in this industry are often small (Srhoj et al., 2024; Tanner et al., 2022), a characteristic that makes them more vulnerable in periods of financial distress, since they are more susceptible to going out of business and often face greater obstacles to access external funding and higher costs of capital (Eggers, 2020; Opler and Titman, 1994; Vivel-Búa et al., 2019). Nonetheless, firm size can also be a liability, since it creates diseconomies of scale, reduced profitability and added probability of failure (Sehgal et al., 2021; Serrasqueiro and Nunes, 2008; Yazdanfar and Öhman, 2020). Size was also found to be negatively associated with recovery speed, meaning that bigger firms face a slower recovery process after disruption (Nguyen et al., 2022). Our findings lean towards the disadvantages of size in this industry, as we find that larger firms are less likely to be resilient. This may be because, although they possess greater resources to handle challenges, they also have deeply rooted habits and procedures that result in more rigid, less adaptable structures, lacking the flexibility required to adapt. Smaller firms, by contrast, often display higher degrees of operational flexibility and adapt more swiftly to changing market conditions (Biggs, 2011; Eggers, 2020; Nguyen et al., 2022; Orchiston, 2013; Tanner et al., 2022). Additionally, their asset-lighter structures allow them to adapt more efficiently (Vivel-Búa et al., 2019), which is likely the core of their resilience.

A few results, however, contradict our initial expectations. For instance, we identify a negative relationship between profitability and resilience, something that is counterintuitive. Similar findings have, however, been reported by Song et al. (2021) in the restaurant industry, which suggest the existence of a complacency effect. According to this view, sustained growth and success in the tourism sector can lead to overconfidence and a reduction in strategic investments. To this point, prior to 2019, tourism consistently outpaced the global economy (UNWTO, 2021b, 2019), experiencing a decade of strong growth after the global financial crisis (Brouder, 2020). This prolonged success may have fostered overconfidence among industry managers, who perceived few imminent threats and thus became complacent (Burnett and Johnston, 2020). As a result, tourism firms may have neglected essential strategic investments and innovation, leaving them more vulnerable to crises. Consequently, when COVID-19 emerged, many of these companies were likely ill-prepared to navigate the unprecedented challenges it posed. Given this behavior, firms that were highly profitable before the pandemic may have experienced larger profitability gaps during the crisis, leading to greater vulnerabilities (Song et al., 2021).

This paper also shows that leverage positively impacts CR, something that is at odds with our initial expectations. A possible explanation is that key stakeholders may be more inclined to provide additional support to these firms, to prevent a complete loss of their initial investments (Andrade and Kaplan, 1998; Jiang et al., 2014). This result is also in line with the agency theory, which points several advantages to the use of debt, such as the tax shield, or the mitigation of agency costs, through the additional discipline and efficiency required to manage cash-flow and fulfill debt payments (Jensen, 1986). Finally, our results also indicate that capital intensity positively impacts CR. This finding, which is also at odds with the initial expectations, is, however, in line with the claim that companies with higher asset growth were more resilient during COVID-19 (Kaczmarek et al., 2021), since fixed assets represent a source of cash-flow in the long run. Similarly, Song et al. (2017) also find evidence that capital-intensive firms experience lower declines in stock value during uncertain times, when compared to their less capital-intensive counterparts.

3.6. Conclusion

This study investigates how different determinants influence the ability of tourism firms to withstand and recover from crises. Our contribution is twofold: first, we offer a comparative analysis of factors impacting the resilience of tourism firms in various countries, responding to the call of Lee et al. (2024). Second, we apply a company resilience index adapted from regional resilience literature, which is also a relevant contribution in its own right. Our findings support the RBV (Wernerfelt, 1984) and dynamic capabilities (Ambrosini and Bowman, 2009) in crisis contexts, by emphasizing the differentiating effect of certain firm-level resources on tourism firms' resilience. To the best of our knowledge, this is the first study to develop a sensitivity index as a measure of resilience within these theoretical frameworks.

The study also underscores the importance of human capital in enhancing CR, noting that reductions in human capital correlate with lower resilience, though further research is needed to fully understand this effect, given its potential to amplify the impact of other determinants (Núñez-Ríos et al., 2022). Additionally, we identify a negative impact of profitability on resilience, likely due to complacency following sustained success. Furthermore, the notably higher resilience of companies headquartered in Sweden warrants further investigation into potential best practices and government policies that could benefit firms elsewhere. This paper also highlights the role of monetary policy, observing that non-Eurosystem companies in the tourism sector show greater resilience in the aftermath of the COVID-19 pandemic, suggesting the need to consider regional economic variations in this type of study. These insights offer valuable guidance for stakeholders in developing strategies to strengthen resilience, particularly in tourism-dependent economies.

Data limitations restricted our analysis of CR in key competitor countries, such as Turkey. Additionally, essential variables like human capital proxies (e.g., education levels) and corporate social responsibility (CSR) practices were excluded due to the lack of reliable data. To mitigate this, our sample includes two alternative proxies for human capital. Yet, future research should incorporate these variables, along with additional managerial characteristics, human capital factors, CSR initiatives, and country-specific factors, to better understand resilience disparities across nations. Moreover, the absence of mandatory reporting for variables required to calculate the GVA has reduced the sample size, affecting data availability. Although these sampling constraints limit the generalizability of our findings, this study provides meaningful insights into CR determinants within the tourism sector.

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CHAPTER 4 – HOW PROFITABLE FIRMS FAIL: FIRM-LEVEL DETERMINANTS OF RESISTANCE AND RECOVERY (PAPER THREE)

Abstract

Why do some profitable firms fail while others thrive during crises? This study investigates the role of profitability in the resilience of tourism firms, focusing on the distinctions between the resistance and recovery phases and the contrast between profit-making and loss-making firms. Using a decomposed company resilience index adapted from the regional resilience literature and a comparative cross-country analysis, we find that profitability plays distinct roles across resilience stages. Moreover, resilience mechanisms differ significantly between profit-makers and loss-makers, emphasizing the dynamic, idiosyncratic and context-specific nature of resilience. Our results contribute to the resource-based view and dynamic capabilities perspective by demonstrating the impact of firm-level resources across crisis phases. This study expands our understanding of how firms can enhance their resilience, highlighting the importance of tailoring resilience-building strategies to firm-specific and context factors, and providing actionable insights for academics, policymakers, and managers.

Keywords: Covid-19; Crisis; Hospitality; Recovery; Resilience; Resistance; Profitability.

4.1. Introduction

The concept of company resilience (CR) is essential for understanding how businesses navigate crises, particularly in vulnerable industries like tourism (Chowdhury et al., 2019; Prayag et al., 2020). Accommodation firms, heavily reliant on mobility (Archanskaia et al., 2023), are particularly susceptible to external shocks that disrupt operations (Dimitrić et al., 2019; Dogru et al., 2023; Vivel-Búa et al., 2019). Consequently, COVID-19 responses, including lockdowns, social distancing, and travel restrictions, significantly affected their performance (Lee et al., 2024).

Despite growing interest in resilience, research often focuses on regional resilience, with limited attention to firm-level dynamics, particularly in accommodation firms. In their review, Hall et al. (2023) note that hospitality resilience receives less attention than tourism destinations, the predominant focus of resilience studies, emphasizing the need to investigate firm-specific factors in the aftermath of global disruptions. The COVID-19 pandemic led to a sharp decline in international flows and GDP (UNWTO, 2021a), exposing significant gaps in firms' ability to resist and recover from disruptions and a slower-than-anticipated recovery for the sector (UNWTO, 2024). Ultimately, as recovery is threatened by geopolitical tensions, inflation, and financial instability (International Monetary Fund, 2023), building resilience within tourism firms is critical, especially as evidence shows that many do not possess the resilience to endure such disruptions (Wieczorek-Kosmala, 2022). However, CR is not only vital for firm survival, but also for developing and sustaining competitive advantage (Vogus and Sutcliffe, 2007), a conclusion that emphasizes the need for resilience-building strategies even during stable periods.

Profitability, often considered a financial health indicator (Jawed et al., 2021; Song et al., 2021), plays a key role in resilience (Ramelli and Wagner, 2020; Wieczorek-Kosmala, 2022). However, recent findings that profitability alone does not shield firms from disruptions (Archanskaia et al., 2023; Bughin, 2024) raise important questions about its role in shaping resilience and across the different stages of disruption. To address this gap, this study utilizes logistic regression models to explore the role of profitability in the resilience of accommodation firms, distinguishing between the resistance and recovery phases, and comparing the resilience mechanisms of profit-makers and loss-makers. Using a decomposed resilience index adapted from the regional resilience literature, we find that profitability plays distinct roles across resilience stages, as do most CR determinants. Furthermore, the results show that profitable firms are not immune to the shock, supporting previous claims that profitability alone does not guarantee resilience. Ultimately, we uncover factors that facilitate the recovery of loss-makers, demonstrating that even constrained firms can enhance their resilience through strategic asset management.

This study makes important theoretical contributions to the understanding of resilience in tourism firms. First, by adapting a regional resilience index to firms in a crisis setting, we provide a cross-country analysis of firm-level factors influencing resilience. Second, we address the call for further research into the role played by firm-level characteristics in CR (Lee et al., 2024). Third, our findings advance the resource-based view (RBV) and the dynamic capabilities perspective (Ambrosini and Bowman, 2009; Barney, 1991) in crisis contexts, by demonstrating how firm-level characteristics influence resilience in the resistance and recovery phases, adding to the body of research about the dynamic nature of resilience. Fifth, our findings reveal heterogeneity in resilience mechanisms between profit-makers and loss-makers, uncovering important differences across operationally similar firms. Lastly, the proposition of a sensitivity index as a resilience metric within this theoretical framework makes a significant contribution on its own.

This study offers valuable insights for managers and policymakers. The resilience index represents a practical self-assessment tool for tourism firms, enabling managers to identify the most resilient peers and best practices. Furthermore, the dual role of profitability urges managers to remain alert in times of sustained profitability, avoiding complacency and overconfidence. Moreover, the heterogeneity of resilience mechanisms highlights the need for tailored resilience strategies, adapted to the idiosyncrasies of each firm. Finally, by addressing the gap in firm-level resilience research and offering tailored strategies for stakeholders, this study provides a valuable roadmap to improve the resilience of a vulnerable industry.

This paper is structured in the following manner: section 4.2 addresses the literature review, section 4.3 details the methodology, section 4.4 reports the results, followed by a discussion in section 4.5. Section 4.6 concludes.

4.2. Literature review

Resilience, initially defined in ecology by Holling (1973), describes the ability of systems to resist and recover from disruptions (Hall et al., 2023). It is a dynamic, context-dependent process, involving the interplay of resources, skills and strategies that evolve throughout different stages of disruption (Amaral and Da Rocha, 2023; Chen et al., 2022; Hoang et al., 2021; Jawed et al., 2021; Liu et al., 2024). In regional resilience literature, systems are considered more resilient if they can resist shocks or rapidly recover from them (Martin, 2012). Resistance and recovery are, therefore, the main stages of resilience. In a comprehensive review of the hospitality and tourism resilience literature, Hall et al.

(2023) identify both as fundamental attributes of resilience frameworks. In this context, resistance, associated with the notion of robustness in complex adaptive systems theory (Martin and Sunley, 2015), represents the degree of vulnerability and sensitivity to shocks (Martin, 2012; Walker et al., 2004) and the ability to withstand and react to maintain stability (Martin and Sunley, 2015; Soroka et al., 2020). Aligned with the notion of persistence (Folke et al., 2010), this is also referred to as the absorption phase (Wieczorek-Kosmala, 2022). From an engineering perspective, recovery refers to the ability and speed of the return to the previous state (Folke, 2006; Holling, 1973). Furthermore, from a complex adaptive systems perspective, recovery also includes the development of new stability domains (Brown et al., 2017), encompassing the adaptability and transformability dimensions of resilience (Walker et al., 2004).

4.2.1. Profitability and resilience

Profitability ratios provide important insights into a firm's survival ability (Esteve-Pérez and Mañez-Castillejo, 2008; Gémar et al., 2019) and efficiency (Kaczmarek et al., 2021). Profitability is also one of the best predictors for insolvency and bankruptcy risk (Fernández-Gámez et al., 2016; Zainol Abidin et al., 2021), with evidence linking low profitability to increased likelihood of failure (Gu and Gao, 2000; Vivel-Búa et al., 2019). Thus, profitability is likely to influence the resilience of companies (Verfürth et al., 2022).

There is some evidence to support such assertion for tourism-related firms. For instance, looking at tourism operators in the Southern Alps, Orchiston (2013) finds resilience tools more common among higher-income businesses, suggesting that income is key for resilience-building investments. More recently, in a study of the cash-driven resilience of tourism firms in emerging markets, Wieczorek-Kosmala (2022) finds that resilient firms are characterized by statistically significantly higher profitability levels, due to their inherent capacity to generate internal funds. It follows that, besides being a sign of financial stability (Jawed et al., 2021; Ramelli and Wagner, 2020; Song et al., 2021) and lower probability of financial distress (Fernández-Gámez et al., 2016; Situm, 2023), profitability can also lead to higher levels of liquidity (Wieczorek-Kosmala, 2022). Thus, profitability should enable flexibility, which, in turn, helps firms endure crises (Ramelli and Wagner, 2020). In contrast, its absence can reduce the capacity to resist disruption (Verfürth et al., 2022). As such, these previous studies tend to suggest that profitability is as a sign of capacity to generate internal funds and obtain additional funding. Thus, profitable firms must be better equipped to navigate through crises (Wieczorek-Kosmala, 2022).

However, there is also evidence that suggests otherwise. In a study of the restaurant industry, Song et al. (2021) find that higher profitability amplifies the negative effects of COVID-19 on stock returns. In the accommodation sector, Archanskaia et al. (2023) illustrate that prior profitability is not a definitive indicator of resilience, as 38.00% of the firms they analyzed, despite being profitable before COVID-19, faced insolvency by the end of 2021. The authors show that most of these firms became insolvent due to the equity depletion resulting from the severe profitability shocks caused by COVID-19, which is consistent with previous assertions of Wieczorek-Kosmala (2022) that the persistence of the reduction in cash-flows caused by COVID-19 may gradually erode this advantage. These are just two examples that stress that past profitability is an incomplete indicator of resilience, especially during crises (Bughin, 2024). Given the divergent perspectives presented in the existing literature, this paper hypothesizes that profitability influences the likelihood of resilience, although the direction of this relationship remains unspecified. Accordingly, our first research hypothesis is as follows:

H1: Profitability impacts the likelihood of CR.

4.2.2. Resistance and recovery: The different roles of profitability

A possible justification for the conflicting results regarding profitability is the dynamic nature of resilience (Amaral and Da Rocha, 2023; Brown et al., 2017; Wided, 2022). Organizations react to uncertainty through a range of different strategies (Lee et al., 2013). Tourism firms, specifically, adopt different resilience approaches, which reflect the different stages of sensemaking and adaptation they experience (Chen et al., 2022). Furthermore, resilience responses also evolve through the stages of a crisis (Chen et al., 2022; Hoang et al., 2021; Jawed et al., 2021). The study by Amaral and Da Rocha (2023) further supports these conclusions, by demonstrating that small family-firms in the tourism industry use different emotions, strategies and capabilities as the pandemic evolves.

While the impact of firm-level characteristics in the resilience of firms during a crisis has been previously explored in the hospitality literature, their influence across different stages of resilience remains unexplored. For instance, previous studies have shown that profitability can influence resistance by mitigating financial vulnerabilities through liquidity and slack resources (Tognazzo et al., 2016; Wieczorek-Kosmala, 2022). For small-sized firms, such as those in tourism, stable pre-crisis profitability levels can provide a critical advantage during the resistance phase, enabling them to generate profits even under constrained conditions (Nguyet, 2023). However, in the presence of additional restrictions – such as lockdowns – profitability alone does not ensure resistance, since firms face additional challenges in maintaining their profitability levels under such circumstances. As a result, many of the firms that were profitable before COVID-19 found themselves at risk of insolvency by the end of 2021 (Archanskaia et al., 2023). Furthermore, the profitability buffer may be even lower, or even negative, if the firm becomes complacent about its sustained profitability. In fact, Burnett and Johnston (2020) document the occurrence of complacency in the tourism industry, due to stable times, past recoveries and no foreseeable threats. Since overconfidence can lead CEOs to higher risk decisions (Malmendier and Tate, 2005), highly profitable firms often overlook strategic investment, falling for the success trap (Levinthal and March, 1993), which leads to increased vulnerability during the resistance phase. In this sense, Bughin (2024) highlights the need for these firms to monitor their resilience levels and avoid complacency, which may leave them largely exposed to risks.

Empirical evidence for the recovery phase is also available. For instance, studies show that profitability enables the allocation of resources to adaptation and growth efforts (Cheong and Hoang, 2021), as a stable financial foundation that supports the recovery process and ensures post-crisis performance (Rasoulian et al., 2023). More recently, Bughin (2024) found profitability to be critical in the recovery phase, when resilient firms demonstrate stronger profit persistence than non-resilient firms, whose profit continues to deteriorate. However, a recent study by Lee et al. (2024) suggests that the effect of profitability may be contingent on the type of disruption and restrictions in place. The results of this study reveal that profitability impacts the resilience of hospitality firms in different ways during the 2008 financial crisis, when compared to the COVID-19 pandemic, likely due to the unique characteristics of each disruption. Extending this perspective, it is plausible that such differences also occur across distinct stages of the same crisis, suggesting that profitability may impact the resistance and recovery phases in different ways. Drawing on insights from both resilience and firm survival literature, this paper proposes its second research hypothesis:

H2: The effects of profitability on CR differ between the resistance phase and the recovery phase.

Furthermore, there is evidence to support the conclusion that, more than a dynamic process, CR is also highly idiosyncratic, triggering different resources, skills and strategies, even among very similar companies. A good example of this is the work of Pongtanalert and Assarut (2022), who detail the mechanisms that small accommodation firms used to survive the shock induced by COVID-19 by activating two types of social capital: bonding and bridging social capital. In this case, similar accommodation businesses achieved similar resilience outcomes by employing different strategies. Additionally, findings that high-performing firms are twice as capable of maintaining their profitability levels under disruptive circumstances (Bughin, 2024) suggest that there may be differing resilience responses among profit-makers and loss-makers. Bughin (2024) highlights the role of pre-crisis performance in distinguishing winners from losers, noting that resilient firms eventually saw their profits recover, while non-resilient firms experience continued negative impacts on their profitability, leading to additional deterioration.

Drawing on these findings, we propose that the effect of profitability may also vary according to the type of firm, since loss-makers often face additional challenges in generating cash-flow and securing the funds to sustain their operations. This leads us to our third and final research hypothesis:

H3: The effects of profitability on CR differ between profit-makers and loss-makers.

4.3. Methodology

4.3.1. Data

This study identifies companies operating under the primary SIC code 7011 (accommodation services) from the Orbis database, covering the period from 2019 to 2022. The sample is restricted to firms headquartered in Belgium, Bulgaria, Croatia, Poland, Portugal, Romania, Serbia, Slovenia, Spain, and Sweden, where companies report the necessary data for constructing the CR index. For data reliability, observations with null or missing values for the variables of interest are excluded, leading to a working sample of 6.038 companies.

4.3.2. The model

A binary logistic regression model is applied to investigate the resilience of the sample to COVID-19 and answer the first research question, exploring whether profitability influences firm resilience in the accommodation sector. Equation (1) presents the general model:

$$ln\left(\frac{P_{(RESILIENT_i)}}{1-P_{(RESILIENT_i)}}\right) = \beta_1 + \beta_2 ROA_i + \beta_3 CAP_i + \beta_4 LEV_i + \beta_5 LIQ_i + \beta_6 SIZE_i + \beta_7 REDHC_i + \beta_8 REDSAL_i + \beta_9 NEGCP_i + \beta_{10} COUNTRY_i + \varepsilon_i \quad (1)$$

The independent variables in Equation (1) are explained in section 3.2.1. As per the dependent variable, it is computed as per Iacobucci and Perugini (2021). Specifically, a resilience index is computed for each firm, as defined in Equation (2):

$$R_i = \frac{\left(\frac{GVA_{i,t+1}}{GVA_{i,t-1}}\right)}{\left(\frac{GVA_{c,t+1}}{GVA_{c,t-1}}\right)} \quad (2)$$

Here, $GVA_{i,t+1}$ ($GVA_{c,t+1}$) represents the gross value added (GVA) of firm i (country c) at the end of the analysis period (i.e., 2022), while $GVA_{i,t-1}$ ($GVA_{c,t-1}$) represents the peak year (i.e., 2019). As shown, the index is constructed in relative terms, comparing a firm's resilience level to the average of its industry within the same country. Consequently, values for R_i above 1 represent higher resilience levels compared to national averages.

To compute the two alternative models, this index is decomposed into resistance and recovery indices, as per Equation (3).

$$R_i = \frac{\left(\frac{GVA_{i,t+1}}{GVA_{i,t-1}}\right)}{\left(\frac{GVA_{c,t+1}}{GVA_{c,t-1}}\right)} = \frac{\left(\frac{GVA_{i,t}}{GVA_{i,t-1}}\right)}{\left(\frac{GVA_{c,t}}{GVA_{c,t-1}}\right)} \times \frac{\left(\frac{GVA_{i,t+1}}{GVA_{i,t}}\right)}{\left(\frac{GVA_{c,t+1}}{GVA_{c,t}}\right)} \tag{3}$$

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Subsequently, we transform these indices into binary dependent variables, distinguishing firms according to their resistance and recovery capacities. Specifically, a resistance (recovery) index above 1 indicates that the firm displays higher resistance (recovery) compared to its country peers.

This allows us to model the likelihood of resistance (Equations 4) and the likelihood of recovery (Equation 5), to answer the second research question, examining whether profitability plays distinct roles in the two stages of resilience.

$$ln\left(\frac{P_{(RESIST_i)}}{1-P_{(RESIST_i)}}\right) = \beta_1 + \beta_2 ROA_i + \beta_3 CAP_i + \beta_4 LEV_i + \beta_5 LIQ_i + \beta_6 SIZE_i + \beta_7 REDHC_i + \beta_8 REDSAL_i + \beta_9 NEGCP_i + \beta_{10} COUNTRY_i + \varepsilon_i \tag{4}$$

$$ln\left(\frac{P_{(RECOVER_i)}}{1-P_{(RECOVER_i)}}\right) = \beta_1 + \beta_2 ROA_i + \beta_3 CAP_i + \beta_4 LEV_i + \beta_5 LIQ_i + \beta_6 SIZE_i + \beta_7 REDHC_i + \beta_8 REDSAL_i + \beta_9 NEGCP_i + \beta_{10} COUNTRY_i + \varepsilon_i \tag{5}$$

Finally, two additional specifications are employed for each one of the three models. These alternative specifications divide the initial sample between profit-makers and loss-makers, whether firms display positive or negative profitability levels, respectively. These specifications respond to the third research question, examining the differences in the determinants and stages of resilience between these important subsamples.

4.3.2.1. Independent variables

This paper investigates the role of profitability in the resilience process, specifically in the resistance and recovery stages. Therefore, the independent variable is profitability, represented by the return on assets (ROA), defined as net income divided by total assets (Kaczmarek et al., 2021; Lee et al., 2024; Situm, 2023; Song et al., 2021; Wieczorek-Kosmala, 2022).

Control variables include five financial characteristics, two human capital proxies and location. Financial controls are capital intensity (CAP), as the ratio of total fixed assets to total assets (Jawed et al., 2021; Lee et al., 2024); leverage (LEV), as the ratio of the total debt to total assets (Lee et al., 2024; Situm, 2023; Song et al., 2021; Wieczorek-Kosmala, 2022); liquidity (LIQ), as the weight of current assets to current debt (Lee et al., 2024; Wieczorek-Kosmala, 2022); firm size (SIZE), as the natural logarithm of total assets (Dimitrić et al., 2019; Hoang et al., 2021; Lee et al., 2024; Nguyen et al., 2022; Song et al., 2021); and solvency issues (NEGCP), a dummy variable that takes the value of 1 if the firm has negative shareholder equity in 2019 and zero otherwise (Dimitrić et al., 2019; Schwaiger et al., 2022; Situm, 2023). Human capital reductions are proxied through two dummy variables: REDHC and REDSAL (Biggs et al., 2012; Chowdhury et al., 2019; Vithana et al., 2023). REDHC takes the value of 1 if there was a reduction in the number of employees in 2020 and zero otherwise; REDSAL takes the value of 1 if there was a reduction in average staff expenditure per employee in 2020 and zero otherwise. Finally, location is a categorical variable represented by country ISO 3166-1 alpha-2 codes (Dimitrić et al., 2019; Kaczmarek et al., 2021; Liu et al., 2024; Situm, 2023).

4.3.1. Diagnostic tests

In this study, we conduct diagnostic tests to evaluate the models' performance and goodness-of-fit. Multicollinearity is assessed through multiple diagnostics, including the correlation matrix, variance inflation factor (VIF) values, eigenvalues, condition indices and linear regression models between independent variables (Thompson et al., 2017). Additionally, the dependent variable is regressed individually on each independent variable to detect any sign, significance, or magnitude changes that could, nevertheless, indicate the presence of multicollinearity within our models.

4.4. Results

4.4.1. Sample characterization

Table 4.1 reports the distribution of firms across countries. As can be seen, firms headquartered in Spain account for nearly half of the sample (44.67%), while Belgium is the country with less representation in the sample, with only 77 observations.

Table 4.1 – Sample characterization

Country	Number of companies	% Resilient	% Profit-makers
BE	77	50.65	68.83
BG	109	46.79	79.82
ES	2697	48.65	83.46
HR	318	41.82	77.36
PL	385	52.47	73.25
PT	928	37.50	80.17
RO	581	58.18	92.08
RS	147	46.26	80.95
SE	672	73.21	69.94
SI	124	28.23	87.90
Total	**6038**	**49.98**	**81.09**

Source: Own elaboration

Table 4.1 shows that 73.21% of Swedish companies are categorized as resilient, as opposed to 28.23% in Slovenia. Notably, nearly half of the firms in the sample are categorized as resilient, indicating a balanced distribution. This, combined with the relative nature of the resilience index, ensures the robustness of this metric, which mitigates the impact of outliers, such as large firms with substantially higher GVAs compared to their counterparts.

The last column of Table 4.1 reveals that 18.91% of the companies in our sample were already unprofitable pre-COVID-19. This proportion is more concerning in Belgium, where 31.17% of the firms exhibit negative pre-crisis profitability, while Romania is the country where the highest percentage of companies operate with positive profitability levels.

4.4.2. Descriptive statistics – independent variables

Descriptive statistics for the independent variables are presented in Table 4.2, covering the total sample and dividing the sample into profit-makers and loss-makers.

Table 4.2 – Descriptive statistics – independent variables computed for the year 2019

Variable	Sample	Mean	Std. Dev.	Minimum	Maximum	Median	Mann–Withney Test Chi-Square Test
	Total	53.25	37.14	0.10	559.68	51.01	
LEV (%)	**Loss-Makers**	71.61	52.70	0.10	559.68	70.07	<0.0001
	Profit-Makers	48.96	30.93	0.14	326.99	47.58	
	Total	55.95	31.93	0	99.95	62.31	
CAP (%)	**Loss-Makers**	60.13	33.30	0	99.86	70.79	<0.0001
	Profit-Makers	54.97	31.52	0	99.95	60.71	
	Total	6.02	16.42	-174.97	149.36	3.57	
ROA (%)	**Loss Makers**	-9.40	19.39	-174.97	0	-3.03	<0.0001
	Profit Makers	9.62	13.28	0	149.36	5.29	
	Total	340.54	1116.19	0.08	21675.22	118.96	
LIQ (%)	**Loss Makers**	295.58	1158.78	0.11	16881.63	76.14	<0.0001
	Profit Makers	351.03	1105.88	0.08	21675.22	131.58	
	Total	14.54	1.83	6.05	22.56	14.72	
SIZE	**Loss Makers**	14.36	1.79	7.64	19.17	14.64	0.0002
	Profit Makers	14.58	1.83	6.05	22.56	14.74	
	Total	0.75	0.43	0	1	1	
REDHC	**Loss Makers**	0.74	0.44	0	1	1	0.2098
	Profit Makers	0.76	0.43	0	1	1	
	Total	0.64	0.48	0	1	1	
REDSAL	**Loss Makers**	0.64	0.48	0	1	1	0.7254
	Profit Makers	0.65	0.48	0	1	1	
	Total	0.05	0.21	0	1	0	
NEGCP	**Loss Makers**	0.15	0.36	0	1	0	<0.0001
	Profit Makers	0.02	0.14	0	1	0	

Source: Own elaboration

As can be seen, on average, debt accounts for 53.25% of total assets of the sampled firms and fixed assets represent an average of 55.95% of total assets. Profitability ranges from -174.97% to 149.36%, with an average of 6.02%. The average liquidity is 3.41 euros of current assets per euro of current debt, indicating a good coverage of short-term debt.

SIZE has an average of 14.54, with a standard deviation of 1.83, ranging from 6.05 to 22.56. Workforce reductions occurred in 75.00% of firms (REDHC) and 64.00% reduced their average staff expenditures in 2020 (REDSAL). Finally, only 5.00% of the companies operated with negative book equity (NEGCP).

Table 4.2 additionally provides separate statistics for profit-makers and loss-makers. Unreported results from Shapiro-Wilk and Kolmogorov–Smirnov indicate a non-normal distribution of the data. Thus, the Mann–Whitney non-parametric test and the Chi-Square test of independence are employed to assess whether firm-level characteristics differ significantly between these two groups. As can be seen, there are statistically significant differences at the 5% level between profit-makers and loss-makers for all the variables, except human capital reductions. Specifically, profit-makers seem to operate with lower leverage and capital intensity, as well as higher liquidity. The proportion of profit-makers with solvency issues is also significantly lower when compared with that of loss-makers.

Table 4.3 reports Spearman's rank correlation coefficients among variables, computed for the year of 2019. The analysis shows that leverage is positively correlated with resilience, meaning that more levered firms are more likely to be resilient. In contrast, profitability and liquidity are negatively associated with resilience and resistance. Importantly, these variables are, however, positively correlated with recovery, suggesting that they play different roles across the two stages. The same pattern is observed for firm size and human capital reductions. Surprisingly, a reduction in the number of employees is associated with a higher recovery capacity, suggesting benefits from leaner structures. Finally, solvency issues positively correlate with resilience, but negatively correlate with resistance, indicating that financially vulnerable firms may still display resilience under certain conditions, if they resist the initial impact of the shock.

Table 4.3 – Correlation matrix

	RESILIENT	RESIST	RECOVER	LEV	CAP	ROA	LIQ	SIZE	REDHC	REDSAL	NEGCP
RESILIENT	1										
RESIST	0.172 ***	1									
RECOVER	0.100 ***	-0.411 ***	1								
LEV	0.100 ***	0.015	-0.010	1							
CAP	0.005	0.071 ***	0.030 **	0.008	1						
ROA	-0.136 ***	-0.073 ***	0.046 ***	-0.243 ***	-0.278 ***	1					
LIQ	-0.030 **	-0.025 **	0.038 ***	-0.468 ***	-0.349 ***	0.246 ***	1				
SIZE	-0.095 ***	-0.073 ***	0.041 ***	-0.157 ***	0.193 ***	-0.078 ***	0.003	1			
REDHC	-0.101 ***	-0.147 ***	0.045 ***	-0.036 ***	-0.011	0.038 ***	-0.022 *	0.099 ***	1		
REDSAL	-0.068 ***	-0.073 ***	0.018	-0.030 **	0.024 *	0.005	0.015	0.011	-0.147 ***	1	
NEGCP	0.034 ***	-0.037 ***	-0.016	0.338 ***	-0.023 *	-0.200 ***	-0.137 ***	-0.109 ***	-0.001	0.019	1

Note: *, **, and * are statistically significant at the 1%, 5%, and 10% level, respectively. Source: Own elaboration**

4.4.3. Regression Results

4.4.3.1. Diagnostic tests

Table 4.4 reports the diagnostic test results for the three specifications of each model.

Table 4.4 – Diagnostic test results

Model	Hosmer-Lemeshow	Area under the ROC curve	VIF values	Highest condition index
RESILIENCE	**0.7818**	**0.665**	**<5**	**10.30728**
Loss-makers	0.1650	0.638	<5	9.34681
Profit-makers	0.8660	0.667	<5	11.13674
RESISTANCE	**0.0258**	**0.684**	**<5**	**10.30728**
Loss-makers	0.0963	0.662	<5	9.34681
Profit-makers	0.0527	0.697	<5	11.13674
RECOVERY	**0.0840**	**0.629**	**<5**	**10.30728**
Loss-makers	0.9374	0.650	<5	9.34681
Profit-makers	0.6374	0.633	<5	11.13674

Source: Own elaboration

As shown, the Hosmer-Lemeshow test indicates good model fits, except for the full sample resistance model. This result suggests that such specification can be improved by including omitted variables, which is confirmed by the model fits of the two alternative specifications. In this case, including pre-crisis profitability distinctions in the analysis significantly enhanced the model fit, improving its calibration.

Table 4.4 also reports the area under the Receiver Operating Characteristic (ROC) curve for each model specification. The areas range from 63.30% to 69.70%, indicating acceptable discrimination (Hosmer et al., 2013). Notably, the profit-makers resistance model exhibits the highest discriminatory power, with an accuracy of 69.70%.

The correlation matrix, reported in Table 4.3, reveals no evidence of strong and statistically significant correlation between variables (Allison, 1999), since all the correlation coefficients fall below the commonly accepted thresholds (Midi et al., 2010). All the VIF values are close to 1 and below the threshold of 2.50 (Allison, 1999; Midi et al., 2010), showing no sign of multicollinearity, which is confirmed by the condition indices.

4.4.3.2. Estimation results: Resilience, resistance and recovery

Table 4.5 presents the results of estimating the three models. As can be seen, in the resilience model, the estimated coefficient for leverage, capital intensity, profitability, size, human capital reductions and location are all statistically significant at conventional levels. Conversely, there is no evidence to support that liquidity and solvency issues significantly impact firm resilience when the other explanatory factors are accounted for.

Table 4.5 – Regression results: Resilience, resistance and recovery models

	RESILIENCE	RESISTANCE	RECOVERY
C	3.206***	3.948***	-3.349***
LEV	0.264***	-0.213**	0.179*
CAP	0.250***	0.699***	0.038
ROA	-1.836***	-1.209***	0.404*
LIQ	0.000	-0.004	0.000
SIZE	-0.124***	-0.142***	0.117***
REDHC	-0.587***	-0.751***	0.224***
REDSAL	-0.249***	-0.310***	0.187***
NEGCP	-0.139	-0.494***	-0.208
COUNTRY – BE	-1.383***	-1.406***	0.860***
COUNTRY – BG	-0.948***	-0.687***	0.402*
COUNTRY – ES	-0.908***	-1.136***	-0.006
COUNTRY – HR	-1.923***	-1.786***	0.649***
COUNTRY – PL	-0.882***	0.292*	-2.474***
COUNTRY – PT	-1.481***	-0.691***	-0.135
COUNTRY – RO	-0.564***	-0.704***	0.820***
COUNTRY – RS	-1.432***	-0.536**	-0.081
COUNTRY – SI	-2.234***	-2.504***	0.683***

Notes: *, **, and * are statistically significant at the 1%, 5%, and 10% level, respectively. Reference category for COUNTRY is Sweden. Source: Own elaboration**

Importantly, Table 4.5 shows that *higher* profitability is associated with *lower* probability of resilience. While this finding may seem paradoxical, similar results have been reported by Song et al. (2021) in the restaurant industry and may suggest the existence of a complacency effect.

Looking at the results for the resistance and recovery models, we conclude that most firm-level characteristics seem to play distinct roles across the different stages of resilience. The resistance stage is supported by a positive impact of capital intensity, while leverage, size, human capital reductions, solvency issues and location have negative and significant coefficients. As per the recovery model, the results evidence a positive and significant effect of leverage, size, human capital reductions and certain country dummies.

Furthermore, all the estimated coefficients for the country dummy variables are negative and statistically significant in the resilience and resistance models, indicating that companies operating in other countries are generally less likely to exhibit resilience compared to those based in Sweden, particularly in the resistance stage. Finally, the constant terms indicate that resistance is more likely than recovery. In fact, it seems that the probability of recovery is very reduced, when the effect of other firm characteristics is not considered.

Table 4.5 also highlights the role of profitability in the resistance and recovery models, indicating a negative association with the likelihood of resistance, but a positive association with the likelihood of recovery. Two key conclusions stem from these results. The first is that profitability does, indeed, impact the resilience of the sample firms. Second, and more importantly, such impact is not uniform across the stages of resilience. In fact, the empirical evidence collected in this paper clearly shows that profitability plays a dual role, acting as a vulnerability during the resistance stage, while serving as a critical enabler during the recovery stage.

This paper now turns to the results obtained with the two alternative specifications of each model, which we discuss in the following section.

4.4.3.3. Estimation results: Profit-makers versus loss-makers

Table 4.6 presents the results of estimating the resilience, resistance and recovery models with the two alternative specifications as each model is now estimated for the subsamples of profit-makers and loss-makers.

As reported in Table 4.6, the resilience of profit-makers is positively influenced by leverage, while negatively impacted by size, human capital reductions, solvency issues and location. These determinants generally align with the base model, with two exceptions. One is that asset structure does not affect the resilience of profit-makers. The second is the statistical significance of solvency issues, underscoring the role played by solvency in the resilience of these firms. Additionally, profit-makers are more impacted by leverage, profitability and size, but they experience fewer negative effects of human capital reductions, compared to the base model. Contrastingly, for loss-makers, resilience is only determined by human capital reductions, and location. A comparison with the base model reveals that loss-makers are more penalized for reducing human capital, but less affected by the negative effects of profitability. Importantly, these firms have lower baseline resilience levels compared to profit-makers, reflecting their weaker financial position. Furthermore, Table 4.6 Furthermore, Table 4.6 reveals that profitability negatively impacts the resilience of both profit-makers and loss-makers.

Table 4.6 – Regression results: Profit-makers and loss-makers

	RESILIENCE		**RESISTANCE**		**RECOVERY**	
	PROFIT MAKERS	**LOSS MAKERS**	**PROFIT MAKERS**	**LOSS MAKERS**	**PROFIT MAKERS**	**LOSS MAKERS**
C	3.780***	1.579**	4.933***	2.773***	-3.617***	-3.055***
LEV	0.380***	-0.061	-0.204*	-0.121	0.115	0.284
CAP	0.173	0.089	0.605***	0.415*	0.011	0.540**
ROA	-2.164***	-0.963**	-2.476***	0.137	0.756***	-0.476
LIQ	0.000	0.002	-0.003	-0.007	0.002	-0.008
SIZE	-0.158***	0.012	-0.185***	-0.064	0.126***	0.099*
REDHC	-0.528***	-0.805***	-0.743***	-0.762***	0.291***	-0.120
REDSAL	-0.233***	-0.353**	-0.288***	-0.397***	0.202***	0.087
NEGCP	-0.473**	0.325	-0.393*	-0.296	-0.196	-0.339
COUNTRY – BE	-1.608***	-0.752	-1.831***	-0.953*	0.991***	0.692
COUNTRY – BG	-1.070***	-0.738	-0.992***	0.009	0.382	0.627
COUNTRY – ES	-1.067***	-0.433**	-1.350***	-0.847***	0.099	-0.285
COUNTRY – HR	-2.266***	-0.924***	-2.213***	-1.232***	0.792***	0.397
COUNTRY – PL	-0.986***	-0.718**	0.425**	-0.115	-2.478***	-2.477***
COUNTRY – PT	-1.723***	-0.849***	-0.906***	-0.468*	-0.055	-0.253
COUNTRY – RO	-0.609***	-0.775**	-0.803***	-0.864**	0.871***	0.801**
COUNTRY – RS	-1.614***	-1.006**	-0.604**	-0.950**	-0.156	0.344
COUNTRY – SI	-2.338***	-1.988***	-2.834***	-1.665***	0.754***	0.736

Notes: *, **, and * are statistically significant at the 1%, 5%, and 10% level, respectively. Reference category for COUNTRY is Sweden. Source: Own elaboration**

Table 4.6 also reveals differences in the resistance phase. Profit-makers are positively influenced by capital intensity, while negatively influenced by leverage, human capital reductions, solvency issues and most country dummies. These results align with the base model. Country effects remain consistent, with Swedish firms maintaining their advantage in resistance, only surpassed by those in Poland. Profit-makers are more penalized by profitability and size, suggesting that their long-term success may leave them more vulnerable. In contrast, the resistance of loss-makers relies only on capital intensity, human capital reductions and location. The fact that the resistance of loss-makers is not influenced by their leverage, profitability, size or solvency issues suggests that these factors were already eroded pre-crisis, leaving them to rely solely on their assets, human capital and geographical context. Compared to profit-makers, loss-makers experience greater penalizations from reducing human capital and lower benefits of capital intensity. Notably, the results show that loss-makers are less likely to resist than profit-makers, a conclusion that is similar to that of the resilience models.

Turning to the role of profitability in the resistance stage, the results in Table 4.6 highlight a notable distinction between profit-makers and loss-makers. Profit-makers experience a significant negative effect of profitability on their resistance capacity, underscoring their heightened vulnerability during this phase. In contrast, loss-makers do not exhibit a significant relationship between profitability and resistance, suggesting that profitability is not a determining factor for their ability to withstand the initial shock.

Finally, we address the recovery models' results in Table 4.6. The recovery of profit-makers is positively influenced by size, human capital reductions and location. These results align with the base model, except for leverage, with stronger positive impacts across all variables. In contrast, the recovery of loss-makers is only supported by capital intensity and size, suggesting that unprofitable firms with higher fixed asset levels may benefit from additional stability and operational continuity during recovery. Unlike the base model, the recovery of these firms is not impacted by leverage or profitability.

Focusing on the role of profitability in the recovery stage, the results once again highlight a clear divergence between profit-makers and loss-makers. For profit-makers, profitability exerts a positive and significant influence on their recovery capacity. In contrast, loss-makers do not experience a significant effect of profitability on recovery, suggesting that their recovery depends more on how this variable evolves during the disruption rather than their pre-crisis profitability.

4.4.3.4. Robustness test results

Several robustness tests are conducted using alternative measures of resilience, size, and profitability. In particular, for an alternative measure of resilience, we benchmark each firm to the sample average, instead of country average. Furthermore, since the hotel industry often operates under franchising and management contracts, this paper computes the logarithm of revenue as an alternative measure of size (Lee and Xiao, 2011). Finally, two alternative measures for profitability are tested, which consist of computing ROA from EBIT and EBITDA. Results from these robustness tests are consistent with those reported above, with consistent conclusions regarding the role of profitability as well as other firm-level characteristics across the two stages of resilience. These are not reported here to save space but are available upon request.

4.5. Discussion

This study enhances our understanding of the role of profitability in the resilience of tourism firms, uncovering important differences between the resistance and recovery phases, as well as between profit-makers and loss-makers.

First, we find that profitability negatively impacts the resilience of firms in the accommodation sector, which contradicts the RBV (Esteve-Pérez and Mañez-Castillejo, 2008). This negative impact is explained by the distinct roles of profitability across the stages of resilience. In fact, our results show that profitability is critical to recovery (Bughin, 2024; Cheong and Hoang, 2021), by ensuring the resources required to resume operations and grow (Delmar et al., 2013; Tognazzo et al., 2016; Wieczorek-Kosmala, 2022). However, our findings indicate that higher profitability increases vulnerabilities in resistance, a paradox that stems from two sources: one, from greater challenges in quickly reducing costs, since these firms already operate at high efficiency levels (Delmar et al., 2013; Esteve-Pérez and Mañez-Castillejo, 2008); two, from the sustained growth in tourism (Brouder, 2020; UNWTO, 2021b) that may foster overconfidence among industry managers, who perceive few imminent threats (Burnett and Johnston, 2020). This behavior may potentially lead to a lack of investment in preparedness and delayed strategic responses during crises, causing highly profitable firms to experience larger profitability gaps during the crisis (Song et al., 2021). In that sense, our results align with those of Archanskaia et al. (2023), Bughin (2024) and Song et al. (2021), who highlight that profitability is not a guarantee of resilience under disruptive conditions.

Second, our findings highlight the distinct roles played by profitability across the resistance and recovery stages. Notably, our results show that this conclusion extends to most of the firm-level characteristics. For example, the results suggest that higher leverage reduces resistance, something previously observed by Ramelli and Wagner

(2020), by reducing the available cash-flow (Dimitrić et al., 2019; Verfürth et al., 2022) and operating performance (González, 2013; Opler and Titman, 1994). After this, the effect of financial leverage amplifies the recovery, by driving operating efficiency (González, 2013), which is consistent with recent findings that higher leverage increases firm value in the hotel industry (Chen et al., 2024), supporting the trade-off and agency theories of capital structure (Jensen, 1986; Jensen and Meckling, 1976). Similarly, while profitability and scale increase challenges in quickly downsizing and reducing costs (Nguyen et al., 2022; Song et al., 2021), they also facilitate the recovery, through advantages in obtaining the resources required at this stage (Situm, 2023; Tascón et al., 2023; Wieczorek-Kosmala, 2022).

Third, our results reveal distinct resilience patterns between profit-makers and loss-makers. Profit-makers benefit from stronger financial positions, demonstrating higher baseline likelihoods of resilience and resistance. However, if overestimated, this financial strength can become a vulnerability, as evidenced by the results of the resistance model. Notably, solvency issues emerge as an additional determinant for these firms, emphasizing that profitable firms must remain vigilant to maintain their financial health during crises. It follows that profitability alone is not a guarantee of resilience for profit-makers; disruptions may temporarily reduce their profitability (Lee et al., 2024), leading to solvency issues that hinder their ability to maintain and secure their operations (Dimitrić et al., 2019; Mselmi et al., 2017).

Conversely, for companies that were already unprofitable before the crisis, resilience depends on their profitability, ability to maintain human capital, and country of headquarters. In fact, our results show that the resistance of loss-makers is not influenced by typical resilience determinants, likely due to pre-COVID-19 constraints. During recovery, these firms rely mainly on their asset structures, suggesting that unprofitable companies can still have a chance of recovery if they have good asset structures that increase their ability to secure funding (Tascón et al., 2023). This result aligns with previous findings that capital-intensive companies experience smaller declines in stock valuation during uncertainty than their less capital-intensive counterparts (Song et al., 2017) and that firms with stronger asset growth were more resilient during COVID-19 (Kaczmarek et al., 2021), since fixed assets provide a long-term cash flow source.

Importantly, human capital reductions display the same pattern between profit-makers and loss-makers across the resilience and resistance models, confirming previous assertions that CR is heavily dependent on the critical role of employees (Biggs et al., 2012; Pongtanalert and Assarut, 2022; Prayag et al., 2020; Schwaiger et al., 2022). For both types of firms, reductions in human capital negatively affect their resistance capacity. In contrast, the recovery of profit-makers benefits from human capital reductions, likely due to the existence of efficiency gains, whereas loss-makers do not experience significant effects.

Furthermore, our results add to the body of evidence that resilience is context-dependent (Amaral and Da Rocha, 2023; Biggs et al., 2012; Liu et al., 2024), revealing a competitive advantage of Sweden specific to the resistance phase, something that can be attributed to the particularities of this disruption. Given the heavy reliance on mobility in the hospitality industry (Archanskaia et al., 2023), Sweden's distinct COVID-19 approach – avoiding strict lockdowns and allowing citizens to travel freely (Andersson and Jonung, 2024) – provided tourism firms with an important advantage, allowing them to maintain their operations, as verified in the restaurant industry by Verfürth et al. (2022). These measures reduced the need for recovery, as evidenced in the recovery models.

In sum, these findings suggest that the resilience of tourism firms varies both according to the context and idiosyncrasies of tourism companies. Resilience is, thus, a multifaceted and dynamic process driven by an interaction of skills and resources, as well as external conditions that help firms make an effective use of their competitive advantages (Amaral and Da Rocha, 2023; Brown et al., 2017; Chen et al., 2022; Wided, 2022).

4.6. Conclusion

This paper explores the role of profitability in the resilience of accommodation firms, revealing significant differences between the resistance and recovery phases. We also find that the resilience of profit-makers and loss-makers is shaped differently, given the specificities of these two groups.

Our findings support our first research hypothesis, demonstrating that profitability does impact the likelihood of resilience of these firms. Importantly, this characteristic affects not only the overall resilience capacity of accommodation firms, but it also plays an important role in both their resistance and recovery capacities.

The impact across stages is, however, far from being uniform, which advances a response to our second research hypothesis. In fact, profitability emerges as both a potential strength and vulnerability. In particular, our findings show that, in the resistance stage, higher profitability is associated with reduced likelihood of resilience, possibly as a result of complacency or challenges in rapid cost-cutting. Conversely, in the recovery stage, profitability has a positive and significant impact, enabling the recovery of the sample firms.

Finally, the results also support our third research hypothesis, since this paper finds that the effects of profitability on CR differ significantly between profit- and loss-makers. While this characteristic adversely affects the likelihood of resilience for both types of firms, its impact differs across stages and types of companies. Notably, the findings indicate that, for profit-making firms, profitability constitutes a vulnerability during the resistance stage but serves as a crucial driver of recovery. In contrast, loss-making firms do not exhibit significant effects of profitability at any stage.

At a more general level, this paper also uncovers other critical differences between profit- and loss-makers. While profit-makers are more resilient, they face greater adaptation challenges in the resistance phase. In fact, the results show that their profitability does not grant them immunity to shocks, emphasizing the need to remain vigilant even when there are no foreseeable threats on the horizon, or risk falling for the success trap. As such, strategic and proactive resilience planning is crucial for these firms, whose managers must avoid complacent or overconfident decision-making and invest in preparedness strategies. In contrast, loss-makers must rely on structural and context factors, such as human capital, capital intensity and location to resist the initial shock. Yet, overall, the combined effect of profitability in the resilience of loss-making companies is positive, implying that they may have developed coping mechanisms that allow them to operate under such constraints. Our findings provide more ailing firms with a pathway to resilience, suggesting that even economically constrained companies can enhance their resilience by strategically leveraging their tangible assets and optimizing their use during crises.

Taken together, this paper's findings illustrate that resilience is highly idiosyncratic, even among firms with similar operational structures, highlighting the need for theoretical frameworks to consider such aspects. Furthermore, these results emphasize the dynamic and context-specific nature of resilience, providing evidence that it is not a static attribute but rather a dynamic process shaped by the interplay of resources and strategies across different stages (Amaral and Da Rocha, 2023; Brown et al., 2017; Chen et al., 2022; Wided, 2022). Such findings challenge traditional linear models of resilience and reinforce the need for dynamic approaches. Furthermore, the dual role of profitability across resilience phases advances our understanding of its interaction with crisis management theory. Finally, our conclusions also advance the RBV (Barney, 1991) and dynamic capabilities perspective (Ambrosini and Bowman, 2009) in crisis contexts. By investigating the differentiating effect of firm-level resources on the resilience, resistance and recovery capacity of tourism firms, we demonstrate that if a firm is not equipped with the right set of skills and resources, it is likely to face challenges to recover after facing a disruptive event. Being the first study to apply a sensitivity index as a decomposed resilience metric within these theoretical frameworks, this research not only advances theoretical understanding of CR, but also offers practical insights for managers and policymakers in the development of strategies to enhance the resilience of tourism companies.

This study is not without limitations. For example, data constraints prevent us from extending the analysis to key competing countries, such as Turkey. Moreover, certain variables, including human capital (e.g., education levels), could not be included due to the unavailability of reliable proxies in the database. We address this issue by using two alternative proxies of human capital. Future research should include more detailed metrics, such as employee turnover rates and training, as well as organizational policies, such as remote work practices. Moreover, while this study incorporates several resilience determinants, it could not account for factors such as innovation capacity and leadership. Mixed-methods approaches can integrate those variables and provide a more holistic understanding of resilience. Furthermore, future research should apply the proposed framework to other types of crises, such as economic recessions or geopolitical conflicts, to determine whether these findings apply to different types of disruptions. Lastly, the non-disclosure of the data required for GVA computations significantly influenced the final sample size. While this limitation affects the generalizability of the results, the conclusions offer important insights into the resilience mechanisms of accommodation firms.

Declaration of competing interest

None.

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CHAPTER 5 – GENERAL CONCLUSION

5.1. Conclusion

Investigating the resilience of tourism firms is crucial given the industry's inherent vulnerabilities (Espiner and Becken, 2014; Prayag et al., 2020). Developing resilience is as a strategy that allows for the mitigation of these weaknesses (Doğantan and Akoğlan Kozak, 2019), increased performance (Chowdhury et al., 2019; Marco-Lajara et al., 2022; Melián-Alzola et al., 2020; Prayag et al., 2018) and long-term sustainability of the industry (Sobaih et al., 2021).

In this sense, this thesis sets out to explore the concept of company resilience in the tourism industry, investigating its determinants, dynamics, and implications across different contexts, types of firms and phases of disruption. These objectives were pursued through three interrelated studies, which provide a comprehensive understanding of how tourism firms can withstand and recover from crises. This section synthesizes the main findings, discusses their theoretical and practical implications, and highlights limitations and opportunities for future research.

5.2. Summary of the main findings

The first study, a systematic literature review, reveals that research on company resilience in the tourism industry is limited. Furthermore, research on metrics and indicators of resilience is scarce (Liu et al., 2021; Yao and Fabbe-Costes, 2018), limiting practitioners' ability to improve the resilience of the companies they manage. Notwithstanding, from the integration of existing studies with research from other industries, this study provides a holistic perspective of the resilience-building process, its antecedents and consequences. In doing so, the study proposes a unified conceptual framework, outlining how company resilience serves as a protective mechanism against internal and external disturbances, reducing their impact in the initial stage and facilitating recovery afterward. Through the application of this conceptual framework, the first study describes company resilience in the tourism industry as a dynamic process, influenced by both firm-level and context factors, including human and social capital, planning and innovation. Furthermore, the results highlight the importance of adopting an interdisciplinary perspective of company resilience in future theory development.

To respond to the lack of metrics that are available for assessing company resilience, the second study proposes an adaptation of existing regional resilience sensitivity indexes. The empirical analysis conducted through the application of this index demonstrated the impact of certain firm-level characteristics on company resilience during COVID-19. In particular, the results show that reductions in human capital, larger firm size, and higher past profitability negatively influence resilience, while leverage and capital intensity positively impact it. These results contribute to the expanding body of evidence that highlights the critical role of human capital in the resilience of tourism firms, reinforcing earlier claims that company resilience is in great part developed through the essential contributions of employees (Biggs, 2011; Biggs et al., 2012; Njunguna et al., 2021; Pongtanalert and Assarut, 2022; Prayag et al., 2020; Schwaiger et al., 2022; Tanner et al., 2022). Country-specific variations, such as Sweden's distinct resilience propensity, and challenges associated with Eurozone membership were also uncovered, with evidence suggesting that this membership may provide firms with a buffering effect, while allowing them to operate under distress without incentives for higher efficiency, eventually translating into lower baseline resilience levels.

The negative effect of profitability uncovered by the second study warrants further investigation. This raises the question of whether this negative impact could be explained by profitability playing distinct roles across the two stages of resilience. In pursuit of this research question, the third study delves into a dynamic perspective of resilience, by decomposing the resilience index into the resistance and recovery phases. In doing so, the third study deepens our insight into the role of profitability on the resilience of tourism firms, through the identification of important distinctions between the resistance and recovery stages, as well as between profitable and non-profitable firms, further emphasizing the need for resilience strategies that are tailored to firm-specific and contextual specificities. Importantly, this study confirms the critical role of human capital identified in the first study and further corroborated in the second paper. In fact, the results of the third study indicate that human capital reductions display the same pattern between profit-makers and loss-makers across the resilience and resistance models, confirming the importance of this attribute. Furthermore, the results from the third study show that profitability enables the recovery stage, but it also increases vulnerabilities in the resistance phase. This paradox potentially arises from two distinct sources: cost-cutting challenges due to high operating efficiency (Delmar et al., 2013; Esteve-Pérez and Mañez-Castillejo, 2008) and complacent overconfidence due to sustained growth (Brouder, 2020; Burnett and Johnston, 2020; UNWTO, 2021). Additionally, the results indicate that this dual role is also true for most firm-level characteristics in the study, such as leverage and firm size. Finally, in relation to the different types of firms operating in this industry, findings from this study highlight different resilience mechanisms between profit-makers and loss-makers, with profit makers demonstrating higher propensity for resistance and overall resilience. However, the study also concludes that even unprofitable companies can recover when equipped with well-structured assets, providing important guidance for these firms in crisis management situations.

In sum, the findings from these studies contribute to a deeper understanding of the resilience mechanisms operating in the tourism industry. The first study establishes the foundational framework, while also integrating the determinants of resilience evidenced in the literature into a unified framework. This allows for the identification of the independent variables required to investigate the resilience of accommodation firms in the second and third studies, which further examine how such firm-level determinants perform across distinct countries, resilience phases and types of firms. Together, these studies illustrate that resilience is not a one-size-fits-all concept, but is influenced by a firm's resources, skills, strategies, and context. Thus, the complexity of the interplay between internal and external factors is emphasized, as well as the need for dynamic resilience responses. This dynamic perspective further informs managers and policymakers of which aspects to prioritize in each stage of disruption, while also highlighting the importance of strategic resource allocation and proactive planning. The theoretical and practical implications of these findings are discussed in the following sections.

5.3. Theoretical implications

This thesis extends the theoretical understanding of resilience in several ways. First, it proposes a common and unified framework of company resilience, including the characteristics, determinants and consequences of the resilience-building process.

Through this framework, this thesis develops the notion of company resilience as a complex and context-dependent dynamic process, calling for interdisciplinary theoretical frameworks that integrate perspectives from economics, sociology, strategy and environmental studies. Within this framework, this research identifies a link between company resilience and business performance – both financial and operational – contributing to the field of organizational performance theory. As a result, this study underscores the need to explore the impact of resilience as a driver of firm performance and the sustainability of the tourism sector.

Second, this thesis explores the resource-based view (Barney, 2001) and dynamic capabilities perspective (Ambrosini and Bowman, 2009) in crisis contexts, demonstrating how certain firm-level resources shape the resilience, resistance and recovery capacity of tourism firms across the distinct stages of disruption. To the best of our knowledge, this study is the first to propose a sensitivity index as a resilience metric within these theoretical frameworks, offering a novel perspective on the longitudinal aspects of resilience. Furthermore, the introduction of this decomposed company resilience index provides a novel tool for the development of company resilience theory, contributing to the development of theoretical models that consider the dynamic perspective of resilience. In doing so, this thesis challenges traditional static views and advocates for future theoretical models to integrate the longitudinal dimension of company resilience, acknowledging that different strategies may be effective at various phases. As a result, these new theoretical advances should also consider that companies can proactively adopt behaviors and build capabilities to enhance resilience (Lengnick-Hall et al., 2011), rather than viewing resilience as an inherent attribute.

Third, through a two-stage comparative analysis of the determinants of resilience across different countries, this study addresses one of the research gaps identified by Lee et al. (2024), advancing the theory on the determinants and context-dependent nature of company resilience. And lastly, this research introduces an adapted company resilience index, originally applied in the regional resilience literature, which is proposed as a measure of resilience and, when decomposed, as a metric of resistance and recovery. The introduction of a novel resilience metric has important practical implications for industry managers, which we discuss in detail in the next section.

5.4. Practical Implications

The findings from this thesis hold important implications for industry stakeholders and policymakers, offering valuable guidance for the development of strategies and policies that strengthen resilience, particularly in tourism-dependent economies.

For managers, this research emphasizes the need to prioritize investments in human capital and stakeholder relationships, promote organizational flexibility, and foster a culture of innovation. It is therefore advisable to implement training and skill development programs, while prioritizing staff retention and minimizing turnover. Giving the important role of collaboration and networking within stakeholders, managers must also promote the dynamics of industry associations to increase their relational capital. Maintaining financial health and avoiding complacency during periods of growth are also essential to building long-term resilience, encouraging managers to remain vigilant and avoid overconfidence during these periods, while exercising prudence in using layoffs or salary reductions as cost-cutting measures in periods where profitability is shortened. Moreover, the proposed resilience index provides a practical tool for benchmarking and self-assessment, enabling firms to identify vulnerabilities and adopt best practices to increase their resilience level.

Finally, our results inform important strategies for managers of loss-making firms, whose resilience mechanisms are very distinct from profitable firms. In fact, these managers are advised to leverage their human capital, capital intensity, and location factors such as government support. Importantly, to increase their chance of recovery, these managers should strategically manage their tangible assets and optimize their use during crises.

For policymakers, this research underscores the need for policies that focus on promoting human capital development, fostering collaboration within the tourism ecosystem, and encouraging innovation and digital transformation. During disruptions, tailored, context-sensitive support mechanisms are advisable, particularly those directed at the SMEs. Flexible policies that increase adaptability in crisis contexts can also significantly enhance resilience, such as layoff mechanisms or innovation incentives. In this sense, there must be an effort to reduce the bureaucracy and standardization of the government support measures, which are often perceived by firms as ineffective for that reason.

Furthermore, there is evidence that strategic planning significantly increases the resilience of tourism firms, but they often lack the resources and capabilities that are required to develop such risk management strategies. Thus, governments must seek to help firms overcome this limitation, by providing training programs that develop these skills and increase the implementation of planning and risk management practices. It is likely that the benefits of fostering firm preparedness surpass the costs of future government support schemes. Finally, the dynamic perspective present in the results of this thesis is also important from a crisis management standpoint, informing managers and policymakers of which aspects to prioritize in each stage of disruption, in designing strategies and support mechanisms.

5.5. Limitations

While this research provides valuable insights, it is not without limitations. For example, the first study, a systematic literature review, there is some degree of subjectivity associated with the inclusion and thematic analysis of papers. To address this limitation, we followed a predefined, validated protocol, while also avoiding the imposition of restrictions on the scope or ranking of journals in the sample, to avoid excluding important publications from the sample. Although every effort was made to include all the relevant publications, some studies may have been inadvertently excluded, especially those from journals not indexed in at least one of the three databases. Nevertheless, this was an essential criterion to guarantee the baseline quality of the included publications and enhance the robustness of the analysis. Additionally, it is possible that this systematic literature review is not fully comprehensive because publications in other formats have been left out, such as book chapters and conference proceedings, which was necessary to avoid the increased resource intensity and time constraints associated with the inclusion of such sources.

Furthermore, in both empirical studies, data availability constraints limited the analysis of company resilience in key competitor countries, such as Turkey, and restricted the inclusion of certain variables, such as human capital proxies (e.g., education levels), CSR practices, leadership and innovation capacity, due to a lack of reliable data in the available databases. While alternative proxies for human capital were employed in these studies, future research should incorporate more detailed metrics, including employee turnover rates, investments in training, and managerial characteristics, to provide a more comprehensive understanding of resilience and the role of human capital in the resilience-building process. Additionally, the influence of organizational policies, such as the adoption of remote work practices and the flexibilization of roles, warrants further investigation within the topic of human capital.

Moreover, the focus on a specific sector, region and disruption may also limit the generalizability of the findings. To address this limitation, future studies should investigate resilience in other industries, regions and types of crises. In fact, due to the unprecedented and singular nature of COVID-19, applying the proposed frameworks to other types of crises, such as economic recessions or geopolitical conflicts, can help determine whether these findings hold in different disruption contexts.

Lastly, the lack of legal requirements for firms to disclose the data involved in the computation of the GVA significantly impacted the sample size. However, although this limitation constrains the generalizability of the findings, these studies still provide valuable insights into the resilience of firms in the tourism industry.

5.6. Future research

This thesis uncovers important future research directions beyond those previously discussed. One of the key areas that require further exploration is the role of human capital in resilience building. Our findings suggest that human capital amplifies the effects of many other determinants of resilience (Núñez-Ríos et al., 2022); yet this amplification impact remains underexplored. Future research should develop or refine metrics that capture critical aspects of human capital, such as employee education levels, training programs, leadership styles, and the innovative capacity of firms. These characteristics can reveal deeper insights into how human capital fosters adaptability and recovery during crises. Additionally, examining the interaction between human and social capital in resilience processes can bridge gaps in understanding, as both elements are likely to operate synergistically. Mixed-methods approaches that integrate both quantitative and qualitative data seem particularly well-suited to investigate these complex mechanisms.

Cross-industry comparisons also hold great potential for expanding the scope of resilience research and enhance the generalizability of this study's findings. In this sense, the application of this framework to other industries, particularly those heavily impacted by COVID-19, such as the creative and events industries, could help identify universal resilience mechanisms. In fact, such comparisons can uncover a set of general best practices that firms across industries can implement to strengthen their resilience. Similarly, resilience can be investigated in industries with unique and distinctive operational models, which could shed light on potential innovative resilience-building strategies that operate in such industries.

Geographical contexts provide another rich area for exploration. While this study highlights the notably higher resilience of companies headquartered in Sweden, future research should investigate the underlying drivers of this competitive advantage, including governmental policies, generalized practices and cultural factors. Similarly, further analysis of the role of Eurozone membership in shaping resilience can enhance the understanding of how monetary policy and regional integration impact the capacity of firms to resist and recover under disruption, whose potential advantages and disadvantages remain unexplored. Hence, expanding the geographic scope of analysis can provide valuable insights into resilience mechanisms in diverse socio-economic, cultural and institutional settings.

Another promising research direction involves exploring resilience across different types of crises. While COVID-19 has dominated the recent literature, investigating how firms respond to financial recessions, geopolitical conflicts, climate-related disasters, and supply chain disruptions can advance the existing frameworks. In this regard, future studies should analyze whether the determinants of resilience vary by crisis type, in line with the recent work of Lee et al. (2024) or whether universal strategies exist.

On a final note, company resilience has demonstrated important effects on the sustainability and survival of tourism firms in an increasingly volatile world. By uncovering its determinants and dynamics, this thesis provides a comprehensive overview of resilience in the tourism industry, advancing theoretical frameworks and offering practical tools to enhance company resilience in a vulnerable sector. These future research directions represent important pathways to continue the development of company resilience research, supporting firms in navigating the challenges of a turbulent business environment and contributing to the sustainability of the industry.

5.7. References

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APPENDICES

APPENDIX A - PUBLICATIONS AND COMMUNICATIONS RESULTING FROM THIS RESEARCH

1. PUBLICATIONS

1.1 PUBLISHED

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2025). Building company resilience: Determinants in the tourism industry. *European Journal of Tourism Research*, *39*, 3907–3907. https://doi.org/10.54055/EJTR.V39I.3654

1.2 UNDER REVISION

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (em revisão). Building resilience in tourism firms: Evidence from COVID-19. *International Journal of Hospitality Management*.

2. COMMUNICATIONS IN SCIENTIFIC CONFERENCES AND MEETINGS

2022

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2022). Resiliência empresarial no setor do turismo: Uma revisão exploratória da literatura. XIII Postgraduate Conference: Management, Hospitality & Tourism. Faro, July 8.

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2022). Company resilience in the tourism industry: An exploratory literature review. TMS ALGARVE 2022: Sustainability Challenges in Tourism, Hospitality and Management – Tourism & Management Studies International Conference. Olhão, November 16 - 19.

2023

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2023). Company resilience in the tourism industry: A Systematic Literature Review. Doctoral day – Faculty of Economics, University of the Algarve. Faro, July 27.

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2023). Company resilience in the tourism industry: A Systematic Literature Review. 21st Interdisciplinary European Conference on Entrepreneurship Research - "From Creative to Circular Entrepreneurship: An Innovative Stairway to Heaven". Covilhã, October 25-27.

2024

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2024). Company resilience in the tourism industry: A systematic literature review. 'BEING SEA-EU' Conference. University of Malta, June 10-12.

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2024). Economic resilience in Tourism: Evidence from COVID-19. Accepted for presentation at the XXI Encuentro Internacional de la Asociación Española de Contabilidad y Administración de Empresas. Faro, September 19-20.

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2024). Company resilience in the tourism industry. Doctoral day – Faculty of Economics, University of the Algarve. Faro, December 13.

2025

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2024). Economic resilience in Tourism: Evidence from COVID-19. Accepted for presentation at the 12th Advances in Hospitality and Tourism Marketing and Management (AHTMM) Conference. Faro, June 30 to July 4.

3. POSTERS

Ramos Jesus, C., Serra Coelho, L. M., & Ramos, C. M. Q. (2023). Company resilience in the European tourism industry. Ciência 2023 – Science and Technology in Portugal Summit, poster.

3. ORGANIZATION OF CONFERENCES

2024

17th Annual Meeting of the Portuguese Economic Journal, held and organized by the Faculty of Economics, University of Algarve; CEFAGE - Centre for Advanced Studies in Management and Economics; and CinTurs - Research Centre for Tourism, Sustainability and Well-being. Faro, July 5-7.

APPENDIX B – COUNTRY ISO 3166-1 ALPHA-2 CODES

COUNTRY CODE	COUNTRY
BE	Belgium
BG	Bulgaria
ES	Spain
HR	Croatia
PL	Poland
PT	Portugal
RO	Romania
RS	Serbia
SE	Sweden
SI	Slovenia

APPENDIX C – ROBUSTNESS TESTS (PAPER TWO)

1. ALTERNATIVE RESILIENCE METRIC – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_WORLD
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESILIENT_WORLD	Total Frequency
1	0	3103
2	1	2935

Probability modeled is RESILIENT_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7960.7417	6020	1.3224	<.0001
Pearson	6059.2188	6020	1.0065	0.3584

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8367.770	7996.742
SC	8374.476	8117.447
-2 Log L	8365.770	7960.742

R-Square	0.0649	Max-rescaled R-Square	0.0865

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	405.0287	17	<.0001
Score	384.3496	17	<.0001
Wald	352.6398	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	3.4473	0.0634
CAP2019	1	13.9879	0.0002
LIQ2019	1	0.3653	0.5456
SIZE2019	1	51.0357	<.0001
REDHC	1	69.4554	<.0001
REDSAL	1	16.6897	<.0001
NEGCP	1	0.7578	0.3840
COUNTRY	9	101.8151	<.0001
ROA2019	1	76.7261	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.2037	0.2882	58.4778	<.0001
LEV2019		1	0.1712	0.0922	3.4473	0.0634
CAP2019		1	0.3447	0.0922	13.9879	0.0002
LIQ2019		1	0.00149	0.00247	0.3653	0.5456
SIZE2019		1	-0.1326	0.0186	51.0357	<.0001
REDHC		1	-0.5342	0.0641	69.4554	<.0001
REDSAL		1	-0.2369	0.0580	16.6897	<.0001
NEGCP		1	-0.1369	0.1573	0.7578	0.3840
COUNTRY	BE	1	-1.8083	0.3113	33.7337	<.0001
COUNTRY	BG	1	0.2718	0.2128	1.6318	0.2015
COUNTRY	ES	1	-0.0808	0.0943	0.7342	0.3915
COUNTRY	HR	1	-0.2949	0.1611	3.3522	0.0671
COUNTRY	PL	1	0.4196	0.1375	9.3070	0.0023
COUNTRY	PT	1	0.2324	0.1086	4.5761	0.0324
COUNTRY	RO	1	0.3094	0.1241	6.2131	0.0127
COUNTRY	RS	1	0.9178	0.2103	19.0366	<.0001
COUNTRY	SI	1	0.2031	0.2057	0.9748	0.3235
ROA2019		1	-1.8136	0.2070	76.7261	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.187	0.991	1.422
CAP2019	1.412	1.178	1.691
LIQ2019	1.001	0.997	1.006

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
SIZE2019	0.876	0.845	0.908
REDHC	0.586	0.517	0.665
REDSAL	0.789	0.704	0.884
NEGCP	0.872	0.641	1.187
COUNTRY BE vs SE	0.164	0.089	0.302
COUNTRY BG vs SE	1.312	0.865	1.991
COUNTRY ES vs SE	0.922	0.767	1.110
COUNTRY HR vs SE	0.745	0.543	1.021
COUNTRY PL vs SE	1.521	1.162	1.992
COUNTRY PT vs SE	1.262	1.020	1.561
COUNTRY RO vs SE	1.363	1.068	1.738
COUNTRY RS vs SE	2.504	1.658	3.781
COUNTRY SI vs SE	1.225	0.819	1.833
ROA2019	0.163	0.109	0.245

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.3	Somers' D	0.285
Percent Discordant	35.7	Gamma	0.285
Percent Tied	0.0	Tau-a	0.142
Pairs	9107305	c	0.643

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
13.5872	8	0.0932

2. ALTERNATIVE RESILIENCE METRIC – EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_WORLD
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	3826
Number of Observations Used	3826

Response Profile		
Ordered Value	RESILIENT_WORLD	Total Frequency
1	0	2097
2	1	1729

Probability modeled is RESILIENT_WORLD=1.

Class Level Information				
Class	Value	Design Variables		
COUNTRY	BE	1	0	0
	ES	0	1	0
	PT	0	0	0
	SI	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5044.7764	3814	1.3227	<.0001
Pearson	4001.2662	3814	1.0491	0.0171

Number of unique profiles: 3826

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5270.512	5068.776
SC	5276.761	5143.771
-2 Log L	5268.512	5044.776

R-Square	0.0568	Max-rescaled R-Square	0.0760

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	223.7354	11	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Score	205.5322	11	<.0001
Wald	186.3348	11	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.6925	0.4053
CAP2019	1	6.2886	0.0122
ROA2019	1	71.1434	<.0001
LIQ2019	1	0.4776	0.4895
SIZE2019	1	18.3489	<.0001
REDHC	1	27.4344	<.0001
REDSAL	1	4.3259	0.0375
NEGCP	1	0.0842	0.7717
COUNTRY	3	47.7761	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.8799	0.3677	26.1424	<.0001
LEV2019		1	0.0965	0.1160	0.6925	0.4053
CAP2019		1	0.2809	0.1120	6.2886	0.0122
ROA2019		1	-2.9379	0.3483	71.1434	<.0001
LIQ2019		1	0.00217	0.00314	0.4776	0.4895
SIZE2019		1	-0.0962	0.0225	18.3489	<.0001
REDHC		1	-0.4273	0.0816	27.4344	<.0001
REDSAL		1	-0.1538	0.0740	4.3259	0.0375
NEGCP		1	-0.0595	0.2051	0.0842	0.7717
COUNTRY	BE	1	-1.9546	0.3150	38.5081	<.0001
COUNTRY	ES	1	-0.3125	0.0799	15.3101	<.0001
COUNTRY	SI	1	0.00842	0.2009	0.0018	0.9666

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.101	0.877	1.383
CAP2019	1.324	1.063	1.649
ROA2019	0.053	0.027	0.105
LIQ2019	1.002	0.996	1.008
SIZE2019	0.908	0.869	0.949
REDHC	0.652	0.556	0.765
REDSAL	0.857	0.742	0.991
NEGCP	0.942	0.630	1.408

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
COUNTRY BE vs PT	0.142	0.076	0.263
COUNTRY ES vs PT	0.732	0.626	0.856
COUNTRY SI vs PT	1.008	0.680	1.495

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.7	Somers' D	0.274
Percent Discordant	36.3	Gamma	0.274
Percent Tied	0.0	Tau-a	0.136
Pairs	3625713	c	0.637

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
18.6073	8	0.0171

3. ALTERNATIVE RESILIENCE METRIC – NON-EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_WORLD
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	2212
Number of Observations Used	2212

Response Profile		
Ordered Value	RESILIENT_WORLD	Total Frequency
1	0	1006
2	1	1206

Probability modeled is RESILIENT_WORLD=1.

Class Level Information						
Class	Value	Design Variables				
COUNTRY	BG	1	0	0	0	0
	HR	0	1	0	0	0
	PL	0	0	1	0	0
	RO	0	0	0	1	0
	RS	0	0	0	0	1
	SE	0	0	0	0	0

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	2874.9002	2198	1.3080	<.0001
Pearson	2225.6010	2198	1.0126	0.3356

Number of unique profiles: 2212

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	3050.375	2902.900
SC	3056.077	2982.723
-2 Log L	3048.375	2874.900

R-Square	0.0754	Max-rescaled R-Square	0.1008

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	173.4750	13	<.0001
Score	163.9379	13	<.0001
Wald	150.2162	13	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	4.4259	0.0354
CAP2019	1	8.9943	0.0027
ROA2019	1	16.1648	<.0001
LIQ2019	1	0.0070	0.9333
SIZE2019	1	39.6677	<.0001
REDHC	1	37.4108	<.0001
REDSAL	1	14.7135	0.0001
NEGCP	1	2.1101	0.1463
COUNTRY	5	45.1066	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.4094	0.5062	45.3574	<.0001
LEV2019		1	0.3271	0.1555	4.4259	0.0354
CAP2019		1	0.5050	0.1684	8.9943	0.0027
ROA2019		1	-1.0574	0.2630	16.1648	<.0001
LIQ2019		1	0.000333	0.00398	0.0070	0.9333
SIZE2019		1	-0.2214	0.0352	39.6677	<.0001
REDHC		1	-0.6481	0.1060	37.4108	<.0001
REDSAL		1	-0.3625	0.0945	14.7135	0.0001
NEGCP		1	-0.3648	0.2511	2.1101	0.1463
COUNTRY	BG	1	0.3991	0.2201	3.2881	0.0698
COUNTRY	HR	1	-0.5609	0.2088	7.2131	0.0072
COUNTRY	PL	1	0.5112	0.1463	12.2118	0.0005
COUNTRY	RO	1	0.2697	0.1363	3.9147	0.0479
COUNTRY	RS	1	0.9272	0.2175	18.1687	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.387	1.023	1.881
CAP2019	1.657	1.191	2.305
ROA2019	0.347	0.207	0.582
LIQ2019	1.000	0.993	1.008
SIZE2019	0.801	0.748	0.859

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
REDHC	0.523	0.425	0.644
REDSAL	0.696	0.578	0.838
NEGCP	0.694	0.424	1.136
COUNTRY BG vs SE	1.490	0.968	2.294
COUNTRY HR vs SE	0.571	0.379	0.859
COUNTRY PL vs SE	1.667	1.252	2.221
COUNTRY RO vs SE	1.310	1.003	1.710
COUNTRY RS vs SE	2.527	1.650	3.871

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.0	Somers' D	0.319
Percent Discordant	34.0	Gamma	0.319
Percent Tied	0.0	Tau-a	0.158
Pairs	1213236	c	0.660

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
11.3467	8	0.1828

4. ALTERNATIVE SIZE METRIC – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	3020
2	1	3018

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7849.7700	6020	1.3039	<.0001
Pearson	6073.7404	6020	1.0089	0.3105

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8372.445	7885.770
SC	8379.151	8006.475
-2 Log L	8370.445	7849.770

R-Square	0.0826	Max-rescaled R-Square	0.1102

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	520.6747	17	<.0001
Score	490.6366	17	<.0001
Wald	442.6458	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	13.3365	0.0003
CAP2019	1	1.3158	0.2513
LIQ2019	1	0.0400	0.8414
SIZE2019_REV	1	31.2377	<.0001
REDHC	1	65.0015	<.0001
REDSAL	1	14.7817	0.0001
NEGCP	1	0.7529	0.3856
COUNTRY	9	283.6915	<.0001
ROA2019	1	59.0933	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.9964	0.3068	95.3669	<.0001
LEV2019		1	0.3373	0.0923	13.3365	0.0003
CAP2019		1	0.1042	0.0908	1.3158	0.2513
LIQ2019		1	-0.00050	0.00249	0.0400	0.8414
SIZE2019_REV		1	-0.1092	0.0195	31.2377	<.0001
REDHC		1	-0.5382	0.0668	65.0015	<.0001
REDSAL		1	-0.2264	0.0589	14.7817	0.0001
NEGCP		1	-0.1360	0.1567	0.7529	0.3856
COUNTRY	BE	1	-1.3981	0.2632	28.2217	<.0001
COUNTRY	BG	1	-1.0662	0.2160	24.3723	<.0001
COUNTRY	ES	1	-1.0044	0.1026	95.8215	<.0001
COUNTRY	HR	1	-1.9973	0.1821	120.2663	<.0001
COUNTRY	PL	1	-0.9539	0.1424	44.8643	<.0001
COUNTRY	PT	1	-1.6175	0.1170	191.0942	<.0001
COUNTRY	RO	1	-0.6313	0.1317	22.9687	<.0001
COUNTRY	RS	1	-1.4925	0.1961	57.9033	<.0001
COUNTRY	SI	1	-2.3044	0.2284	101.7498	<.0001
ROA2019		1	-1.5870	0.2065	59.0933	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.401	1.169	1.679
CAP2019	1.110	0.929	1.326
LIQ2019	1.000	0.995	1.004

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
SIZE2019_REV		0.897	0.863	0.932
REDHC		0.584	0.512	0.665
REDSAL		0.797	0.710	0.895
NEGCP		0.873	0.642	1.187
COUNTRY	BE vs SE	0.247	0.148	0.414
COUNTRY	BG vs SE	0.344	0.225	0.526
COUNTRY	ES vs SE	0.366	0.300	0.448
COUNTRY	HR vs SE	0.136	0.095	0.194
COUNTRY	PL vs SE	0.385	0.291	0.509
COUNTRY	PT vs SE	0.198	0.158	0.250
COUNTRY	RO vs SE	0.532	0.411	0.689
COUNTRY	RS vs SE	0.225	0.153	0.330
COUNTRY	SI vs SE	0.100	0.064	0.156
ROA2019		0.205	0.136	0.307

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.4	Somers' D	0.327
Percent Discordant	33.6	Gamma	0.327
Percent Tied	0.0	Tau-a	0.164
Pairs	9114360	c	0.664

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.8972	8	0.7685

5. ALTERNATIVE SIZE METRIC – EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	3826
Number of Observations Used	3826

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2092
2	1	1734

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information				
Class	Value	Design Variables		
COUNTRY	BE	1	0	0
	ES	0	1	0
	PT	0	0	0
	SI	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5041.7128	3814	1.3219	<.0001
Pearson	3922.5997	3814	1.0285	0.1076

Number of unique profiles: 3826

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5272.415	5065.713
SC	5278.665	5140.708
-2 Log L	5270.415	5041.713

R-Square	0.0580	Max-rescaled R-Square	0.0776

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	228.7022	11	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Score	213.3957	11	<.0001
Wald	194.7317	11	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	4.4997	0.0339
CAP2019	1	1.6335	0.2012
ROA2019	1	61.2737	<.0001
LIQ2019	1	0.0507	0.8218
SIZE2019_REV	1	12.6126	0.0004
REDHC	1	29.6186	<.0001
REDSAL	1	5.9125	0.0150
NEGCP	1	0.0453	0.8315
COUNTRY	3	81.8384	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	0.9472	0.3372	7.8913	0.0050
LEV2019		1	0.2462	0.1161	4.4997	0.0339
CAP2019		1	0.1419	0.1110	1.6335	0.2012
ROA2019		1	-2.6105	0.3335	61.2737	<.0001
LIQ2019		1	0.000710	0.00315	0.0507	0.8218
SIZE2019_REV		1	-0.0802	0.0226	12.6126	0.0004
REDHC		1	-0.4580	0.0842	29.6186	<.0001
REDSAL		1	-0.1816	0.0747	5.9125	0.0150
NEGCP		1	0.0435	0.2047	0.0453	0.8315
COUNTRY	BE	1	0.2626	0.2562	1.0506	0.3054
COUNTRY	ES	1	0.6073	0.0819	55.0378	<.0001
COUNTRY	SI	1	-0.6723	0.2190	9.4288	0.0021

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.279	1.019	1.606
CAP2019	1.152	0.927	1.432
ROA2019	0.073	0.038	0.141
LIQ2019	1.001	0.995	1.007
SIZE2019_REV	0.923	0.883	0.965
REDHC	0.633	0.536	0.746
REDSAL	0.834	0.720	0.965
NEGCP	1.045	0.699	1.560

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
COUNTRY	BE vs PT	1.300	0.787	2.148
COUNTRY	ES vs PT	1.836	1.563	2.155
COUNTRY	SI vs PT	0.511	0.332	0.784

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.9	Somers' D	0.278
Percent Discordant	36.1	Gamma	0.278
Percent Tied	0.0	Tau-a	0.138
Pairs	3627528	c	0.639

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
8.5497	8	0.3817

6. ALTERNATIVE SIZE METRIC – NON-EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	2212
Number of Observations Used	2212

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	928
2	1	1284

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information						
Class	Value	Design Variables				
COUNTRY	BG	1	0	0	0	0
	HR	0	1	0	0	0
	PL	0	0	1	0	0
	RO	0	0	0	1	0
	RS	0	0	0	0	1
	SE	0	0	0	0	0

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	2772.7599	2198	1.2615	<.0001
Pearson	2242.5363	2198	1.0203	0.2491

Number of unique profiles: 2212

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	3010.938	2800.760
SC	3016.640	2880.583
-2 Log L	3008.938	2772.760

R-Square	0.1013	Max-rescaled R-Square	0.1362

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	236.1785	13	<.0001
Score	223.0240	13	<.0001
Wald	200.9629	13	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	12.0346	0.0005
CAP2019	1	0.0000	0.9949
ROA2019	1	8.5701	0.0034
LIQ2019	1	0.8024	0.3704
SIZE2019_REV	1	21.3954	<.0001
REDHC	1	32.3070	<.0001
REDSAL	1	8.6923	0.0032
NEGCP	1	4.4764	0.0344
COUNTRY	5	102.9414	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	4.1038	0.5997	46.8313	<.0001
LEV2019		1	0.5410	0.1560	12.0346	0.0005
CAP2019		1	-0.00102	0.1601	0.0000	0.9949
ROA2019		1	-0.7971	0.2723	8.5701	0.0034
LIQ2019		1	-0.00361	0.00403	0.8024	0.3704
SIZE2019_REV		1	-0.1862	0.0403	21.3954	<.0001
REDHC		1	-0.6371	0.1121	32.3070	<.0001
REDSAL		1	-0.2845	0.0965	8.6923	0.0032
NEGCP		1	-0.5268	0.2490	4.4764	0.0344
COUNTRY	BG	1	-0.9776	0.2213	19.5109	<.0001
COUNTRY	HR	1	-2.2829	0.2680	72.5586	<.0001
COUNTRY	PL	1	-0.8822	0.1511	34.1130	<.0001
COUNTRY	RO	1	-0.6569	0.1474	19.8744	<.0001
COUNTRY	RS	1	-1.5193	0.2079	53.4121	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.718	1.265	2.332
CAP2019	0.999	0.730	1.367
ROA2019	0.451	0.264	0.768
LIQ2019	0.996	0.989	1.004
SIZE2019_REV	0.830	0.767	0.898

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
REDHC		0.529	0.425	0.659
REDSAL		0.752	0.623	0.909
NEGCP		0.590	0.362	0.962
COUNTRY	BG vs SE	0.376	0.244	0.581
COUNTRY	HR vs SE	0.102	0.060	0.172
COUNTRY	PL vs SE	0.414	0.308	0.556
COUNTRY	RO vs SE	0.518	0.388	0.692
COUNTRY	RS vs SE	0.219	0.146	0.329

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.0	Somers' D	0.380
Percent Discordant	31.0	Gamma	0.380
Percent Tied	0.0	Tau-a	0.185
Pairs	1191552	c	0.690

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
10.3591	8	0.2407

7. ALTERNATIVE PROFITABILITY METRIC (EBIT) – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	3020
2	1	3018

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7842.1248	6020	1.3027	<.0001
Pearson	6070.2690	6020	1.0084	0.3217

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8372.445	7878.125
SC	8379.151	7998.830
-2 Log L	8370.445	7842.125

R-Square	0.0838	Max-rescaled R-Square	0.1117

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	528.3199	17	<.0001
Score	494.4700	17	<.0001
Wald	446.9400	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	9.7059	0.0018
CAP2019	1	7.8401	0.0051
LIQ2019	1	0.0773	0.7810
SIZE2019	1	45.2213	<.0001
REDHC	1	78.5667	<.0001
REDSAL	1	17.3498	<.0001
NEGCP	1	0.8526	0.3558
COUNTRY	9	274.0571	<.0001
ROA2019_EBIT	1	71.6983	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.2159	0.2972	117.0792	<.0001
LEV2019		1	0.2888	0.0927	9.7059	0.0018
CAP2019		1	0.2604	0.0930	7.8401	0.0051
LIQ2019		1	0.000688	0.00247	0.0773	0.7810
SIZE2019		1	-0.1261	0.0188	45.2213	<.0001
REDHC		1	-0.5778	0.0652	78.5667	<.0001
REDSAL		1	-0.2443	0.0586	17.3498	<.0001
NEGCP		1	-0.1451	0.1571	0.8526	0.3558
COUNTRY	BE	1	-1.3691	0.2600	27.7269	<.0001
COUNTRY	BG	1	-0.9329	0.2166	18.5536	<.0001
COUNTRY	ES	1	-0.8922	0.1019	76.6601	<.0001
COUNTRY	HR	1	-1.9260	0.1692	129.5026	<.0001
COUNTRY	PL	1	-0.8747	0.1424	37.7442	<.0001
COUNTRY	PT	1	-1.4694	0.1169	157.9887	<.0001
COUNTRY	RO	1	-0.5821	0.1301	20.0089	<.0001
COUNTRY	RS	1	-1.4422	0.1962	54.0364	<.0001
COUNTRY	SI	1	-2.2239	0.2270	95.9922	<.0001
ROA2019_EBIT		1	-1.5641	0.1847	71.6983	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.335	1.113	1.601
CAP2019	1.297	1.081	1.557
LIQ2019	1.001	0.996	1.006

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
SIZE2019		0.882	0.850	0.915
REDHC		0.561	0.494	0.638
REDSAL		0.783	0.698	0.879
NEGCP		0.865	0.636	1.177
COUNTRY	BE vs SE	0.254	0.153	0.423
COUNTRY	BG vs SE	0.393	0.257	0.601
COUNTRY	ES vs SE	0.410	0.336	0.500
COUNTRY	HR vs SE	0.146	0.105	0.203
COUNTRY	PL vs SE	0.417	0.315	0.551
COUNTRY	PT vs SE	0.230	0.183	0.289
COUNTRY	RO vs SE	0.559	0.433	0.721
COUNTRY	RS vs SE	0.236	0.161	0.347
COUNTRY	SI vs SE	0.108	0.069	0.169
ROA2019_EBIT		0.209	0.146	0.301

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.4	Somers' D	0.327
Percent Discordant	33.6	Gamma	0.327
Percent Tied	0.0	Tau-a	0.164
Pairs	9114360	c	0.664

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.3472	8	0.6084

8. ALTERNATIVE PROFITABILITY METRIC (EBIT) – EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	3826
Number of Observations Used	3826

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2092
2	1	1734

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information				
Class	Value	Design Variables		
COUNTRY	BE	1	0	0
	ES	0	1	0
	PT	0	0	0
	SI	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5042.0165	3814	1.3220	<.0001
Pearson	3841.1325	3814	1.0071	0.3754

Number of unique profiles: 3826

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5272.415	5066.017
SC	5278.665	5141.011
-2 Log L	5270.415	5042.017

R-Square	0.0579	Max-rescaled R-Square	0.0775

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	228.3985	11	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Score	213.7422	11	<.0001
Wald	194.8159	11	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	3.6706	0.0554
CAP2019	1	4.3553	0.0369
ROA2019_EBIT	1	70.0016	<.0001
LIQ2019	1	0.1692	0.6808
SIZE2019	1	18.0423	<.0001
REDHC	1	36.1788	<.0001
REDSAL	1	6.7628	0.0093
NEGCP	1	0.0063	0.9367
COUNTRY	3	79.7834	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.2829	0.3678	12.1629	0.0005
LEV2019		1	0.2231	0.1164	3.6706	0.0554
CAP2019		1	0.2333	0.1118	4.3553	0.0369
ROA2019_EBIT		1	-2.3072	0.2758	70.0016	<.0001
LIQ2019		1	0.00129	0.00314	0.1692	0.6808
SIZE2019		1	-0.0956	0.0225	18.0423	<.0001
REDHC		1	-0.4946	0.0822	36.1788	<.0001
REDSAL		1	-0.1931	0.0743	6.7628	0.0093
NEGCP		1	0.0163	0.2056	0.0063	0.9367
COUNTRY	BE	1	0.1773	0.2603	0.4639	0.4958
COUNTRY	ES	1	0.5820	0.0822	50.1270	<.0001
COUNTRY	SI	1	-0.7238	0.2199	10.8352	0.0010

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.250	0.995	1.570
CAP2019	1.263	1.014	1.572
ROA2019_EBIT	0.100	0.058	0.171
LIQ2019	1.001	0.995	1.007
SIZE2019	0.909	0.870	0.950
REDHC	0.610	0.519	0.716
REDSAL	0.824	0.713	0.954
NEGCP	1.016	0.679	1.521

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
COUNTRY	BE vs PT	1.194	0.717	1.989
COUNTRY	ES vs PT	1.790	1.523	2.102
COUNTRY	SI vs PT	0.485	0.315	0.746

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.6	Somers' D	0.272
Percent Discordant	36.4	Gamma	0.272
Percent Tied	0.0	Tau-a	0.135
Pairs	3627528	c	0.636

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.9281	8	0.5444

9. ALTERNATIVE PROFITABILITY METRIC (EBIT) – NON-EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	2212
Number of Observations Used	2212

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	928
2	1	1284

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information						
Class	Value	Design Variables				
COUNTRY	BG	1	0	0	0	0
	HR	0	1	0	0	0
	PL	0	0	1	0	0
	RO	0	0	0	1	0
	RS	0	0	0	0	1
	SE	0	0	0	0	0

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	2766.0785	2198	1.2585	<.0001
Pearson	2237.4167	2198	1.0179	0.2739

Number of unique profiles: 2212

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	3010.938	2794.079
SC	3016.640	2873.902
-2 Log L	3008.938	2766.079

R-Square	0.1040	Max-rescaled R-Square	0.1399

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	242.8599	13	<.0001
Score	228.5837	13	<.0001
Wald	205.4001	13	<.0001

Type 3 Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
LEV2019	1	8.9688	0.0027
CAP2019	1	4.6554	0.0310
ROA2019_EBIT	1	9.3929	0.0022
LIQ2019	1	0.0018	0.9659
SIZE2019	1	31.6487	<.0001
REDHC	1	37.7916	<.0001
REDSAL	1	10.7988	0.0010
NEGCP	1	3.4978	0.0614
COUNTRY	5	118.3721	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	4.1646	0.5213	63.8278	<.0001
LEV2019		1	0.4677	0.1562	8.9688	0.0027
CAP2019		1	0.3719	0.1724	4.6554	0.0310
ROA2019_EBIT		1	-0.7958	0.2597	9.3929	0.0022
LIQ2019		1	-0.00017	0.00401	0.0018	0.9659
SIZE2019		1	-0.2005	0.0356	31.6487	<.0001
REDHC		1	-0.6718	0.1093	37.7916	<.0001
REDSAL		1	-0.3166	0.0963	10.7988	0.0010
NEGCP		1	-0.4661	0.2492	3.4978	0.0614
COUNTRY	**BG**	1	-0.8106	0.2228	13.2403	0.0003
COUNTRY	**HR**	1	-2.1427	0.2218	93.3670	<.0001
COUNTRY	**PL**	1	-0.7881	0.1505	27.4205	<.0001
COUNTRY	**RO**	1	-0.6027	0.1425	17.8969	<.0001
COUNTRY	**RS**	1	-1.4309	0.2047	48.8521	<.0001

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Wald Confidence Limits**	
LEV2019	1.596	1.175	2.168
CAP2019	1.451	1.035	2.034
ROA2019_EBIT	0.451	0.271	0.751
LIQ2019	1.000	0.992	1.008
SIZE2019	0.818	0.763	0.878

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
REDHC		0.511	0.412	0.633
REDSAL		0.729	0.603	0.880
NEGCP		0.627	0.385	1.023
COUNTRY	BG vs SE	0.445	0.287	0.688
COUNTRY	HR vs SE	0.117	0.076	0.181
COUNTRY	PL vs SE	0.455	0.339	0.611
COUNTRY	RO vs SE	0.547	0.414	0.724
COUNTRY	RS vs SE	0.239	0.160	0.357

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.2	Somers' D	0.384
Percent Discordant	30.8	Gamma	0.384
Percent Tied	0.0	Tau-a	0.187
Pairs	1191552	c	0.692

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
5.4275	8	0.7111

10. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	5899

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2969
2	1	2930

Probability modeled is RESILIENT_COUNTRY=1.

Note: 139 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7662.8595	5881	1.3030	<.0001
Pearson	5932.6423	5881	1.0088	0.3153

Number of unique profiles: 5899

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8179.493	7698.859
SC	8186.175	7819.145

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	**Intercept Only**	**Intercept and Covariates**
-2 Log L	8177.493	7662.859

R-Square	0.0835	**Max-rescaled R-Square**	0.1114

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	514.6331	17	<.0001
Score	481.0675	17	<.0001
Wald	434.2409	17	<.0001

Type 3 Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
LEV2019	1	7.2685	0.0070
CAP2019	1	9.9062	0.0016
LIQ2019	1	0.1378	0.7105
SIZE2019	1	46.3608	<.0001
REDHC	1	63.3827	<.0001
REDSAL	1	16.0057	<.0001
NEGCP	1	0.8172	0.3660
COUNTRY	9	277.6366	<.0001
ROA2019_EBITDA	1	80.1277	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	3.3534	0.3076	118.8537	<.0001
LEV2019		1	0.2517	0.0934	7.2685	0.0070
CAP2019		1	0.2955	0.0939	9.9062	0.0016
LIQ2019		1	0.000939	0.00253	0.1378	0.7105
SIZE2019		1	-0.1304	0.0191	46.3608	<.0001
REDHC		1	-0.5295	0.0665	63.3827	<.0001
REDSAL		1	-0.2374	0.0593	16.0057	<.0001
NEGCP		1	-0.1454	0.1608	0.8172	0.3660
COUNTRY	**BE**	1	-1.3577	0.2599	27.2951	<.0001
COUNTRY	**BG**	1	-0.9850	0.2168	20.6402	<.0001
COUNTRY	**ES**	1	-0.9493	0.1030	84.8921	<.0001
COUNTRY	**HR**	1	-2.0216	0.1728	136.8862	<.0001
COUNTRY	**PL**	1	-0.9239	0.1437	41.3428	<.0001
COUNTRY	**PT**	1	-1.5101	0.1183	163.0302	<.0001
COUNTRY	**RO**	1	-0.6276	0.1307	23.0587	<.0001
COUNTRY	**RS**	1	-1.4875	0.2042	53.0736	<.0001
COUNTRY	**SI**	1	-2.2593	0.2301	96.4473	<.0001
ROA2019_EBITDA		1	-1.6475	0.1841	80.1277	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		1.286	1.071	1.544
CAP2019		1.344	1.118	1.615
LIQ2019		1.001	0.996	1.006
SIZE2019		0.878	0.845	0.911
REDHC		0.589	0.517	0.671
REDSAL		0.789	0.702	0.886
NEGCP		0.865	0.631	1.185
COUNTRY	BE vs SE	0.257	0.155	0.428
COUNTRY	BG vs SE	0.373	0.244	0.571
COUNTRY	ES vs SE	0.387	0.316	0.474
COUNTRY	HR vs SE	0.132	0.094	0.186
COUNTRY	PL vs SE	0.397	0.300	0.526
COUNTRY	PT vs SE	0.221	0.175	0.279
COUNTRY	RO vs SE	0.534	0.413	0.690
COUNTRY	RS vs SE	0.226	0.151	0.337
COUNTRY	SI vs SE	0.104	0.067	0.164
ROA2019_EBITDA		0.193	0.134	0.276

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.3	Somers' D	0.327
Percent Discordant	33.7	Gamma	0.327
Percent Tied	0.0	Tau-a	0.163
Pairs	8699170	c	0.663

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.2694	8	0.8320

11. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	3826
Number of Observations Used	3743

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2059
2	1	1684

Probability modeled is RESILIENT_COUNTRY=1.

Note: 83 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information				
Class	Value	Design Variables		
COUNTRY	BE	1	0	0
	ES	0	1	0
	PT	0	0	0
	SI	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	4933.8104	3731	1.3224	<.0001
Pearson	3758.5823	3731	1.0074	0.3721

Number of unique profiles: 3743

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5153.267	4957.810
SC	5159.494	5032.542
-2 Log L	5151.267	4933.810

R-Square	0.0564	Max-rescaled R-Square	0.0755

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	217.4561	11	<.0001
Score	203.6038	11	<.0001
Wald	186.5007	11	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.6691	0.1023
CAP2019	1	6.2122	0.0127
ROA2019_EBITDA	1	72.7386	<.0001
LIQ2019	1	0.3435	0.5578
SIZE2019	1	20.0733	<.0001
REDHC	1	29.0925	<.0001
REDSAL	1	6.0200	0.0141
NEGCP	1	0.0105	0.9186
COUNTRY	3	73.3460	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.4367	0.3785	14.4042	0.0001
LEV2019		1	0.1912	0.1171	2.6691	0.1023
CAP2019		1	0.2803	0.1124	6.2122	0.0127
ROA2019_EBITDA		1	-2.2862	0.2681	72.7386	<.0001
LIQ2019		1	0.00191	0.00326	0.3435	0.5578
SIZE2019		1	-0.1028	0.0229	20.0733	<.0001
REDHC		1	-0.4521	0.0838	29.0925	<.0001
REDSAL		1	-0.1840	0.0750	6.0200	0.0141
NEGCP		1	0.0215	0.2106	0.0105	0.9186
COUNTRY	BE	1	0.2427	0.2600	0.8707	0.3508
COUNTRY	ES	1	0.5611	0.0831	45.6388	<.0001
COUNTRY	SI	1	-0.7178	0.2225	10.4022	0.0013

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.211	0.963	1.523
CAP2019	1.323	1.062	1.650
ROA2019_EBITDA	0.102	0.060	0.172
LIQ2019	1.002	0.996	1.008
SIZE2019	0.902	0.863	0.944
REDHC	0.636	0.540	0.750
REDSAL	0.832	0.718	0.964

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
NEGCP		1.022	0.676	1.544
COUNTRY	BE vs PT	1.275	0.766	2.122
COUNTRY	ES vs PT	1.753	1.489	2.062
COUNTRY	SI vs PT	0.488	0.315	0.755

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.5	Somers' D	0.270
Percent Discordant	36.5	Gamma	0.270
Percent Tied	0.0	Tau-a	0.134
Pairs	3467356	c	0.635

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
10.8713	8	0.2091

12. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – NON-EUROZONE SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	2212
Number of Observations Used	2156

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	910
2	1	1246

Probability modeled is RESILIENT_COUNTRY=1.

Note: 56 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information						
Class	Value	Design Variables				
COUNTRY	BG	1	0	0	0	0
	HR	0	1	0	0	0
	PL	0	0	1	0	0
	RO	0	0	0	1	0
	RS	0	0	0	0	1
	SE	0	0	0	0	0

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	2700.0570	2142	1.2605	<.0001
Pearson	2181.4826	2142	1.0184	0.2710

Number of unique profiles: 2156

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	2938.273	2728.057
SC	2943.949	2807.521
-2 Log L	2936.273	2700.057

Logistic Regression Results

The LOGISTIC Procedure

R-Square	0.1038	Max-rescaled R-Square	0.1395

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	236.2160	13	<.0001
Score	221.8995	13	<.0001
Wald	199.1985	13	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	6.7877	0.0092
CAP2019	1	5.4360	0.0197
ROA2019_EBITDA	1	13.3335	0.0003
LIQ2019	1	0.0085	0.9265
SIZE2019	1	31.1864	<.0001
REDHC	1	31.0164	<.0001
REDSAL	1	10.4760	0.0012
NEGCP	1	3.0860	0.0790
COUNTRY	5	121.5394	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	4.2580	0.5395	62.2872	<.0001
LEV2019		1	0.4096	0.1572	6.7877	0.0092
CAP2019		1	0.4067	0.1744	5.4360	0.0197
ROA2019_EBITDA		1	-0.9565	0.2620	13.3335	0.0003
LIQ2019		1	-0.00037	0.00400	0.0085	0.9265
SIZE2019		1	-0.2030	0.0364	31.1864	<.0001
REDHC		1	-0.6209	0.1115	31.0164	<.0001
REDSAL		1	-0.3163	0.0977	10.4760	0.0012
NEGCP		1	-0.4461	0.2539	3.0860	0.0790
COUNTRY	BG	1	-0.8537	0.2229	14.6747	0.0001
COUNTRY	HR	1	-2.2247	0.2257	97.1942	<.0001
COUNTRY	PL	1	-0.8227	0.1518	29.3673	<.0001
COUNTRY	RO	1	-0.6273	0.1424	19.4066	<.0001
COUNTRY	RS	1	-1.4586	0.2133	46.7501	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.506	1.107	2.050
CAP2019	1.502	1.067	2.114
ROA2019_EBITDA	0.384	0.230	0.642
LIQ2019	1.000	0.992	1.008

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
SIZE2019		0.816	0.760	0.877
REDHC		0.537	0.432	0.669
REDSAL		0.729	0.602	0.883
NEGCP		0.640	0.389	1.053
COUNTRY	BG vs SE	0.426	0.275	0.659
COUNTRY	HR vs SE	0.108	0.069	0.168
COUNTRY	PL vs SE	0.439	0.326	0.591
COUNTRY	RO vs SE	0.534	0.404	0.706
COUNTRY	RS vs SE	0.233	0.153	0.353

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.1	Somers' D	0.383
Percent Discordant	30.9	Gamma	0.383
Percent Tied	0.0	Tau-a	0.187
Pairs	1133860	c	0.691

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
5.4009	8	0.7140

APPENDIX D – ROBUSTNESS TESTS (PAPER THREE)

1. ALTERNATIVE RESILIENCE METRIC – RESILIENCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_WORLD
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESILIENT_WORLD	Total Frequency
1	0	3103
2	1	2935

Probability modeled is RESILIENT_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7960.7417	6020	1.3224	<.0001
Pearson	6059.2188	6020	1.0065	0.3584

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8367.770	7996.742
SC	8374.476	8117.447

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	8365.770	7960.742

R-Square	0.0649	Max-rescaled R-Square	0.0865

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	405.0287	17	<.0001
Score	384.3496	17	<.0001
Wald	352.6398	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	3.4473	0.0634
CAP2019	1	13.9879	0.0002
ROA2019	1	76.7261	<.0001
LIQ2019	1	0.3653	0.5456
SIZE2019	1	51.0357	<.0001
REDHC	1	69.4554	<.0001
REDSAL	1	16.6897	<.0001
NEGCP	1	0.7578	0.3840
COUNTRY	9	101.8151	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.2037	0.2882	58.4778	<.0001
LEV2019		1	0.1712	0.0922	3.4473	0.0634
CAP2019		1	0.3447	0.0922	13.9879	0.0002
ROA2019		1	-1.8136	0.2070	76.7261	<.0001
LIQ2019		1	0.00149	0.00247	0.3653	0.5456
SIZE2019		1	-0.1326	0.0186	51.0357	<.0001
REDHC		1	-0.5342	0.0641	69.4554	<.0001
REDSAL		1	-0.2369	0.0580	16.6897	<.0001
NEGCP		1	-0.1369	0.1573	0.7578	0.3840
COUNTRY	BE	1	-1.8083	0.3113	33.7337	<.0001
COUNTRY	BG	1	0.2718	0.2128	1.6318	0.2015
COUNTRY	ES	1	-0.0808	0.0943	0.7342	0.3915
COUNTRY	HR	1	-0.2949	0.1611	3.3522	0.0671
COUNTRY	PL	1	0.4196	0.1375	9.3070	0.0023
COUNTRY	PT	1	0.2324	0.1086	4.5761	0.0324
COUNTRY	RO	1	0.3094	0.1241	6.2131	0.0127
COUNTRY	RS	1	0.9178	0.2103	19.0366	<.0001
COUNTRY	SI	1	0.2031	0.2057	0.9748	0.3235

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.187	0.991	1.422
CAP2019	1.412	1.178	1.691
ROA2019	0.163	0.109	0.245
LIQ2019	1.001	0.997	1.006
SIZE2019	0.876	0.845	0.908
REDHC	0.586	0.517	0.665
REDSAL	0.789	0.704	0.884
NEGCP	0.872	0.641	1.187
COUNTRY BE vs SE	0.164	0.089	0.302
COUNTRY BG vs SE	1.312	0.865	1.991
COUNTRY ES vs SE	0.922	0.767	1.110
COUNTRY HR vs SE	0.745	0.543	1.021
COUNTRY PL vs SE	1.521	1.162	1.992
COUNTRY PT vs SE	1.262	1.020	1.561
COUNTRY RO vs SE	1.363	1.068	1.738
COUNTRY RS vs SE	2.504	1.658	3.781
COUNTRY SI vs SE	1.225	0.819	1.833

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.3	Somers' D	0.285
Percent Discordant	35.7	Gamma	0.285
Percent Tied	0.0	Tau-a	0.142
Pairs	9107305	c	0.643

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
13.5872	8	0.0932

2. ALTERNATIVE RESILIENCE METRIC – RESILIENCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_WORLD
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RESILIENT_WORLD	Total Frequency
1	0	2655
2	1	2241

Probability modeled is RESILIENT_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6430.3122	4878	1.3182	<.0001
Pearson	4899.5516	4878	1.0044	0.4111

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6754.248	6466.312
SC	6760.744	6583.243

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	6752.248	6430.312

R-Square	0.0636	Max-rescaled R-Square	0.0851

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	321.9358	17	<.0001
Score	308.9292	17	<.0001
Wald	284.9024	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	6.3465	0.0118
CAP2019	1	7.7264	0.0054
ROA2019	1	46.7118	<.0001
LIQ2019	1	0.1668	0.6830
SIZE2019	1	53.3636	<.0001
REDHC	1	47.6966	<.0001
REDSAL	1	13.6004	0.0002
NEGCP	1	2.5772	0.1084
COUNTRY	9	95.6027	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.4676	0.3367	53.6956	<.0001
LEV2019		1	0.2763	0.1097	6.3465	0.0118
CAP2019		1	0.2943	0.1059	7.7264	0.0054
ROA2019		1	-1.8852	0.2758	46.7118	<.0001
LIQ2019		1	0.00113	0.00278	0.1668	0.6830
SIZE2019		1	-0.1528	0.0209	53.3636	<.0001
REDHC		1	-0.4924	0.0713	47.6966	<.0001
REDSAL		1	-0.2373	0.0643	13.6004	0.0002
NEGCP		1	-0.3655	0.2277	2.5772	0.1084
COUNTRY	BE	1	-2.1299	0.4088	27.1457	<.0001
COUNTRY	BG	1	0.2742	0.2398	1.3072	0.2529
COUNTRY	ES	1	-0.1613	0.1096	2.1662	0.1411
COUNTRY	HR	1	-0.4435	0.1876	5.5878	0.0181
COUNTRY	PL	1	0.3840	0.1589	5.8385	0.0157
COUNTRY	PT	1	0.1460	0.1252	1.3605	0.2435
COUNTRY	RO	1	0.3238	0.1365	5.6286	0.0177
COUNTRY	RS	1	0.9737	0.2379	16.7499	<.0001
COUNTRY	SI	1	0.1815	0.2229	0.6636	0.4153

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.318	1.063	1.635
CAP2019	1.342	1.091	1.652
ROA2019	0.152	0.088	0.261
LIQ2019	1.001	0.996	1.007
SIZE2019	0.858	0.824	0.894
REDHC	0.611	0.531	0.703
REDSAL	0.789	0.695	0.895
NEGCP	0.694	0.444	1.084
COUNTRY BE vs SE	0.119	0.053	0.265
COUNTRY BG vs SE	1.315	0.822	2.105
COUNTRY ES vs SE	0.851	0.687	1.055
COUNTRY HR vs SE	0.642	0.444	0.927
COUNTRY PL vs SE	1.468	1.075	2.005
COUNTRY PT vs SE	1.157	0.905	1.479
COUNTRY RO vs SE	1.382	1.058	1.806
COUNTRY RS vs SE	2.648	1.661	4.221
COUNTRY SI vs SE	1.199	0.775	1.856

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.9	Somers' D	0.279
Percent Discordant	36.1	Gamma	0.279
Percent Tied	0.0	Tau-a	0.138
Pairs	5949855	c	0.639

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
12.2906	8	0.1387

3. ALTERNATIVE RESILIENCE METRIC – RESILIENCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_WORLD
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RESILIENT_WORLD	Total Frequency
1	0	448
2	1	694

Probability modeled is RESILIENT_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1482.4253	1124	1.3189	<.0001
Pearson	1138.7852	1124	1.0132	0.3728

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1531.739	1518.425
SC	1536.780	1609.155

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	1529.739	1482.425

R-Square	0.0406	Max-rescaled R-Square	0.0550

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	47.3140	17	0.0001
Score	45.7864	17	0.0002
Wald	42.8671	17	0.0005

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.4927	0.4827
CAP2019	1	0.6368	0.4249
ROA2019	1	5.4659	0.0194
LIQ2019	1	0.0815	0.7752
SIZE2019	1	0.5329	0.4654
REDHC	1	18.8553	<.0001
REDSAL	1	3.1486	0.0760
NEGCP	1	0.4364	0.5089
COUNTRY	9	13.8877	0.1264

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.2268	0.6944	3.1208	0.0773
LEV2019		1	-0.1162	0.1656	0.4927	0.4827
CAP2019		1	0.1687	0.2114	0.6368	0.4249
ROA2019		1	-0.9959	0.4260	5.4659	0.0194
LIQ2019		1	0.00163	0.00572	0.0815	0.7752
SIZE2019		1	-0.0336	0.0460	0.5329	0.4654
REDHC		1	-0.6603	0.1521	18.8553	<.0001
REDSAL		1	-0.2442	0.1376	3.1486	0.0760
NEGCP		1	0.1608	0.2434	0.4364	0.5089
COUNTRY	BE	1	-1.1210	0.5125	4.7837	0.0287
COUNTRY	BG	1	0.1220	0.4696	0.0675	0.7950
COUNTRY	ES	1	0.2127	0.1943	1.1979	0.2737
COUNTRY	HR	1	0.2395	0.3462	0.4784	0.4891
COUNTRY	PL	1	0.4379	0.2779	2.4828	0.1151
COUNTRY	PT	1	0.4779	0.2329	4.2109	0.0402
COUNTRY	RO	1	0.1087	0.3543	0.0942	0.7589
COUNTRY	RS	1	0.5591	0.4598	1.4784	0.2240
COUNTRY	SI	1	0.2920	0.5853	0.2490	0.6178

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.890	0.644	1.232
CAP2019	1.184	0.782	1.791
ROA2019	0.369	0.160	0.851
LIQ2019	1.002	0.990	1.013
SIZE2019	0.967	0.884	1.058
REDHC	0.517	0.384	0.696
REDSAL	0.783	0.598	1.026
NEGCP	1.174	0.729	1.893
COUNTRY BE vs SE	0.326	0.119	0.890
COUNTRY BG vs SE	1.130	0.450	2.836
COUNTRY ES vs SE	1.237	0.845	1.811
COUNTRY HR vs SE	1.271	0.645	2.504
COUNTRY PL vs SE	1.549	0.899	2.671
COUNTRY PT vs SE	1.613	1.022	2.546
COUNTRY RO vs SE	1.115	0.557	2.233
COUNTRY RS vs SE	1.749	0.710	4.307
COUNTRY SI vs SE	1.339	0.425	4.217

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	60.7	Somers' D	0.214
Percent Discordant	39.3	Gamma	0.214
Percent Tied	0.0	Tau-a	0.102
Pairs	310912	c	0.607

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
2.4538	8	0.9639

4. ALTERNATIVE RESILIENCE METRIC – RESISTANCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information		
Data Set	WORK.SORTTEMPTABLESORTED	
Response Variable	RESIST_WORLD	RESIST_WORLD
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESIST_WORLD	Total Frequency
1	0	2574
2	1	3464

Probability modeled is RESIST_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7092.1800	6020	1.1781	<.0001
Pearson	6087.1972	6020	1.0112	0.2689

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8240.780	7128.180
SC	8247.486	7248.885

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	**Intercept Only**	**Intercept and Covariates**
-2 Log L	8238.780	7092.180

R-Square	0.1730	**Max-rescaled R-Square**	0.2323

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	1146.6003	17	<.0001
Score	1054.1742	17	<.0001
Wald	907.2553	17	<.0001

Type 3 Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
LEV2019	1	7.1379	0.0075
CAP2019	1	43.1525	<.0001
ROA2019	1	33.5454	<.0001
LIQ2019	1	1.9654	0.1609
SIZE2019	1	62.4777	<.0001
REDHC	1	104.1557	<.0001
REDSAL	1	17.1238	<.0001
NEGCP	1	3.0168	0.0824
COUNTRY	9	658.9867	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	4.5749	0.3173	207.8970	<.0001
LEV2019		1	-0.2585	0.0968	7.1379	0.0075
CAP2019		1	0.6456	0.0983	43.1525	<.0001
ROA2019		1	-1.2157	0.2099	33.5454	<.0001
LIQ2019		1	-0.00374	0.00267	1.9654	0.1609
SIZE2019		1	-0.1545	0.0195	62.4777	<.0001
REDHC		1	-0.7236	0.0709	104.1557	<.0001
REDSAL		1	-0.2611	0.0631	17.1238	<.0001
NEGCP		1	-0.2861	0.1647	3.0168	0.0824
COUNTRY	**BE**	1	-2.2028	0.2694	66.8671	<.0001
COUNTRY	**BG**	1	-0.1473	0.2664	0.3058	0.5803
COUNTRY	**ES**	1	-2.0817	0.1183	309.7075	<.0001
COUNTRY	**HR**	1	-2.0466	0.1809	128.0251	<.0001
COUNTRY	**PL**	1	-0.8991	0.1598	31.6581	<.0001
COUNTRY	**PT**	1	-1.2921	0.1307	97.7581	<.0001
COUNTRY	**RO**	1	-0.1491	0.1602	0.8664	0.3519
COUNTRY	**RS**	1	-0.3950	0.2500	2.4957	0.1142
COUNTRY	**SI**	1	-0.2025	0.2821	0.5151	0.4729

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.772	0.639	0.933
CAP2019	1.907	1.573	2.312
ROA2019	0.297	0.197	0.447
LIQ2019	0.996	0.991	1.001
SIZE2019	0.857	0.825	0.890
REDHC	0.485	0.422	0.557
REDSAL	0.770	0.681	0.872
NEGCP	0.751	0.544	1.037
COUNTRY BE vs SE	0.110	0.065	0.187
COUNTRY BG vs SE	0.863	0.512	1.455
COUNTRY ES vs SE	0.125	0.099	0.157
COUNTRY HR vs SE	0.129	0.091	0.184
COUNTRY PL vs SE	0.407	0.298	0.557
COUNTRY PT vs SE	0.275	0.213	0.355
COUNTRY RO vs SE	0.861	0.629	1.179
COUNTRY RS vs SE	0.674	0.413	1.100
COUNTRY SI vs SE	0.817	0.470	1.420

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	74.6	Somers' D	0.491
Percent Discordant	25.4	Gamma	0.491
Percent Tied	0.0	Tau-a	0.240
Pairs	8916336	c	0.746

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
7.6354	8	0.4699

5. ALTERNATIVE RESILIENCE METRIC – RESISTANCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information		
Data Set	WORK.SORTTEMPTABLESORTED	
Response Variable	RESIST_WORLD	RESIST_WORLD
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RESIST_WORLD	Total Frequency
1	0	2131
2	1	2765

Probability modeled is RESIST_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5603.7557	4878	1.1488	<.0001
Pearson	4909.7712	4878	1.0065	0.3716

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6706.967	5639.756
SC	6713.464	5756.687

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	6704.967	5603.756

R-Square	0.2014	Max-rescaled R-Square	0.2701

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1101.2116	17	<.0001
Score	997.4217	17	<.0001
Wald	825.5799	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	5.6548	0.0174
CAP2019	1	22.7874	<.0001
ROA2019	1	71.5651	<.0001
LIQ2019	1	0.8564	0.3548
SIZE2019	1	79.3405	<.0001
REDHC	1	84.8217	<.0001
REDSAL	1	10.5334	0.0012
NEGCP	1	0.1696	0.6805
COUNTRY	9	613.0827	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	5.7205	0.3842	221.6820	<.0001
LEV2019		1	-0.2841	0.1195	5.6548	0.0174
CAP2019		1	0.5463	0.1144	22.7874	<.0001
ROA2019		1	-2.5439	0.3007	71.5651	<.0001
LIQ2019		1	-0.00291	0.00315	0.8564	0.3548
SIZE2019		1	-0.1993	0.0224	79.3405	<.0001
REDHC		1	-0.7413	0.0805	84.8217	<.0001
REDSAL		1	-0.2305	0.0710	10.5334	0.0012
NEGCP		1	-0.1008	0.2447	0.1696	0.6805
COUNTRY	BE	1	-2.6872	0.3292	66.6447	<.0001
COUNTRY	BG	1	-0.4945	0.2980	2.7536	0.0970
COUNTRY	ES	1	-2.4384	0.1468	275.8100	<.0001
COUNTRY	HR	1	-2.5344	0.2199	132.7938	<.0001
COUNTRY	PL	1	-1.0234	0.1946	27.6508	<.0001
COUNTRY	PT	1	-1.6273	0.1592	104.4536	<.0001
COUNTRY	RO	1	-0.2626	0.1856	2.0031	0.1570
COUNTRY	RS	1	-0.3951	0.3149	1.5739	0.2096
COUNTRY	SI	1	-0.7015	0.2996	5.4806	0.0192

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.753	0.596	0.951
CAP2019	1.727	1.380	2.161
ROA2019	0.079	0.044	0.142
LIQ2019	0.997	0.991	1.003
SIZE2019	0.819	0.784	0.856
REDHC	0.476	0.407	0.558
REDSAL	0.794	0.691	0.913
NEGCP	0.904	0.560	1.461
COUNTRY BE vs SE	0.068	0.036	0.130
COUNTRY BG vs SE	0.610	0.340	1.094
COUNTRY ES vs SE	0.087	0.065	0.116
COUNTRY HR vs SE	0.079	0.052	0.122
COUNTRY PL vs SE	0.359	0.245	0.526
COUNTRY PT vs SE	0.196	0.144	0.268
COUNTRY RO vs SE	0.769	0.535	1.106
COUNTRY RS vs SE	0.674	0.363	1.249
COUNTRY SI vs SE	0.496	0.276	0.892

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	76.3	Somers' D	0.527
Percent Discordant	23.7	Gamma	0.527
Percent Tied	0.0	Tau-a	0.259
Pairs	5892215	c	0.763

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
10.5460	8	0.2288

6. ALTERNATIVE RESILIENCE METRIC – RESISTANCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information		
Data Set	WORK.SORTTEMPTABLESORTED	
Response Variable	RESIST_WORLD	RESIST_WORLD
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RESIST_WORLD	Total Frequency
1	0	443
2	1	699

Probability modeled is RESIST_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1400.0620	1124	1.2456	<.0001
Pearson	1129.1811	1124	1.0046	0.4510

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1527.271	1436.062
SC	1532.311	1526.792

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	1525.271	1400.062

R-Square	0.1038	Max-rescaled R-Square	0.1409

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	125.2086	17	<.0001
Score	113.7534	17	<.0001
Wald	95.6675	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.3666	0.5449
CAP2019	1	1.6656	0.1968
ROA2019	1	1.2966	0.2548
LIQ2019	1	1.9490	0.1627
SIZE2019	1	1.8271	0.1765
REDHC	1	15.3376	<.0001
REDSAL	1	6.3343	0.0118
NEGCP	1	0.8925	0.3448
COUNTRY	9	57.3922	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.0152	0.7178	17.6456	<.0001
LEV2019		1	-0.1005	0.1660	0.3666	0.5449
CAP2019		1	0.2811	0.2178	1.6656	0.1968
ROA2019		1	0.4579	0.4021	1.2966	0.2548
LIQ2019		1	-0.00780	0.00559	1.9490	0.1627
SIZE2019		1	-0.0632	0.0468	1.8271	0.1765
REDHC		1	-0.6072	0.1550	15.3376	<.0001
REDSAL		1	-0.3612	0.1435	6.3343	0.0118
NEGCP		1	-0.2274	0.2407	0.8925	0.3448
COUNTRY	BE	1	-1.6412	0.4934	11.0639	0.0009
COUNTRY	BG	1	0.5533	0.6622	0.6981	0.4034
COUNTRY	ES	1	-1.4314	0.2216	41.7255	<.0001
COUNTRY	HR	1	-1.4013	0.3618	15.0037	0.0001
COUNTRY	PL	1	-0.8261	0.2955	7.8166	0.0052
COUNTRY	PT	1	-0.8234	0.2572	10.2505	0.0014
COUNTRY	RO	1	-0.5074	0.3893	1.6989	0.1924
COUNTRY	RS	1	-0.9226	0.4508	4.1885	0.0407
COUNTRY	SI	1	13.8853	522.5	0.0007	0.9788

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.904	0.653	1.252
CAP2019	1.325	0.864	2.030
ROA2019	1.581	0.719	3.477
LIQ2019	0.992	0.981	1.003
SIZE2019	0.939	0.856	1.029
REDHC	0.545	0.402	0.738
REDSAL	0.697	0.526	0.923
NEGCP	0.797	0.497	1.277
COUNTRY BE vs SE	0.194	0.074	0.510
COUNTRY BG vs SE	1.739	0.475	6.367
COUNTRY ES vs SE	0.239	0.155	0.369
COUNTRY HR vs SE	0.246	0.121	0.500
COUNTRY PL vs SE	0.438	0.245	0.781
COUNTRY PT vs SE	0.439	0.265	0.727
COUNTRY RO vs SE	0.602	0.281	1.291
COUNTRY RS vs SE	0.397	0.164	0.962
COUNTRY SI vs SE	>999.999	<0.001	>999.999

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.1	Somers' D	0.382
Percent Discordant	30.9	Gamma	0.382
Percent Tied	0.0	Tau-a	0.182
Pairs	309657	c	0.691

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
14.4210	8	0.0714

7. ALTERNATIVE RESILIENCE METRIC – RECOVERY MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information		
Data Set	WORK.SORTTEMPTABLESORTED	
Response Variable	RECOVER_WORLD	RECOVER_WORLD
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RECOVER_WORLD	Total Frequency
1	0	4436
2	1	1602

Probability modeled is RECOVER_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6606.2480	6020	1.0974	<.0001
Pearson	6074.8773	6020	1.0091	0.3069

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6988.544	6642.248
SC	6995.250	6762.953

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	6986.544	6606.248

R-Square	0.0610	Max-rescaled R-Square	0.0890

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	380.2962	17	<.0001
Score	340.8217	17	<.0001
Wald	305.7279	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.2064	0.1374
CAP2019	1	3.2902	0.0697
ROA2019	1	3.2203	0.0727
LIQ2019	1	0.0337	0.8542
SIZE2019	1	32.4850	<.0001
REDHC	1	12.5002	0.0004
REDSAL	1	3.7215	0.0537
NEGCP	1	3.5195	0.0607
COUNTRY	9	222.2498	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-4.5941	0.3425	179.9241	<.0001
LEV2019		1	0.1503	0.1012	2.2064	0.1374
CAP2019		1	0.1870	0.1031	3.2902	0.0697
ROA2019		1	0.4001	0.2229	3.2203	0.0727
LIQ2019		1	0.000502	0.00273	0.0337	0.8542
SIZE2019		1	0.1157	0.0203	32.4850	<.0001
REDHC		1	0.2634	0.0745	12.5002	0.0004
REDSAL		1	0.1283	0.0665	3.7215	0.0537
NEGCP		1	-0.3439	0.1833	3.5195	0.0607
COUNTRY	BE	1	2.1039	0.2939	51.2437	<.0001
COUNTRY	BG	1	0.3718	0.3239	1.3177	0.2510
COUNTRY	ES	1	1.7201	0.1541	124.6246	<.0001
COUNTRY	HR	1	1.8297	0.2106	75.4760	<.0001
COUNTRY	PL	1	1.0572	0.1959	29.1187	<.0001
COUNTRY	PT	1	1.5305	0.1650	86.0840	<.0001
COUNTRY	RO	1	0.7681	0.1895	16.4363	<.0001
COUNTRY	RS	1	0.8352	0.2730	9.3596	0.0022
COUNTRY	SI	1	0.9102	0.2830	10.3415	0.0013

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.162	0.953	1.417
CAP2019	1.206	0.985	1.476
ROA2019	1.492	0.964	2.310
LIQ2019	1.001	0.995	1.006
SIZE2019	1.123	1.079	1.168
REDHC	1.301	1.125	1.506
REDSAL	1.137	0.998	1.295
NEGCP	0.709	0.495	1.016
COUNTRY BE vs SE	8.198	4.608	14.585
COUNTRY BG vs SE	1.450	0.769	2.736
COUNTRY ES vs SE	5.585	4.129	7.554
COUNTRY HR vs SE	6.232	4.124	9.416
COUNTRY PL vs SE	2.878	1.961	4.226
COUNTRY PT vs SE	4.620	3.344	6.384
COUNTRY RO vs SE	2.156	1.487	3.125
COUNTRY RS vs SE	2.305	1.350	3.936
COUNTRY SI vs SE	2.485	1.427	4.327

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	65.6	Somers' D	0.312
Percent Discordant	34.4	Gamma	0.312
Percent Tied	0.0	Tau-a	0.122
Pairs	7106472	c	0.656

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
12.0273	8	0.1500

8. ALTERNATIVE RESILIENCE METRIC – RECOVERY MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information		
Data Set	WORK.SORTTEMPTABLESORTED	
Response Variable	RECOVER_WORLD	RECOVER_WORLD
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RECOVER_WORLD	Total Frequency
1	0	3567
2	1	1329

Probability modeled is RECOVER_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5362.4421	4878	1.0993	<.0001
Pearson	4903.6852	4878	1.0053	0.3950

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5727.303	5398.442
SC	5733.799	5515.373

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	5725.303	5362.442

R-Square	0.0714	Max-rescaled R-Square	0.1036

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	362.8604	17	<.0001
Score	321.9519	17	<.0001
Wald	282.6971	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.4405	0.5069
CAP2019	1	1.4145	0.2343
ROA2019	1	4.2067	0.0403
LIQ2019	1	0.1118	0.7381
SIZE2019	1	29.2723	<.0001
REDHC	1	21.8504	<.0001
REDSAL	1	2.1632	0.1413
NEGCP	1	0.2392	0.6248
COUNTRY	9	203.4560	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-5.0024	0.4059	151.9082	<.0001
LEV2019		1	0.0810	0.1221	0.4405	0.5069
CAP2019		1	0.1399	0.1177	1.4145	0.2343
ROA2019		1	0.5838	0.2846	4.2067	0.0403
LIQ2019		1	0.00103	0.00308	0.1118	0.7381
SIZE2019		1	0.1223	0.0226	29.2723	<.0001
REDHC		1	0.3966	0.0848	21.8504	<.0001
REDSAL		1	0.1079	0.0734	2.1632	0.1413
NEGCP		1	-0.1264	0.2584	0.2392	0.6248
COUNTRY	BE	1	2.3868	0.3617	43.5417	<.0001
COUNTRY	BG	1	0.6871	0.3668	3.5085	0.0611
COUNTRY	ES	1	2.0074	0.1978	102.9505	<.0001
COUNTRY	HR	1	2.1492	0.2590	68.8347	<.0001
COUNTRY	PL	1	1.2977	0.2428	28.5685	<.0001
COUNTRY	PT	1	1.8159	0.2087	75.7320	<.0001
COUNTRY	RO	1	0.9248	0.2298	16.2001	<.0001
COUNTRY	RS	1	0.8739	0.3391	6.6434	0.0100
COUNTRY	SI	1	1.0905	0.3292	10.9753	0.0009

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.084	0.854	1.378
CAP2019	1.150	0.913	1.449
ROA2019	1.793	1.026	3.132
LIQ2019	1.001	0.995	1.007
SIZE2019	1.130	1.081	1.181
REDHC	1.487	1.259	1.756
REDSAL	1.114	0.965	1.286
NEGCP	0.881	0.531	1.462
COUNTRY BE vs SE	10.878	5.354	22.103
COUNTRY BG vs SE	1.988	0.969	4.080
COUNTRY ES vs SE	7.444	5.051	10.970
COUNTRY HR vs SE	8.578	5.163	14.253
COUNTRY PL vs SE	3.661	2.275	5.892
COUNTRY PT vs SE	6.147	4.083	9.252
COUNTRY RO vs SE	2.521	1.607	3.955
COUNTRY RS vs SE	2.396	1.233	4.657
COUNTRY SI vs SE	2.976	1.561	5.673

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.7	Somers' D	0.333
Percent Discordant	33.3	Gamma	0.333
Percent Tied	0.0	Tau-a	0.132
Pairs	4740543	c	0.667

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
9.9072	8	0.2716

9. ALTERNATIVE RESILIENCE METRIC – RECOVERY MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information		
Data Set	WORK.SORTTEMPTABLESORTED	
Response Variable	RECOVER_WORLD	RECOVER_WORLD
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RECOVER_WORLD	Total Frequency
1	0	869
2	1	273

Probability modeled is RECOVER_WORLD=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1196.2268	1124	1.0643	0.0660
Pearson	1151.6847	1124	1.0246	0.2765

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1258.171	1232.227
SC	1263.212	1322.956

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	1256.171	1196.227

R-Square	0.0511	Max-rescaled R-Square	0.0767

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	59.9444	17	<.0001
Score	55.5777	17	<.0001
Wald	51.8169	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.7344	0.0982
CAP2019	1	6.5319	0.0106
ROA2019	1	0.0500	0.8231
LIQ2019	1	0.0307	0.8608
SIZE2019	1	1.8661	0.1719
REDHC	1	3.1872	0.0742
REDSAL	1	2.3041	0.1290
NEGCP	1	5.2618	0.0218
COUNTRY	9	22.7854	0.0067

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.5239	0.8142	18.7328	<.0001
LEV2019		1	0.3014	0.1823	2.7344	0.0982
CAP2019		1	0.6408	0.2507	6.5319	0.0106
ROA2019		1	-0.1041	0.4657	0.0500	0.8231
LIQ2019		1	-0.00111	0.00635	0.0307	0.8608
SIZE2019		1	0.0723	0.0529	1.8661	0.1719
REDHC		1	-0.2886	0.1617	3.1872	0.0742
REDSAL		1	0.2474	0.1630	2.3041	0.1290
NEGCP		1	-0.6606	0.2880	5.2618	0.0218
COUNTRY	BE	1	1.4671	0.5381	7.4334	0.0064
COUNTRY	BG	1	-0.4068	0.7900	0.2652	0.6066
COUNTRY	ES	1	1.0407	0.2680	15.0828	0.0001
COUNTRY	HR	1	1.0506	0.4143	6.4317	0.0112
COUNTRY	PL	1	0.5447	0.3546	2.3599	0.1245
COUNTRY	PT	1	0.9311	0.2995	9.6664	0.0019
COUNTRY	RO	1	1.1833	0.4199	7.9410	0.0048
COUNTRY	RS	1	1.0794	0.4950	4.7542	0.0292
COUNTRY	SI	1	0.9992	0.6382	2.4515	0.1174

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.352	0.946	1.932
CAP2019	1.898	1.161	3.103
ROA2019	0.901	0.362	2.245
LIQ2019	0.999	0.987	1.011
SIZE2019	1.075	0.969	1.193
REDHC	0.749	0.546	1.029
REDSAL	1.281	0.930	1.763
NEGCP	0.517	0.294	0.908
COUNTRY BE vs SE	4.336	1.510	12.450
COUNTRY BG vs SE	0.666	0.142	3.132
COUNTRY ES vs SE	2.831	1.674	4.787
COUNTRY HR vs SE	2.859	1.270	6.440
COUNTRY PL vs SE	1.724	0.860	3.454
COUNTRY PT vs SE	2.537	1.411	4.563
COUNTRY RO vs SE	3.265	1.434	7.436
COUNTRY RS vs SE	2.943	1.115	7.765
COUNTRY SI vs SE	2.716	0.778	9.488

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	65.0	Somers' D	0.301
Percent Discordant	35.0	Gamma	0.301
Percent Tied	0.0	Tau-a	0.109
Pairs	237237	c	0.650

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.2714	8	0.8318

10. ALTERNATIVE SIZE METRIC – RESILIENCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	3020
2	1	3018

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7849.7700	6020	1.3039	<.0001
Pearson	6073.7404	6020	1.0089	0.3105

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8372.445	7885.770
SC	8379.151	8006.475
-2 Log L	8370.445	7849.770

R-Square	0.0826	Max-rescaled R-Square	0.1102

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	520.6747	17	<.0001
Score	490.6366	17	<.0001
Wald	442.6458	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	13.3365	0.0003
CAP2019	1	1.3158	0.2513
ROA2019	1	59.0933	<.0001
LIQ2019	1	0.0400	0.8414
SIZE2019_REV	1	31.2377	<.0001
REDHC	1	65.0015	<.0001
REDSAL	1	14.7817	0.0001
NEGCP	1	0.7529	0.3856
COUNTRY	9	283.6915	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.9964	0.3068	95.3669	<.0001
LEV2019		1	0.3373	0.0923	13.3365	0.0003
CAP2019		1	0.1042	0.0908	1.3158	0.2513
ROA2019		1	-1.5870	0.2065	59.0933	<.0001
LIQ2019		1	-0.00050	0.00249	0.0400	0.8414
SIZE2019_REV		1	-0.1092	0.0195	31.2377	<.0001
REDHC		1	-0.5382	0.0668	65.0015	<.0001
REDSAL		1	-0.2264	0.0589	14.7817	0.0001
NEGCP		1	-0.1360	0.1567	0.7529	0.3856
COUNTRY	BE	1	-1.3981	0.2632	28.2217	<.0001
COUNTRY	BG	1	-1.0662	0.2160	24.3723	<.0001
COUNTRY	ES	1	-1.0044	0.1026	95.8215	<.0001
COUNTRY	HR	1	-1.9973	0.1821	120.2663	<.0001
COUNTRY	PL	1	-0.9539	0.1424	44.8643	<.0001
COUNTRY	PT	1	-1.6175	0.1170	191.0942	<.0001
COUNTRY	RO	1	-0.6313	0.1317	22.9687	<.0001
COUNTRY	RS	1	-1.4925	0.1961	57.9033	<.0001
COUNTRY	SI	1	-2.3044	0.2284	101.7498	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.401	1.169	1.679
CAP2019	1.110	0.929	1.326
ROA2019	0.205	0.136	0.307

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.000	0.995	1.004
SIZE2019_REV		0.897	0.863	0.932
REDHC		0.584	0.512	0.665
REDSAL		0.797	0.710	0.895
NEGCP		0.873	0.642	1.187
COUNTRY	BE vs SE	0.247	0.148	0.414
COUNTRY	BG vs SE	0.344	0.225	0.526
COUNTRY	ES vs SE	0.366	0.300	0.448
COUNTRY	HR vs SE	0.136	0.095	0.194
COUNTRY	PL vs SE	0.385	0.291	0.509
COUNTRY	PT vs SE	0.198	0.158	0.250
COUNTRY	RO vs SE	0.532	0.411	0.689
COUNTRY	RS vs SE	0.225	0.153	0.330
COUNTRY	SI vs SE	0.100	0.064	0.156

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.4	Somers' D	0.327
Percent Discordant	33.6	Gamma	0.327
Percent Tied	0.0	Tau-a	0.164
Pairs	9114360	c	0.664

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.8972	8	0.7685

11. ALTERNATIVE SIZE METRIC – RESILIENCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2590
2	1	2306

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6357.0531	4878	1.3032	<.0001
Pearson	4891.9266	4878	1.0029	0.4413

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6772.814	6393.053
SC	6779.310	6509.984
-2 Log L	6770.814	6357.053

R-Square	0.0810	Max-rescaled R-Square	0.1082

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	413.7610	17	<.0001
Score	395.5340	17	<.0001
Wald	360.3365	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	19.2429	<.0001
CAP2019	1	0.1095	0.7408
ROA2019	1	39.2043	<.0001
LIQ2019	1	0.1173	0.7320
SIZE2019_REV	1	21.6740	<.0001
REDHC	1	46.0434	<.0001
REDSAL	1	11.0995	0.0009
NEGCP	1	4.5851	0.0323
COUNTRY	9	263.0316	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.9271	0.3498	70.0112	<.0001
LEV2019		1	0.4791	0.1092	19.2429	<.0001
CAP2019		1	0.0347	0.1048	0.1095	0.7408
ROA2019		1	-1.6645	0.2658	39.2043	<.0001
LIQ2019		1	-0.00097	0.00282	0.1173	0.7320
SIZE2019_REV		1	-0.1023	0.0220	21.6740	<.0001
REDHC		1	-0.5031	0.0741	46.0434	<.0001
REDSAL		1	-0.2173	0.0652	11.0995	0.0009
NEGCP		1	-0.4882	0.2280	4.5851	0.0323
COUNTRY	BE	1	-1.4411	0.3144	21.0159	<.0001
COUNTRY	BG	1	-1.1734	0.2444	23.0452	<.0001
COUNTRY	ES	1	-1.1372	0.1194	90.7731	<.0001
COUNTRY	HR	1	-2.1213	0.2099	102.1079	<.0001
COUNTRY	PL	1	-1.0392	0.1654	39.4920	<.0001
COUNTRY	PT	1	-1.8365	0.1369	180.0389	<.0001
COUNTRY	RO	1	-0.6458	0.1461	19.5412	<.0001
COUNTRY	RS	1	-1.6079	0.2217	52.6012	<.0001
COUNTRY	SI	1	-2.3463	0.2483	89.3117	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.615	1.304	2.000
CAP2019	1.035	0.843	1.271
ROA2019	0.189	0.112	0.319

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.999	0.994	1.005
SIZE2019_REV		0.903	0.865	0.942
REDHC		0.605	0.523	0.699
REDSAL		0.805	0.708	0.914
NEGCP		0.614	0.393	0.960
COUNTRY	BE vs SE	0.237	0.128	0.438
COUNTRY	BG vs SE	0.309	0.192	0.499
COUNTRY	ES vs SE	0.321	0.254	0.405
COUNTRY	HR vs SE	0.120	0.079	0.181
COUNTRY	PL vs SE	0.354	0.256	0.489
COUNTRY	PT vs SE	0.159	0.122	0.208
COUNTRY	RO vs SE	0.524	0.394	0.698
COUNTRY	RS vs SE	0.200	0.130	0.309
COUNTRY	SI vs SE	0.096	0.059	0.156

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	65.9	Somers' D	0.318
Percent Discordant	34.1	Gamma	0.318
Percent Tied	0.0	Tau-a	0.159
Pairs	5972540	c	0.659

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.1706	8	0.8414

12. ALTERNATIVE SIZE METRIC – RESILIENCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	430
2	1	712

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1443.4169	1124	1.2842	<.0001
Pearson	1142.7429	1124	1.0167	0.3419

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1514.787	1479.417
SC	1519.827	1570.147
-2 Log L	1512.787	1443.417

R-Square	0.0589	Max-rescaled R-Square	0.0803

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.3699	17	<.0001
Score	66.3081	17	<.0001
Wald	61.9869	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.1254	0.7232
CAP2019	1	0.1070	0.7435
ROA2019	1	4.8258	0.0280
LIQ2019	1	0.0019	0.9653
SIZE2019_REV	1	2.1911	0.1388
REDHC	1	21.2486	<.0001
REDSAL	1	5.3510	0.0207
NEGCP	1	1.5275	0.2165
COUNTRY	9	26.7346	0.0015

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.6908	0.7015	14.7142	0.0001
LEV2019		1	-0.0598	0.1690	0.1254	0.7232
CAP2019		1	0.0693	0.2117	0.1070	0.7435
ROA2019		1	-0.9500	0.4324	4.8258	0.0280
LIQ2019		1	0.000248	0.00570	0.0019	0.9653
SIZE2019_REV		1	-0.0680	0.0460	2.1911	0.1388
REDHC		1	-0.7420	0.1610	21.2486	<.0001
REDSAL		1	-0.3277	0.1417	5.3510	0.0207
NEGCP		1	0.3033	0.2454	1.5275	0.2165
COUNTRY	BE	1	-1.0348	0.4932	4.4025	0.0359
COUNTRY	BG	1	-0.7524	0.4749	2.5101	0.1131
COUNTRY	ES	1	-0.4920	0.2143	5.2727	0.0217
COUNTRY	HR	1	-1.2978	0.3890	11.1300	0.0008
COUNTRY	PL	1	-0.7284	0.2838	6.5850	0.0103
COUNTRY	PT	1	-0.8836	0.2414	13.4013	0.0003
COUNTRY	RO	1	-0.8325	0.3670	5.1455	0.0233
COUNTRY	RS	1	-1.0611	0.4422	5.7583	0.0164
COUNTRY	SI	1	-2.1398	0.6105	12.2829	0.0005

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.942	0.676	1.312
CAP2019	1.072	0.708	1.623
ROA2019	0.387	0.166	0.903

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.000	0.989	1.011
SIZE2019_REV		0.934	0.854	1.022
REDHC		0.476	0.347	0.653
REDSAL		0.721	0.546	0.951
NEGCP		1.354	0.837	2.191
COUNTRY	BE vs SE	0.355	0.135	0.934
COUNTRY	BG vs SE	0.471	0.186	1.195
COUNTRY	ES vs SE	0.611	0.402	0.930
COUNTRY	HR vs SE	0.273	0.127	0.585
COUNTRY	PL vs SE	0.483	0.277	0.842
COUNTRY	PT vs SE	0.413	0.258	0.663
COUNTRY	RO vs SE	0.435	0.212	0.893
COUNTRY	RS vs SE	0.346	0.145	0.823
COUNTRY	SI vs SE	0.118	0.036	0.389

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.0	Somers' D	0.281
Percent Discordant	36.0	Gamma	0.281
Percent Tied	0.0	Tau-a	0.132
Pairs	306160	c	0.640

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
8.1714	8	0.4169

13. ALTERNATIVE SIZE METRIC – RESISTANCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	2446
2	1	3592

Probability modeled is RESIST_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7523.2511	6020	1.2497	<.0001
Pearson	6065.1039	6020	1.0075	0.3387

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8153.612	7559.251
SC	8160.318	7679.956
-2 Log L	8151.612	7523.251

R-Square	0.0988	Max-rescaled R-Square	0.1334

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	628.3608	17	<.0001
Score	589.2177	17	<.0001
Wald	532.1664	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	1.8629	0.1723
CAP2019	1	32.0953	<.0001
ROA2019	1	25.2337	<.0001
LIQ2019	1	4.0893	0.0432
SIZE2019_REV	1	50.2245	<.0001
REDHC	1	91.5695	<.0001
REDSAL	1	21.5986	<.0001
NEGCP	1	9.5914	0.0020
COUNTRY	9	320.7371	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.9679	0.3196	154.1403	<.0001
LEV2019		1	-0.1265	0.0927	1.8629	0.1723
CAP2019		1	0.5253	0.0927	32.0953	<.0001
ROA2019		1	-0.9574	0.1906	25.2337	<.0001
LIQ2019		1	-0.00517	0.00255	4.0893	0.0432
SIZE2019_REV		1	-0.1431	0.0202	50.2245	<.0001
REDHC		1	-0.6808	0.0711	91.5695	<.0001
REDSAL		1	-0.2821	0.0607	21.5986	<.0001
NEGCP		1	-0.4930	0.1592	9.5914	0.0020
COUNTRY	BE	1	-1.4997	0.2681	31.3032	<.0001
COUNTRY	BG	1	-0.8358	0.2225	14.1074	0.0002
COUNTRY	ES	1	-1.2587	0.1070	138.3909	<.0001
COUNTRY	HR	1	-1.9657	0.1856	112.1690	<.0001
COUNTRY	PL	1	0.2001	0.1677	1.4240	0.2327
COUNTRY	PT	1	-0.8610	0.1208	50.8108	<.0001
COUNTRY	RO	1	-0.8013	0.1371	34.1698	<.0001
COUNTRY	RS	1	-0.6356	0.2167	8.6039	0.0034
COUNTRY	SI	1	-2.6145	0.2273	132.2793	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.881	0.735	1.057
CAP2019	1.691	1.410	2.028
ROA2019	0.384	0.264	0.558

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.995	0.990	1.000
SIZE2019_REV		0.867	0.833	0.902
REDHC		0.506	0.440	0.582
REDSAL		0.754	0.670	0.849
NEGCP		0.611	0.447	0.834
COUNTRY	BE vs SE	0.223	0.132	0.377
COUNTRY	BG vs SE	0.434	0.280	0.671
COUNTRY	ES vs SE	0.284	0.230	0.350
COUNTRY	HR vs SE	0.140	0.097	0.202
COUNTRY	PL vs SE	1.222	0.879	1.697
COUNTRY	PT vs SE	0.423	0.334	0.536
COUNTRY	RO vs SE	0.449	0.343	0.587
COUNTRY	RS vs SE	0.530	0.346	0.810
COUNTRY	SI vs SE	0.073	0.047	0.114

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	68.4	Somers' D	0.367
Percent Discordant	31.6	Gamma	0.367
Percent Tied	0.0	Tau-a	0.177
Pairs	8786032	c	0.684

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.1781	8	0.6273

14. ALTERNATIVE SIZE METRIC – RESISTANCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	2012
2	1	2884

Probability modeled is RESIST_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6045.5114	4878	1.2393	<.0001
Pearson	4898.8793	4878	1.0043	0.4138

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6633.158	6081.511
SC	6639.654	6198.443
-2 Log L	6631.158	6045.511

R-Square	0.1127	Max-rescaled R-Square	0.1520

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	585.6469	17	<.0001
Score	543.0481	17	<.0001
Wald	478.2122	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.5652	0.4522
CAP2019	1	16.9529	<.0001
ROA2019	1	50.9090	<.0001
LIQ2019	1	2.1876	0.1391
SIZE2019_REV	1	46.9608	<.0001
REDHC	1	73.8436	<.0001
REDSAL	1	14.9953	0.0001
NEGCP	1	3.2109	0.0732
COUNTRY	9	307.8229	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	4.4600	0.3702	145.1362	<.0001
LEV2019		1	-0.0850	0.1131	0.5652	0.4522
CAP2019		1	0.4457	0.1083	16.9529	<.0001
ROA2019		1	-1.8941	0.2655	50.9090	<.0001
LIQ2019		1	-0.00432	0.00292	2.1876	0.1391
SIZE2019_REV		1	-0.1570	0.0229	46.9608	<.0001
REDHC		1	-0.6855	0.0798	73.8436	<.0001
REDSAL		1	-0.2615	0.0675	14.9953	0.0001
NEGCP		1	-0.4133	0.2307	3.2109	0.0732
COUNTRY	BE	1	-1.7886	0.3223	30.8027	<.0001
COUNTRY	BG	1	-1.1261	0.2510	20.1279	<.0001
COUNTRY	ES	1	-1.4538	0.1280	128.9755	<.0001
COUNTRY	HR	1	-2.2416	0.2164	107.3022	<.0001
COUNTRY	PL	1	0.3405	0.2085	2.6672	0.1024
COUNTRY	PT	1	-1.0670	0.1430	55.6848	<.0001
COUNTRY	RO	1	-0.8881	0.1557	32.5220	<.0001
COUNTRY	RS	1	-0.6510	0.2561	6.4600	0.0110
COUNTRY	SI	1	-2.9012	0.2530	131.5258	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.918	0.736	1.146
CAP2019	1.562	1.263	1.931
ROA2019	0.150	0.089	0.253

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.996	0.990	1.001
SIZE2019_REV		0.855	0.817	0.894
REDHC		0.504	0.431	0.589
REDSAL		0.770	0.674	0.879
NEGCP		0.661	0.421	1.040
COUNTRY	BE vs SE	0.167	0.089	0.314
COUNTRY	BG vs SE	0.324	0.198	0.530
COUNTRY	ES vs SE	0.234	0.182	0.300
COUNTRY	HR vs SE	0.106	0.070	0.162
COUNTRY	PL vs SE	1.406	0.934	2.115
COUNTRY	PT vs SE	0.344	0.260	0.455
COUNTRY	RO vs SE	0.411	0.303	0.558
COUNTRY	RS vs SE	0.522	0.316	0.862
COUNTRY	SI vs SE	0.055	0.033	0.090

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.3	Somers' D	0.386
Percent Discordant	30.7	Gamma	0.386
Percent Tied	0.0	Tau-a	0.187
Pairs	5802608	c	0.693

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
19.4492	8	0.0126

15. ALTERNATIVE SIZE METRIC – RESISTANCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	434
2	1	708

Probability modeled is RESIST_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1427.8448	1124	1.2703	<.0001
Pearson	1146.8721	1124	1.0203	0.3109

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1518.762	1463.845
SC	1523.802	1554.574
-2 Log L	1516.762	1427.845

R-Square	0.0749	Max-rescaled R-Square	0.1019

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	88.9169	17	<.0001
Score	85.1836	17	<.0001
Wald	79.6189	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.3569	0.5502
CAP2019	1	2.1237	0.1450
ROA2019	1	0.0129	0.9096
LIQ2019	1	2.2956	0.1297
SIZE2019_REV	1	5.0388	0.0248
REDHC	1	17.7849	<.0001
REDSAL	1	6.7055	0.0096
NEGCP	1	1.5243	0.2170
COUNTRY	9	35.3369	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.3270	0.7055	22.2353	<.0001
LEV2019		1	-0.0985	0.1649	0.3569	0.5502
CAP2019		1	0.3102	0.2128	2.1237	0.1450
ROA2019		1	0.0422	0.3718	0.0129	0.9096
LIQ2019		1	-0.00846	0.00558	2.2956	0.1297
SIZE2019_REV		1	-0.1038	0.0462	5.0388	0.0248
REDHC		1	-0.6822	0.1618	17.7849	<.0001
REDSAL		1	-0.3695	0.1427	6.7055	0.0096
NEGCP		1	-0.2955	0.2393	1.5243	0.2170
COUNTRY	BE	1	-1.1349	0.4966	5.2220	0.0223
COUNTRY	BG	1	-0.1039	0.5233	0.0394	0.8426
COUNTRY	ES	1	-0.9494	0.2142	19.6437	<.0001
COUNTRY	HR	1	-1.5323	0.3920	15.2760	<.0001
COUNTRY	PL	1	-0.1792	0.2982	0.3614	0.5478
COUNTRY	PT	1	-0.5824	0.2474	5.5431	0.0186
COUNTRY	RO	1	-0.9733	0.3645	7.1298	0.0076
COUNTRY	RS	1	-1.0590	0.4385	5.8337	0.0157
COUNTRY	SI	1	-1.8373	0.5829	9.9343	0.0016

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.906	0.656	1.252
CAP2019	1.364	0.899	2.070
ROA2019	1.043	0.503	2.162

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.992	0.981	1.002
SIZE2019_REV		0.901	0.823	0.987
REDHC		0.505	0.368	0.694
REDSAL		0.691	0.522	0.914
NEGCP		0.744	0.466	1.190
COUNTRY	BE vs SE	0.321	0.121	0.851
COUNTRY	BG vs SE	0.901	0.323	2.514
COUNTRY	ES vs SE	0.387	0.254	0.589
COUNTRY	HR vs SE	0.216	0.100	0.466
COUNTRY	PL vs SE	0.836	0.466	1.500
COUNTRY	PT vs SE	0.559	0.344	0.907
COUNTRY	RO vs SE	0.378	0.185	0.772
COUNTRY	RS vs SE	0.347	0.147	0.819
COUNTRY	SI vs SE	0.159	0.051	0.499

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.5	Somers' D	0.331
Percent Discordant	33.5	Gamma	0.331
Percent Tied	0.0	Tau-a	0.156
Pairs	307272	c	0.665

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
11.4121	8	0.1794

16. ALTERNATIVE SIZE METRIC – RECOVERY MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	4581
2	1	1457

Probability modeled is RECOVER_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6403.3854	6020	1.0637	0.0003
Pearson	6056.7525	6020	1.0061	0.3668

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6674.951	6439.385
SC	6681.657	6560.090
-2 Log L	6672.951	6403.385

R-Square	0.0437	Max-rescaled R-Square	0.0653

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	269.5657	17	<.0001
Score	231.3514	17	<.0001
Wald	183.6840	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	1.1257	0.2887
CAP2019	1	2.8529	0.0912
ROA2019	1	1.2085	0.2716
LIQ2019	1	0.3505	0.5538
SIZE2019_REV	1	11.7953	0.0006
REDHC	1	6.8419	0.0089
REDSAL	1	6.6998	0.0096
NEGCP	1	1.2995	0.2543
COUNTRY	9	153.2131	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-2.7901	0.3493	63.8212	<.0001
LEV2019		1	0.1106	0.1042	1.1257	0.2887
CAP2019		1	0.1760	0.1042	2.8529	0.0912
ROA2019		1	0.2282	0.2076	1.2085	0.2716
LIQ2019		1	0.00159	0.00268	0.3505	0.5538
SIZE2019_REV		1	0.0769	0.0224	11.7953	0.0006
REDHC		1	0.2043	0.0781	6.8419	0.0089
REDSAL		1	0.1747	0.0675	6.6998	0.0096
NEGCP		1	-0.2130	0.1869	1.2995	0.2543
COUNTRY	BE	1	0.7787	0.2776	7.8708	0.0050
COUNTRY	BG	1	0.5175	0.2275	5.1739	0.0229
COUNTRY	ES	1	0.0772	0.1104	0.4886	0.4845
COUNTRY	HR	1	0.6043	0.1963	9.4772	0.0021
COUNTRY	PL	1	-2.4022	0.3365	50.9603	<.0001
COUNTRY	PT	1	-0.00901	0.1273	0.0050	0.9436
COUNTRY	RO	1	0.8613	0.1366	39.7742	<.0001
COUNTRY	RS	1	-0.0345	0.2322	0.0221	0.8818
COUNTRY	SI	1	0.7212	0.2168	11.0692	0.0009

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.117	0.911	1.370
CAP2019	1.192	0.972	1.463
ROA2019	1.256	0.836	1.887

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.002	0.996	1.007
SIZE2019_REV		1.080	1.034	1.128
REDHC		1.227	1.053	1.430
REDSAL		1.191	1.043	1.359
NEGCP		0.808	0.560	1.166
COUNTRY	BE vs SE	2.179	1.265	3.754
COUNTRY	BG vs SE	1.678	1.074	2.621
COUNTRY	ES vs SE	1.080	0.870	1.341
COUNTRY	HR vs SE	1.830	1.246	2.688
COUNTRY	PL vs SE	0.091	0.047	0.175
COUNTRY	PT vs SE	0.991	0.772	1.272
COUNTRY	RO vs SE	2.366	1.811	3.092
COUNTRY	RS vs SE	0.966	0.613	1.523
COUNTRY	SI vs SE	2.057	1.345	3.146

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	62.1	Somers' D	0.242
Percent Discordant	37.9	Gamma	0.242
Percent Tied	0.0	Tau-a	0.089
Pairs	6674517	c	0.621

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
7.1371	8	0.5219

17. ALTERNATIVE SIZE METRIC – RECOVERY MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	3686
2	1	1210

Probability modeled is RECOVER_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5252.8296	4878	1.0768	0.0001
Pearson	4885.3904	4878	1.0015	0.4675

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5477.411	5288.830
SC	5483.907	5405.761
-2 Log L	5475.411	5252.830

R-Square	0.0444	Max-rescaled R-Square	0.0660

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	222.5809	17	<.0001
Score	191.7919	17	<.0001
Wald	153.4746	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.0826	0.7738
CAP2019	1	1.0067	0.3157
ROA2019	1	2.0590	0.1513
LIQ2019	1	0.9492	0.3299
SIZE2019_REV	1	10.0676	0.0015
REDHC	1	10.3384	0.0013
REDSAL	1	6.6104	0.0101
NEGCP	1	0.4623	0.4966
COUNTRY	9	121.6148	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-2.9070	0.3965	53.7405	<.0001
LEV2019		1	0.0359	0.1250	0.0826	0.7738
CAP2019		1	0.1203	0.1199	1.0067	0.3157
ROA2019		1	0.3930	0.2739	2.0590	0.1513
LIQ2019		1	0.00281	0.00288	0.9492	0.3299
SIZE2019_REV		1	0.0793	0.0250	10.0676	0.0015
REDHC		1	0.2799	0.0870	10.3384	0.0013
REDSAL		1	0.1908	0.0742	6.6104	0.0101
NEGCP		1	-0.1810	0.2661	0.4623	0.4966
COUNTRY	BE	1	0.8559	0.3322	6.6369	0.0100
COUNTRY	BG	1	0.4747	0.2609	3.3101	0.0689
COUNTRY	ES	1	0.1635	0.1295	1.5920	0.2070
COUNTRY	HR	1	0.6891	0.2253	9.3576	0.0022
COUNTRY	PL	1	-2.4196	0.4015	36.3154	<.0001
COUNTRY	PT	1	0.0497	0.1486	0.1117	0.7382
COUNTRY	RO	1	0.9019	0.1535	34.5218	<.0001
COUNTRY	RS	1	-0.1443	0.2753	0.2747	0.6002
COUNTRY	SI	1	0.7700	0.2395	10.3406	0.0013

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.037	0.811	1.324
CAP2019	1.128	0.892	1.427
ROA2019	1.481	0.866	2.534

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.003	0.997	1.008
SIZE2019_REV		1.083	1.031	1.137
REDHC		1.323	1.115	1.569
REDSAL		1.210	1.046	1.400
NEGCP		0.834	0.495	1.406
COUNTRY	BE vs SE	2.353	1.227	4.513
COUNTRY	BG vs SE	1.608	0.964	2.681
COUNTRY	ES vs SE	1.178	0.914	1.518
COUNTRY	HR vs SE	1.992	1.281	3.098
COUNTRY	PL vs SE	0.089	0.040	0.195
COUNTRY	PT vs SE	1.051	0.785	1.406
COUNTRY	RO vs SE	2.464	1.824	3.329
COUNTRY	RS vs SE	0.866	0.505	1.485
COUNTRY	SI vs SE	2.160	1.351	3.453

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	62.3	Somers' D	0.247
Percent Discordant	37.7	Gamma	0.247
Percent Tied	0.0	Tau-a	0.092
Pairs	4460060	c	0.623

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.4493	8	0.5970

18. ALTERNATIVE SIZE METRIC – RECOVERY MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	895
2	1	247

Probability modeled is RECOVER_COUNTRY=1.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1126.8427	1124	1.0025	0.4705
Pearson	1147.9491	1124	1.0213	0.3031

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1194.633	1162.843
SC	1199.673	1253.572
-2 Log L	1192.633	1126.843

R-Square	0.0560	Max-rescaled R-Square	0.0864

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	65.7901	17	<.0001
Score	58.1977	17	<.0001
Wald	47.6033	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	1.8988	0.1682
CAP2019	1	6.3283	0.0119
ROA2019	1	0.6116	0.4342
LIQ2019	1	0.5949	0.4405
SIZE2019_REV	1	1.0818	0.2983
REDHC	1	0.6689	0.4134
REDSAL	1	0.2382	0.6255
NEGCP	1	1.5310	0.2160
COUNTRY	9	35.6833	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-2.4587	0.8101	9.2104	0.0024
LEV2019		1	0.2645	0.1919	1.8988	0.1682
CAP2019		1	0.6601	0.2624	6.3283	0.0119
ROA2019		1	-0.3310	0.4232	0.6116	0.4342
LIQ2019		1	-0.00717	0.00929	0.5949	0.4405
SIZE2019_REV		1	0.0561	0.0539	1.0818	0.2983
REDHC		1	-0.1480	0.1810	0.6689	0.4134
REDSAL		1	0.0810	0.1659	0.2382	0.6255
NEGCP		1	-0.3697	0.2988	1.5310	0.2160
COUNTRY	BE	1	0.5910	0.5266	1.2596	0.2617
COUNTRY	BG	1	0.7522	0.4859	2.3970	0.1216
COUNTRY	ES	1	-0.2136	0.2340	0.8327	0.3615
COUNTRY	HR	1	0.3449	0.4329	0.6347	0.4256
COUNTRY	PL	1	-2.4016	0.6216	14.9292	0.0001
COUNTRY	PT	1	-0.1395	0.2680	0.2710	0.6027
COUNTRY	RO	1	0.8726	0.3727	5.4800	0.0192
COUNTRY	RS	1	0.4314	0.4573	0.8900	0.3455
COUNTRY	SI	1	0.7727	0.5752	1.8049	0.1791

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.303	0.894	1.898
CAP2019	1.935	1.157	3.236
ROA2019	0.718	0.313	1.646

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.993	0.975	1.011
SIZE2019_REV		1.058	0.952	1.175
REDHC		0.862	0.605	1.230
REDSAL		1.084	0.783	1.501
NEGCP		0.691	0.385	1.241
COUNTRY	BE vs SE	1.806	0.643	5.069
COUNTRY	BG vs SE	2.122	0.819	5.499
COUNTRY	ES vs SE	0.808	0.511	1.278
COUNTRY	HR vs SE	1.412	0.604	3.298
COUNTRY	PL vs SE	0.091	0.027	0.306
COUNTRY	PT vs SE	0.870	0.514	1.471
COUNTRY	RO vs SE	2.393	1.153	4.968
COUNTRY	RS vs SE	1.539	0.628	3.773
COUNTRY	SI vs SE	2.166	0.701	6.686

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.8	Somers' D	0.296
Percent Discordant	35.2	Gamma	0.296
Percent Tied	0.0	Tau-a	0.100
Pairs	221065	c	0.648

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.8437	8	0.7741

19. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RESILIENCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	5899

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2969
2	1	2930

Probability modeled is RESILIENT_COUNTRY=1.

Note: 139 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7662.8595	5881	1.3030	<.0001
Pearson	5932.6423	5881	1.0088	0.3153

Number of unique profiles: 5899

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8179.493	7698.859
SC	8186.175	7819.145

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	8177.493	7662.859

R-Square	0.0835	Max-rescaled R-Square	0.1114

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	514.6331	17	<.0001
Score	481.0675	17	<.0001
Wald	434.2409	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	7.2685	0.0070
CAP2019	1	9.9062	0.0016
ROA2019_EBITDA	1	80.1277	<.0001
LIQ2019	1	0.1378	0.7105
SIZE2019	1	46.3608	<.0001
REDHC	1	63.3827	<.0001
REDSAL	1	16.0057	<.0001
NEGCP	1	0.8172	0.3660
COUNTRY	9	277.6366	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.3534	0.3076	118.8537	<.0001
LEV2019		1	0.2517	0.0934	7.2685	0.0070
CAP2019		1	0.2955	0.0939	9.9062	0.0016
ROA2019_EBITDA		1	-1.6475	0.1841	80.1277	<.0001
LIQ2019		1	0.000939	0.00253	0.1378	0.7105
SIZE2019		1	-0.1304	0.0191	46.3608	<.0001
REDHC		1	-0.5295	0.0665	63.3827	<.0001
REDSAL		1	-0.2374	0.0593	16.0057	<.0001
NEGCP		1	-0.1454	0.1608	0.8172	0.3660
COUNTRY	BE	1	-1.3577	0.2599	27.2951	<.0001
COUNTRY	BG	1	-0.9850	0.2168	20.6402	<.0001
COUNTRY	ES	1	-0.9493	0.1030	84.8921	<.0001
COUNTRY	HR	1	-2.0216	0.1728	136.8862	<.0001
COUNTRY	PL	1	-0.9239	0.1437	41.3428	<.0001
COUNTRY	PT	1	-1.5101	0.1183	163.0302	<.0001
COUNTRY	RO	1	-0.6276	0.1307	23.0587	<.0001
COUNTRY	RS	1	-1.4875	0.2042	53.0736	<.0001
COUNTRY	SI	1	-2.2593	0.2301	96.4473	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.286	1.071	1.544
CAP2019	1.344	1.118	1.615
ROA2019_EBITDA	0.193	0.134	0.276
LIQ2019	1.001	0.996	1.006
SIZE2019	0.878	0.845	0.911
REDHC	0.589	0.517	0.671
REDSAL	0.789	0.702	0.886
NEGCP	0.865	0.631	1.185
COUNTRY BE vs SE	0.257	0.155	0.428
COUNTRY BG vs SE	0.373	0.244	0.571
COUNTRY ES vs SE	0.387	0.316	0.474
COUNTRY HR vs SE	0.132	0.094	0.186
COUNTRY PL vs SE	0.397	0.300	0.526
COUNTRY PT vs SE	0.221	0.175	0.279
COUNTRY RO vs SE	0.534	0.413	0.690
COUNTRY RS vs SE	0.226	0.151	0.337
COUNTRY SI vs SE	0.104	0.067	0.164

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.3	Somers' D	0.327
Percent Discordant	33.7	Gamma	0.327
Percent Tied	0.0	Tau-a	0.163
Pairs	8699170	c	0.663

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.2694	8	0.8320

20. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RESILIENCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4795

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2546
2	1	2249

Probability modeled is RESILIENT_COUNTRY=1.

Note: 101 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6201.4647	4777	1.2982	<.0001
Pearson	4789.8725	4777	1.0027	0.4450

Number of unique profiles: 4795

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6630.874	6237.465
SC	6637.349	6354.021

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	6628.874	6201.465

R-Square	0.0853	Max-rescaled R-Square	0.1139

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	427.4089	17	<.0001
Score	403.8618	17	<.0001
Wald	368.3003	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	10.8123	0.0010
CAP2019	1	5.8402	0.0157
ROA2019_EBITDA	1	55.1585	<.0001
LIQ2019	1	0.0007	0.9787
SIZE2019	1	53.8655	<.0001
REDHC	1	43.2405	<.0001
REDSAL	1	12.0980	0.0005
NEGCP	1	3.8318	0.0503
COUNTRY	9	263.0997	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.8036	0.3602	111.5312	<.0001
LEV2019		1	0.3669	0.1116	10.8123	0.0010
CAP2019		1	0.2571	0.1064	5.8402	0.0157
ROA2019_EBITDA		1	-1.6544	0.2228	55.1585	<.0001
LIQ2019		1	-0.00007	0.00280	0.0007	0.9787
SIZE2019		1	-0.1594	0.0217	53.8655	<.0001
REDHC		1	-0.4869	0.0741	43.2405	<.0001
REDSAL		1	-0.2291	0.0659	12.0980	0.0005
NEGCP		1	-0.4567	0.2333	3.8318	0.0503
COUNTRY	BE	1	-1.5370	0.3123	24.2197	<.0001
COUNTRY	BG	1	-1.0943	0.2458	19.8239	<.0001
COUNTRY	ES	1	-1.0807	0.1202	80.8738	<.0001
COUNTRY	HR	1	-2.3224	0.2041	129.4852	<.0001
COUNTRY	PL	1	-1.0156	0.1670	36.9621	<.0001
COUNTRY	PT	1	-1.7220	0.1380	155.6602	<.0001
COUNTRY	RO	1	-0.6766	0.1458	21.5349	<.0001
COUNTRY	RS	1	-1.6630	0.2321	51.3356	<.0001
COUNTRY	SI	1	-2.3435	0.2513	86.9410	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		1.443	1.160	1.796
CAP2019		1.293	1.050	1.593
ROA2019_EBITDA		0.191	0.124	0.296
LIQ2019		1.000	0.994	1.005
SIZE2019		0.853	0.817	0.890
REDHC		0.615	0.531	0.710
REDSAL		0.795	0.699	0.905
NEGCP		0.633	0.401	1.001
COUNTRY	BE vs SE	0.215	0.117	0.397
COUNTRY	BG vs SE	0.335	0.207	0.542
COUNTRY	ES vs SE	0.339	0.268	0.429
COUNTRY	HR vs SE	0.098	0.066	0.146
COUNTRY	PL vs SE	0.362	0.261	0.502
COUNTRY	PT vs SE	0.179	0.136	0.234
COUNTRY	RO vs SE	0.508	0.382	0.676
COUNTRY	RS vs SE	0.190	0.120	0.299
COUNTRY	SI vs SE	0.096	0.059	0.157

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.3	Somers' D	0.327
Percent Discordant	33.7	Gamma	0.327
Percent Tied	0.0	Tau-a	0.163
Pairs	5725954	c	0.663

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
1.9038	8	0.9838

21. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RESILIENCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1104

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	423
2	1	681

Probability modeled is RESILIENT_COUNTRY=1.

Note: 38 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1403.1745	1086	1.2921	<.0001
Pearson	1113.7805	1086	1.0256	0.2725

Number of unique profiles: 1104

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1471.614	1439.175
SC	1476.621	1529.295

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	1469.614	1403.175

R-Square	0.0584	Max-rescaled R-Square	0.0794

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	66.4398	17	<.0001
Score	62.5242	17	<.0001
Wald	57.6557	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.1661	0.6836
CAP2019	1	0.7840	0.3759
ROA2019_EBITDA	1	9.6514	0.0019
LIQ2019	1	0.6490	0.4205
SIZE2019	1	0.1529	0.6957
REDHC	1	19.0843	<.0001
REDSAL	1	5.4903	0.0191
NEGCP	1	0.9214	0.3371
COUNTRY	9	22.7483	0.0068

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.3628	0.7095	3.6896	0.0548
LEV2019		1	-0.0687	0.1686	0.1661	0.6836
CAP2019		1	0.1955	0.2208	0.7840	0.3759
ROA2019_EBITDA		1	-1.6271	0.5237	9.6514	0.0019
LIQ2019		1	0.00545	0.00677	0.6490	0.4205
SIZE2019		1	0.0183	0.0467	0.1529	0.6957
REDHC		1	-0.6958	0.1593	19.0843	<.0001
REDSAL		1	-0.3342	0.1426	5.4903	0.0191
NEGCP		1	0.2408	0.2508	0.9214	0.3371
COUNTRY	BE	1	-0.6104	0.4865	1.5741	0.2096
COUNTRY	BG	1	-0.7329	0.4763	2.3680	0.1238
COUNTRY	ES	1	-0.4687	0.2101	4.9758	0.0257
COUNTRY	HR	1	-0.9353	0.3552	6.9337	0.0085
COUNTRY	PL	1	-0.7305	0.2867	6.4932	0.0108
COUNTRY	PT	1	-0.8465	0.2435	12.0810	0.0005
COUNTRY	RO	1	-0.7800	0.3652	4.5602	0.0327
COUNTRY	RS	1	-0.9675	0.4558	4.5050	0.0338
COUNTRY	SI	1	-2.0019	0.6190	10.4602	0.0012

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		0.934	0.671	1.299
CAP2019		1.216	0.789	1.875
ROA2019_EBITDA		0.197	0.070	0.549
LIQ2019		1.005	0.992	1.019
SIZE2019		1.018	0.929	1.116
REDHC		0.499	0.365	0.681
REDSAL		0.716	0.541	0.947
NEGCP		1.272	0.778	2.080
COUNTRY	BE vs SE	0.543	0.209	1.409
COUNTRY	BG vs SE	0.480	0.189	1.222
COUNTRY	ES vs SE	0.626	0.415	0.945
COUNTRY	HR vs SE	0.392	0.196	0.787
COUNTRY	PL vs SE	0.482	0.275	0.845
COUNTRY	PT vs SE	0.429	0.266	0.691
COUNTRY	RO vs SE	0.458	0.224	0.938
COUNTRY	RS vs SE	0.380	0.156	0.929
COUNTRY	SI vs SE	0.135	0.040	0.454

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.3	Somers' D	0.286
Percent Discordant	35.7	Gamma	0.286
Percent Tied	0.0	Tau-a	0.135
Pairs	288063	c	0.643

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
11.0624	8	0.1982

22. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RESISTANCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	5899

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	2398
2	1	3501

Probability modeled is RESIST_COUNTRY=1.

Note: 139 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7316.4685	5881	1.2441	<.0001
Pearson	5914.9454	5881	1.0058	0.3750

Number of unique profiles: 5899

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	7972.292	7352.469
SC	7978.974	7472.754

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	7970.292	7316.469

R-Square	0.1049	Max-rescaled R-Square	0.1416

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	653.8232	17	<.0001
Score	610.1920	17	<.0001
Wald	547.6014	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	5.8449	0.0156
CAP2019	1	60.6979	<.0001
ROA2019_EBITDA	1	53.1252	<.0001
LIQ2019	1	1.5738	0.2097
SIZE2019	1	64.7410	<.0001
REDHC	1	111.8614	<.0001
REDSAL	1	27.3168	<.0001
NEGCP	1	10.2727	0.0014
COUNTRY	9	313.0509	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	4.2562	0.3151	182.4831	<.0001
LEV2019		1	-0.2289	0.0947	5.8449	0.0156
CAP2019		1	0.7518	0.0965	60.6979	<.0001
ROA2019_EBITDA		1	-1.2742	0.1748	53.1252	<.0001
LIQ2019		1	-0.00322	0.00257	1.5738	0.2097
SIZE2019		1	-0.1564	0.0194	64.7410	<.0001
REDHC		1	-0.7572	0.0716	111.8614	<.0001
REDSAL		1	-0.3205	0.0613	27.3168	<.0001
NEGCP		1	-0.5246	0.1637	10.2727	0.0014
COUNTRY	BE	1	-1.4150	0.2655	28.4018	<.0001
COUNTRY	BG	1	-0.7068	0.2243	9.9266	0.0016
COUNTRY	ES	1	-1.1641	0.1075	117.1811	<.0001
COUNTRY	HR	1	-1.8543	0.1749	112.4531	<.0001
COUNTRY	PL	1	0.2687	0.1696	2.5118	0.1130
COUNTRY	PT	1	-0.6888	0.1226	31.5657	<.0001
COUNTRY	RO	1	-0.7457	0.1364	29.8742	<.0001
COUNTRY	RS	1	-0.6488	0.2253	8.2915	0.0040
COUNTRY	SI	1	-2.5622	0.2296	124.5500	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		0.795	0.661	0.958
CAP2019		2.121	1.755	2.562
ROA2019_EBITDA		0.280	0.199	0.394
LIQ2019		0.997	0.992	1.002
SIZE2019		0.855	0.823	0.888
REDHC		0.469	0.408	0.540
REDSAL		0.726	0.644	0.818
NEGCP		0.592	0.429	0.816
COUNTRY	BE vs SE	0.243	0.144	0.409
COUNTRY	BG vs SE	0.493	0.318	0.766
COUNTRY	ES vs SE	0.312	0.253	0.385
COUNTRY	HR vs SE	0.157	0.111	0.221
COUNTRY	PL vs SE	1.308	0.938	1.824
COUNTRY	PT vs SE	0.502	0.395	0.639
COUNTRY	RO vs SE	0.474	0.363	0.620
COUNTRY	RS vs SE	0.523	0.336	0.813
COUNTRY	SI vs SE	0.077	0.049	0.121

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.0	Somers' D	0.379
Percent Discordant	31.0	Gamma	0.379
Percent Tied	0.0	Tau-a	0.183
Pairs	8395398	c	0.690

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
19.5198	8	0.0123

23. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RESISTANCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4795

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	1977
2	1	2818

Probability modeled is RESIST_COUNTRY=1.

Note: 101 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5870.6759	4777	1.2289	<.0001
Pearson	4776.8810	4777	1.0000	0.4978

Number of unique profiles: 4795

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6501.012	5906.676
SC	6507.487	6023.232

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	6499.012	5870.676

R-Square	0.1228	Max-rescaled R-Square	0.1655

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	628.3360	17	<.0001
Score	574.2895	17	<.0001
Wald	503.9227	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.8832	0.0895
CAP2019	1	42.8074	<.0001
ROA2019_EBITDA	1	87.5611	<.0001
LIQ2019	1	1.0393	0.3080
SIZE2019	1	83.5199	<.0001
REDHC	1	83.9294	<.0001
REDSAL	1	17.3313	<.0001
NEGCP	1	3.6419	0.0563
COUNTRY	9	308.6152	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	5.2666	0.3763	195.8971	<.0001
LEV2019		1	-0.1968	0.1159	2.8832	0.0895
CAP2019		1	0.7209	0.1102	42.8074	<.0001
ROA2019_EBITDA		1	-2.1474	0.2295	87.5611	<.0001
LIQ2019		1	-0.00296	0.00290	1.0393	0.3080
SIZE2019		1	-0.2032	0.0222	83.5199	<.0001
REDHC		1	-0.7363	0.0804	83.9294	<.0001
REDSAL		1	-0.2844	0.0683	17.3313	<.0001
NEGCP		1	-0.4511	0.2364	3.6419	0.0563
COUNTRY	BE	1	-1.8184	0.3209	32.1019	<.0001
COUNTRY	BG	1	-1.0195	0.2533	16.1996	<.0001
COUNTRY	ES	1	-1.3775	0.1293	113.4612	<.0001
COUNTRY	HR	1	-2.3006	0.2090	121.2098	<.0001
COUNTRY	PL	1	0.3897	0.2116	3.3911	0.0656
COUNTRY	PT	1	-0.9103	0.1450	39.4277	<.0001
COUNTRY	RO	1	-0.8927	0.1559	32.7801	<.0001
COUNTRY	RS	1	-0.6899	0.2696	6.5478	0.0105
COUNTRY	SI	1	-2.9052	0.2566	128.1751	<.0001

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		0.821	0.654	1.031
CAP2019		2.056	1.657	2.552
ROA2019_EBITDA		0.117	0.074	0.183
LIQ2019		0.997	0.991	1.003
SIZE2019		0.816	0.781	0.852
REDHC		0.479	0.409	0.561
REDSAL		0.752	0.658	0.860
NEGCP		0.637	0.401	1.012
COUNTRY	BE vs SE	0.162	0.087	0.304
COUNTRY	BG vs SE	0.361	0.220	0.593
COUNTRY	ES vs SE	0.252	0.196	0.325
COUNTRY	HR vs SE	0.100	0.067	0.151
COUNTRY	PL vs SE	1.477	0.975	2.236
COUNTRY	PT vs SE	0.402	0.303	0.535
COUNTRY	RO vs SE	0.410	0.302	0.556
COUNTRY	RS vs SE	0.502	0.296	0.851
COUNTRY	SI vs SE	0.055	0.033	0.091

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	70.3	Somers' D	0.406
Percent Discordant	29.7	Gamma	0.406
Percent Tied	0.0	Tau-a	0.197
Pairs	5571186	c	0.703

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
12.5669	8	0.1276

24. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RESISTANCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1104

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	421
2	1	683

Probability modeled is RESIST_COUNTRY=1.

Note: 38 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1380.3612	1086	1.2711	<.0001
Pearson	1104.8182	1086	1.0173	0.3388

Number of unique profiles: 1104

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1469.694	1416.361
SC	1474.701	1506.482

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	1467.694	1380.361

R-Square	0.0761	Max-rescaled R-Square	0.1034

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	87.3331	17	<.0001
Score	83.7950	17	<.0001
Wald	78.3352	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.7546	0.3850
CAP2019	1	4.2975	0.0382
ROA2019_EBITDA	1	0.0722	0.7881
LIQ2019	1	0.5582	0.4550
SIZE2019	1	1.4748	0.2246
REDHC	1	24.4080	<.0001
REDSAL	1	9.8668	0.0017
NEGCP	1	1.1654	0.2803
COUNTRY	9	32.9942	0.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.7043	0.7156	14.2804	0.0002
LEV2019		1	-0.1444	0.1662	0.7546	0.3850
CAP2019		1	0.4619	0.2228	4.2975	0.0382
ROA2019_EBITDA		1	0.1097	0.4084	0.0722	0.7881
LIQ2019		1	-0.00442	0.00592	0.5582	0.4550
SIZE2019		1	-0.0570	0.0469	1.4748	0.2246
REDHC		1	-0.8058	0.1631	24.4080	<.0001
REDSAL		1	-0.4535	0.1444	9.8668	0.0017
NEGCP		1	-0.2666	0.2469	1.1654	0.2803
COUNTRY	BE	1	-0.9048	0.4919	3.3826	0.0659
COUNTRY	BG	1	0.00781	0.5280	0.0002	0.9882
COUNTRY	ES	1	-0.8424	0.2106	16.0059	<.0001
COUNTRY	HR	1	-1.2138	0.3594	11.4100	0.0007
COUNTRY	PL	1	-0.1355	0.3010	0.2025	0.6527
COUNTRY	PT	1	-0.4105	0.2520	2.6550	0.1032
COUNTRY	RO	1	-0.8694	0.3635	5.7199	0.0168
COUNTRY	RS	1	-1.1832	0.4565	6.7170	0.0095
COUNTRY	SI	1	-1.6588	0.5763	8.2855	0.0040

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		0.866	0.625	1.199
CAP2019		1.587	1.026	2.456
ROA2019_EBITDA		1.116	0.501	2.485
LIQ2019		0.996	0.984	1.007
SIZE2019		0.945	0.862	1.036
REDHC		0.447	0.325	0.615
REDSAL		0.635	0.479	0.843
NEGCP		0.766	0.472	1.243
COUNTRY	BE vs SE	0.405	0.154	1.061
COUNTRY	BG vs SE	1.008	0.358	2.837
COUNTRY	ES vs SE	0.431	0.285	0.651
COUNTRY	HR vs SE	0.297	0.147	0.601
COUNTRY	PL vs SE	0.873	0.484	1.575
COUNTRY	PT vs SE	0.663	0.405	1.087
COUNTRY	RO vs SE	0.419	0.206	0.855
COUNTRY	RS vs SE	0.306	0.125	0.749
COUNTRY	SI vs SE	0.190	0.062	0.589

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.7	Somers' D	0.333
Percent Discordant	33.3	Gamma	0.333
Percent Tied	0.0	Tau-a	0.157
Pairs	287543	c	0.667

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
5.3176	8	0.7232

25. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RECOVERY MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	5899

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	4460
2	1	1439

Probability modeled is RECOVER_COUNTRY=1.

Note: 139 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6266.6565	5881	1.0656	0.0002
Pearson	5938.9336	5881	1.0099	0.2951

Number of unique profiles: 5899

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6556.717	6302.656
SC	6563.400	6422.942

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	6554.717	6266.656

R-Square	0.0477	Max-rescaled R-Square	0.0710

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	288.0610	17	<.0001
Score	246.9865	17	<.0001
Wald	195.1008	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.2060	0.1375
CAP2019	1	0.0057	0.9398
ROA2019_EBITDA	1	3.0991	0.0783
LIQ2019	1	0.0887	0.7658
SIZE2019	1	29.9015	<.0001
REDHC	1	7.3726	0.0066
REDSAL	1	7.7027	0.0055
NEGCP	1	1.3207	0.2505
COUNTRY	9	165.5021	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.3462	0.3407	96.4637	<.0001
LEV2019		1	0.1565	0.1054	2.2060	0.1375
CAP2019		1	0.00809	0.1073	0.0057	0.9398
ROA2019_EBITDA		1	0.3258	0.1851	3.0991	0.0783
LIQ2019		1	0.000814	0.00273	0.0887	0.7658
SIZE2019		1	0.1172	0.0214	29.9015	<.0001
REDHC		1	0.2108	0.0776	7.3726	0.0066
REDSAL		1	0.1886	0.0680	7.7027	0.0055
NEGCP		1	-0.2205	0.1918	1.3207	0.2505
COUNTRY	BE	1	0.8701	0.2732	10.1451	0.0014
COUNTRY	BG	1	0.4268	0.2291	3.4699	0.0625
COUNTRY	ES	1	0.0300	0.1111	0.0728	0.7873
COUNTRY	HR	1	0.7071	0.1824	15.0284	0.0001
COUNTRY	PL	1	-2.5430	0.3532	51.8421	<.0001
COUNTRY	PT	1	-0.1098	0.1294	0.7200	0.3962
COUNTRY	RO	1	0.8541	0.1353	39.8805	<.0001
COUNTRY	RS	1	-0.0325	0.2402	0.0183	0.8925
COUNTRY	SI	1	0.7402	0.2171	11.6304	0.0006

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		1.169	0.951	1.438
CAP2019		1.008	0.817	1.244
ROA2019_EBITDA		1.385	0.964	1.991
LIQ2019		1.001	0.995	1.006
SIZE2019		1.124	1.078	1.173
REDHC		1.235	1.060	1.438
REDSAL		1.208	1.057	1.380
NEGCP		0.802	0.551	1.168
COUNTRY	BE vs SE	2.387	1.397	4.078
COUNTRY	BG vs SE	1.532	0.978	2.401
COUNTRY	ES vs SE	1.030	0.829	1.281
COUNTRY	HR vs SE	2.028	1.419	2.900
COUNTRY	PL vs SE	0.079	0.039	0.157
COUNTRY	PT vs SE	0.896	0.695	1.155
COUNTRY	RO vs SE	2.349	1.802	3.062
COUNTRY	RS vs SE	0.968	0.605	1.550
COUNTRY	SI vs SE	2.096	1.370	3.208

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	62.9	Somers' D	0.258
Percent Discordant	37.1	Gamma	0.258
Percent Tied	0.0	Tau-a	0.095
Pairs	6417940	c	0.629

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
10.8340	8	0.2113

26. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RECOVERY MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4795

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	3595
2	1	1200

Probability modeled is RECOVER_COUNTRY=1.

Note: 101 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5156.7040	4777	1.0795	<.0001
Pearson	4794.4206	4777	1.0036	0.4267

Number of unique profiles: 4795

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5397.539	5192.704
SC	5404.014	5309.260

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	5395.539	5156.704

R-Square	0.0486	Max-rescaled R-Square	0.0719

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	238.8348	17	<.0001
Score	204.7623	17	<.0001
Wald	161.8850	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.5605	0.4540
CAP2019	1	0.3086	0.5786
ROA2019_EBITDA	1	4.5551	0.0328
LIQ2019	1	0.4144	0.5197
SIZE2019	1	27.6429	<.0001
REDHC	1	9.2598	0.0023
REDSAL	1	7.3990	0.0065
NEGCP	1	0.3332	0.5638
COUNTRY	9	133.5162	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.5504	0.3935	81.4128	<.0001
LEV2019		1	0.0952	0.1271	0.5605	0.4540
CAP2019		1	-0.0669	0.1204	0.3086	0.5786
ROA2019_EBITDA		1	0.4787	0.2243	4.5551	0.0328
LIQ2019		1	0.00187	0.00291	0.4144	0.5197
SIZE2019		1	0.1254	0.0238	27.6429	<.0001
REDHC		1	0.2630	0.0864	9.2598	0.0023
REDSAL		1	0.2030	0.0746	7.3990	0.0065
NEGCP		1	-0.1554	0.2692	0.3332	0.5638
COUNTRY	BE	1	0.9744	0.3282	8.8128	0.0030
COUNTRY	BG	1	0.4059	0.2627	2.3871	0.1223
COUNTRY	ES	1	0.1306	0.1306	1.0001	0.3173
COUNTRY	HR	1	0.8447	0.2132	15.7028	<.0001
COUNTRY	PL	1	-2.5917	0.4308	36.1976	<.0001
COUNTRY	PT	1	-0.0246	0.1502	0.0268	0.8699
COUNTRY	RO	1	0.9195	0.1529	36.1637	<.0001
COUNTRY	RS	1	-0.0787	0.2834	0.0771	0.7812
COUNTRY	SI	1	0.8085	0.2402	11.3256	0.0008

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		1.100	0.857	1.411
CAP2019		0.935	0.739	1.184
ROA2019_EBITDA		1.614	1.040	2.505
LIQ2019		1.002	0.996	1.008
SIZE2019		1.134	1.082	1.188
REDHC		1.301	1.098	1.541
REDSAL		1.225	1.058	1.418
NEGCP		0.856	0.505	1.451
COUNTRY	BE vs SE	2.650	1.392	5.042
COUNTRY	BG vs SE	1.501	0.897	2.511
COUNTRY	ES vs SE	1.139	0.882	1.472
COUNTRY	HR vs SE	2.327	1.533	3.534
COUNTRY	PL vs SE	0.075	0.032	0.174
COUNTRY	PT vs SE	0.976	0.727	1.310
COUNTRY	RO vs SE	2.508	1.859	3.384
COUNTRY	RS vs SE	0.924	0.530	1.611
COUNTRY	SI vs SE	2.244	1.402	3.594

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.1	Somers' D	0.262
Percent Discordant	36.9	Gamma	0.262
Percent Tied	0.0	Tau-a	0.098
Pairs	4314000	c	0.631

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
3.9227	8	0.8640

27. ALTERNATIVE PROFITABILITY METRIC (EBITDA) – RECOVERY MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1104

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	865
2	1	239

Probability modeled is RECOVER_COUNTRY=1.

Note: 38 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1086.3045	1086	1.0003	0.4917
Pearson	1107.8707	1086	1.0201	0.3155

Number of unique profiles: 1104

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1155.511	1122.304
SC	1160.518	1212.425

Logistic Regression Results

The LOGISTIC Procedure

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
-2 Log L	1153.511	1086.304

R-Square	0.0591	Max-rescaled R-Square	0.0911

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	67.2070	17	<.0001
Score	59.8290	17	<.0001
Wald	49.2603	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	1.8848	0.1698
CAP2019	1	5.6576	0.0174
ROA2019_EBITDA	1	2.1215	0.1452
LIQ2019	1	0.6507	0.4199
SIZE2019	1	2.7411	0.0978
REDHC	1	0.1465	0.7019
REDSAL	1	0.2817	0.5956
NEGCP	1	1.6316	0.2015
COUNTRY	9	36.6752	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.0464	0.8500	12.8457	0.0003
LEV2019		1	0.2670	0.1945	1.8848	0.1698
CAP2019		1	0.6536	0.2748	5.6576	0.0174
ROA2019_EBITDA		1	-0.6845	0.4700	2.1215	0.1452
LIQ2019		1	-0.00769	0.00954	0.6507	0.4199
SIZE2019		1	0.0940	0.0568	2.7411	0.0978
REDHC		1	-0.0692	0.1808	0.1465	0.7019
REDSAL		1	0.0893	0.1682	0.2817	0.5956
NEGCP		1	-0.3962	0.3102	1.6316	0.2015
COUNTRY	BE	1	0.7254	0.5226	1.9264	0.1652
COUNTRY	BG	1	0.6165	0.4913	1.5747	0.2095
COUNTRY	ES	1	-0.2798	0.2317	1.4586	0.2272
COUNTRY	HR	1	0.3996	0.3952	1.0225	0.3119
COUNTRY	PL	1	-2.4664	0.6236	15.6410	<.0001
COUNTRY	PT	1	-0.3005	0.2764	1.1817	0.2770
COUNTRY	RO	1	0.7933	0.3718	4.5528	0.0329
COUNTRY	RS	1	0.2738	0.4806	0.3245	0.5689
COUNTRY	SI	1	0.7202	0.5681	1.6071	0.2049

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LEV2019		1.306	0.892	1.912
CAP2019		1.922	1.122	3.294
ROA2019_EBITDA		0.504	0.201	1.267
LIQ2019		0.992	0.974	1.011
SIZE2019		1.099	0.983	1.228
REDHC		0.933	0.655	1.330
REDSAL		1.093	0.786	1.520
NEGCP		0.673	0.366	1.236
COUNTRY	BE vs SE	2.065	0.742	5.753
COUNTRY	BG vs SE	1.852	0.707	4.852
COUNTRY	ES vs SE	0.756	0.480	1.190
COUNTRY	HR vs SE	1.491	0.687	3.236
COUNTRY	PL vs SE	0.085	0.025	0.288
COUNTRY	PT vs SE	0.740	0.431	1.273
COUNTRY	RO vs SE	2.211	1.067	4.581
COUNTRY	RS vs SE	1.315	0.513	3.373
COUNTRY	SI vs SE	2.055	0.675	6.257

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	65.2	Somers' D	0.305
Percent Discordant	34.8	Gamma	0.305
Percent Tied	0.0	Tau-a	0.103
Pairs	206735	c	0.652

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
2.3570	8	0.9681

28. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RESILIENCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	3020
2	1	3018

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7842.1248	6020	1.3027	<.0001
Pearson	6070.2690	6020	1.0084	0.3217

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8372.445	7878.125
SC	8379.151	7998.830
-2 Log L	8370.445	7842.125

R-Square	0.0838	Max-rescaled R-Square	0.1117

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	528.3199	17	<.0001
Score	494.4700	17	<.0001
Wald	446.9400	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	9.7059	0.0018
CAP2019	1	7.8401	0.0051
ROA2019_EBIT	1	71.6983	<.0001
LIQ2019	1	0.0773	0.7810
SIZE2019	1	45.2213	<.0001
REDHC	1	78.5667	<.0001
REDSAL	1	17.3498	<.0001
NEGCP	1	0.8526	0.3558
COUNTRY	9	274.0571	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.2159	0.2972	117.0792	<.0001
LEV2019		1	0.2888	0.0927	9.7059	0.0018
CAP2019		1	0.2604	0.0930	7.8401	0.0051
ROA2019_EBIT		1	-1.5641	0.1847	71.6983	<.0001
LIQ2019		1	0.000688	0.00247	0.0773	0.7810
SIZE2019		1	-0.1261	0.0188	45.2213	<.0001
REDHC		1	-0.5778	0.0652	78.5667	<.0001
REDSAL		1	-0.2443	0.0586	17.3498	<.0001
NEGCP		1	-0.1451	0.1571	0.8526	0.3558
COUNTRY	BE	1	-1.3691	0.2600	27.7269	<.0001
COUNTRY	BG	1	-0.9329	0.2166	18.5536	<.0001
COUNTRY	ES	1	-0.8922	0.1019	76.6601	<.0001
COUNTRY	HR	1	-1.9260	0.1692	129.5026	<.0001
COUNTRY	PL	1	-0.8747	0.1424	37.7442	<.0001
COUNTRY	PT	1	-1.4694	0.1169	157.9887	<.0001
COUNTRY	RO	1	-0.5821	0.1301	20.0089	<.0001
COUNTRY	RS	1	-1.4422	0.1962	54.0364	<.0001
COUNTRY	SI	1	-2.2239	0.2270	95.9922	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.335	1.113	1.601
CAP2019	1.297	1.081	1.557
ROA2019_EBIT	0.209	0.146	0.301

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.001	0.996	1.006
SIZE2019		0.882	0.850	0.915
REDHC		0.561	0.494	0.638
REDSAL		0.783	0.698	0.879
NEGCP		0.865	0.636	1.177
COUNTRY	BE vs SE	0.254	0.153	0.423
COUNTRY	BG vs SE	0.393	0.257	0.601
COUNTRY	ES vs SE	0.410	0.336	0.500
COUNTRY	HR vs SE	0.146	0.105	0.203
COUNTRY	PL vs SE	0.417	0.315	0.551
COUNTRY	PT vs SE	0.230	0.183	0.289
COUNTRY	RO vs SE	0.559	0.433	0.721
COUNTRY	RS vs SE	0.236	0.161	0.347
COUNTRY	SI vs SE	0.108	0.069	0.169

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.4	Somers' D	0.327
Percent Discordant	33.6	Gamma	0.327
Percent Tied	0.0	Tau-a	0.164
Pairs	9114360	c	0.664

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.3472	8	0.6084

29. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RESILIENCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	2590
2	1	2306

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6335.5222	4878	1.2988	<.0001
Pearson	4892.1954	4878	1.0029	0.4403

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6772.814	6371.522
SC	6779.310	6488.453
-2 Log L	6770.814	6335.522

R-Square	0.0851	Max-rescaled R-Square	0.1136

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	435.2919	17	<.0001
Score	411.5138	17	<.0001
Wald	375.8994	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	13.9757	0.0002
CAP2019	1	4.1197	0.0424
ROA2019_EBIT	1	48.8748	<.0001
LIQ2019	1	0.0027	0.9586
SIZE2019	1	53.7854	<.0001
REDHC	1	51.1843	<.0001
REDSAL	1	12.4073	0.0004
NEGCP	1	4.4785	0.0343
COUNTRY	9	261.2255	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.6581	0.3475	110.8403	<.0001
LEV2019		1	0.4119	0.1102	13.9757	0.0002
CAP2019		1	0.2156	0.1062	4.1197	0.0424
ROA2019_EBIT		1	-1.6211	0.2319	48.8748	<.0001
LIQ2019		1	0.000145	0.00279	0.0027	0.9586
SIZE2019		1	-0.1558	0.0212	53.7854	<.0001
REDHC		1	-0.5197	0.0726	51.1843	<.0001
REDSAL		1	-0.2294	0.0651	12.4073	0.0004
NEGCP		1	-0.4838	0.2286	4.4785	0.0343
COUNTRY	BE	1	-1.5476	0.3125	24.5232	<.0001
COUNTRY	BG	1	-1.0393	0.2451	17.9742	<.0001
COUNTRY	ES	1	-1.0233	0.1183	74.8715	<.0001
COUNTRY	HR	1	-2.2217	0.1993	124.2624	<.0001
COUNTRY	PL	1	-0.9651	0.1652	34.1342	<.0001
COUNTRY	PT	1	-1.6814	0.1361	152.5598	<.0001
COUNTRY	RO	1	-0.6235	0.1444	18.6351	<.0001
COUNTRY	RS	1	-1.6011	0.2225	51.7991	<.0001
COUNTRY	SI	1	-2.2962	0.2470	86.4078	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.510	1.216	1.873
CAP2019	1.241	1.007	1.528
ROA2019_EBIT	0.198	0.125	0.311

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.000	0.995	1.006
SIZE2019		0.856	0.821	0.892
REDHC		0.595	0.516	0.686
REDSAL		0.795	0.700	0.903
NEGCP		0.616	0.394	0.965
COUNTRY	BE vs SE	0.213	0.115	0.393
COUNTRY	BG vs SE	0.354	0.219	0.572
COUNTRY	ES vs SE	0.359	0.285	0.453
COUNTRY	HR vs SE	0.108	0.073	0.160
COUNTRY	PL vs SE	0.381	0.276	0.527
COUNTRY	PT vs SE	0.186	0.143	0.243
COUNTRY	RO vs SE	0.536	0.404	0.711
COUNTRY	RS vs SE	0.202	0.130	0.312
COUNTRY	SI vs SE	0.101	0.062	0.163

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.4	Somers' D	0.327
Percent Discordant	33.6	Gamma	0.327
Percent Tied	0.0	Tau-a	0.163
Pairs	5972540	c	0.664

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.0419	8	0.6425

30. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RESILIENCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESILIENT_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RESILIENT_COUNTRY	Total Frequency
1	0	430
2	1	712

Probability modeled is RESILIENT_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1442.5942	1124	1.2834	<.0001
Pearson	1145.8801	1124	1.0195	0.3183

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1514.787	1478.594
SC	1519.827	1569.324
-2 Log L	1512.787	1442.594

R-Square	0.0596	Max-rescaled R-Square	0.0812

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	70.1927	17	<.0001
Score	66.8141	17	<.0001
Wald	62.1803	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.1620	0.6874
CAP2019	1	0.2602	0.6100
ROA2019_EBIT	1	7.2686	0.0070
LIQ2019	1	0.0713	0.7895
SIZE2019	1	0.1606	0.6886
REDHC	1	26.6227	<.0001
REDSAL	1	6.4784	0.0109
NEGCP	1	1.4080	0.2354
COUNTRY	9	23.3838	0.0054

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.4515	0.7075	4.2086	0.0402
LEV2019		1	-0.0678	0.1685	0.1620	0.6874
CAP2019		1	0.1096	0.2148	0.2602	0.6100
ROA2019_EBIT		1	-1.2538	0.4650	7.2686	0.0070
LIQ2019		1	0.00151	0.00565	0.0713	0.7895
SIZE2019		1	0.0186	0.0464	0.1606	0.6886
REDHC		1	-0.8059	0.1562	26.6227	<.0001
REDSAL		1	-0.3582	0.1407	6.4784	0.0109
NEGCP		1	0.2922	0.2463	1.4080	0.2354
COUNTRY	BE	1	-0.6763	0.4872	1.9272	0.1651
COUNTRY	BG	1	-0.7001	0.4770	2.1537	0.1422
COUNTRY	ES	1	-0.4165	0.2105	3.9147	0.0479
COUNTRY	HR	1	-0.8769	0.3517	6.2156	0.0127
COUNTRY	PL	1	-0.7014	0.2853	6.0431	0.0140
COUNTRY	PT	1	-0.8307	0.2420	11.7821	0.0006
COUNTRY	RO	1	-0.7476	0.3654	4.1857	0.0408
COUNTRY	RS	1	-0.9830	0.4404	4.9825	0.0256
COUNTRY	SI	1	-2.0125	0.6129	10.7815	0.0010

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.934	0.672	1.300
CAP2019	1.116	0.732	1.700
ROA2019_EBIT	0.285	0.115	0.710

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.002	0.990	1.013
SIZE2019		1.019	0.930	1.116
REDHC		0.447	0.329	0.607
REDSAL		0.699	0.530	0.921
NEGCP		1.339	0.827	2.170
COUNTRY	BE vs SE	0.508	0.196	1.321
COUNTRY	BG vs SE	0.497	0.195	1.265
COUNTRY	ES vs SE	0.659	0.436	0.996
COUNTRY	HR vs SE	0.416	0.209	0.829
COUNTRY	PL vs SE	0.496	0.283	0.867
COUNTRY	PT vs SE	0.436	0.271	0.700
COUNTRY	RO vs SE	0.473	0.231	0.969
COUNTRY	RS vs SE	0.374	0.158	0.887
COUNTRY	SI vs SE	0.134	0.040	0.444

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.2	Somers' D	0.283
Percent Discordant	35.8	Gamma	0.283
Percent Tied	0.0	Tau-a	0.133
Pairs	306160	c	0.642

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.4742	8	0.5943

31. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RESISTANCE MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	2446
2	1	3592

Probability modeled is RESIST_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	7503.4621	6020	1.2464	<.0001
Pearson	6051.1589	6020	1.0052	0.3861

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	8153.612	7539.462
SC	8160.318	7660.167
-2 Log L	8151.612	7503.462

R-Square	0.1018	Max-rescaled R-Square	0.1374

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	648.1497	17	<.0001
Score	605.3864	17	<.0001
Wald	544.8213	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	5.1204	0.0236
CAP2019	1	50.9423	<.0001
ROA2019_EBIT	1	51.0580	<.0001
LIQ2019	1	2.2861	0.1305
SIZE2019	1	59.9504	<.0001
REDHC	1	113.5954	<.0001
REDSAL	1	25.3368	<.0001
NEGCP	1	10.8799	0.0010
COUNTRY	9	311.9779	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	4.0466	0.3043	176.8240	<.0001
LEV2019		1	-0.2113	0.0934	5.1204	0.0236
CAP2019		1	0.6804	0.0953	50.9423	<.0001
ROA2019_EBIT		1	-1.2624	0.1767	51.0580	<.0001
LIQ2019		1	-0.00379	0.00251	2.2861	0.1305
SIZE2019		1	-0.1472	0.0190	59.9504	<.0001
REDHC		1	-0.7436	0.0698	113.5954	<.0001
REDSAL		1	-0.3047	0.0605	25.3368	<.0001
NEGCP		1	-0.5259	0.1594	10.8799	0.0010
COUNTRY	BE	1	-1.4105	0.2646	28.4067	<.0001
COUNTRY	BG	1	-0.6728	0.2238	9.0420	0.0026
COUNTRY	ES	1	-1.1239	0.1064	111.5407	<.0001
COUNTRY	HR	1	-1.8058	0.1716	110.7006	<.0001
COUNTRY	PL	1	0.3006	0.1681	3.1972	0.0738
COUNTRY	PT	1	-0.6816	0.1212	31.6194	<.0001
COUNTRY	RO	1	-0.6966	0.1357	26.3388	<.0001
COUNTRY	RS	1	-0.5526	0.2167	6.5026	0.0108
COUNTRY	SI	1	-2.5114	0.2261	123.3193	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.810	0.674	0.972
CAP2019	1.975	1.638	2.380
ROA2019_EBIT	0.283	0.200	0.400

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.996	0.991	1.001
SIZE2019		0.863	0.832	0.896
REDHC		0.475	0.415	0.545
REDSAL		0.737	0.655	0.830
NEGCP		0.591	0.432	0.808
COUNTRY	BE vs SE	0.244	0.145	0.410
COUNTRY	BG vs SE	0.510	0.329	0.791
COUNTRY	ES vs SE	0.325	0.264	0.400
COUNTRY	HR vs SE	0.164	0.117	0.230
COUNTRY	PL vs SE	1.351	0.972	1.878
COUNTRY	PT vs SE	0.506	0.399	0.641
COUNTRY	RO vs SE	0.498	0.382	0.650
COUNTRY	RS vs SE	0.575	0.376	0.880
COUNTRY	SI vs SE	0.081	0.052	0.126

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	68.6	Somers' D	0.372
Percent Discordant	31.4	Gamma	0.372
Percent Tied	0.0	Tau-a	0.179
Pairs	8786032	c	0.686

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
19.3187	8	0.0132

32. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RESISTANCE MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	2012
2	1	2884

Probability modeled is RESIST_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6006.3350	4878	1.2313	<.0001
Pearson	4877.5473	4878	0.9999	0.4991

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6633.158	6042.335
SC	6639.654	6159.266
-2 Log L	6631.158	6006.335

R-Square	0.1198	Max-rescaled R-Square	0.1615

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	624.8234	17	<.0001
Score	570.7806	17	<.0001
Wald	502.6921	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.5122	0.1130
CAP2019	1	30.4393	<.0001
ROA2019_EBIT	1	88.3414	<.0001
LIQ2019	1	1.1646	0.2805
SIZE2019	1	78.3442	<.0001
REDHC	1	86.4687	<.0001
REDSAL	1	17.1292	<.0001
NEGCP	1	3.0828	0.0791
COUNTRY	9	308.3783	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	5.0243	0.3626	192.0234	<.0001
LEV2019		1	-0.1811	0.1143	2.5122	0.1130
CAP2019		1	0.6060	0.1098	30.4393	<.0001
ROA2019_EBIT		1	-2.2696	0.2415	88.3414	<.0001
LIQ2019		1	-0.00311	0.00288	1.1646	0.2805
SIZE2019		1	-0.1921	0.0217	78.3442	<.0001
REDHC		1	-0.7306	0.0786	86.4687	<.0001
REDSAL		1	-0.2794	0.0675	17.1292	<.0001
NEGCP		1	-0.4055	0.2310	3.0828	0.0791
COUNTRY	BE	1	-1.8263	0.3204	32.4838	<.0001
COUNTRY	BG	1	-0.9689	0.2523	14.7445	0.0001
COUNTRY	ES	1	-1.3172	0.1273	106.9910	<.0001
COUNTRY	HR	1	-2.2340	0.2045	119.3275	<.0001
COUNTRY	PL	1	0.4359	0.2093	4.3380	0.0373
COUNTRY	PT	1	-0.8789	0.1431	37.7234	<.0001
COUNTRY	RO	1	-0.8114	0.1544	27.6133	<.0001
COUNTRY	RS	1	-0.6218	0.2567	5.8685	0.0154
COUNTRY	SI	1	-2.8289	0.2517	126.2841	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.834	0.667	1.044
CAP2019	1.833	1.478	2.273
ROA2019_EBIT	0.103	0.064	0.166

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.997	0.991	1.003
SIZE2019		0.825	0.791	0.861
REDHC		0.482	0.413	0.562
REDSAL		0.756	0.663	0.863
NEGCP		0.667	0.424	1.048
COUNTRY	BE vs SE	0.161	0.086	0.302
COUNTRY	BG vs SE	0.379	0.231	0.622
COUNTRY	ES vs SE	0.268	0.209	0.344
COUNTRY	HR vs SE	0.107	0.072	0.160
COUNTRY	PL vs SE	1.546	1.026	2.330
COUNTRY	PT vs SE	0.415	0.314	0.550
COUNTRY	RO vs SE	0.444	0.328	0.601
COUNTRY	RS vs SE	0.537	0.325	0.888
COUNTRY	SI vs SE	0.059	0.036	0.097

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	70.0	Somers' D	0.400
Percent Discordant	30.0	Gamma	0.400
Percent Tied	0.0	Tau-a	0.194
Pairs	5802608	c	0.700

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
13.4348	8	0.0977

33. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RESISTANCE MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RESIST_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RESIST_COUNTRY	Total Frequency
1	0	434
2	1	708

Probability modeled is RESIST_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1431.2080	1124	1.2733	<.0001
Pearson	1141.8921	1124	1.0159	0.3485

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1518.762	1467.208
SC	1523.802	1557.938
-2 Log L	1516.762	1431.208

R-Square	0.0722	Max-rescaled R-Square	0.0982

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	85.5536	17	<.0001
Score	82.1674	17	<.0001
Wald	77.0475	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.6268	0.4285
CAP2019	1	3.8776	0.0489
ROA2019_EBIT	1	0.0133	0.9080
LIQ2019	1	1.4683	0.2256
SIZE2019	1	1.7809	0.1820
REDHC	1	23.6736	<.0001
REDSAL	1	7.8730	0.0050
NEGCP	1	1.5247	0.2169
COUNTRY	9	32.0068	0.0002

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	2.7308	0.7069	14.9216	0.0001
LEV2019		1	-0.1300	0.1642	0.6268	0.4285
CAP2019		1	0.4249	0.2158	3.8776	0.0489
ROA2019_EBIT		1	0.0446	0.3863	0.0133	0.9080
LIQ2019		1	-0.00658	0.00543	1.4683	0.2256
SIZE2019		1	-0.0618	0.0463	1.7809	0.1820
REDHC		1	-0.7633	0.1569	23.6736	<.0001
REDSAL		1	-0.3973	0.1416	7.8730	0.0050
NEGCP		1	-0.2964	0.2400	1.5247	0.2169
COUNTRY	BE	1	-0.9350	0.4906	3.6316	0.0567
COUNTRY	BG	1	0.0133	0.5271	0.0006	0.9798
COUNTRY	ES	1	-0.8407	0.2100	16.0210	<.0001
COUNTRY	HR	1	-1.2185	0.3540	11.8511	0.0006
COUNTRY	PL	1	-0.1122	0.2992	0.1407	0.7076
COUNTRY	PT	1	-0.4602	0.2480	3.4448	0.0635
COUNTRY	RO	1	-0.8594	0.3626	5.6173	0.0178
COUNTRY	RS	1	-0.9447	0.4365	4.6839	0.0304
COUNTRY	SI	1	-1.6694	0.5737	8.4677	0.0036

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	0.878	0.636	1.211
CAP2019	1.529	1.002	2.334
ROA2019_EBIT	1.046	0.490	2.229

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.993	0.983	1.004
SIZE2019		0.940	0.858	1.029
REDHC		0.466	0.343	0.634
REDSAL		0.672	0.509	0.887
NEGCP		0.744	0.464	1.190
COUNTRY	BE vs SE	0.393	0.150	1.027
COUNTRY	BG vs SE	1.013	0.361	2.848
COUNTRY	ES vs SE	0.431	0.286	0.651
COUNTRY	HR vs SE	0.296	0.148	0.592
COUNTRY	PL vs SE	0.894	0.497	1.607
COUNTRY	PT vs SE	0.631	0.388	1.026
COUNTRY	RO vs SE	0.423	0.208	0.862
COUNTRY	RS vs SE	0.389	0.165	0.915
COUNTRY	SI vs SE	0.188	0.061	0.580

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	66.2	Somers' D	0.323
Percent Discordant	33.8	Gamma	0.323
Percent Tied	0.0	Tau-a	0.153
Pairs	307272	c	0.662

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
15.9607	8	0.0429

34. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RECOVERY MODEL – FULL SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	6038
Number of Observations Used	6038

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	4581
2	1	1457

Probability modeled is RECOVER_COUNTRY=1.

Class Level Information											
Class	Value	Design Variables									
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	6382.8508	6020	1.0603	0.0006
Pearson	6080.3503	6020	1.0100	0.2897

Number of unique profiles: 6038

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	6674.951	6418.851
SC	6681.657	6539.556
-2 Log L	6672.951	6382.851

R-Square	0.0469	Max-rescaled R-Square	0.0701

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	290.1003	17	<.0001
Score	251.2882	17	<.0001
Wald	202.5749	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.8906	0.0891
CAP2019	1	0.1742	0.6764
ROA2019_EBIT	1	4.8399	0.0278
LIQ2019	1	0.1073	0.7432
SIZE2019	1	31.6591	<.0001
REDHC	1	8.3899	0.0038
REDSAL	1	7.5471	0.0060
NEGCP	1	1.1153	0.2909
COUNTRY	9	166.5684	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.3790	0.3321	103.5280	<.0001
LEV2019		1	0.1777	0.1045	2.8906	0.0891
CAP2019		1	0.0445	0.1066	0.1742	0.6764
ROA2019_EBIT		1	0.4153	0.1888	4.8399	0.0278
LIQ2019		1	0.000886	0.00270	0.1073	0.7432
SIZE2019		1	0.1189	0.0211	31.6591	<.0001
REDHC		1	0.2210	0.0763	8.3899	0.0038
REDSAL		1	0.1852	0.0674	7.5471	0.0060
NEGCP		1	-0.1979	0.1874	1.1153	0.2909
COUNTRY	BE	1	0.8610	0.2727	9.9725	0.0016
COUNTRY	BG	1	0.3967	0.2287	3.0074	0.0829
COUNTRY	ES	1	-0.0108	0.1101	0.0097	0.9215
COUNTRY	HR	1	0.6546	0.1803	13.1847	0.0003
COUNTRY	PL	1	-2.4772	0.3368	54.1094	<.0001
COUNTRY	PT	1	-0.1382	0.1281	1.1639	0.2807
COUNTRY	RO	1	0.8173	0.1347	36.8099	<.0001
COUNTRY	RS	1	-0.0760	0.2320	0.1074	0.7431
COUNTRY	SI	1	0.6833	0.2152	10.0874	0.0015

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.194	0.973	1.466
CAP2019	1.045	0.848	1.288
ROA2019_EBIT	1.515	1.046	2.193

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.001	0.996	1.006
SIZE2019		1.126	1.081	1.174
REDHC		1.247	1.074	1.449
REDSAL		1.203	1.054	1.373
NEGCP		0.820	0.568	1.185
COUNTRY	BE vs SE	2.366	1.386	4.037
COUNTRY	BG vs SE	1.487	0.950	2.328
COUNTRY	ES vs SE	0.989	0.797	1.227
COUNTRY	HR vs SE	1.924	1.352	2.740
COUNTRY	PL vs SE	0.084	0.043	0.162
COUNTRY	PT vs SE	0.871	0.678	1.119
COUNTRY	RO vs SE	2.264	1.739	2.949
COUNTRY	RS vs SE	0.927	0.588	1.460
COUNTRY	SI vs SE	1.980	1.299	3.019

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.0	Somers' D	0.260
Percent Discordant	37.0	Gamma	0.260
Percent Tied	0.0	Tau-a	0.095
Pairs	6674517	c	0.630

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
10.4116	8	0.2373

35. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RECOVERY MODEL – PROFIT MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	4896
Number of Observations Used	4896

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	3686
2	1	1210

Probability modeled is RECOVER_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	5233.0228	4878	1.0728	0.0002
Pearson	4896.6519	4878	1.0038	0.4226

Number of unique profiles: 4896

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	5477.411	5269.023
SC	5483.907	5385.954
-2 Log L	5475.411	5233.023

R-Square	0.0483	Max-rescaled R-Square	0.0718

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	242.3877	17	<.0001
Score	210.6318	17	<.0001
Wald	171.6093	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	0.6923	0.4054
CAP2019	1	0.0027	0.9586
ROA2019_EBIT	1	7.7473	0.0054
LIQ2019	1	0.5602	0.4542
SIZE2019	1	29.6322	<.0001
REDHC	1	11.2693	0.0008
REDSAL	1	7.2143	0.0072
NEGCP	1	0.5086	0.4757
COUNTRY	9	135.0320	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.6249	0.3833	89.4194	<.0001
LEV2019		1	0.1049	0.1261	0.6923	0.4054
CAP2019		1	0.00627	0.1209	0.0027	0.9586
ROA2019_EBIT		1	0.6525	0.2344	7.7473	0.0054
LIQ2019		1	0.00217	0.00290	0.5602	0.4542
SIZE2019		1	0.1280	0.0235	29.6322	<.0001
REDHC		1	0.2866	0.0854	11.2693	0.0008
REDSAL		1	0.1992	0.0742	7.2143	0.0072
NEGCP		1	-0.1904	0.2670	0.5086	0.4757
COUNTRY	BE	1	0.9850	0.3279	9.0253	0.0027
COUNTRY	BG	1	0.3734	0.2620	2.0307	0.1541
COUNTRY	ES	1	0.0863	0.1288	0.4490	0.5028
COUNTRY	HR	1	0.7924	0.2105	14.1698	0.0002
COUNTRY	PL	1	-2.4811	0.4017	38.1470	<.0001
COUNTRY	PT	1	-0.0648	0.1487	0.1901	0.6629
COUNTRY	RO	1	0.8743	0.1516	33.2717	<.0001
COUNTRY	RS	1	-0.1515	0.2752	0.3031	0.5820
COUNTRY	SI	1	0.7469	0.2377	9.8772	0.0017

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.111	0.867	1.422
CAP2019	1.006	0.794	1.275
ROA2019_EBIT	1.920	1.213	3.040

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates				
Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		1.002	0.996	1.008
SIZE2019		1.137	1.085	1.190
REDHC		1.332	1.127	1.575
REDSAL		1.220	1.055	1.411
NEGCP		0.827	0.490	1.395
COUNTRY	BE vs SE	2.678	1.408	5.092
COUNTRY	BG vs SE	1.453	0.869	2.428
COUNTRY	ES vs SE	1.090	0.847	1.403
COUNTRY	HR vs SE	2.209	1.462	3.337
COUNTRY	PL vs SE	0.084	0.038	0.184
COUNTRY	PT vs SE	0.937	0.700	1.254
COUNTRY	RO vs SE	2.397	1.781	3.226
COUNTRY	RS vs SE	0.859	0.501	1.474
COUNTRY	SI vs SE	2.111	1.325	3.363

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	63.3	Somers' D	0.266
Percent Discordant	36.7	Gamma	0.266
Percent Tied	0.0	Tau-a	0.099
Pairs	4460060	c	0.633

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
7.5580	8	0.4778

36. ALTERNATIVE PROFITABILITY METRIC (EBIT) – RECOVERY MODEL – LOSS MAKERS SAMPLE

Logistic Regression Results

The LOGISTIC Procedure

Model Information	
Data Set	WORK.SORTTEMPTABLESORTED
Response Variable	RECOVER_COUNTRY
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	1142
Number of Observations Used	1142

Response Profile		
Ordered Value	RECOVER_COUNTRY	Total Frequency
1	0	895
2	1	247

Probability modeled is RECOVER_COUNTRY=1.

Class Level Information										
Class	Value	Design Variables								
COUNTRY	BE	1	0	0	0	0	0	0	0	0
	BG	0	1	0	0	0	0	0	0	0
	ES	0	0	1	0	0	0	0	0	0
	HR	0	0	0	1	0	0	0	0	0
	PL	0	0	0	0	1	0	0	0	0
	PT	0	0	0	0	0	1	0	0	0
	RO	0	0	0	0	0	0	1	0	0
	RS	0	0	0	0	0	0	0	1	0
	SE	0	0	0	0	0	0	0	0	0
	SI	0	0	0	0	0	0	0	0	1

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Deviance and Pearson Goodness-of-Fit Statistics				
Criterion	Value	DF	Value/DF	Pr > ChiSq
Deviance	1124.7370	1124	1.0007	0.4882
Pearson	1145.5235	1124	1.0191	0.3209

Number of unique profiles: 1142

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1194.633	1160.737
SC	1199.673	1251.467
-2 Log L	1192.633	1124.737

R-Square	0.0577	Max-rescaled R-Square	0.0891

Logistic Regression Results

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	67.8959	17	<.0001
Score	60.2808	17	<.0001
Wald	49.4136	17	<.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
LEV2019	1	2.2968	0.1296
CAP2019	1	4.1515	0.0416
ROA2019_EBIT	1	1.2513	0.2633
LIQ2019	1	0.7553	0.3848
SIZE2019	1	3.2036	0.0735
REDHC	1	0.4613	0.4970
REDSAL	1	0.2779	0.5981
NEGCP	1	1.3617	0.2432
COUNTRY	9	37.4807	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-3.0744	0.8398	13.4007	0.0003
LEV2019		1	0.2896	0.1911	2.2968	0.1296
CAP2019		1	0.5386	0.2644	4.1515	0.0416
ROA2019_EBIT		1	-0.4959	0.4433	1.2513	0.2633
LIQ2019		1	-0.00822	0.00946	0.7553	0.3848
SIZE2019		1	0.1005	0.0561	3.2036	0.0735
REDHC		1	-0.1183	0.1741	0.4613	0.4970
REDSAL		1	0.0871	0.1652	0.2779	0.5981
NEGCP		1	-0.3501	0.3001	1.3617	0.2432
COUNTRY	BE	1	0.7072	0.5209	1.8431	0.1746
COUNTRY	BG	1	0.6382	0.4900	1.6961	0.1928
COUNTRY	ES	1	-0.2834	0.2303	1.5152	0.2184
COUNTRY	HR	1	0.4043	0.3897	1.0763	0.2995
COUNTRY	PL	1	-2.4738	0.6228	15.7762	<.0001
COUNTRY	PT	1	-0.2515	0.2705	0.8643	0.3525
COUNTRY	RO	1	0.8071	0.3709	4.7361	0.0295
COUNTRY	RS	1	0.3483	0.4585	0.5773	0.4474
COUNTRY	SI	1	0.7356	0.5662	1.6874	0.1939

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
LEV2019	1.336	0.919	1.943
CAP2019	1.714	1.021	2.877
ROA2019_EBIT	0.609	0.255	1.452

Logistic Regression Results

The LOGISTIC Procedure

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
LIQ2019		0.992	0.974	1.010
SIZE2019		1.106	0.990	1.234
REDHC		0.888	0.632	1.250
REDSAL		1.091	0.789	1.508
NEGCP		0.705	0.391	1.269
COUNTRY	BE vs SE	2.028	0.731	5.631
COUNTRY	BG vs SE	1.893	0.725	4.947
COUNTRY	ES vs SE	0.753	0.480	1.183
COUNTRY	HR vs SE	1.498	0.698	3.216
COUNTRY	PL vs SE	0.084	0.025	0.286
COUNTRY	PT vs SE	0.778	0.458	1.321
COUNTRY	RO vs SE	2.241	1.084	4.636
COUNTRY	RS vs SE	1.417	0.577	3.480
COUNTRY	SI vs SE	2.087	0.688	6.330

Association of Predicted Probabilities and Observed Responses

Percent Concordant	64.9	Somers' D	0.298
Percent Discordant	35.1	Gamma	0.298
Percent Tied	0.0	Tau-a	0.101
Pairs	221065	c	0.649

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
3.3987	8	0.9069