TÉCNICO LISBOA

Decoding Judicial Efficiency: A Data-Driven Analysis of Portuguese First Instance Courts

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”Success is not final, failure is not fatal: It is the courage to continue that counts.”

- **Winston Churchill**

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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Resumo

Um sistema de justiça eficiente é um desafio universal, mas os problemas e soluções geralmente estão enraizados em contextos locais. Na Europa, as disparidades na eficiência dos tribunais revelam uma interação complexa de fatores. Portugal, enfrentando desafios comuns a outros países europeus, constitui um estudo de caso interessante. Os tribunais judiciais portugueses são a linha de frente do sistema de justiça, lidando com uma vasta gama de processos. Estes tribunais têm enfrentado desafios relacionados com a acumulação de processos, e a morosidade na resolução dos casos. Este estudo avalia a eficiência e produtividade dos FICs portugueses através da Data Envelopment Analysis (DEA) e do Meta Malmquist Index (MMI). Foram implementados dois modelos DEA: um utilizando juízes, oficiais de justiça e volume de processos como inputs, e outro incorporando fatores contextuais, como advogados, agentes de execução e solicitadores. Os outputs incluem processos concluídos em várias áreas jurídicas (cível, criminal, criminal laboral, laboral e tutelar). Os resultados mostram que os principais inputs — juízes, oficiais de justiça e volume de processos — são os maiores responsáveis pela eficiência, enquanto variáveis de contexto têm impacto mínimo. Os resultados do MMI destacam a importância da mudança tecnológica (TC) em relação à eficiência (EC), evidenciando a transformação digital. A pandemia de COVID-19 causou uma queda temporária na produtividade. Este estudo reforça a necessidade de reformas e inovações no sistema judicial português, especialmente na gestão dos elevados volumes de processos. Pesquisas futuras podem explorar modelos DEA mais avançados e integrar aprendizagem automática para prever tendências de eficiência.

Palavras-chave: *Data Envelopment Analysis*, Índice de *Meta-Malmquist*, Tribunais Judiciais de Primeira Instância, Eficiência Técnica, Mudança Tecnológica, Mudança de Eficiência.

Abstract

The goal for an efficient and effective justice system is a universal challenge, yet the problems and solutions are often rooted in local contexts. Within Europe, significant disparities in court efficiency reveal a complex interplay of factors. Portugal's First Instance Courts (FICs) face operational inefficiencies and resource constraints, motivating this study to address a research gap by using data science to improve judicial efficiency.

This study evaluates the efficiency and productivity of Portuguese Judicial FICs through Data Envelopment Analysis (DEA) and the Meta Malmquist Index (MMI). Two DEA models were analyzed: one using judges, justice officials, and caseload as inputs, and another incorporating context factors such as number of lawyers, solicitors and enforcement agents. The outputs measured were completed cases across legal domains (civil, criminal, labour, criminal labour and tutelar).

The findings show that core inputs — judges, justice officials, and caseload — are primary efficiency drivers, with additional context variables making minimal impact. The MMI results underscore the importance of technological change (TC) over efficiency change (EC), demonstrating the role of digital transformation. The COVID-19 pandemic caused a temporary decline in productivity.

This research highlights the need for ongoing reforms and innovation in the Portuguese judicial system, particularly in managing high caseloads. Future work could explore more advanced DEA models and integrate machine learning to predict efficiency trends.

Keywords: Data Envelopment Analysis, Meta-Malmquist Index, Portuguese Judicial First Instance Courts, Efficiency, Efficiency Change, Technology Change.

Contents

Acknowledgments . . . iv
Resumo . . . v
Abstract . . . vi
List of Tables . . . ix
List of Figures . . . x
Acronyms . . . xiii

1 Introduction **1**
1.1 Problem Description . . . 1
1.2 Motivation . . . 2
1.3 Objectives . . . 2
1.4 Research Methodology . . . 2
1.5 Outline . . . 3

2 Literature Review **5**
2.1 Overview of the Portuguese Judicial System Structure . . . 5
2.1.1 Legal Professions in Portugal . . . 6
2.1.2 Different Procedural Areas . . . 7
2.2 Efficiency Measurement . . . 9
2.2.1 Data Envelopment Analysis . . . 12
2.2.2 Efficiency Measurement in Judicial Courts . . . 13
2.2.3 Challenges and Opportunities in Judicial Efficiency Analysis . . . 17
2.3 Productivity Analysis and Malmquist Index . . . 18
2.3.1 Meta Malmquist Index . . . 19

3 Methodological Framework **21**
3.1 Data Envelopment Analysis Model Implementation . . . 21
3.2 Meta Malmquist Index Implementation . . . 26
3.3 Dataset . . . 28
3.4 Software and Packages . . . 28

4 Application Details **29**
4.1 Overview 29
4.2 Preliminary Analysis 30
4.2.1 Judicial Resources 34
4.2.2 Incoming, Pending and Completed Cases 36
4.2.3 Context Variables 43
4.2.4 Disposition Time and Clearance Rate 45

5 Results and Discussion **51**
5.1 Output-Oriented Variable Returns to Scale Data Envelopment Analysis Model 51
5.2 Meta-Malmquist Index 63
5.3 Implications and Recommendations 67

6 Conclusions **70**

References **72**

List of Tables

2.1 Inputs and outputs of each study using Data Envelopment Analysis to analyse judicial efficiency. Adapted from Ippoliti and Tria (2020). 15

3.1 Summary of inputs, outputs, and Decision-Making Units for Models 1 and 2. 26

4.1 Minimum, maximum, mean (μ), standard deviation (σ), 1st quartile ($Q1$), 3rd quartile ($Q3$) and interquartile range (IQR) for input variables. 31
4.2 Minimum, maximum, mean (μ), standard deviation (σ), 1st quartile ($Q1$), 3rd quartile ($Q3$) and interquartile range (IQR) for output variables. 31
4.3 Organization of Portuguese Judicial First Instance Courts according to Region(s) NUTS II regions. 34

5.1 Number of First Instance Courts per Region(s) NUTS II. 59
5.2 Mean of inputs per Region(s) NUTS II. 60
5.3 Mean of outputs per Region(s) NUTS II. 61
5.4 Results of Kruskal-Wallis rank sum test for model 1 and for model 2. 62
5.5 Geometric mean of Meta Malmquist Index results. 64

List of Figures

1.1 Research methodology. 4

7figure.caption.13

2.2 Different types of procedural areas that exist in the Portuguese First Instance Courts. . . 8

2.3 Relationship between performance, efficiency, and effectiveness. Retrieved from Brunsson (2017). 9

2.4 Revolutionary studies on production frontier techniques. Adapted from Camanho and D'Inverno (2023). 12

4.1 Scatter plot matrix of inputs and outputs variables. 32

4.2 Correlation matrix of inputs and outputs variables. 33

4.3 Average number of judges over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 35

4.4 Average number of justice officials over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 35

4.5 Evolution of the number of incoming cases, completed cases and pending cases from 2015 to 2023. Dark blue: completed cases, light blue: incoming cases, and orange: pending cases. 38

4.6 Average number of completed civil cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 38

4.7 Average number of completed criminal cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 39

4.8 Average number of completed criminal labor cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. . . . 39

4.9 Average number of completed labor cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 40

4.10 Average number of completed tutelar cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 41

4.11 Average number of completed cases (all) over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 41

4.12 Average caseload over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 42

4.13 Average caseload per judge over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 43

4.14 Average number of lawyers over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 44

4.15 Average number of solicitors over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 44

4.16 Average number of enforcement agents over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*. 45

4.17 Heatmap of the disposition time for all First Instance Courts between 2015 and 2023. Blue: shorter disposition times, red: longer disposition times. 47

4.18 Heatmap of the clearance rate for all First Instance Courts between 2015 and 2023. Blue: higher clearance rates, red: lower clearance rates. 48

4.19 Heatmap of the disposition time from civil cases for all First Instance Courts between 2015 and 2023. Blue: shorter disposition times, red: longer disposition times. 49

4.20 Heatmap of the clearance rate from civil cases for all First Instance Courts between 2015 and 2023. Blue: higher clearance rates, red: lower clearance rates. 50

5.1 Technical efficiency scores for model 1 from 2015 to 2023. Values closer to red indicate higher technical efficiency scores, signifying poorer technical efficiency. Courts in these ranges have greater room for improvement in their efficiency. In contrast, values closer to blue suggest lower technical efficiency scores, representing better technical efficiency. Courts with these scores are more efficient. 52

5.2 Technical efficiency scores for model 2 from 2015 to 2023. Values closer to red indicate higher technical efficiency scores, signifying poorer technical efficiency. Courts in these ranges have greater room for improvement in their efficiency. In contrast, values closer to blue suggest lower technical efficiency scores, representing better technical efficiency. Courts with these scores are more efficient. 58
5.3 Meta Malmquist Index for Model 1 and Model 2 from 2015/2016 to 2022/2023. 65
5.4 Technology Change for Model 1 and Model 2 from 2015/2016 to 2022/2023. 65
5.5 Efficiency Change for Model 1 and Model 2 from 2015/2016 to 2022/2023. 66

Acronyms

CC	Completed Cases
CCNLS	Corrected Concave Nonparametric Least Squares
COLS	Corrected Ordinary Least Squares
CR	Clearance Rate
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DGPJ	Direção-Geral da Política de Justiça
DMU	Decision Making Unit
DT	Disposition Time
EC	Efficiency Change
FDH	Free Disposal Hull
FIC	First Instance Court
IC	Incoming Cases
KPI	Key Performance Indicator
MI	Malmquist Index
MMI	Meta Malmquist Index
NUTS	Nomenclature of Territorial Units for Statistics
PC	Pending Cases
SFA	Stochastic Frontier Analysis
StoNED	Stochastic Nonparametric Envelopment of Data
TC	Technological Change
TG	Technology Gap
VRS	Variable Returns to Scale

Chapter 1

Introduction

This chapter sets up the framework for researching the efficiency of Portuguese judicial First Instance Courts. Section 1.1 describes the problem being addressed. Section 1.2 highlights the importance of judicial efficiency in the overall legal system. Section 1.3 outlines the study's main goals, including benchmarking court efficiency and proposing solutions for improvement. Section 1.4 explains the research methodology to be used. Section 1.5 provides a brief overview of the subsequent chapter of the dissertation.

1.1 Problem Description

Justice systems across European countries are cornerstone institutions upholding the rule of law, equity, and justice. However, the efficiency and performance of these systems, particularly at the first instance court level, have been subjects of critical analysis and debate (CEPEJ, 2020, 2022a).

Efficiency in the context of justice systems primarily refers to how quickly and economically these systems process and resolve cases. This includes minimizing delays, reducing costs, and optimizing resource use, all while maintaining a high standard of procedural integrity. Efficiency ensures that justice is delivered without unnecessary waste or expense (Dakolias, 1999).

Performance, on the other hand, encompasses a broader evaluation of how well these systems achieve their intended outcomes, including upholding the law, ensuring fairness, and providing accessibility. It directly impacts public trust and the protection of rights, both of which are fundamental to the smooth functioning of democracies. Thus, performance in justice systems is not just about procedural outcomes but also about the quality and effectiveness of those outcomes in fostering justice and equity (Dakolias, 1999; Garoupa & Ginsburg, 2009).

Portugal, mirroring the challenges faced by its European counterparts, presents a compelling case study for examining these issues. The country's judicial First Instance Court (FIC) are the front-line of its justice system, handling a broad spectrum of cases, from civil disputes to criminal proceedings. Despite their critical role, these courts have encountered challenges related to cases backlog, prolonged case resolution times, and varying levels of performance across different jurisdictions (Santos & Amado,

2014; Lopes, 2023).

The problem, therefore, centers on a critical examination of the efficiency and productivity of Portuguese judicial FICs, situated within the broader European judicial landscape, aiming to identify the key challenges and areas for improvement within Portugal's judicial system.

In the field of data science, the application of quantitative methods and analytical tools offers a unique opportunity through which the efficiency and performance of judicial systems can be examined. By leveraging data on case processing times, outcomes, and other relevant metrics, it is possible to characterize the operational dynamics of Portugal's judicial FICs within the larger European context. This approach not only aids in identifying underlying patterns and inefficiencies but also in Benchmarking Portugal's performance against that of other European nation.

1.2 Motivation

The goal for an efficient and effective justice system is a universal challenge that transcends borders, yet the specificity of the problems and the solutions are often deeply rooted in the local context. Within the European judicial landscape, significant disparities in court efficiency and performance metrics highlight a complex interplay of factors that contribute to these variances. Portugal's judicial FICs, in particular, represent a critical juncture where the ideals of timely and fair justice are tested against the realities of operational inefficiencies and resource constraints.

The motivation for this study arises from a clear gap in existing research, particularly in the use of data science to improve judicial efficiency. Despite growing interest in applying technology and data analytics in the judicial sector, there are few comprehensive studies that use a data-driven approach to examine judicial system performance, especially in the Portuguese context.

1.3 Objectives

The principal objective of this study is to conduct a comprehensive analysis of the efficiency and performance of Portuguese judicial FICs using Data Envelopment Analysis (DEA) and the Meta Malmquist Index (MMI). This research aims to uncover regional disparities in court performance and identify the underlying factors contributing to these differences. By applying DEA and MMI, the study seeks to provide a detailed comparative assessment of judicial efficiency within Portugal, offering insights that can inform policy and judicial reforms.

1.4 Research Methodology

The methodology of this study focuses on assessing judicial efficiency in Portuguese Judicial FICs. As shown in Figure 1.1, the research follows several interconnected steps:

1. Identify Inefficiencies: Recognize inefficiencies within Portuguese Judicial FICs.

2. Literature Review: Conduct an extensive survey of existing research, theories, and methodologies to frame the problem with a robust theoretical foundation.

3. Data Collection: Collect data during an internship at the *Direção-Geral da Política de Justiça (DGPJ)*, compiling a comprehensive dataset of operational metrics and performance indices.

4. Data Organisation, Model Creation and Analysis of Outcomes: Use DEA to evaluate court efficiency. Define a benchmarking model and productivity index such as MMI to measure and compare efficiency levels. Identify patterns, interpret findings, and understand their implications for the Portuguese judicial system.

5. Challenges and Opportunities: Reflect on research findings, discuss challenges, and identify opportunities for improvement in the judicial system. Suggest directions for future research.

1.5 Outline

This dissertation is divided into six main chapters, aligned with the objectives and methodology described earlier.

Introduction chapter outlines the research problem, its significance, the methodology, and the research roadmap. The Literature Review chapter establishes a foundational understanding of judicial efficiency and productivity. It reviews existing methodologies for measuring judicial efficiency, drawing on studies from various countries to provide context for the study's methodology and analysis. The Methodological Framework chapter details the specific approaches and analytical frameworks used in this dissertation, focusing on DEA and MMI to assess judicial efficiency and performance. It explains the data collection process, criteria for selecting variables, and the rationale behind the chosen methodologies, ensuring transparency and reproducibility. Application Details, and Results and Discussion Chapter present and examine the study's empirical findings. It uses benchmarking methods and descriptive statistical analysis to explore efficiency and performance disparities among Portuguese judicial FICs. It interprets these results in the context of the study's objectives, discussing regional variations and potential drivers behind these differences. Conclusion chapter summarizes the study's findings, drawing conclusions about the efficiency and performance of Portuguese judicial FICs. It reflects on the implications for judicial reform and policy-making while suggesting improvement areas and future research. This chapter gives the main points of the study contributions, offering insights into how data science can improve judicial systems.

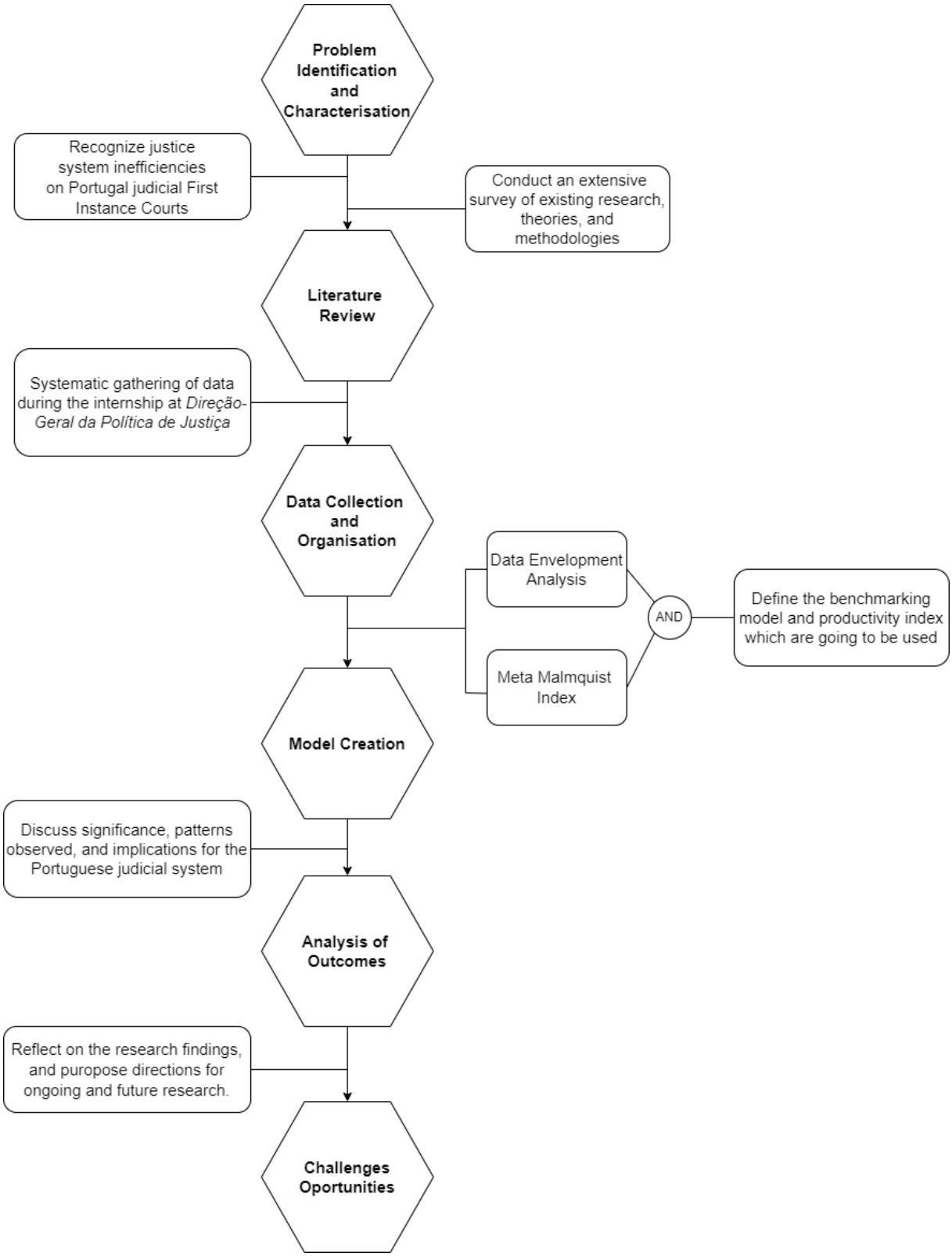

Figure 1.1: Research methodology.

Chapter 2

Literature Review

This chapter provides a literature review, outlining key methodologies for assessing judicial efficiency, with a focus on the Portuguese judicial system. Section 2.1 explores the structure of the Portuguese judicial system, with Subsection 2.1.1 covering the roles of legal professionals, and Subsection 2.1.2 addressing the procedural diversity within the system. Section 2.2 discusses efficiency measurement, focusing on Data Envelopment Analysis in Subsection 2.2.1. Subsection 2.2.2 reviews Data Envelopment Analysis' application in judicial courts, while Subsection 2.2.3 highlights the challenges and opportunities in this field. Section 2.3 covers the Malmquist Index for analyzing productivity over time. Subsection 2.3.1 introduces the Meta Malmquist Index, which extends the Mamlmquist Index by enabling productivity comparisons across different groups with varying technologies.

2.1 Overview of the Portuguese Judicial System Structure

To understand the intricacies of efficiency measurement methods within the Portuguese judicial system, it is essential to first acquaint oneself with the structure and workings of the Portuguese Justice System. All the information presented in this section has been sourced from the *Constituição da República Portuguesa* (Parlamento, 2005) and *Lei n.º 62/2013, de 26 de Agosto* (Procudadoria-Geral Distrital de Lisboa, 2013), which provide a comprehensive insight into the legal and operational frameworks governing the justice sector in Portugal. These documents serve as references for a deeper understanding of the methodologies and indicators used in assessing the efficiency of the judicial system within the country.

The organs of sovereignty in Portugal include Republic's President, Government, Republic's Assemnbly, and Judiciary. Portugal's judiciary is a system of courts, independent of other sovereignty organs, adhering strictly to the law, in which several courts operate, each having its own distinct jurisdiction.

As it can bee seen in Figure 2.1, Portugal has several types of courts, specifically, constitutional, judicial, audit, administrative and tax, peace and arbitration. The Constitutional Court plays a crucial role in reviewing the constitutionality of legal enactments, ensuring they align with the Portuguese Constitution. Meanwhile, the Audit Court is entrusted with the responsibility of supervising public expenditures and

conducting audits on the financial activities of public entities.

The Portuguese judicial system is structured to ensure that justice is administered effectively at multiple levels, with a particular emphasis on the role of judicial FICs. These courts serve as the primary access point for citizens to engage with the legal system, playing a foundational role in adjudicating civil, criminal, and administrative disputes.

Portugal's national landscape is divided into 23 FICs, and with each corresponding to a district capital. These courts have jurisdiction over various types of cases, with their scope often covering multiple municipalities. They are distributed across various regions including *Açores*, *Aveiro*, *Beja*, *Braga*, *Bragança*, *Castelo Branco*, *Coimbra*, *Évora*, *Faro*, *Guarda*, *Leiria*, *Lisboa*, *Lisboa Norte*, *Lisboa Oeste*, *Madeira*, *Portalegre*, *Porto*, *Porto Este*, *Santarém*, *Setúbal*, *Viana do Castelo*, *Vila Real*, and *Viseu*. These courts are further divided into benches, which are categorized by the nature and complexity of cases. General jurisdiction courts address a wide range of civil and criminal cases, while specialized courts within FICs focus on areas like labor disputes, family law, and commercial litigation. This specialization enables more efficient and accurate adjudication by ensuring that cases are overseen by judges with specific expertise.

The decisions made by FICs, particularly in complex civil and criminal cases, are crucial as they often lay the groundwork for potential appeals and higher court interventions. So, the role of judicial FICs is complemented by the existence of the Courts of Appeal and the Supreme Court of Justice. The Courts of Appeal serve as intermediate courts, tasked with reviewing and reassessing decisions made by the FICs and other lower courts. Historically, the Courts of Appeal are situated in five major regions: *Lisboa*, *Porto*, *Coimbra*, *Évora*, and *Guimarães*. At the top of the judicial system is the Supreme Court of Justice, located in *Lisboa*. This court holds the highest authority in the judicial framework, tasked with resolving legal issues of national importance and ensuring consistency in the interpretation of the law across Portugal. Figure 2.1 provides a representation of the 3-tier hierarchy.

Portuguese judiciary also includes specialized courts such as Administrative and Tax Courts, which focus on disputes involving public administration and taxation and share the same 3-tier hierarchy of judicial courts. At last, there are Peace and Arbitration Courts.

2.1.1 Legal Professions in Portugal

Portugal's legal framework is upheld by several professionals, each playing a unique role within the justice system. At the core of this system are judges, who are enshrined in the Portuguese Constitution as members of a sovereign entity—the Courts.

Judges, bound solely by the law, are tasked with delivering justice on behalf of the population. In Portugal, they are categorized based on the hierarchy of courts they serve. Judges that serve Supreme Court of Justice are known as *Conselheiros* and they are at the top of this hierarchy. If they serve Second Instance Courts, they are designated *Desembargadores* and handle appellate matters. Trial court judges, or *Juízes de Direito*, preside over FICs. The same hierarchy happens with the Administrative and Tax Courts.

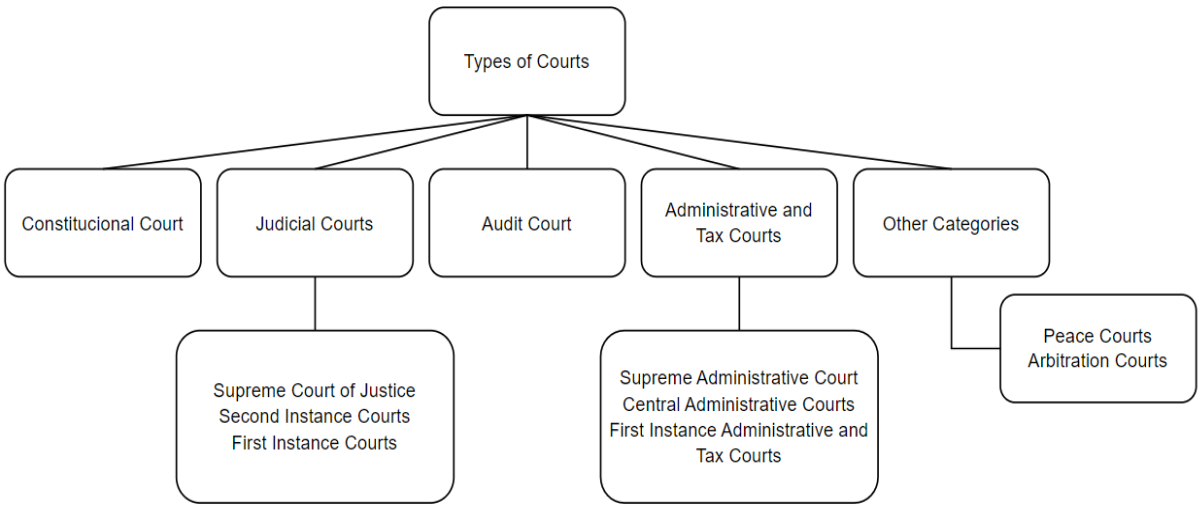

Figure 2.1: Flowchart of the different types of courts in the Portuguese Judicial System, with special emphasis for Judicial Courts which have a 3-tier hierarchy. Adapted from OECD (2020).

Besides judges, Portugal's legal system comprises several other key professions: lawyers, prosecutors, legal advisers and solicitors, enforcement agents, notaries, registrars and court officials, mediators and judicial administrators. Lawyers are crucial in representing clients in legal matters, requiring registration with the *Ordem dos Advogados*. Prosecutors play a vital role in upholding the state's legal interests. Legal advisers and solicitors offer legal advice and court representation in instances where lawyer representation is not mandatory. Enforcement agents are instrumental in ensuring the smooth execution of legal procedures, including the delivery of legal notices and facilitating evictions. Both lawyers and solicitors are authorized to perform similar legal activities, with the notable exception of legal representation, which is exclusive to lawyers in certain judicial scenarios. Solicitors and enforcement agents have to be enrolled in *Ordem dos Solicitadores e Agentes de Execução*. Notaries are dedicated to handling non-litigious legal matters such as document authentication, state matters, and other formal proceedings. Registrars and court officials, each with distinct responsibilities ranging from the registration of legal acts and facts to providing procedural assistance in courts. Mediators and judicial administrators also contribute significantly to the legal system, facilitating dispute resolution outside courtrooms and overseeing insolvency proceedings, respectively.

2.1.2 Different Procedural Areas

Portugal's judicial system is multifaceted, reflecting the complexity of legal issues that arise in modern society. The judicial system has different procedural areas, each with its distinct scope, purpose, and processes, as can be seen in Figure 2.2.

Civil justice deals with disputes between individuals or organizations, typically involving private law matters. This area encompasses a wide range of issues, including contracts, property rights, family law (such as divorce and custody), inheritance, and personal injury cases. The primary objective is to resolve disputes and provide judicial relief such as compensation or the enforcement of rights. Civil

proceedings in Portugal are governed by the Civil Code.

The criminal justice area addresses behaviors that are considered offenses against society or the state. It aims bring offenders to justice and hold them accountable in a court of law while ensuring public safety. Criminal law in Portugal covers various offenses, from minor infractions to serious crimes like theft, assault, and murder. The process involves investigation, prosecution, trial, and, if found guilty, sentencing of the accused. Criminal proceedings are guided by the Penal Code and the Criminal Code.

Labour justice focuses on disputes arising from employment relationships and workplace issues. This includes matters related to contracts of employment, wages, working hours, health and safety regulations, discrimination, and wrongful termination. The Labour Code in Portugal provides the legal framework for these issues, and disputes are typically handled by specialized labor courts. The aim is to protect the rights of workers and employers and to maintain harmonious labor relations.

Although not a traditional category in many jurisdictions, criminal labor justice involves criminal offenses related to the labor sector. This could include violations of labor law such as illegal employment practices, workplace safety violations resulting in harm, and exploitation of workers. These matters are typically prosecuted under criminal law but are distinct due to their labor-related context.

Tutelary justice is specifically concerned with protecting the rights and welfare of minors and individuals who are legally incapable of managing their own affairs. This area of justice deals with issues such as guardianship, adoption, and juvenile delinquency. The aim is to provide a legal framework that safeguards the interests of these vulnerable groups, ensuring they are cared for and protected from abuse or neglect.

Military justice represents a specialized branch of the legal system, designed to address matters specifically related to the military and its people. This procedural area is distinct from civilian justice systems and is primarily concerned with the enforcement of military discipline, the regulation of conduct among military personnel, and the investigation and prosecution of military-specific offenses.

Each of these procedural areas plays a crucial role in the administration of justice in Portugal, ensuring that the legal system is able to handle the diverse range of issues that can arise in society.

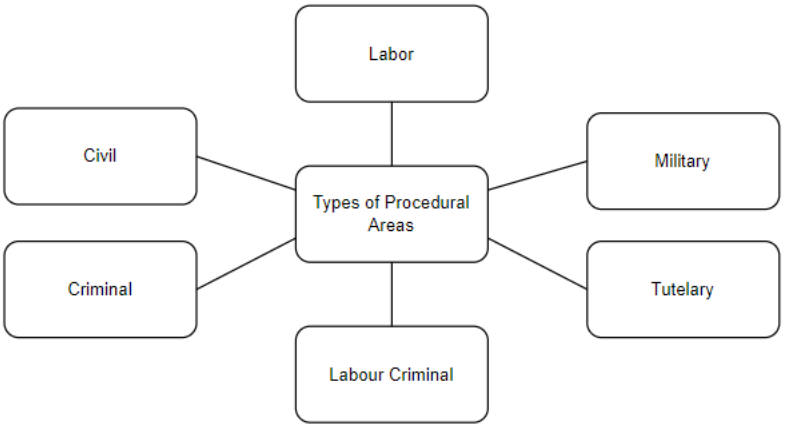

Figure 2.2: Different types of procedural areas that exist in the Portuguese First Instance Courts.

2.2 Efficiency Measurement

Performance encapsulates the overall achievement and operational success of an organization, individual, or system, integrating both efficiency and effectiveness metrics to provide a comprehensive evaluation. In a business context, performance measurement is crucial for strategic planning, decision-making, and continuous improvement, guiding managers in identifying strengths, weaknesses, and areas for enhancement (Kaplan & Norton, 1996). High performance reflects the ability not only to achieve set objectives with minimal resources but also to adapt and respond to changing environments, maintain high levels of customer satisfaction, and innovate in product and service delivery (Neely, Gregory, & Platts, 1995; Richard, Devinney, Yip, & Johnson, 2009).

The relationship between performance, effectiveness, and efficiency is comprehensively established in Figure 2.3, which serves as a visual representation of how these fundamental concepts interlink within organizational or operational contexts. This figure elucidates the dynamics where efficiency emphasizes the optimal use of resources to achieve outputs, and effectiveness focuses on the achievement of objectives, showcasing how both contribute to overall performance. Performance, depicted as the overarching outcome, is influenced by the delicate balance and interaction between achieving goals (effectiveness) and doing so with minimal waste of resources (efficiency) (Brunsson, 2017).

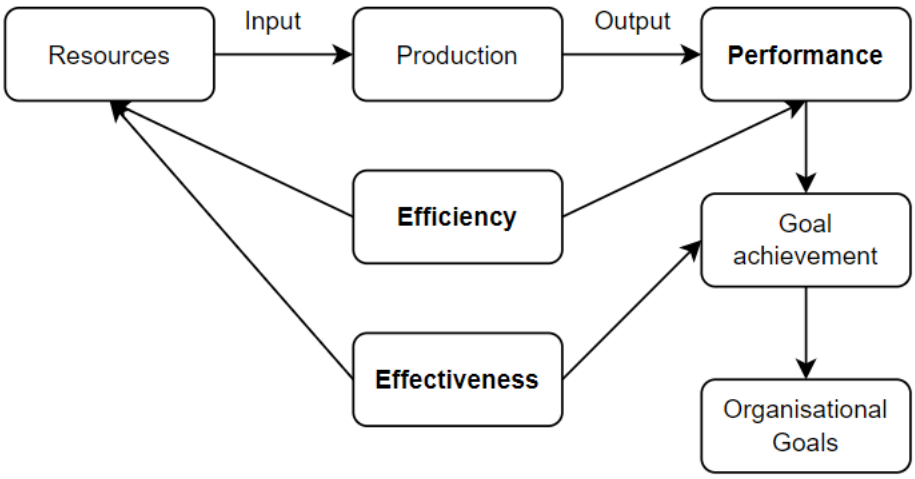

Figure 2.3: Relationship between performance, efficiency, and effectiveness. Retrieved from Brunsson (2017).

There are several studies that use various efficiency perspectives, each tailored to analyze specific aspects of performance and resource utilization in various fields such as economics, business, and public administration (Meireles, 2023).

In court context, technical efficiency refers to the ability of courts to maximize outputs (e.g., as case resolutions) from a given set of inputs (e.g., judges, administrative staff, and infrastructures) or, conversely, to minimize the use of resources while maintaining the same level of output (Coelli, Rao, O'Donnell, & Battese, 2005; Elbialy & García-Rubio, 2011; Pereira & Marques, 2022). This concept is important for understanding how well courts use their resources but does not consider the costs

associated with those resources. Economic efficiency extends the concept of technical efficiency by incorporating cost considerations. In the context of courts, economic efficiency would assess whether the courts are not only using their resources efficiently in operational terms but also minimizing the cost of producing judicial outputs (Coelli, Rao, O'Donnell, & Battese, 2005; Carmignani & Giacomelli, 2009). Cost efficiency, in particular, evaluates whether courts are operating at the minimum cost possible. For instance, cost efficiency can be calculated as the ratio between the minimum cost of producing a certain number of case resolutions and the actual observed cost. A court that is technically efficient may still be economically inefficient if the mix of resources used does not lead to the minimum cost (Coelli, Rao, O'Donnell, & Battese, 2005). Allocative efficiency, closely related to economic efficiency, refers to whether the courts are using the correct mix of inputs relative to their costs. Even if a court is technically efficient, it may not be allocatively efficient if the combination of inputs (e.g., judges, administrative staff, or technological resources) is not optimal given their respective prices or availability. Achieving allocative efficiency means that the resources are distributed in such a way that maximizes the value or welfare generated by the judicial system, ensuring that each resource is used where it provides the highest value (Coelli, Rao, O'Donnell, & Battese, 2005).

Frontier methods originated from the need to evaluate the performance of entities by comparing them against the best performers in a group or industry. These methods use the concept of a production frontier to delineate the maximum possible output that can be achieved from a given set of inputs. A Decision Making Unit (DMU) is an entity being evaluated, typically an organization, department, or a unit within a company, which converts inputs (resources like labor, capital) into outputs (products, services) (Farrell, 1957). The concept of the "frontier" is central to these methods. It represents an ideal line or surface where the most efficient DMUs lie, serving as a benchmark for others. DMUs operating on the frontier are considered efficient, while those away from it have room for improvement (Coelli, Rao, O'Donnell, & Battese, 2005). Analyzing the frontier approaches reveals two major types: parametric and non-parametric methods.

Parametric methods rely on a predefined functional form to estimate the production frontier. They assume a specific mathematical relationship between inputs and outputs, allowing for the estimation of efficiency scores based on deviations from this frontier. Key parametric methods include Stochastic Frontier Analysis (SFA) and Corrected Ordinary Least Squares (COLS) (Camanho & D'Inverno, 2023).

SFA was introduced by Aigner, Lovell, and Schmidt (1977) and accounts for random errors and inefficiency in the production process. It is widely used in sectors where external random shocks significantly affect output, such as agriculture and banking.

COLS, initially proposed by Winsten (2018), adjusts the estimated production function upwards to touch the frontier formed by the most efficient units. This method corrects for the bias in traditional regression analysis that averages both efficient and inefficient production.

Non-parametric methods do not presume a specific functional form for the production frontier. Instead, they use mathematical programming techniques to construct the frontier from the observed data, making them flexible in accommodating a wide variety of production processes. The parametric methods include DEA, Free Disposal Hull (FDH), Corrected Concave Nonparametric Least Squares (CC-

NLS), DEA and Bootstrap, and Stochastic Nonparametric Envelopment of Data (StoNED) (Camanho & D'Inverno, 2023).

Developed by Charnes, Cooper, and Rhodes (1978), DEA stands out for its ability to handle multiple inputs and outputs without requiring a predefined form for the production function, a significant advantage over traditional efficiency analysis techniques. It assumes the production possibility set is convex. This convexity assumption implies that any linear combination of inputs can lead to a feasible linear combination of outputs. It basically presumes that inputs and outputs can be scaled up or down at a constant rate, allowing for the identification of efficiencies based on a smooth, continuous frontier that envelops the observed data points.

Introduced by Deprins, Simar, and Tulkens (1984), FDH is a non-parametric approach that constructs the frontier by connecting points representing the most efficient units. Unlike DEA, FDH does not assume convexity of the production set, making it suitable for analyzing production processes where inputs and outputs do not necessarily change at a constant rate. FDH models the production frontier using the actual observed combinations of inputs and outputs, resulting in a stepwise frontier that can capture the inefficiencies of DMUs. In FDH, the efficient frontier is formed by the observed points (DMUs) that are considered efficient, and the production possibility set is shaped like steps. Since FDH does not assume convexity, the frontier does not connect the DMUs smoothly as in DEA. Instead, it is characterized by flat horizontal and vertical segments forming a step-like shape.

CCNLS is an advanced method that addresses some of the limitations of traditional non-parametric approaches by incorporating a correction mechanism that ensures the estimated production frontier is concave. This method is particularly useful when the underlying technology or production process is assumed to exhibit diminishing returns to scale. By enforcing concavity, CCNLS provides a more realistic representation of the production possibilities, especially in industries where increasing the scale of inputs does not proportionately increase outputs (Kuosmanen & Johnson, 2010).

The integration of bootstrap techniques with DEA marks a significant advancement in non-parametric efficiency analysis. Bootstrapping, a resampling method that estimates the distribution of a statistic by repeatedly drawing samples with replacement from the data, enables the calculation of confidence intervals around DEA efficiency scores. This approach strengthens the robustness of DEA results by introducing statistical inference capabilities, including significance tests and confidence intervals (Simar & Wilson, 1998).

StoNED combines elements of both SFA and non-parametric DEA to create a framework that captures the advantages of both stochastic and non-parametric approaches. StoNED uses a non-parametric approach to construct the frontier but also incorporates a stochastic element to account for statistical noise, thereby acknowledging the randomness in the data. This method provides a more nuanced analysis of efficiency, recognizing that deviations from the frontier can be due to both inefficiency and random variation. StoNED is particularly valuable in settings where it is essential to distinguish between these two sources of deviation (Kuosmanen & Kortelainen, 2012).

The focus thesis will shift exclusively towards an in-depth exploration of DEA, examining its various models, including input-oriented and output-oriented approaches, as well as understanding the distinc-

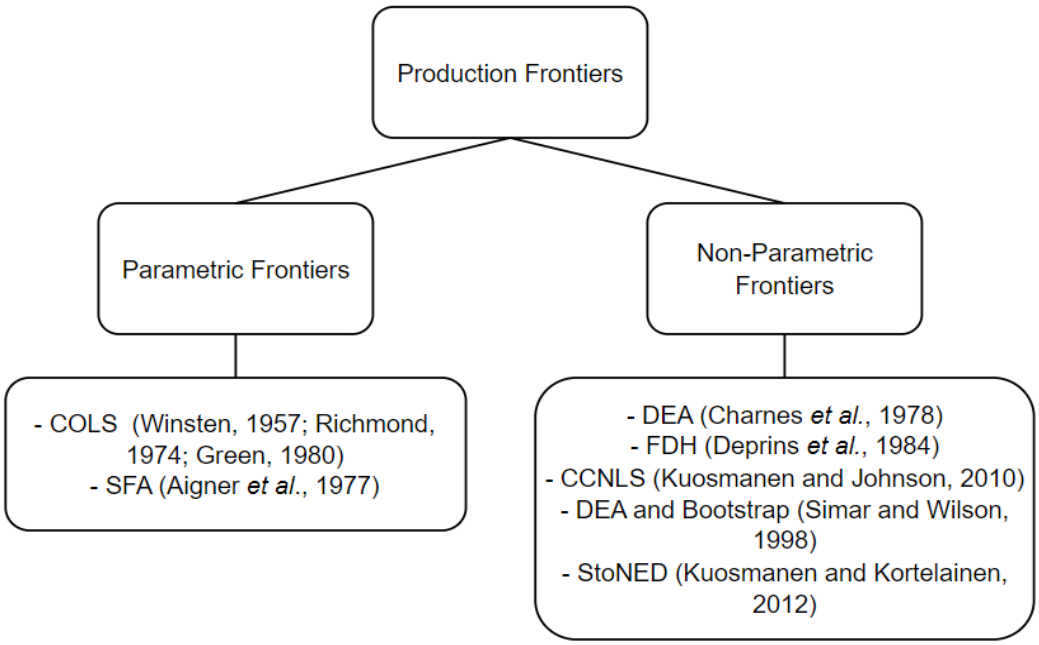

Figure 2.4: Revolutionary studies on production frontier techniques. Adapted from Camanho and D'Inverno (2023).

tions between different returns to scale assumptions.

2.2.1 Data Envelopment Analysis

The evolution of DEA from its inception with the Ratio Model provides a fascinating journey through the development of efficiency assessment. Beginning with the Ratio Model, DEA introduces a method to quantify the efficiency of a DMU through a simple yet powerful concept: the ratio of weighted outputs to weighted inputs. This foundational approach underscores the importance of assigning optimal weights to both inputs and outputs, reflecting their relative significance in the efficiency evaluation process. It is a critical step that allows for a customized assessment of each DMU, ensuring that each entity is evaluated under the most favorable conditions possible (Cooper, Seiford, & Zhu, 2011; Camanho & D'Inverno, 2023).

This model sets the stage by emphasizing the efficiency of a DMU as a singular score, derived from the aggregation of outputs to inputs, facilitated by the optimal selection of weights. Analysing deeper DEA's methodologies, there are two fundamental formulations: the primal (multiplier) and the dual (envelopment) approaches (Cooper et al., 2011). The primal formulation is centered around optimizing the weights applied to inputs and outputs, thereby deriving an efficiency score that reflects the DMU's performance in the most favorable light. Conversely, the dual formulation constructs an efficiency frontier, identifying how a DMU can adjust its inputs or outputs to achieve efficiency, depending on whether the model is input-oriented or output-oriented (Thanassoulis, Portela, & Despić, 2008).

The distinction between output-oriented and input-oriented DEA models marks a pivotal expansion in DEA's analytical capacity. Output-oriented models prioritize maximizing outputs with given inputs,

aligning with objectives aimed at productivity or service level enhancements without increasing resource consumption. In contrast, input-oriented models focus on minimizing inputs for a given level of outputs, catering to goals related to cost reduction, resource conservation, and operational efficiency (Cooper et al., 2011; Camanho & D'Inverno, 2023). These orientations allow DEA to offer tailored insights into DMU performance, enhancing its applicability across various operational goals (Yong-baeJi & Lee, 2010). Constant Returns to Scale (CRS) assumes a proportional relationship between changes in inputs and outputs. In this model, if the inputs of a DMU double, the outputs are expected to double as well. This assumption is ideal for evaluating DMUs that are operating at their optimal scale, where changes in scale do not affect the efficiency of input-output conversion. CRS provides a simpler, more rigid framework for analyzing efficiency, particularly when the scale of operations is not expected to affect performance. In contrast, Variable Returns to Scale (VRS) does not assume this proportionality. Under VRS, changes in inputs may lead to disproportionate changes in outputs. For example, if inputs are doubled, outputs may increase by less than double (reflecting decreasing returns to scale) or by more than double (reflecting increasing returns to scale). VRS provides a more flexible approach for analyzing DMUs of different sizes and operational scales, making it particularly useful when scale effects are expected to play a role in efficiency evaluation. The choice between CRS and VRS is crucial in DEA model formulations, as it significantly influences the results of the analysis by incorporating or excluding scale efficiency considerations. This choice affects both the primal and dual approaches in the DEA framework, depending on whether the model includes the assumption of scale proportionality (Cooper et al., 2011; Thanassoulis et al., 2008; Camanho & D'Inverno, 2023).

2.2.2 Efficiency Measurement in Judicial Courts

Judicial efficiency is the cornerstone of a functional legal system, ensuring that justice is delivered both impartially and in a timely manner. Evaluating this efficiency, however, is a complex task that requires a multi-dimensional approach, encompassing various facets of the judicial system. Saez Garcia (1997) and Prillaman (2000) highlight the need for dimensions like independence, efficiency, and accessibility in performance evaluations. Staats, Bowler, and Hiskey (2005) further emphasize examining multiple dimensions of judicial performance, including independence, efficiency, accessibility, accountability, and effectiveness.

Dakolias (1999) identifies several Key Performance Indicator (KPI) for assessing court performance, such as the congestion rate, which measures the backlog of cases compared to the court's capacity to resolve them. This is expressed as a ratio or percentage, signaling inefficiencies in case processing. Other crucial indicators include the number of pending cases, reflecting unresolved case volumes, and disposition time, which measures the duration from the start to the closure of cases. These metrics provide clear insights into the court's ability to deliver judgments efficiently. Schneider (2005) explores productivity metrics, such as confirmation rates, which measure how many decisions are upheld upon appeal, and the number of finished cases. Schauffler (2007) outlines essential KPIs, including access and fairness, clearance rates, disposition time, and cost per case. Voigt (2016) build on these frame-

works by using metrics such as caseload per judge, clearance rates, and congestion rates (the ratio of caseload to resolved cases) to assess court efficiency. Silva (2018) explores how DEA can be used to evaluate court efficiency by linking specific inputs to particular outputs (e.g., case types).

More advanced methods like DEA, used since 1992, offer a sophisticated approach to measuring judicial efficiency by considering multiple input and output factors. Table 2.1 presents a comprehensive overview of relevant studies in Europe. When examining judicial efficiency across Europe over the years through DEA, the focus typically is on the operational dynamics of FICs or Second Instance Courts. This analysis incorporates a comprehensive set of inputs to capture the multifaceted nature of judicial functioning. These inputs encompass the number of judges, which directly influences decision-making capacity; court staff, pivotal for administrative support; pending cases and incoming cases, reflecting the demand and throughput of the judicial process; workload, indicating the overall burden on the system; law clerks, essential for legal research and drafting; the physical area of the court, and judicial expenditure, a crucial measure of the financial resources allocated to the judiciary. On the output side, the analysis considers settled cases - same as Completed Cases (CC) - as a primary measure of judicial output, alongside more specific categories like settled civil cases and settled criminal cases, providing insight into the efficiency with which courts manage different types of legal disputes. This intricate blend of inputs and outputs allows for a nuanced assessment of judicial efficiency, shedding light on how resources are deployed to meet the demands placed on the judiciary and highlighting areas where improvements could enhance the overall efficiency of the legal system in Europe.

Table 2.1: Inputs and outputs of each study using Data Envelopment Analysis to analyse judicial efficiency. Adapted from Ippoliti and Tria (2020).

Study	Judicial System	Input	Output
Kittelsen and Førsund (1992)	Norway (First Instance Courts)	judges, staff	settled cases (7 categories)
Pedraja-Chaparro and Salinas-Jimenez (1996)	Spain (Administrative Litigation Division of High Courts)	judges, staff	settled cases with sentence settled cases without sentence
Schneider (2005)	German (Labour Courts)	judges pending cases	settled cases, published decisions
Deyneli (2012)	Europe (First Instance Courts)	judges staff	settled civil cases settled criminal cases, population
Finocchiaro Castro and Guccio (2014)	Italy (First and Second Instance Courts)	pending cases judges staff	aggregate settled cases with sentence and without sentence
Ippoliti (2014)	Italy (First Instance Courts)	judges, pending cases incoming cases	settled cases
Ippoliti, Melcarne, and Ramello (2015a) Ippoliti, Melcarne, and Ramello (2015b)	Europe (First Instance Courts)	judges, pending cases staff, incoming cases	settled cases
Santos and Amado (2014)	Portugal (First Instance Courts)	judges, staff	settled cases (43 outputs)
Castro and Guccio (2015)	Italy (First Instance Courts)	judges, staff, workload	settled cases

Table 2.1 continued from previous page

Ippoliti (2015)	Italy (First Instance Courts)	judges, staff, workload	settled cases
Melcarne and Ramello (2015)	Europe (First Instance Courts)	judges, pending cases staff, incoming cases	settled cases
Peyrache and Zago (2016)	Italy (First Instance Courts)	judges, staff pending cases	settled cases
Castro and Guccio (2018)	Italy (First Instance Courts)	judges, staff, workload	settled cases
Falavigna, Ippoliti, and Ramello (2018)	Italy (First Instance Courts)	judges, pending cases incoming cases	settled cases
Mattsson, Månsson, Andersson, and Bonander (2018)	Sweden (First Instance Courts)	judges, other personnel law clerks, area of the court	settled civil cases settled criminal cases, settled matters
Falavigna, Ippoliti, and Manello (2019)	Italy (First Instance Courts)	judges, pending cases staff, incoming cases	settled civil cases settled criminal cases
Mattsson and Tidanå (2019)	Sweden (First Instance Courts)	judges, area of the court law clercks, other personnel	settled criminal cases settled civil cases,, settled matters
Agrell, Mattsson, and Månsson (2020)	Sweden (First Instance Courts)	judges, area of the court law clercks, other personnel	settled criminal cases settled civil cases, settled matters
Ippoliti and Tria (2020)	Italy (First Instance Courts)	judges, staff, workload	settled cases
Falavigna and Ippoliti (2022)	Italy (First Instance Courts)	judges, staff judicial expenditure	settled cases

2.2.3 Challenges and Opportunities in Judicial Efficiency Analysis

Analyzing judicial efficiency encompasses various challenges that arise from the inherent complexity of justice systems and the qualitative nature of judicial outcomes (Ippoliti et al., 2015b). Despite these challenges, there are significant opportunities to enhance judicial performance and accountability through methodical efficiency analysis. One of the primary obstacles in judicial efficiency analysis is the limited availability of high-quality data. Judicial systems may not consistently collect or standardize data, making it challenging to perform comprehensive analyses. The sensitive nature of judicial data further complicates its collection and use, posing significant difficulties for researchers aiming to assess judicial performance accurately (Voigt, 2016). The diversity of judicial systems and their operations complicates the development of universal metrics for efficiency analysis. Variables such as legal frameworks, procedural laws, and case types vary widely, making it difficult to compare efficiency across different jurisdictions or to establish benchmarks for performance (Deyneli, 2012; Mazzocchi, Quintano, & Rocca, 2024). Focusing on quantitative efficiency metrics, such as case resolution rates, without considering the quality of judicial decisions can lead to a skewed understanding of judicial efficiency. Ensuring that efficiency analyses also account for the fairness, legal integrity, and substantive justice of judicial outcomes is a critical challenge (Oh & Lee, 2010; Mazzocchi et al., 2024).

Regarding opportunities in judicial efficiency analysis, advancements in technology offer significant opportunities to overcome data challenges in judicial efficiency analysis (Deyneli, 2012). Digitisation of case management systems can enhance data collection, standardization, and analysis, providing a more robust foundation for assessing judicial performance (Nissi, Giacalone, & Cusatelli, 2019; Mazzocchi et al., 2024). Efficiency analysis tools, including DEA, facilitate the identification of high-performing courts and the dissemination of best practices (Deyneli, 2012; Afsharian & Ahn, 2015). Benchmarking against these standards can motivate systemic improvements, leading to more efficient and effective judicial processes (Ippoliti et al., 2015b). Empirical evidence derived from efficiency analyses can be instrumental in shaping judicial reforms and policy decisions (Deyneli, 2012; Mazzocchi et al., 2024). By identifying inefficiencies and their underlying causes, such analyses can direct resources and reforms towards areas with the most significant impact on judicial performance. Conducting and publishing efficiency analyses enhance the transparency of judicial operations and hold courts accountable for their performance. This openness can increase public trust in the judiciary, reinforcing the importance of efficiency and quality in justice delivery (Mazzocchi et al., 2024).

In summary, while the path to comprehensive judicial efficiency analysis is full of challenges, the potential benefits it offers are substantial. By leveraging technological advancements, adopting best practices, and using empirical evidence to guide reforms, judicial systems can significantly improve their efficiency, fairness, and public trust. This balanced approach to efficiency analysis, acknowledging both its limitations and potentials, may be crucial for the ongoing improvement of judicial systems globally.

2.3 Productivity Analysis and Malmquist Index

To perform a longitudinal analysis of efficiency, it is essential to use the Malmquist Index (MI). This is because DEA scores, which are based on time-specific frontiers, are not directly comparable across different periods. Two units may have the same efficiency score (e.g., 80%) in different years, but their actual performance may differ if the efficiency frontiers in those periods have shifted due to technological changes or other factors. MI helps address this issue by separating efficiency changes (how well a unit performs relative to the frontier in its own time period) from frontier shifts (how the frontier itself evolves over time) (Fåre, Grosskopf, Lindgren, & Roos, 1992). This allows for a more accurate comparison of performance across multiple time periods (Coelli, Rao, O'Donnell, & Battese, 2005).

MI's capability to measure productivity between two temporal points is crucial for tracking changes in efficiency, as it accounts for both the evolution of the entities under consideration — whether they are firms, public sector organizations, or entire industries — and the shifts in the technology frontier, which represents best practices at any given time (Fåre, Grosskopf, Norris, & Zhang, 1994; Lovell, 2003). This ability to disentangle efficiency improvements from technological advancements is particularly valuable in sectors such as healthcare, education, and the judicial system (Zhu, 2014). By providing insights into both operational performance and external changes in best practices, the MI becomes a powerful tool for identifying areas that require improvement and for benchmarking performance, making it a key element in strategic planning and policy development.

Calculating the MI requires a nuanced understanding of its formulation and the methodologies employed to derive its values. The MI is quantitatively expressed through a formula that decomposes productivity changes into two distinct components (Fåre et al., 1994).

Efficiency Change (EC) measures the catch-up effect, representing the degree to which a DMU has approached or move back from the efficiency frontier. This component reflects improvements or deterioration in a DMU's own performance relative to its past efficiency. Technological Change (TC) quantifies the frontier-shift, indicating shifts in the efficiency frontier itself, which could be due to innovation or overall improvements in the industry's best practices. This measures the external environment's impact on productivity, independent of the DMU's own efforts (Fåre et al., 1994). The calculation of the MI using DEA is a sophisticated process that leverages the strengths of DEA for efficiency and productivity analysis (Coelli, Rao, O'Donnell, & Battese, 2005). Since DEA is responsible for constructing the efficiency frontier by enveloping all observed DMUs within a given dataset, it provides the necessary benchmarks for evaluating both EC and TC components of the MI.

In the context of the MI calculation, DEA is applied to data from two different time periods to identify the efficiency frontiers for each period (Fåre et al., 1994). By comparing a DMU's relative position to these frontiers over time, DEA makes easier the measurement of EC by evaluating how the DMU's efficiency relative to the frontier has changed. Similarly, by observing how the frontier itself has shifted, DEA allows for the assessment of TC, thus capturing the overall technological advancement or regression within the sector under study (Coelli, Rao, O'Donnell, & Battese, 2005).

This dual application of DEA not only enables the decomposition of productivity changes into catch-

up and frontier-shift effects but also ensures that the MI reflects both internal improvements or declines in efficiency and external changes in technology or best practices (Fåre et al., 1994). Given its ability to dissect these complex dimensions of productivity, the MI, calculated through DEA, becomes an indispensable tool for analyzing productivity dynamics, particularly in sectors such as justice, where operational efficiency and technological advancements play critical roles in performance and outcomes (Emrouznejad & Thanassoulis, 2010).

Building on this foundation, it is important to note that the MI is fundamentally based on efficiency measures. These measures can vary depending on how the MI is modified. Different approaches to efficiency, such as input or output orientations, radial models, and additive models, influence the structure of the MI (Zhou, Ang, & Poh, 2008). For instance, the traditional MI based on radial measures decomposes multiplicatively, while an MI based on additive measures decomposes additively, often referred to as the Luenberger Index (Kumar, 2006). These variations allow for flexibility in how productivity changes are analyzed, but all remain rooted in the core concept of measuring efficiency relative to changing frontiers over time (Fåre et al., 1994; Zhou et al., 2008).

2.3.1 Meta Malmquist Index

The MMI builds upon the conventional Malmquist Index by integrating a metafrontier framework. This extension allows for the comparison of productivity changes across different groups, such as countries or firms, that operate under varying technologies. The metafrontier represents the best possible production technology that could be achieved if all groups had access to the most advanced technology available among them. This approach not only compares productivity changes within each group using group-specific frontiers but also assesses how these groups perform relative to a universal standard—the metafrontier. The concept of meta-production functions, which aggregate group-specific production functions, was first introduced by Hayami in 1969 (as referenced by Battese and Rao (2002), and O'Donnell (2008)). This idea was initially applied to estimate stochastic meta-frontiers and later adapted by Pastor and Lovell (2005) to calculate a global Malmquist Index. Their work laid the groundwork for the MMI, allowing for a more comprehensive analysis of productivity that spans multiple groups. Further advancements were made by Portela and Thanassoulis (2006), who expanded the MMI's application, enabling the comparison not only of period-specific frontiers but also of unit-specific production frontiers over time.

Additionally, Tulkens and Vanden Eeckaut (1995) introduced the notion of inter-temporal technology in time series analysis, a concept closely related to what is now termed meta-technology in this framework. This body of work highlights the evolution of the MMI as a powerful tool for examining productivity changes in environments with heterogeneous technologies, providing deeper insights into cross-group efficiency comparisons.

MMI is particularly useful in comparative studies of productivity and efficiency across entities operating in diverse environments or sectors. For example, it can be applied to comparative analysis across countries, by analyzing productivity changes in countries with varying levels of technological develop-

ment or different regulatory environments. It can also be applied to studies where there is a comparison of productivity across sectors that have access to different levels of technology or operate under different regulatory frameworks, and to regional studies assessing productivity changes across regions within a country that might have unequal access to infrastructure or technology (Walheer, 2022).

When compared to the traditional MI, MMI offers distinct advantages that enhance its applicability and utility in analyzing productivity changes across different entities. These advantages, are particularly relevant in understanding the index's superiority in certain analytical contexts.

One of the key advantages of the MMI is its flexibility in comparing productivity across different entities by using a global or meta-technology frontier. Unlike traditional Malmquist indices, which rely on a base period or a specific time frame, the MMI uses a global technology reference that is constructed from the entire dataset, providing a broader and more comprehensive analytical perspective (Portela, Thanassoulis, Horncastle, & Maugg, 2011; Afsharian & Ahn, 2015).

Another advantage is its computational simplicity. The MMI requires solving fewer DEA models compared to traditional methods, reducing both the complexity and time needed for analysis. This efficiency makes it particularly useful for large datasets and longitudinal studies, where tracking productivity changes over time is essential (Walheer, 2022).

The MMI also satisfies the circularity property, ensuring that productivity comparisons between any two periods remain consistent, regardless of the intermediate periods. This feature enhances its reliability for long-term studies by providing a stable and coherent measure of productivity changes across multiple time periods (Afsharian & Ahn, 2015).

Additionally, the MMI is well-suited for analyzing technological changes in environments where economies of scale vary, making it particularly effective in industries or sectors where returns to scale are not constant. Its adaptability to VRS frontiers allows for a more exact understanding of productivity changes, particularly in sectors where scale effects play a significant role (Afsharian & Ahn, 2015).

Finally, the MMI is designed to accommodate Hicks-neutral technological change, meaning that shifts in the production frontier occur without changing its shape or curvature. This ensures that the index accurately reflects changes in technology without introducing distortions, maintaining the integrity of productivity comparisons across different periods (Walheer, 2022).

Chapter 3

Methodological Framework

This chapter provides a detailed overview of the methodologies and tools used to evaluate the efficiency of the justice system, structured into three key sections. Section 3.1 provides a comprehensive look at the implementation of DEA, providing information regarding the choice of this type of model, the inputs, the outputs and the procedure followed to apply DEA in this study. Section 3.2 focuses on the implementation of MMI to help capturing the dynamic aspects of efficiency changes within the justice system. Section 3.3 describes the dataset gathered and used in this analysis, while Section 3.4 discusses the software tools and statistical packages that support the implementation of the methodologies described earlier.

3.1 Data Envelopment Analysis Model Implementation

The DEA model stands out as an optimal choice for analyzing the efficiency of Portuguese FICs primarily due to its flexibility and adaptability in handling multiple input and output variables without necessitating a predefined form of the production function. This characteristic is particularly beneficial in the legal sector, where the efficiency metrics can be multifaceted, ranging from the number of resolved cases to the duration of proceedings and the allocation of judicial resources (Deyneli, 2012).

Moreover, the usefulness of DEA in this context is further underscored by its widespread application in evaluating judicial systems in other countries. As previously observed in Table 2.1, numerous studies have successfully implemented DEA to investigate the efficiency of courts, demonstrating its effectiveness in uncovering inefficiencies and facilitating comparisons across different legal systems. This global application of DEA not only validates its relevance and adaptability to the judicial sector but also offers valuable insights and benchmarks for Portuguese FICs to aspire to. By drawing on the methodological framework and findings from these international studies, Portugal can tailor DEA to address its unique judicial challenges, fostering improvements in court performance and ultimately enhancing the delivery of justice.

In the context of judicial courts, the primary objective often is to maximize the output, i.e., the number of cases completed, without necessarily increasing the inputs. This approach aligns with policy goals

focused on improving service delivery and court performance. Judicial courts usually operate under fixed or limited resources (Lopes, 2023). Thus, an output-oriented model is more realistic as it seeks to optimize outputs within these constraints.

Judicial courts vary in size, caseload, and resource availability. VRS allows for these differences by not assuming a proportional increase in outputs with an increase in inputs, which is often the reality in judicial settings. VRS models provide a more nuanced understanding of efficiency, especially useful in the varied and complex environment of judicial systems. They allow for the assessment of each DMU in relation to its specific scale of operations (Lopes, 2023).

Regarding the approach used for the DEA, the distinction between the primal multiplier approach and the dual envelopment approach pertains to the mathematical formulation of the DEA model. The primal multiplier approach focuses on optimizing the weights assigned to inputs and outputs directly, which can lead to a focus on efficiency scores without explicitly aggregating inputs. In contrast, the dual envelopment approach involves solving a series of linear programming problems to envelop the data points, emphasizing input minimization or output maximization directly. For this study, the approach that avoids aggregation of inputs is preferred, aligning with the objective to evaluate how efficiently courts can maximize outputs given their individual sets of inputs. This choice ensures that the analysis remains sensitive to the unique configurations of resources and case types across the different courts.

In this dissertation, the focus is to evaluate the efficiency of the Portuguese judicial system at the foundational level, specifically targeting the FICs. These courts serve as the primary layer for the adjudication of civil, criminal, and other cases within the legal framework of Portugal. For the purposes of this analysis, these courts are designated as DMUs. Across Portugal, there are a total of 23 FICs, each serving as a unique DMU.

The selection of inputs for the DEA in assessing the efficiency of FICs in Portugal is grounded in a comprehensive understanding of the factors that contribute to the courts' operational capacity and performance. These inputs have been carefully chosen to reflect the resources that are directly involved in the processing and completion of cases. Each input represents a critical component of the judicial system's infrastructure, influencing its ability to deliver justice effectively. Below is a justification for each chosen input:

1. Number of Justice Officials: This broad category includes court officials, technical assistants, clerks to the court, informatics personnel, and operational staff. These individuals are fundamental to the day-to-day operations of the courts, supporting the administrative and technical aspects of case management, record-keeping, and court logistics. The efficiency and effectiveness of these operations directly impact the courts' ability to process and complete cases. Recognizing the roles within this category underscores the multifaceted nature of court operations and the diverse skill sets required to support judicial processes.

2. Number of Judges: The role of judges involves not just adjudicating cases but also managing court proceedings, interpreting laws, and ensuring that justice is delivered fairly and efficiently. The number of judges in a court directly impacts the court's capacity to handle its caseload, influence

the speed at which cases are processed, and affect the quality of justice delivered.

3. Caseload : The caseload corresponds to the sum of incoming cases and pending cases. By considering caseload, the workload pressure and operational efficiency of the judicial system in processing cases are accounted for. This metric captures the responsiveness and throughput of the judicial system, indicating how effectively it manages its resources to handle and solve cases.

In addition to the primary inputs, such as the number of judges, justice officials, and caseload, it is essential to consider context variables that may influence the efficiency of judicial courts at a regional level. These variables reflect the broader legal infrastructure within each region and capture external factors that impact the court's ability to process cases. Therefore, it was decided to include the number of solicitors, enforcement agents, and lawyers—specific to each region—as additional inputs in the DEA model. These variables provide insight into the legal resources available within the jurisdiction of the courts and how they affect regional judicial efficiency.

1. Number of Lawyers enrolled in the *Ordem dos Advogados*: Lawyers play a crucial role in the judicial process, representing the interests of parties involved in legal disputes. The number of lawyers available influences the capacity of the legal system to handle cases, as they contribute to the preparation, presentation, and argument of cases in court. This input reflects the legal representation capacity within the jurisdiction of the courts being analyzed.

2. Number of Solicitors Enrolled in the *Ordem dos Solicitadores e Agentes de Execução*: Solicitors contribute to the legal process, by handling various pre-trial and trial preparations, such as document filing, evidence preparation, and other legal formalities. They ensure that all necessary paperwork and procedures are completed in a timely and correct manner, which can directly influence the efficiency of case processing.

3. Number of Enforcement Agents Enrolled in the *Ordem dos Solicitadores e Agentes de Execução*: Enforcement agents are responsible for carrying out the actions required to enforce the decisions made by the courts. This includes executing repossessions, collecting debts, and ensuring that court orders are put into practice. Their work is a direct extension of the court's function, translating judicial decisions into tangible outcomes.

The choice of outputs in the DEA analysis for evaluating the efficiency of FICs in Portugal is crucial for accurately reflecting the courts' productivity and effectiveness. These outputs - civil CC, criminal CC, criminal labor CC, labor CC and tutelar CC - have been selected to provide a comprehensive view of the judicial system's performance across various legal domains. The justification for each type of output, considering the case-mix index, highlights the complexity and diversity of the judicial workload, acknowledging that different cases require varying amounts of time, resources, and strategies to resolve.

Civil cases cover a wide range of disputes, including contracts, torts, property, and family law. They often involve complex legal issues and can vary significantly in duration and resource intensity. The inclusion of completed civil cases as an output recognizes the importance of civil justice in resolving disputes between individuals and entities, impacting economic and social relations.

Criminal cases involve the prosecution of individuals or entities accused of violating laws, which can range from minor offenses to serious crimes. The completion of criminal cases as an output measures the court's ability to process and adjudicate cases efficiently, upholding justice while ensuring the rights of the accused. The case-mix index for criminal cases considers the differences in case severity, legal requirements, and the need for specialized investigative and procedural resources.

Labor cases pertain to disputes between employers and employees or issues related to labor laws and regulations. These cases are essential for enforcing labor rights and ensuring fair workplace practices. Including completed labor cases as an output reflects the court's role in resolving employment disputes, which can have significant implications for individuals' livelihoods and the broader economy. The case-mix index for labor cases accounts for the varying complexity of employment laws and the potential for cases to involve intricate questions of law and fact.

Tutelary cases involve matters related to the protection of minors and individuals who are unable to protect their interests due to age, disability, or other reasons. These cases are vital for safeguarding the rights and well-being of vulnerable populations. The inclusion of completed tutelary cases highlights the judicial system's capacity to handle sensitive and urgent matters that require a specialized approach and prioritization. The case-mix index for tutelary cases acknowledges the unique challenges and responsibilities involved in these proceedings.

The decision to exclude military cases from the analysis is based on their limited relevance to the overall performance and efficiency of the courts in serving the general population, as this type of case is only solved in some DMUs such as *Lisboa* and *Porto* FICs. Military cases often involve specific legal frameworks and procedures that are distinct from civilian cases. By focusing on civil, criminal, labor, and tutelary cases, the analysis more accurately reflects the courts' role in addressing the legal needs and disputes most relevant to the wider society.

Incorporating the case-mix index into the analysis of these outputs allows to acquire a more profound understanding of court efficiency, recognizing that not all cases are equal in terms of their demands on the judicial system. This approach enables the DEA model to account for the inherent variability in case types, ensuring a fair and comprehensive assessment of court performance.

In this analysis,the efficiency of Portuguese judicial FICs will be examined through two distinct DEA models. Traditionally, the usual approach, Model 1, focuses solely on the roles of judges and judicial officials as inputs. However, in an effort to explore the influence of additional legal professionals on court efficiency, there is Model 2. This extended model includes lawyers, enforcement agents, and solicitors, offering a comprehensive view of the entire judicial process. In terms of outputs, both models include as outputs the civil, criminal, labour, criminal labour and tutelary CC.

The mathematical formulation of DEA model presented in the following Equation 3.1 can be explained as follows. ϕ_k is the technical efficiency score of the DMU being evaluated. The objective of the model is to maximize this score, representing the proportional increase in outputs that could be achieved by the DMU while keeping inputs constant. x_{ik} represents the amount of input i used by the DMU being evaluated (indexed by k). x_{ij} is the amount of input i used by each DMU in the dataset (indexed by j). y_{rk} is the amount of output r produced by the DMU being evaluated (indexed by k). y_{rj} is the amount of

output r produced by each DMU in the dataset (indexed by j). λ_j are the weights assigned to each DMU in the dataset. In the context of DEA, these weights are used to construct a virtual DMU against which the DMU being evaluated is compared. The virtual DMU is a linear combination of all other DMUs in the dataset. i is the index for inputs, ranging from 1 to m, where m is the total number of different inputs considered in the model. r is the index for outputs, ranging from 1 to s, where s is the total number of different outputs considered in the model. j is the index for DMUs in the dataset, ranging from 1 to n, where n is the total number of DMUs. $\mathbb{R}$ denotes the set of real numbers. It indicates that ϕ, the efficiency score, is a real number.

The first constraint ensures that for each input i, the amount used by the DMU under evaluation cannot exceed the weighted sum of that input across all DMUs in the dataset. This represents the input feasibility condition. The second constraint ensures that for each output r, the weighted sum of that output across all DMUs must be at least as large as the efficiency score ϕ times the output of the DMU under evaluation. This represents the condition that the DMU could potentially increase its outputs proportionally by the efficiency score ϕ. The third constraint ensures that the sum of the weights λ_j is equal to 1, which is a condition specific to the VRS assumption. This ensures that the scale of operations is considered in the efficiency evaluation. The fourth constraint requires that all λ_j weights are non-negative, ensuring a meaningful linear combination of DMUs.

$$
\begin{aligned}
&\max \phi_k \\
&\text{subject to} \\
&\quad x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \forall i = 1, \ldots, m \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq \phi y_{rk}, \forall r = 1, \ldots, s \\
&\quad \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, \forall j = 1, \ldots, n \\
&\quad \phi_k \in \mathbb{R}
\end{aligned}
\tag{3.1}
$$

The optimized value of ϕ_k for each DMU provides the technical efficiency score. Since it is a output-oriented model, a score greater than 1 for any court implies that there is room for improvement in outputs relative to the inputs used. Conversely, a score of 1 signifies that the court is operating at peak efficiency, being on the efficiency frontier.

Table 3.1 provides a concise summary of the inputs, outputs, and DMUs for both models described in the preceding sections. It encapsulates the components and structure of two distinct DEA models that evaluate the efficiency of judicial services across Portugal.

Table 3.1: Summary of inputs, outputs, and Decision-Making Units for Models 1 and 2.

	Inputs	Outputs	DMUs
Model 1	Number of i_1 : Justice Officials i_2 : Judges i_3 : Caseload	Number of Completed r_1 : Civil Cases r_2 : Criminal Cases r_3 : Criminal Labour Cases r_4 : Labour Cases r_5 : Tutelary Cases	*Açores, Aveiro, Beja, Braga, Bragança, Castelo Branco, Coimbra, Évora, Faro, Guarda, Leiria, Lisboa, Lisboa Norte, Lisboa Oeste, Madeira, Portalegre, Porto, Porto Este, Santarém, Setúbal, Viana do Castelo, Vila Real, Viseu*
Model 2	Number of: i_1 : Justice Officials i_2 : Judges i_3 : Caseload i_4 : Enforcement Agents i_5 : Lawyers i_6 : Solicitors	Number of Completed r_1 : Civil Cases r_2 : Criminal Cases r_3 : Criminal Labour Cases r_4 : Labour Cases r_5 : Tutelary Cases	

3.2 Meta Malmquist Index Implementation

The MMI is an advanced methodological tool used in this study to track the efficiency changes of Portuguese judicial FICs over time. This index extends beyond traditional DEA models by not only capturing shifts in efficiency levels but also decomposing these changes into components that reflect technological progress, efficiency variation, and scale efficiency changes.

The application of the MMI allows for an analysis of the performance of the 23 Portuguese FICs. This approach is particularly well-suited for the judicial context, where both internal operational improvements and external environmental shifts can influence efficiency. The MMI provides a multifaceted view of efficiency evolution, enabling the identification of underlying factors driving changes across multiple time periods. EC component measures shifts in the productivity of courts, considering the same technology. It allows for the assessment of whether courts have become more or less efficient in using their resources (inputs) to maximize their outputs (CC) over time. TC component evaluates how technological progress or regression in the judicial system affects the production frontier. It reflects the impact of digitisation, process optimization, and other systemic improvements on the overall capability of courts to handle cases more efficiently. Technology Gap (TG) component provides insight into how each court's use of technology compares to the most technologically advanced court within the same judicial system. This can reveal which courts are lagging in adopting best practices or innovations that could enhance their operational efficiency and effectiveness in case processing..

The choice to employ the MMI in this study is justified by the need to understand not only the efficiency of each court at a given time but also how these courts evolve in response to policy reforms,

technological advancements, and changes in demand for judicial services. By decomposing the overall efficiency change into specific components, this approach provides insights into the drivers of performance improvements or declines, offering valuable guidance for policymakers, judicial administrators, and stakeholders interested in enhancing the effectiveness of the judicial system.

The upcoming section explains the MMI according to the one used in Portela et al. (2011), offering an analytical framework for assessing productivity changes over time and across different entities within a meta-technology context. Equation 3.2 calculates the meta-efficiency score of a DMU j by incorporating the TG, reflecting both its operational efficiency and technological context. $\theta_{j,t}$ represents the efficiency score of the j-th DMU at time t. This score is derived from a DEA models and reflects the relative efficiency of the DMU compared to a frontier composed of other DMUs. $TG_{j,t}$ denotes the TG for the j-th DMU at time t. This factor adjusts the efficiency score to account for the technological environment or the TG that the DMU faces compared to the frontier technology. $\theta^m_{j,t}$ is the adjusted efficiency score that incorporates the technology gap. This adjusted score provides a more accurate representation of the DMU's performance, considering both its operational efficiency and the technological context in which it operates, it measures the distance between the period-specific frontier and the meta-frontier for unit j at time t.

$$\theta^m_{j,t} = \theta_{j,t} \times TG_{j,t} \tag{3.2}$$

The MMI measures the productivity change of a unit over time, adjusting for changes in technology, through the ratio of adjusted efficiency scores between two periods, as it is in Equation 3.3. $MMI_{j,t+1}$ calculates the productivity change of the j DMU from time t to $t+1$, incorporating adjustments for technological change. This ratio compares the adjusted efficiency scores across two periods, providing insight into how the DMU's productivity, adjusted for technological context, has evolved.

$$MMI_{j,t+1} = \frac{\theta^m_{j,t+1}}{\theta^m_{j,t}} \tag{3.3}$$

Equation 3.4 provides an expanded view of the MMI calculation by breaking it down into two components. $\frac{\theta_{j,t+1}}{\theta_{j,t}}$ reflects the change in the efficiency, while $\frac{TG_{j,t+1}}{TG_{j,t}}$ reflects the frontier shift. Multiplying these two ratios gives the MMI, which captures both the operational efficiency change and the technological change, providing a comprehensive view of the DMU's productivity evolution over time.

$$MMI_{j,t+1} = \frac{\theta_{j,t+1}}{\theta_{j,t}} \times \frac{TG_{j,t+1}}{TG_{j,t}} \tag{3.4}$$

Incorporating this index into the DEA analysis enriches the understanding of efficiency within Portuguese judicial FICs, offering a comprehensive overview of progress over time and pinpointing specific areas where targeted interventions can lead to substantial efficiency gains. This detailed analysis supports the development of evidence-based strategies to bolster the performance of the judicial sector, ultimately contributing to a more effective and responsive justice system in Portugal.

3.3 Dataset

The dataset that is going be used in the DEA models and in MMI was provided by DGPJ and spans from 2015 to 2023, providing a post-judiciary reform snapshot of the Portuguese legal system. It consists of 207 observations across 23 FICs, i.e., 23 observations per year within the study period.

The dataset includes a detailed breakdown of numeric variables such as the number of justice officials, judges, lawyers, solicitors, and enforcement agents, providing a thorough overview of human resources in the judiciary. Additionally, it captures the number of CC across various categories: civil, criminal, labour, criminal labour, and tutelary. These variables allow for an in-depth analysis of case throughput and efficiency in handling different types of legal disputes. The dataset includes the qualitative variable FIC, which categorizes each observation, allowing for comparative assessments among different jurisdictions. Besides those variables mentioned above, the dataset also includes more data about efficiency indicators such as Clearance Rate (CR), Disposition Time (DT), and the numbers of Incoming Cases (IC) and Pending Cases (PC) per procedural area. These metrics are critical for assessing the courts' capacity to manage and resolve cases, although they are not directly used in the DEA model calculations.

Due to the meticulous data collection process at the DGPJ facilities, the dataset benefits from high reliability, containing no instances of null or zero values, thus eliminating the need for preprocessing steps such as data imputation or cleaning. This ensures that the dataset is ready for immediate analysis without concerns about data accuracy or integrity.

Each variable in the dataset not only reflects operational metrics but also serves as a vital component for evaluating judicial performance in the context of the post-reform environment. This structured and granular approach to data collection allows for precise DEA model application, leading to insightful conclusions about the efficiency and productivity of the courts. The firsthand experience gained during the internship at the DGPJ facilities further enriches the interpretation and analysis of the data, providing an insider perspective that enhances the overall understanding of operational nuances within the Portuguese legal system.

3.4 Software and Packages

The methodology adopted for the analysis encompasses the use of the R programming language, specifically to calculate DEA using *Bencharmking* package. This technique will assess the operational efficiency of several DMUs. Additionally, R will be instrumental in computing the MMI to track productivity changes over time, a critical factor in longitudinal efficiency analysis. Complementing R, Python programming language will be used, namely libraries such as *Matplotlib* and *Seaborn*, to create detailed and interactive graphical representations of data.

Chapter 4

Application Details

Chapter 4 outlines the key elements and data involved in the application of efficiency analysis to Portuguese First Instance Courts. The chapter is divided into several sections that describe the resources, case metrics, and variables used in the study. Section 4.1 provides an overview of the methodology and datasets employed in the analysis. Section 4.2 presents a preliminary analysis, which is further subdivided into four parts: Subsection 4.2.1 examines the judicial resources, such as the number of judges and judicial officials. Subsection 4.2.2 reviews case-related metrics, including the number of incoming, pending, and completed cases, providing insight into court workload and throughput. Subsection 4.2.3 introduces the context variables, such as the number of lawyers, solicitors, and enforcement agents, which account for regional variations in legal infrastructure. Subsection 4.2.4 focuses on performance indicators, particularly DT and CR, which are crucial for understanding and giving further context to the efficiency of case processing.

4.1 Overview

This study aims to assess the efficiency and productivity of Portuguese judicial FICs, with a special focus on identifying regional differences in court efficiency and productivity, and the factors driving them. By applying advanced benchmarking methods, such as DEA and MMI, the research offers a detailed comparison of court performance across Portugal's regions. These tools are crucial for analyzing efficiency and monitoring changes in productivity over time.

A key factor in this study is the extensive and varied data needed to conduct a thorough analysis. The complexity of evaluating judicial efficiency and productivity requires access to datasets that include a broad spectrum of performance indicators. This diversity of data is essential to achieve the study's objective of offering a comprehensive understanding of efficiency variations and the factors that influence them.

Additionally, it is important to contextualize this study within the broader European judicial evaluation landscape. The CEPEJ consistently evaluates the justice systems across Europe. Although Portugal has demonstrated promising results in recent CEPEJ reports, highlighting overall improvements, there

remains a critical need to explore the variances between different regions within the country (CEPEJ, 2020, 2022a). This regional analysis is crucial, as it contributes to a deeper understanding of Portugal's performance in the context of CEPEJ's ongoing evaluations, offering insights into localized challenges and achievements within the Portuguese judicial system.

4.2 Preliminary Analysis

As part of the thorough analysis of the dataset, Tables 4.1 and 4.2 includes basic statistical measures for inputs and outputs, namely minimum, maximum, mean (μ), standard deviation (σ), first Quartile ($Q1$), third Quartile ($Q3$) and Interquartile Range (IQR), respectively. The overall mean value of each input and output across all DMUs, offering a broad sense of the average resource availability and case resolutions. Standard deviation will provide the aggregate variability or dispersion around the mean for each variable across all DMUs, indicating the general spread of data points within the national system.

The inputs present wide variability (Table 4.1). The number of justice officials also varies widely, from as few as 51 to as many as 784. Courts with more justice officials can distribute the workload more evenly, which may help them resolve cases faster. The standard deviation (177.35) indicates a large variability in staffing across courts, which again influences how well they can function. The number of judges across courts ranges from a minimum of 13 to a maximum of 218. On average, courts have about 55 judges. There's a noticeable difference between courts, with some having significantly fewer judges than others. The caseload per court varies dramatically, from as low as 7,801 cases to as high as 368,047. On average, courts handle approximately 58,300 cases, but there is a very large difference across courts (the standard deviation is 65,846). This means some courts could be overwhelmed with cases, while others have far fewer. The variation in the number of judges, caseload, and justice officials shows that courts operate under very different conditions. Some courts are handling far more cases with fewer resources, while others may be better staffed and still have fewer cases to manage. Enforcement agents, lawyers, and solicitors, being context variables, show considerable variation (e.g., lawyers with an IQR of 1,021.50), reflecting external factors beyond court control that could skew productivity measures.

The outputs similarly show substantial variability (Table 4.2). The range of civil cases is vast (2,269 to 93,798), highlighting differences in the type and complexity of cases each court handles. The other categories show more moderate variability, with criminal cases having a mean of 3,444.84 and labour cases a mean of 2,146.52. Understanding how these outputs correlate with inputs (especially caseload and judges) will be critical in determining if certain courts are operating efficiently or if disparities exist due to input allocation.

Table 4.1: Minimum, maximum, mean (μ), standard deviation (σ), 1^{st} quartile ($Q1$), 3^{rd} quartile ($Q3$) and interquartile range (IQR) for input variables.

Inputs	min	max	μ	σ	$Q1$	$Q3$	IQR
i_1 : Justice Officials	51	784	217.85	177.35	104.50	245.00	140.50
i_2 : Judges	13	218	54.67	46.16	23.00	67.00	44.00
i_3 : Caseload	7,801	36,8047	58,300.05	65,846.85	16,138.50	69,998.50	53,860.00
i_4 : Enforcement Agents	0	278	50.66	62.92	8.00	63.50	55.50
i_5 : Lawyers	113	12,889	1,431.32	2,475.28	250.50	1,272.00	1,021.50
i_6 : Solicitors	9	600	166.73	146.35	52.50	236.00	183.50

Table 4.2: Minimum, maximum, mean (μ), standard deviation (σ), 1^{st} quartile ($Q1$), 3^{rd} quartile ($Q3$) and interquartile range (IQR) for output variables.

Outputs	min	max	μ	σ	Q1	Q3	IQR
r_1 : Civil Cases	2,269	93,798	18,246.86	19,075.88	5,540.50	21,557.00	16,016.50
r_2 : Criminal Cases	602	14,224	3,444.84	2,973.16	1,206.50	4,695.50	3,489.00
r_3 : Criminal Labour Cases	3	516	84.57	73.28	33.50	115.00	81.50
r_4 : Labour Cases	247	11,314	2,146.52	2,299.74	595.00	2,707.00	2,112.00
r_5 : Tutelar Cases	380	14,057	2,543.18	2,357.32	833.00	3,134.00	2,301.00

Figure 4.1 represents a scatter plot matrix of inputs and outputs variables. Each diagonal element of the scatter matrix represents a histogram of the variable listed on that row/column. As observed, the distributions are right-skewed, indicating that while most FICs manage relatively small numbers of cases or employ fewer officials, a few handle significantly higher volumes, which is expected given that certain regions have larger populations than others. The scatter plots in the matrix highlight relationships between pairs of variables, helping to identify potential correlations. Although the histograms show long tails, suggesting the presence of outliers, these differences are likely influenced by regional population disparities, reflecting the varying demands on judicial resources across different areas.

In the pursuit of assessing the correlation between input and output variables, Figure 4.2 shows a heatmap of the Pearson correlation matrix. Correlation coefficients range from -1 to 1, where values closer to 1 indicate a strong positive correlation, values closer to -1 indicate a strong negative correlation, and values around 0 indicate no correlation.

By investigating the correlation matrix, it is possible to see that the correlation between the number of judges and CC is generally strong across most case types. This suggests that courts with a higher number of CC tend to allocate more judges to handle the workload. For example, there is a robust positive correlation between judges and the overall caseload (0.92), implying that courts with a larger

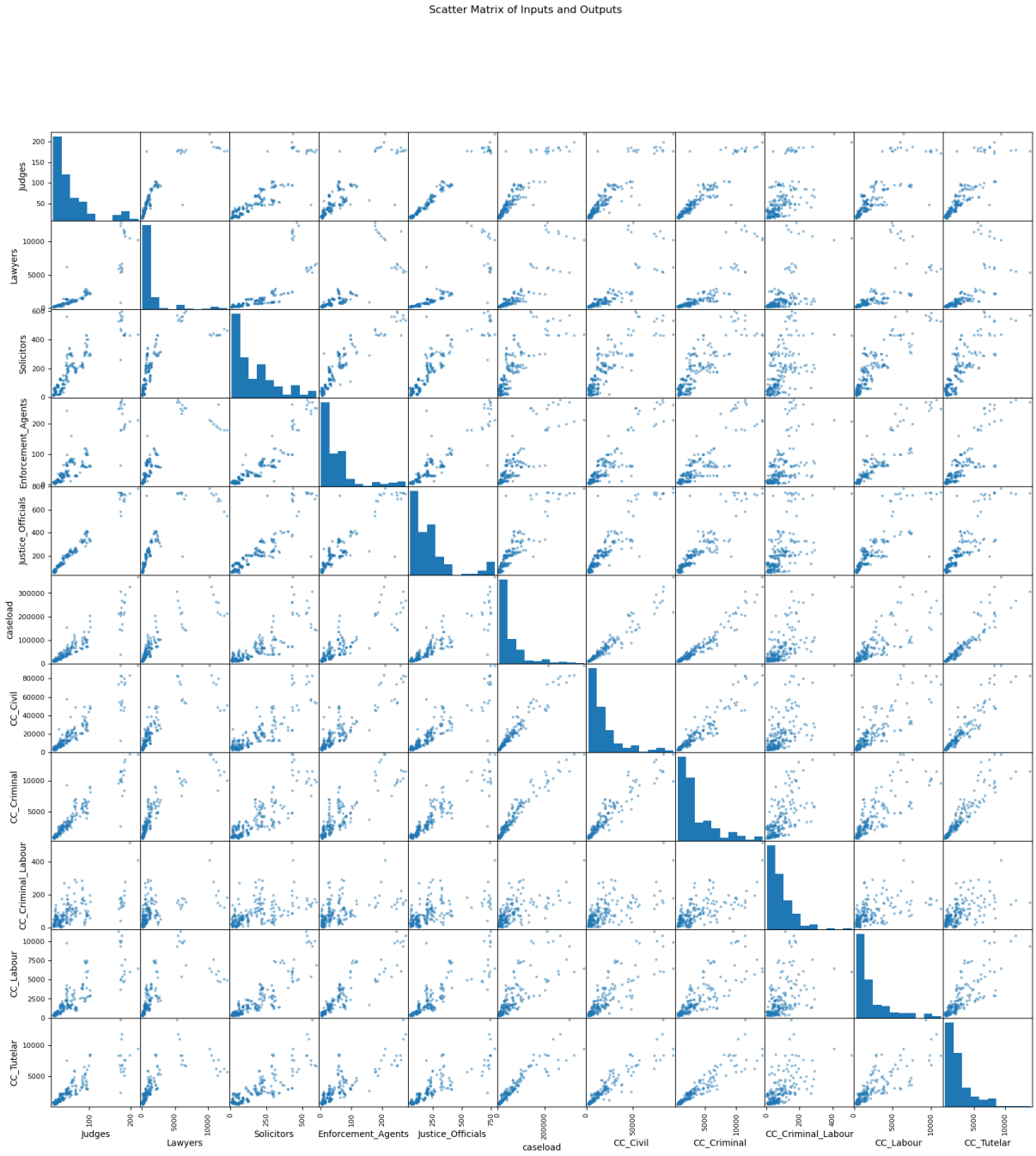

Figure 4.1: Scatter plot matrix of inputs and outputs variables.

caseload typically have more judges. The same trend is observed for the number of CC across different categories, reflecting that courts with higher activity and throughput tend to have more judicial resources.

However, this relationship is not consistent across all types of cases. Specifically, the correlation between judges and criminal labor cases is weaker, with a correlation coefficient of 0.62. This indicates that the number of judges does not increase as proportionally in courts handling criminal labor cases as it does with other case types. The weaker correlation suggests that criminal labor cases may either demand fewer judges to complete or occur less frequently compared to other types of cases.

When looking at justice officials, the pattern is similar. There is a strong positive correlation between

justice officials and caseload (0.91), meaning that courts with larger caseloads tend to have more administrative personnel. This reflects the administrative needs associated with managing the flow of cases. However, like with judges, the correlation between justice officials and criminal labor cases is weaker (0.60).

Overall, the correlation between lawyers, solicitors, and enforcement agents with caseload and CC demonstrates that courts in regions with larger case volumes tend to have more of these professionals involved. Since they are distributed by region — through bar enrollment for lawyers and association enrollment for enforcement agents and solicitors — their presence aligns with the varying demands of the courts. However, in the case of criminal labor cases, the weaker correlations suggest that fewer professionals are involved, likely due to the specialized or less frequent nature of these cases in certain regions. Nevertheless, it is important to keep in mind that correlation does not imply causation, and the reverse is not necessarily true either.

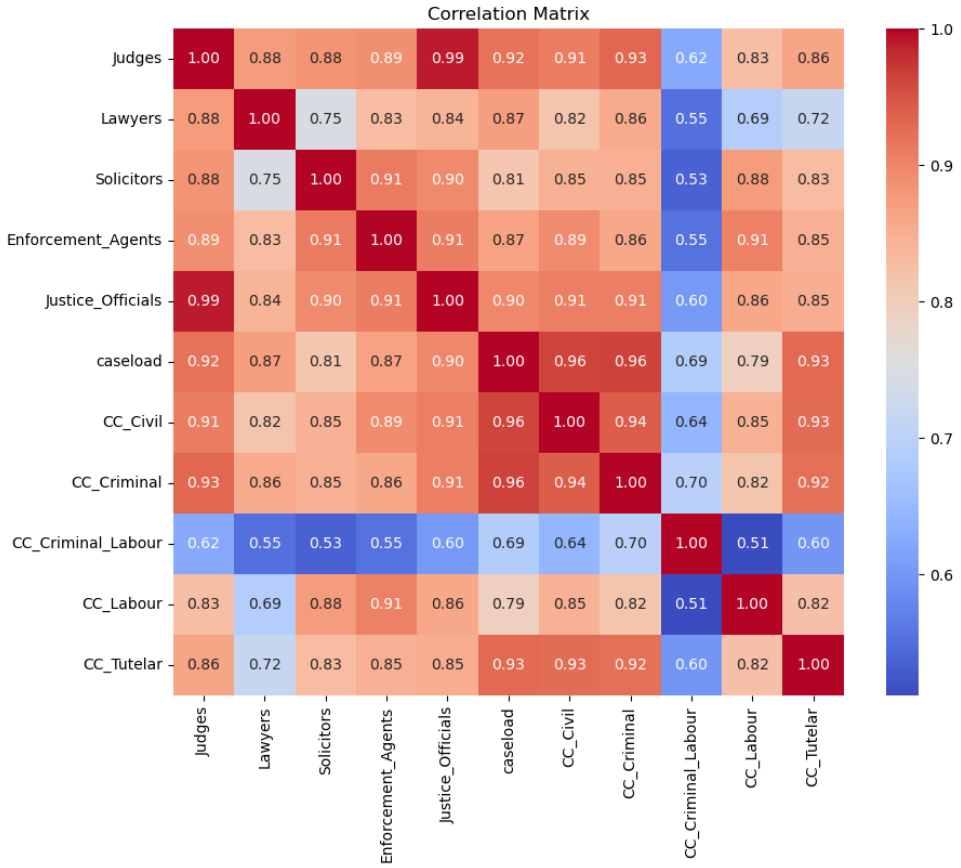

Figure 4.2: Correlation matrix of inputs and outputs variables.

In the context of analyzing the distribution and trends of judicial resources in Portugal, first it is necessary to understand how FICs are organized across the country. It is possible to group FICs according to the Region(s) Nomenclature of Territorial Units for Statistics (NUTS) II, which can be found in Table 4.3.

Table 4.3: Organization of Portuguese Judicial First Instance Courts according to Region(s) NUTS II regions.

Region(s) NUTS II	**First Instance Courts**
Alentejo	*Beja, Évora, Portalegre, Setúbal*
Algarve	*Faro*
Área Metropolitana de Lisboa	*Lisboa, Lisboa Norte, Lisboa Oeste*
Centro	*Aveiro, Castelo Branco, Coimbra, Guarda, Leiria, Santarém, Viseu*
Norte	*Braga, Bragança, Porto, Porto Este, Viana do Castelo, Vila Real*
Região Autonóma da Madeira	*Madeira*
Região Autonóma dos Açores	*Açores*

Building on this organization, it is possible to explore the allocation of judicial resources, the number of cases and the context variables across these regions.

4.2.1 Judicial Resources

Figure 4.3 depicts the trend in the average number of judges across different regions from 2015 to 2023. The data reveals that the *Área Metropolitana de Lisboa* consistently has the highest number of judges, starting at around 130 in 2015 and gradually decreasing to about 110 by 2023. This decline may reflect budget constraints, retirements, or shifts in judicial allocations. Other regions, such as *Norte* and *Algarve*, maintain a more stable number of judges. *Centro* shows a slightly lower but stable number of judges, typically following behind *Norte* and *Algarve*. Regions with smaller populations, such as *Região Autónoma dos Açores* and *Região Autónoma da Madeira*, have consistently lower numbers of judges, while *Alentejo* has the lowest average number of judges among all regions, reflecting its smaller judicial demands.

Figure 4.4 illustrates the trend in the average number of justice officials from 2015 to 2023. Similar to the pattern observed for judges, the *Área Metropolitana de Lisboa* has the highest number of justice officials, starting at around 450 and declining to approximately 350 by 2023. This reduction parallels the trend observed for judges and may be attributed to similar factors such as budget cuts or administrative restructuring. The regions of *Norte* and *Algarve* maintain steady numbers of justice officials, with fluctuations around 200 and 300, indicating a consistent support structure for judicial processes, specifically for *Norte*. *Centro* follows, while the *Região Autónoma dos Açores* and *Região Autónoma da Madeira* maintain lower but stable numbers of justice officials, consistently below 150. *Alentejo* has even lower numbers, below 100, than these island regions, further indicating reduced staffing requirements in this region.

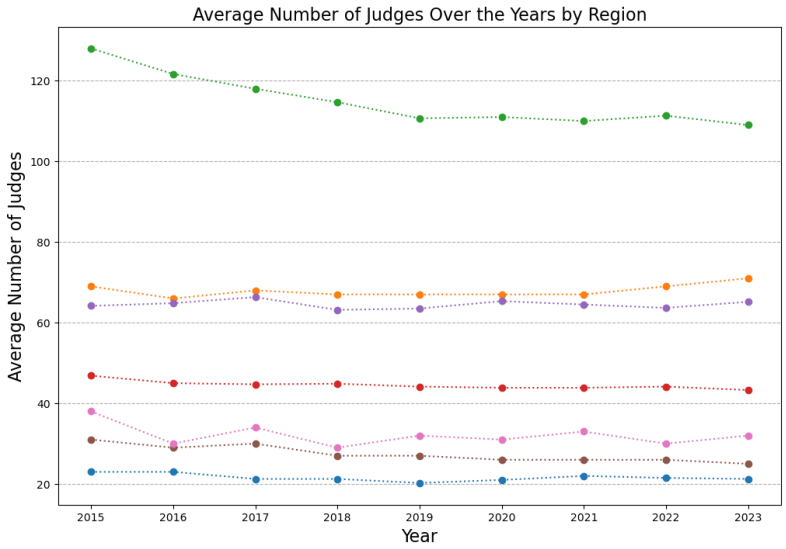

Figure 4.3: Average number of judges over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

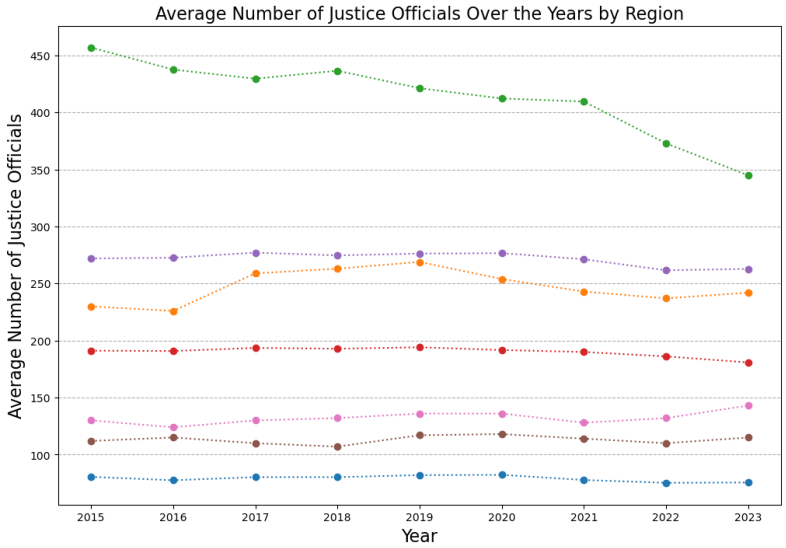

Figure 4.4: Average number of justice officials over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

The data presented in these Figures 4.3 and 4.4 highlight regional variations in judicial and administrative staffing over the past decade. The *Área Metropolitana de Lisboa* stands out with the highest numbers but shows a declining trend, suggesting potential systemic changes or resource reallocations. Other regions display more stability, reflecting consistent judicial and administrative requirements.

4.2.2 Incoming, Pending and Completed Cases

Having thoroughly examined the allocation of various judicial and legal resources across different regions, the focus now shifts to the operational side of the judicial system.

Specifically, the analysis will cover several key metrics that provide a comprehensive overview of the judicial system's performance. These include the number of CC, IC, PC over the years. Understanding these metrics is crucial for assessing the efficiency and effectiveness of the judicial system in handling its caseload.

The PC refer to the total number of legal actions that have been initiated in a court of law but have not yet been resolved or concluded by a final judgment or decision. These cases remain in the judicial system awaiting further action, such as a trial, settlement, dismissal, or another form of resolution. The status of a case as pending indicates that it is in process and still requires judicial attention to reach closure. The PC can accumulate over time, reflecting the capacity and efficiency of a judicial system to process and adjudicate matters within its purview. There is a difference between PC at the 31^{st} of December and 1^{st} of January, due to several factors, including statutory deadlines and judicial vacations. Legal deadlines are often calculated in calendar days, excluding weekends and holidays, but some specific deadlines might consider the judicial year, which traditionally aligns with the calendar year. Thus, processes pending at the beginning or end of the year may be affected differently by these statutory deadlines, especially if the process involves steps or measures that must be taken within a certain timeframe before the year ends or as the new year begins. The Portuguese legal system traditionally observes judicial vacations, a period during which courts do not conduct regular hearings or sessions. This period typically includes part of December and early January (22^{nd} December and 3^{rd} January). Therefore, processes pending as of the 31st of December might see a delay in movement or decisions until after the judicial vacations conclude, usually after the first week of January. On the other hand, processes pending at the beginning of the year might also be affected by the tail end of this vacation period, but they have the entire year ahead for progression (Portal Europeu da Justiça, 2023). For clarification, the ones used for this analysis are PC at the 31^{st} December.

The IC are those legal matters that are newly filed or brought before a court within a specific reporting period. These cases add to the workload of the judicial system, requiring allocation of resources such as time, personnel, and administrative support for their processing and adjudication. Incoming cases can vary widely in nature, complexity, and required handling time. The measure of IC provides insight into the current demands being placed on the judicial system and can serve as an indicator of societal trends, legal disputes, and the public's access to legal recourse.

Caseload refers to the total number of cases a judicial entity is handling at any given time. It includes both pending and incoming cases.

The upcoming graphs offer insights into the trends and patterns that characterize the judicial workload. This analysis will help identify any bottlenecks or areas where the judicial process may be delayed, as well as regions that are managing their caseloads effectively.

Figure 4.5 depicts the number of IC, CC, and PC by year from 2015 to 2023. Each year is represented by three distinct bars: light blue for IC, dark blue for CC, and orange for PC. This visualization allows

for a comprehensive examination of trends and changes in case volumes and judicial efficiency over the specified period.

The data indicates a general decline in the number of IC from 2015 to 2023. Starting at 604,866 in 2015, the IC reached a low of 428,615 in 2021. This downward trend could be attributed to various factors, including changes in legal policies, societal behaviors, or external factors such as the COVID-19 pandemic, which likely disrupted normal court operations and reduced the number of cases being filed. However, there is a slight increase in incoming cases in 2022 and 2023, with numbers rising to 447,983 and 471,343, respectively, suggesting a return to more typical filing rates post-pandemic.

CC also show a declining trend from 2015 to 2020, decreasing from 746,669 in 2015 to 469,595 in 2020. This decline aligns with the trend in incoming cases, indicating a proportional response in the judiciary's capacity to process and complete cases. Notably, there is a marked increase in CC in 2021 and 2022, peaking at 492,497 and 489,992, respectively, before slightly decreasing to 469,589 in 2023. This uptick in CC post-2020 may reflect efforts to address the backlog exacerbated by the pandemic, as well as adaptations to new operating procedures and efficiencies within the judicial system.

The number of PC consistently surpasses both IC and CC each year, highlighting a persistent backlog within the judicial system. The highest number of pending cases was recorded in 2015, reaching 1,131,264. From this peak, there is a gradual decline in pending cases until 2020, where the number drops to 684,762. This trend suggests that while fewer cases were filed and completed, efforts were made to reduce the backlog. However, from 2021 onwards, there is a slight increase in PC, rising to 620,880 in 2021, and further to 578,871 and 580,625 in 2022 and 2023, respectively. This increase indicates ongoing challenges in fully eliminating the backlog, despite improvements in case processing.

General Trends

- 2015-2016: The judicial system faced a significant backlog, with PC exceeding 1 million in both years. Despite a high number of CC, the volume of IC continued to add to the pending load.
- 2017-2019: Both IC and CC decreased, yet the number of PC remained high. This suggests that although fewer cases were being filed and processed, the existing backlog was substantial and difficult to manage.
- 2020: A notable decline in all categories is observed, likely due to the COVID-19 pandemic, which disrupted normal court operations.
- 2021-2023: There is a resurgence in IC and CC. Despite the slight increase in PC, the numbers remain lower than the pre-pandemic peak, indicating that efforts to manage the backlog have had some success, though challenges persist.

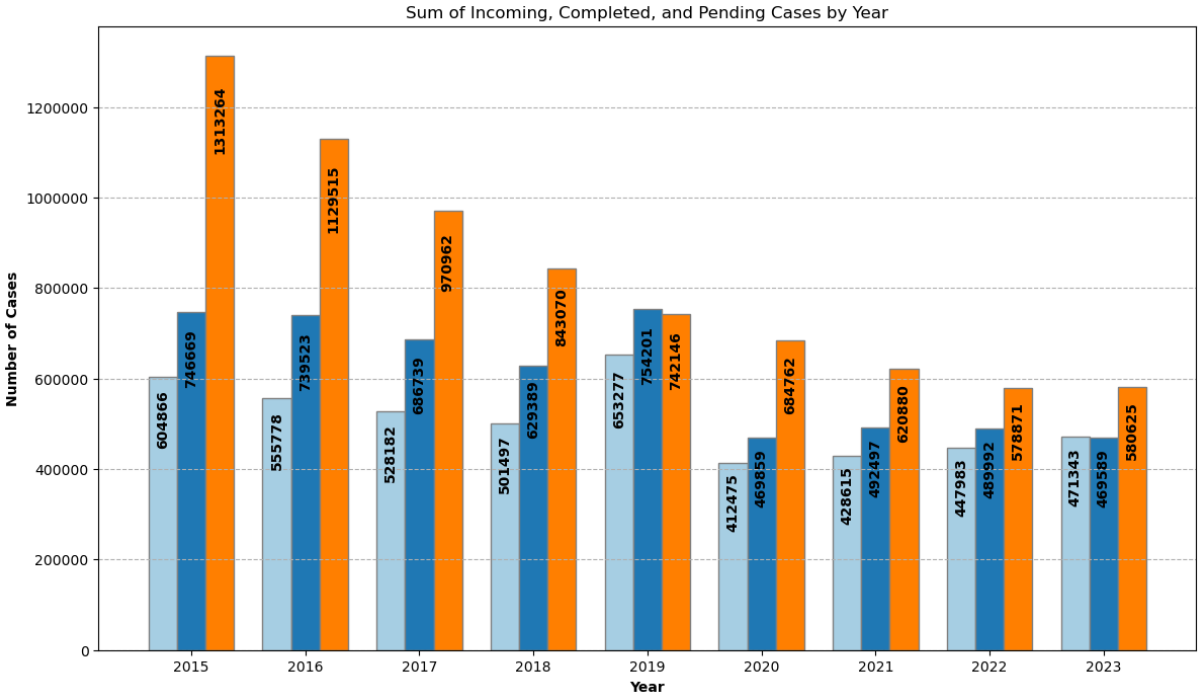

Figure 4.5: Evolution of the number of incoming cases, completed cases and pending cases from 2015 to 2023. Dark blue: completed cases, light blue: incoming cases, and orange: pending cases.

The average number of civil CC, depicted in Figure 4.6, shows a clear downward trend from 2015 to 2023. Again, *Área Metropolitana de Lisboa* leads with the highest number of civil CC, although it also demonstrates a significant reduction, particularly post-2019. This trend may highlight successful implementation of measures to streamline civil case proceedings or a decrease in civil disputes. Other regions exhibit a more gradual decline, with most regions showing spikes in the same year (e.g., 2019) that suggest intermittent increases in civil caseloads.

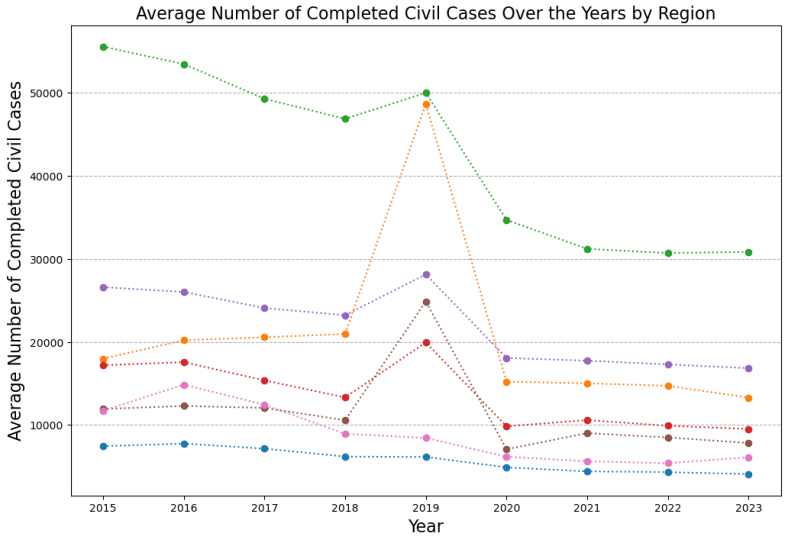

Figure 4.6: Average number of completed civil cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.7 illustrates the trend in the average number of criminal CC across different regions from 2015 to 2023. The data indicates a general decline in the number of criminal CC over this period, with the *Área Metropolitana de Lisboa* consistently reporting the highest number of cases. This region shows a significant decrease in criminal CC from 2019 to 2020, followed by a slight increase and stabilization in subsequent years.

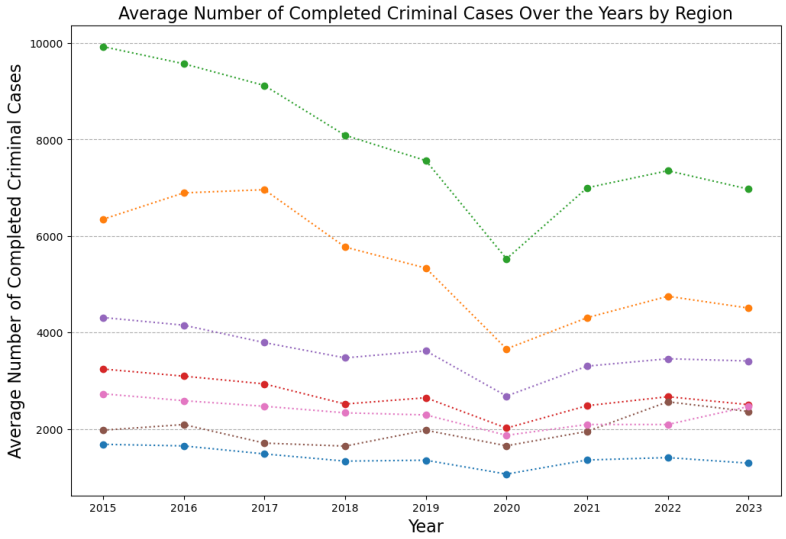

Figure 4.7: Average number of completed criminal cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.8, the trends in criminal labor CC from 2015 to 2023 are presented. The data shows a pronounced peak in 2016, especially in the *Área Metropolitana de Lisboa*, which then sharply declines. By 2020, the number of criminal labor CC had significantly decreased across all regions, with some slight increases in the following years.

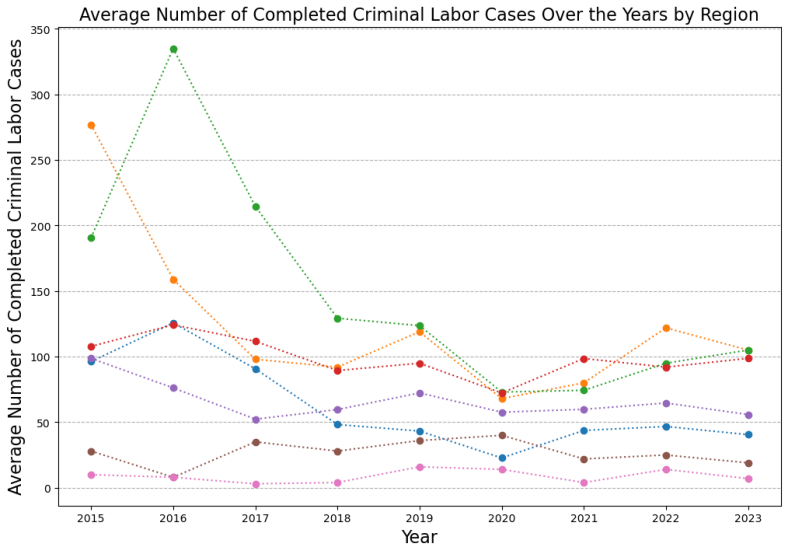

Figure 4.8: Average number of completed criminal labor cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.9 presents the average number of labour CC over the years. *Área Metropolitana de Lisboa* and *Norte* report the highest number of labour CC, with noticeable variability year on year. The trend indicates a peak around 2017, followed by a general decline in 2020. The consistency in the lower number of labour CC in regions like *Alentejo*, *Região Autónoma dos Açores* and *Região Autónoma da Madeira* reflect fewer disputes.

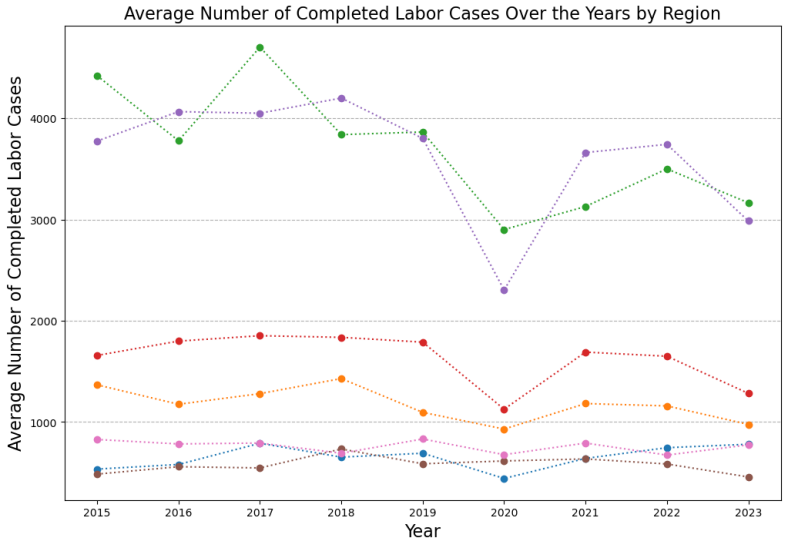

Figure 4.9: Average number of completed labor cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Finally, Figure 4.10 shows the trends for tutelar CC. The data reveals a steady decline in tutelar CC across all regions, with *Área Metropolitana de Lisboa* starting from a high base but reducing significantly over time. This decline indicates potential improvements in protective measures for minors and a more efficient judicial process in handling tutelar cases. Other regions also show consistent decreases, reflecting broader national trends in child protection and family law proceedings.

The data across Figure 4.11 collectively indicates an overall trend towards fewer CC in various categories from 2015 to 2023. This trend is particularly pronounced in the *Área Metropolitana de Lisboa*, which consistently reports higher case numbers but also shows significant declines. The shape of the lines in the graph encompassing all CC mirrors or closely resembles the shape of the civil CC, emphasizing that the number of civil CC is significantly higher than other types of cases.

While variations among other regions highlight differences in caseloads and judicial handling efficiency, further analysis would help achieve a stronger correlation between these trends and specific regional policies, economic conditions, and legal reforms, offering deeper insight into the underlying causes of these changes.

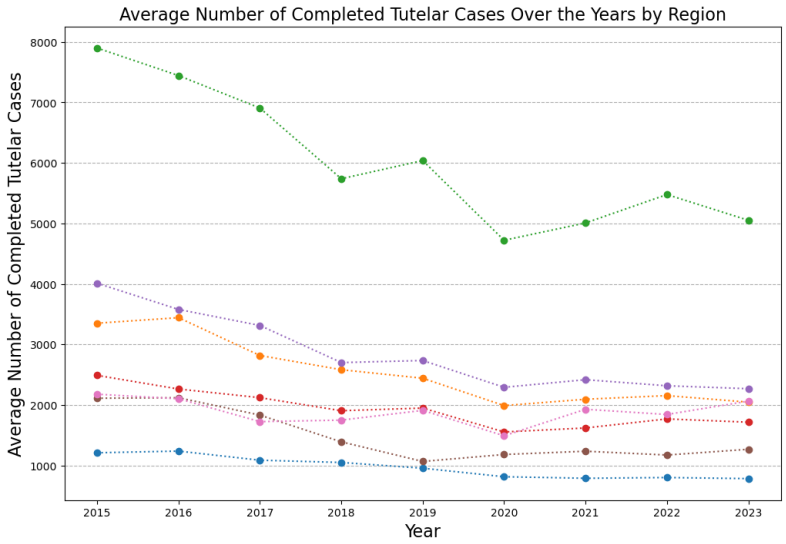

Figure 4.10: Average number of completed tutelar cases over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

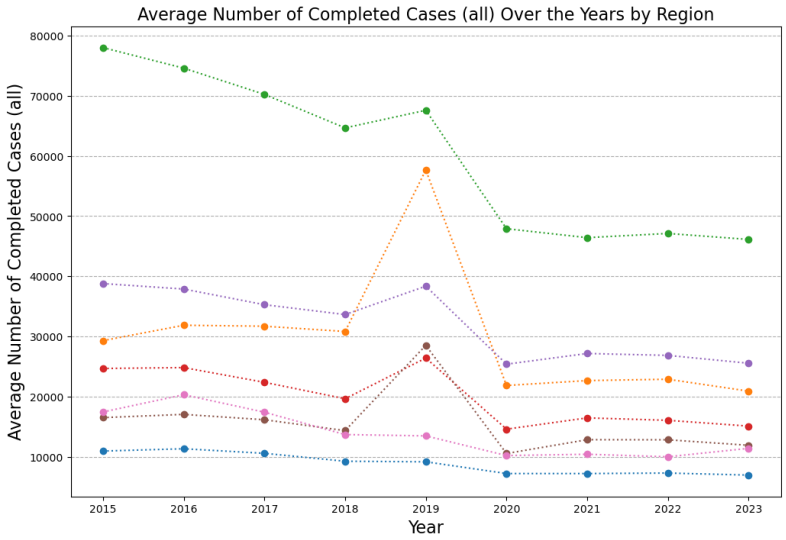

Figure 4.11: Average number of completed cases (all) over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.12 illustrates the trend in the average caseload across different regions from 2015 to 2023. The data reveals a general decline in caseloads over the period, particularly in the *Área Metropolitana de Lisboa*, which shows the highest initial caseload of over 200,000 in 2015, decreasing steadily to around 125,000 by 2023. This reduction may indicate improvements in case processing efficiency and administrative measures to manage and reduce the backlog. Other regions, such as *Algarve* and *Norte*, also show a decline in caseloads, albeit at lower levels compared to *Área Metropolitana de Lisboa*. The steady decrease suggests similar efforts to enhance judicial efficiency and manage caseloads effectively across these regions. Smaller regions, such as *Alentejo*, *Região Autónoma dos Açores* and *Região Autónoma da Madeira*, maintain relatively stable but lower average caseloads throughout the period,

reflecting their smaller populations and judicial demands.

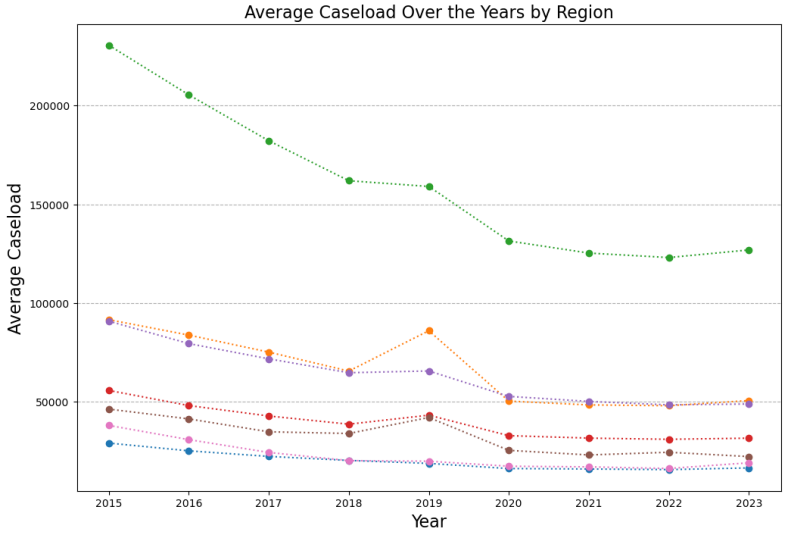

Figure 4.12: Average caseload over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.13 shows the trend in the average caseload per judge from 2015 to 2023. This figure provides insight into the workload and efficiency of the judicial system in different regions. The data indicates a general decline in the caseload per judge over the period, with the highest values observed in the *Área Metropolitana de Lisboa*, which started with over 1,800 cases per judge in 2015 and reduced to about 1,200 by 2023. Other regions, such as *Região Autonóma da Madeira* and *Algarve*, show similar declining trends, with caseloads per judge decreasing from around 1,200 in 2015 to approximately 800 by 2023. These trends indicate effective measures to balance the caseload among judges and enhance judicial performance. Smaller regions, such as the *Região Autónoma dos Açores*, exhibit lower average caseloads per judge, maintaining figures between 600 and 1,000 cases per judge, reflecting their smaller judicial demands.

General Trends

- 2015-2016: The highest average caseloads and caseloads per judge are observed during these years, particularly in the *Área Metropolitana de Lisboa*. This period highlights the initial challenges faced by the judicial system in managing large volumes of cases.
- 2017-2018: A noticeable decline in average caseloads and caseloads per judge across most regions.
- 2019:An increase in average caseloads per judge among almost regions.
- 2020: A sharp decline in both metrics, likely due to the COVID-19 pandemic, which disrupted court operations and led to reduced case filings and completions.
- 2021-2023: A stabilization in average caseloads and caseloads per judge, with slight increases observed in some regions, reflecting a return to normalcy post-pandemic and the ongoing efforts

to manage judicial workloads effectively.

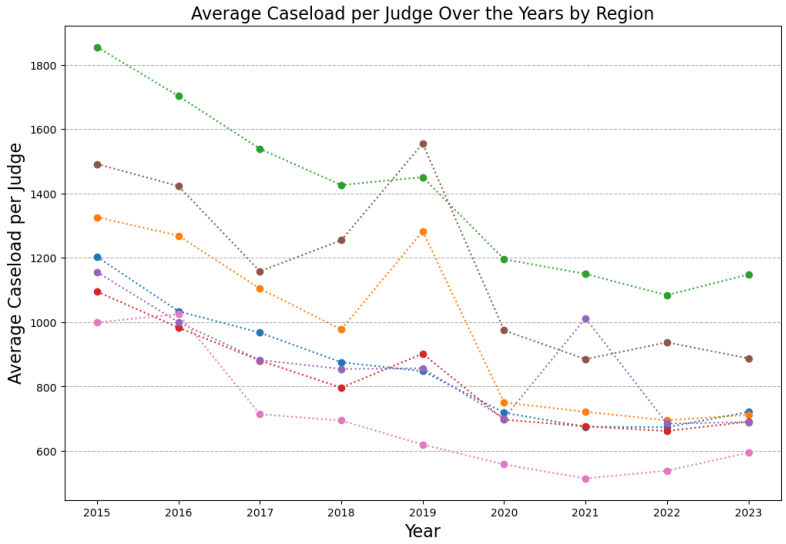

Figure 4.13: Average caseload per judge over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

4.2.3 Context Variables

Figure 4.14 illustrates the trend in the average number of lawyers across different regions from 2015 to 2023. The data reveals a consistent increase in the number of lawyers in all regions. *Área Metropolitana de Lisboa* has the highest number of lawyers, growing from approximately 4,500 in 2015 to over 5,500 by 2023. This growth indicates an increasing demand for legal services in the *Área Metropolitana de Lisboa*, likely due to higher population density and more complex legal needs. *Norte* and *Algarve* regions also show a steady increase in the number of lawyers, albeit at a slower rate compared to Lisbon. These regions see growth from around 1,000 to 2,000 lawyers over the same period, followed by *Centro* region. This trend suggests a broadening of legal services across these regions, reflecting economic and demographic changes. Smaller regions, such as the *Alentejo*, *Região Autónoma dos Açores* and *Região Autónoma da Madeira*, maintain a relatively stable but lower number of lawyers, consistent with their smaller populations and judicial demands.

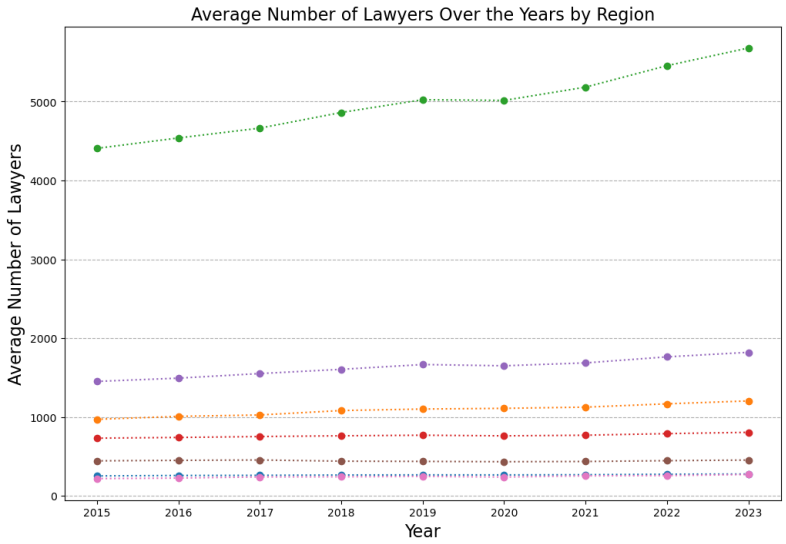

Figure 4.14: Average number of lawyers over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.15 presents the average number of solicitors from 2015 to 2023. The data shows a more stable trend compared to the number of lawyers, with gradual increases observed in most regions. *Área Metropolitana de Lisboa* again leads, maintaining above 300 solicitors throughout the period with a slight increase towards 2022. *Norte* and *Algarve* regions display a consistent number of solicitors, around 150 and 250, followed by *Centro* region. These trends reflect a steady demand for solicitors' services in these regions, aligning with their economic activities and legal needs. Other regions such as *Alentejo*, *Região Autónoma dos Açores* and *Região Autónoma da Madeira* show smaller but steady numbers of solicitors, indicating localized demand and supply dynamics.

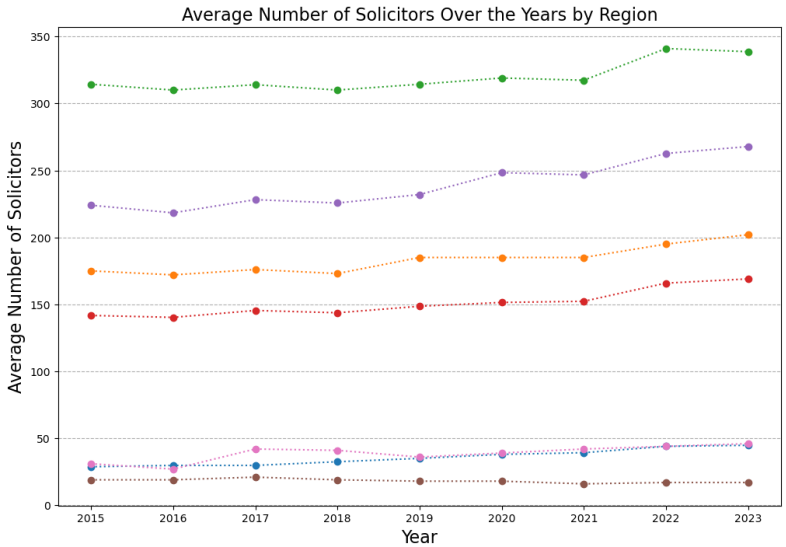

Figure 4.15: Average number of solicitors over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

Figure 4.16 depicts the trend in the average number of enforcement agents from 2015 to 2023. The data reveals fluctuations, especially notable in the *Centro*, which experienced a peak in 2016 but then declined and stabilized. *Área Metropolitana de Lisboa* shows the highest number of enforcement agents, peaking in 2019 and stabilizing between 100 and 120 enforcement agents. *Norte* region displays a consistent number of enforcement agents, with slight decreases observed over the years. Other regions such as *Algarve*, *Região Autónoma dos Açores*, and *Região Autónoma da Madeira* maintain lower numbers, reflecting their smaller scale of enforcement activities.

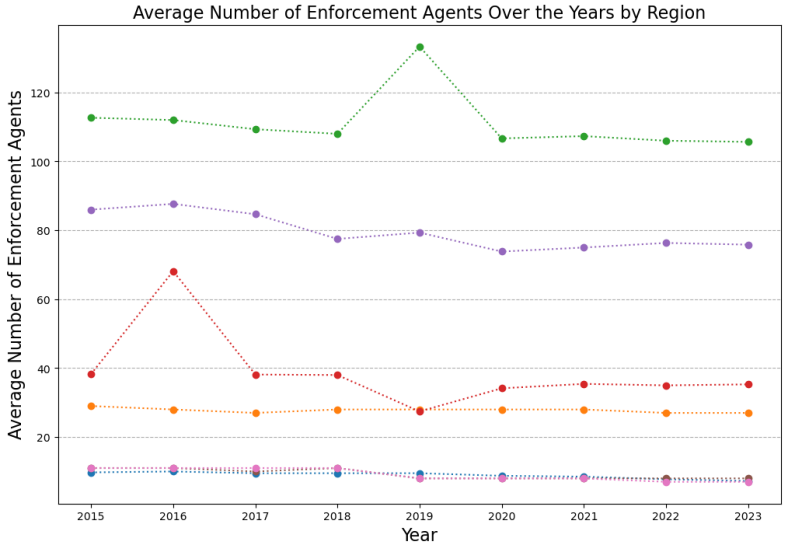

Figure 4.16: Average number of enforcement agents over time by Region(s) NUTS II. Purple: *Norte*, red: *Centro*, green: *Área Metropolitana de Lisboa*, blue: *Alentejo*, orange: *Algarve*, pink: *Região Autónoma dos Açores*, brown: *Região Autónoma da Madeira*.

The data across Figures 4.14, 4.15 and 4.16 highlights varying trends in the number of legal professionals across different regions from 2015 to 2023. The *Área Metropolitana de Lisboa* consistently leads in numbers for all categories, reflecting its central role in legal and judicial activities. Other regions show steady trends with some fluctuations, indicating localized demands and adjustments in legal services. These insights are crucial for understanding the distribution and dynamics of legal professionals across regions, which impacts the accessibility and efficiency of legal services and judicial processes.

4.2.4 Disposition Time and Clearance Rate

These additional metrics are crucial for a comprehensive analysis as they provide context to the efficiency measurements derived from the DEA model. DT provides insights into the speed and timeliness of case processing, while the CR offers a perspective on the system's effectiveness in keeping up with incoming cases. They are calculated through Equations 4.1 and 4.2. Instead of being organized by Regions NUTS II, as the previous variables, they are displayed by FIC instead.

$$\text{Disposition Time (DT)} = \frac{\text{Number of Pending Cases}}{\text{Number of Completed Cases}} \times 365 \tag{4.1}$$

$$\text{Clearance Rate (\% CR)} = \frac{\text{Number of Completed Cases}}{\text{Number of Incoming Cases}} \times 100 \tag{4.2}$$

The first heatmap, on Figure 4.17, provides insights into the DT across different jurisdictions including all types of cases, offering a visual representation that highlights variances in case processing duration. The colors range from blue to red, representing shorter to longer DT, respectively. Short DT indicate a more efficient FIC that resolves cases swiftly. Conversely, longer DT might suggest inefficiencies, potential backlogs, and prolonged legal uncertainty for the parties involved. Therefore, this metric is crucial for evaluating the effectiveness and responsiveness of the civil justice system.

The courts in *Área Metropolitana de Lisboa* consistently show high DTs suggesting that cases in this region take a longer time to resolve. Throughout the observed period, *Lisboa*'s DTs remain on the higher end of the spectrum, which might point to persistent backlogs or systemic inefficiencies within the civil justice system there. The highest DT was registered in *Lisboa* on 2020. Looking at *Centro* region, *Santarém*, the DR exhibited a gradual improvement from 2015 to 2019, starting at 658 days and decreasing to 409 days. This positive trend showed early efforts towards a more efficient judicial process. Yet, 2020 marked an anomalous year for *Santarém* as the DT surged to 713 days, representing a substantial increase that likely reflects external disruptions, potentially from the COVID-19 pandemic, which impacted various sectors globally. Following this peak, the region made a notable recovery in 2021, with the DT reducing to 425 days, and maintained relative stability in 2022 with a DT of 483 days.

Although not the lowest DT in 2023, *Porto Este* FIC in *Norte* region shows consistent improvement over the years, reaching a DT of 279 in 2023, which is moderately efficient compared to other regions.

Also in *Algarve* region, DT trend in *Faro* from 2015 to 2022 paints a picture of significant changes and adaptation within the judicial system. Beginning at an 801 day peak in 2015, *Faro*'s DT displayed a consistent year-over-year decrease, reflecting concerted efforts to enhance judicial efficiency. By 2016, the DT had been reduced to 665 days, and the downward trajectory continued through 2017 and 2018, reaching 584 and 506 days, respectively. The most dramatic improvement appeared in 2019, with the DT plummeting to 225 days, which suggests a period of optimal judicial performance and management. However, this positive trend faced a setback in 2020, with DT rising to 534 days—a possible consequence of the global challenges imposed by the COVID-19 pandemic, which had widespread impacts on many institutional processes. In response, 2021 saw a reduction in DT to 464 days, indicating resilience and a commitment to reclaiming the efficiency gains made prior to 2020. This rebound continued into 2022, with the DT being further reduced to 430 days, still higher than the 2019 low but well below the starting point in 2015.

In 2019, courts across Portugal generally showed strong performance in terms of DT, meaning they were able to resolve cases efficiently. However, in the following year, there was a noticeable increase in DT across all courts. This significant shift raises the question of whether the COVID-19 pandemic played a role in this change. The pandemic likely disrupted court operations, causing delays due to lockdowns, limited in-person hearings, and adjustments to remote work, all of which could have contributed to the longer times required to resolve cases in the years that followed.

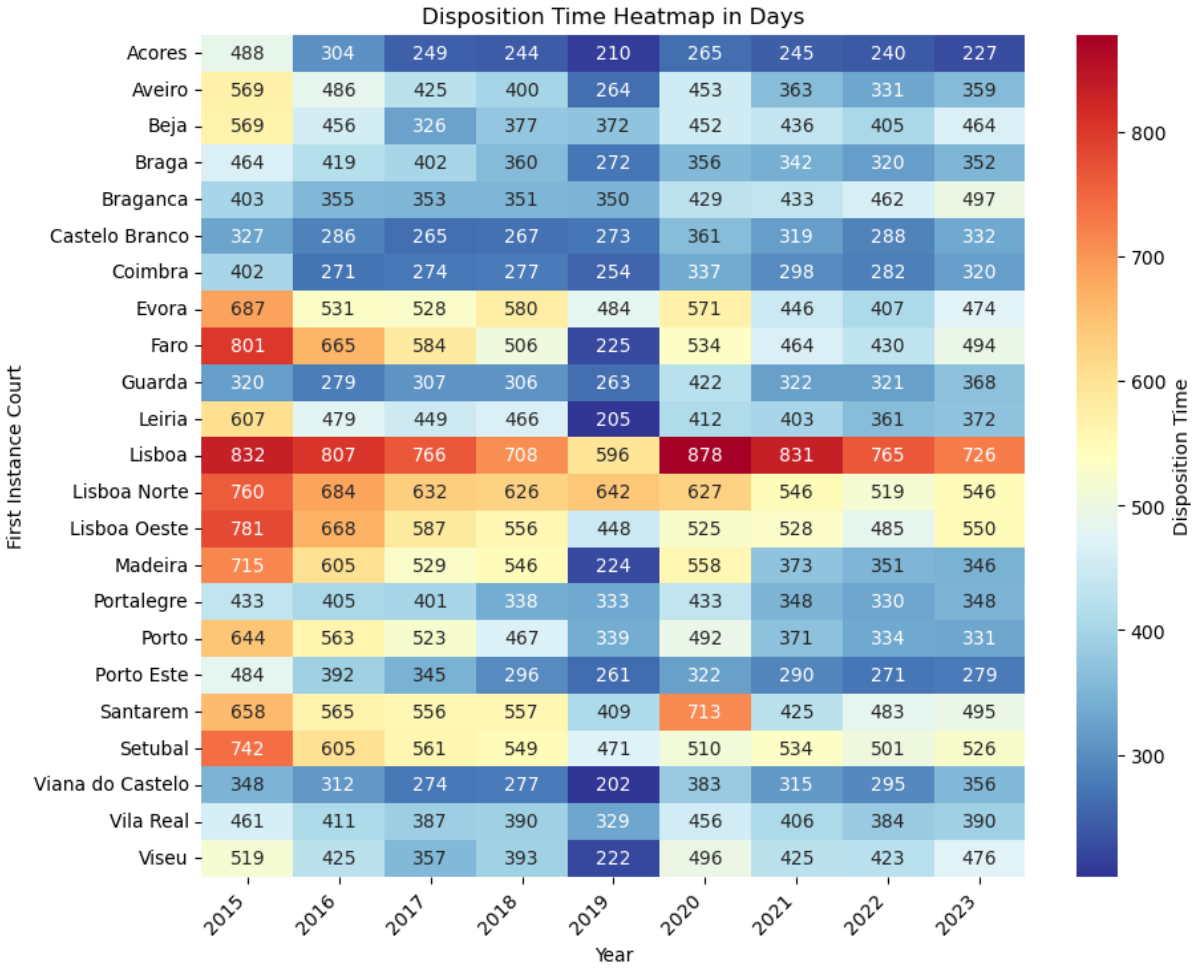

Figure 4.17: Heatmap of the disposition time for all First Instance Courts between 2015 and 2023. Blue: shorter disposition times, red: longer disposition times.

Concurrently, the second heatmap, on Figure 4.18, illustrates the CR, emphasizing the efficiency of courts in balancing incoming and resolved cases within the same timeframe. Expressed as a percentage, a CR of 100% indicates that the court is keeping up with its incoming caseload, resolving as many cases as it receives. A CR above 100% signifies that the court is reducing its backlog of cases, while a rate below 100% suggests an accumulating backlog, potentially leading to increased wait times and decreased access to justice. These visual tools are instrumental in identifying performance disparities and efficiency bottlenecks, enabling a comprehensive understanding of operational dynamics across the judiciary landscape. The comparative analysis aims to spotlight systemic strengths and challenges, contributing to the discourse on judicial reform and efficiency optimization.

Most FICs show a fluctuation in CR over the years, with some years being more efficient than others. FICs like *Açores* and *Coimbra* in certain years (e.g., *Açores* in 2016 with a CR of 146.59% and *Coimbra* in 2016 with a CR of 149.80%) show exceptionally high CR, suggesting that these regions were able to resolve a significant number of cases more than the incoming ones. Some FICs exhibit significant drops in CR at certain points, such as *Guarda*, dropping to 92.28% in 2020, indicating a challenging year where the number of resolved cases might not have kept pace with new or pending cases. By

2022, most regions seem to be maintaining a CR close to or above 100%, with the notable exception of *Bragança*, which shows a CR of 97.63%, suggesting potential issues in resolving cases efficiently. However, in 2023, almost all FICs showed a CR below 100%, indicating that they were unable to resolve as many cases as were filed. This means that the courts are accumulating a backlog of unresolved cases. Several factors could contribute to this, such as an increasing caseload, limited resources, or inefficiencies in the judicial process. The lingering effects of the COVID-19 pandemic may also still be impacting court operations, slowing down the processing of cases and affecting overall productivity.

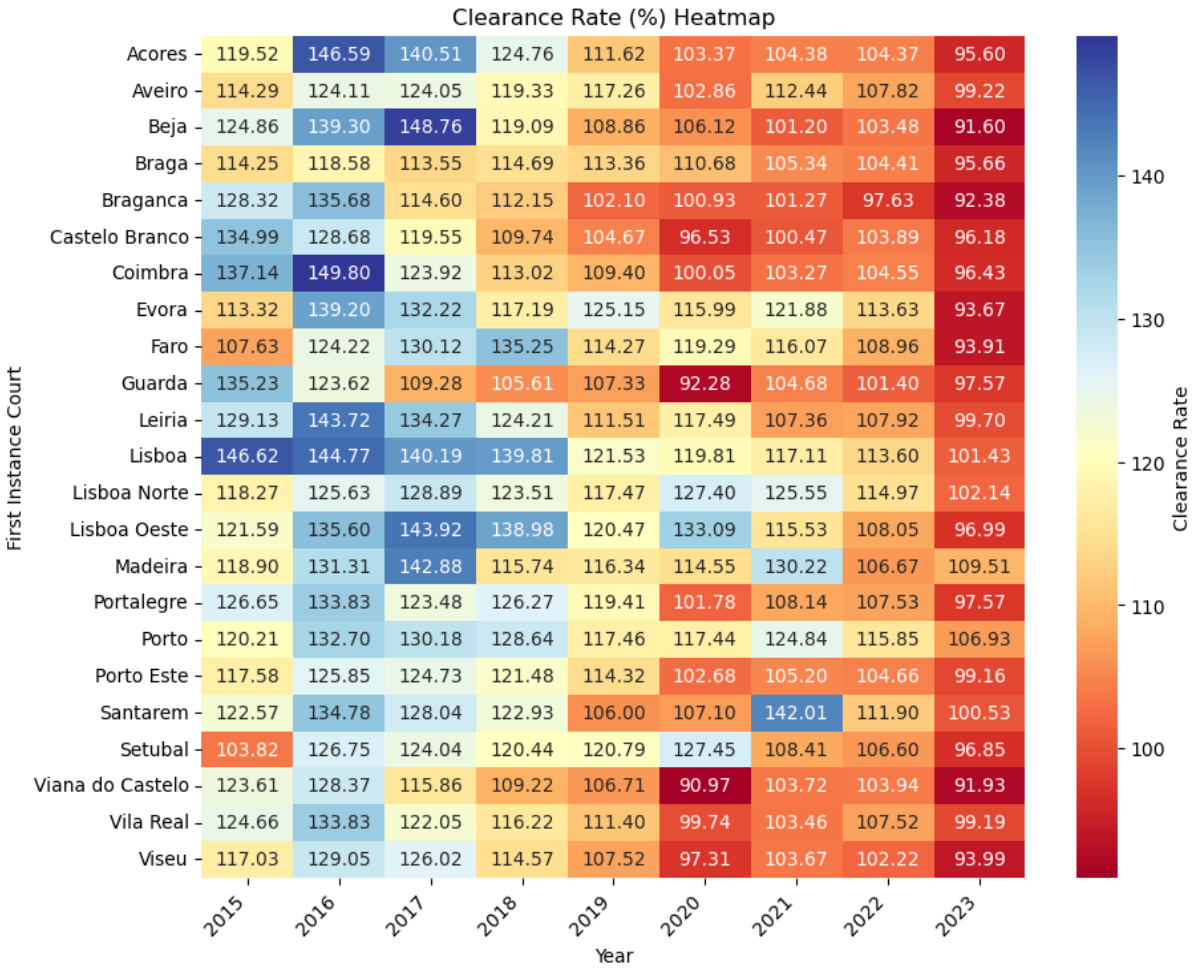

Figure 4.18: Heatmap of the clearance rate for all First Instance Courts between 2015 and 2023. Blue: higher clearance rates, red: lower clearance rates.

Civil cases are particularly interesting due to their prevalence in the judicial system. Given their significant volume, understanding exclusively civil cases is crucial. Therefore, it is important to delve deeper into civil cases by analyzing their DT (Figure 4.19) and CR (Figure 4.20). This analysis will provide insights into the efficiency and effectiveness of the judicial system in handling civil cases, offering a comprehensive understanding of how quickly these cases are resolved and the proportion of cases that are concluded relative to the number of incoming cases.

There is a noticeable improvement in DT across many courts over the years, with a general trend towards shorter times, except for the courts of *Área Metropolitana de Lisboa*, which includes the courts

: *Lisboa*, *Lisboa Norte* and *Lisboa Oeste*. In *Algarve*, *Faro* saw a dramatic reduction from 1,108 days in 2015 to 616 days in 2023. However, some courts, such as *Évora* and *Madeira*, displayed significant fluctuations in DT. *Évora*'s DT decreased from 901 days in 2015 to 618 days in 2023, but experienced a peak of 739 days in 2018. *Madeira* improved from 891 days in 2015 to 426 days in 2023, showing a substantial reduction. Consistently, some courts maintained shorter DT throughout the years. For instance, *Castelo Branco*'s times ranged from 393 days in 2015 to 439 days in 2023.

It is possible to observe a similar pattern in the DT of all cases when looking specifically at civil cases. In particular, *Área Metropolitana de Lisboa* presents a concerning situation. DT in these regions is significantly higher when compared to other regions, indicating that courts are taking much longer to resolve civil cases. This disparity suggests that the courts in the *Lisboa* area are facing unique challenges, which may be due to higher caseloads or resource constraints, contributing to these elevated DT.

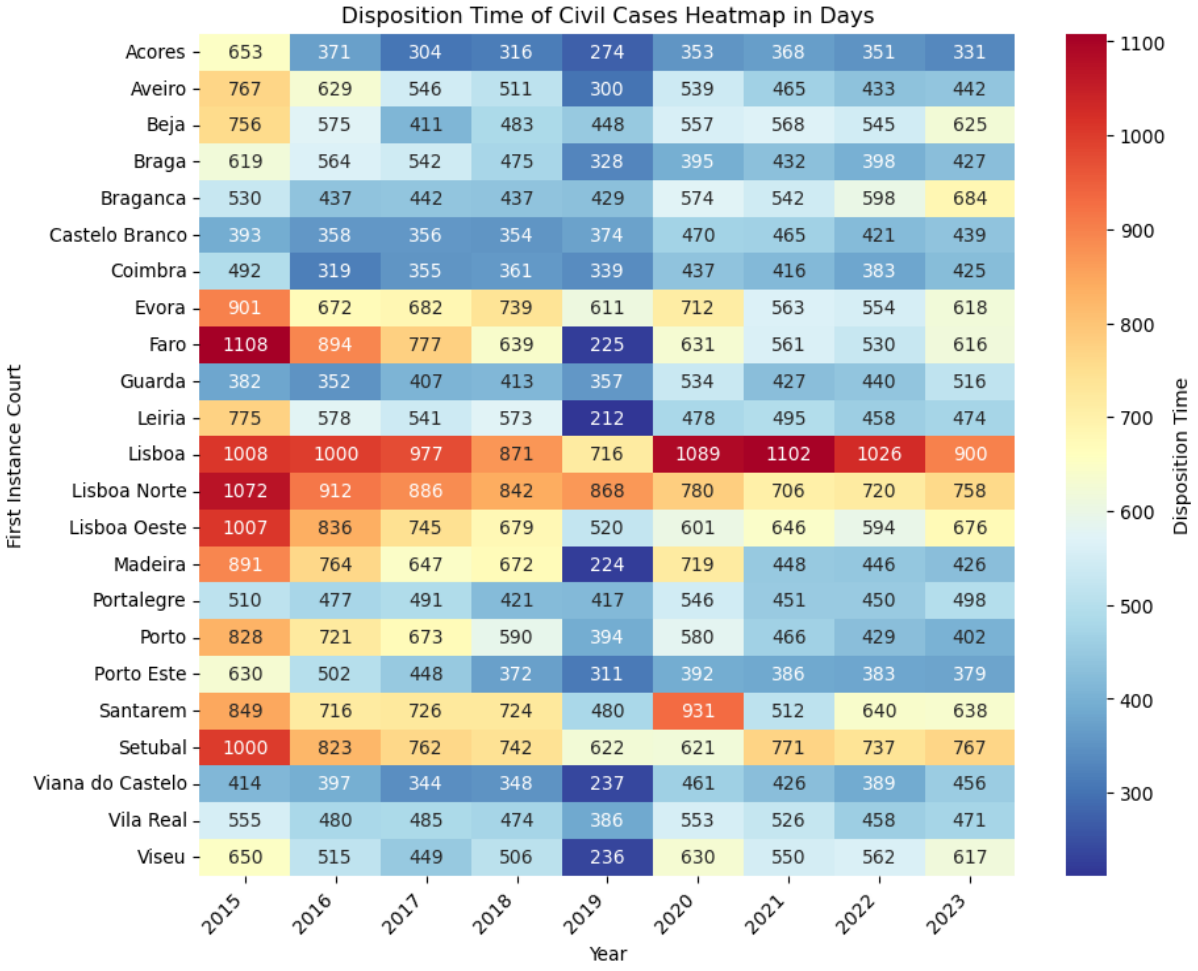

Figure 4.19: Heatmap of the disposition time from civil cases for all First Instance Courts between 2015 and 2023. Blue: shorter disposition times, red: longer disposition times.

Many courts experienced fluctuations in their CR over the years, with no clear uniform trend of improvement or decline. Courts such as *Lisboa*,*Lisboa Norte* and *Lisboa Oeste* consistently showed high CR, indicating their ability to effectively handle their caseload. As previously seen, *Lisboa* shows

a higher DT but also has a CR above 100%, indicating an interesting dynamic. A CR above 100% means that the courts are resolving more cases than are being filed, which suggests they are effectively working through their caseload and possibly reducing backlogs. However, the higher DT suggests that even though they are resolving a large number of cases, it still takes a long time to do so. This could imply that the courts in Lisbon are managing to close older cases that have been pending for a while, thus improving the CR, but the overall speed of resolving cases is still slow. This situation could be due to a high volume of complex or older cases that take longer to process, despite the courts' efficiency in handling new filings.

The CR for civil cases was significantly higher at the beginning of the years analyzed, indicating that courts were resolving more cases than were being filed. However, in recent years, this CR has declined and is no longer as high when compared to previous years. This shift may suggest an increase in the complexity of cases, greater pressure on the courts, or a reduced capacity to handle the caseload, making it harder for courts to maintain the same level of case resolution as observed in earlier years.

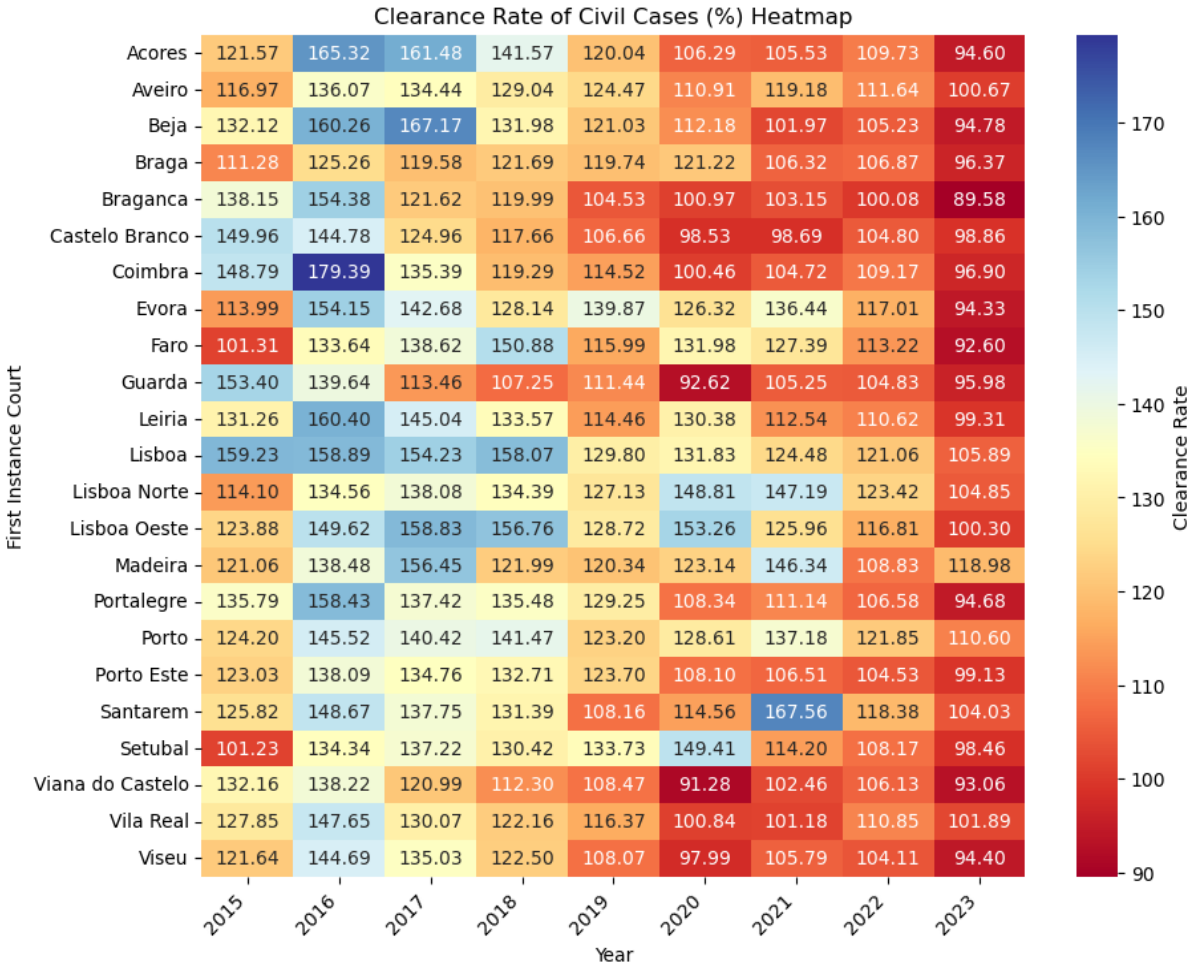

Figure 4.20: Heatmap of the clearance rate from civil cases for all First Instance Courts between 2015 and 2023. Blue: higher clearance rates, red: lower clearance rates.

Chapter 5

Results and Discussion

Chapter 5 presents the results of the efficiency and productivity analysis conducted on Portuguese judicial First Instance Courts. The chapter is organized into three sections. Section 5.1 discusses the findings from the Output-Oriented Variable Returns to Scale DEA model, highlighting the efficiency scores and evaluates them using Kruskal-Wallis test to verify if there are statistically significant differences between the medians of three or more independent groups. Section 5.2 introduces Meta Malmquist Index results, providing an analysis of efficiency changes and technology changes over time and comparative insights into performance across the periods studied. Finally, Section 5.3 addresses the implications of these results, offering recommendations for improving judicial efficiency based on the analysis and its outcomes.

5.1 Output-Oriented Variable Returns to Scale Data Envelopment Analysis Model

As previously mentioned, the development of two output-oriented VRS models is planned to evaluate the efficiency of each FIC, treated as DMUs. As the models are output-oriented, the focus is on maximizing outputs while keeping inputs constant. As they assume VRS, they account for the fact that courts might not be operating at optimal scale, meaning their efficiency can vary depending on their size and resource use, helping identifying how much each court can potentially increase its CC without requiring additional inputs.

Before going into a more detailed analysis, it is vital to comprehend the interpretation of technical efficiency scores as provided by DEA. A technical efficiency score of 1 is indicative of a region being at the forefront of best practices, demonstrating an effective maximization of outputs from its inputs. Otherwise, scores above 1 suggests that a region possesses considerable scope for enhancement. The deviation from the score of 1 quantifies the possible increase in outputs that could be achieved without requiring additional resources. For example, a score of 1.2 suggests a potential to increase outputs by 20% with the same input level. These scores involve evaluating the proximity of each region to optimal performance and identifying areas where strategic interventions could significantly raise their efficiency

to the level of the most exemplary regions.

Figure 5.1 illustrates the technical efficiency scores of FICs in Portugal over the period from 2015 to 2023, based on a specific efficiency model 1, while Figure 5.2 shows the results for model 2.

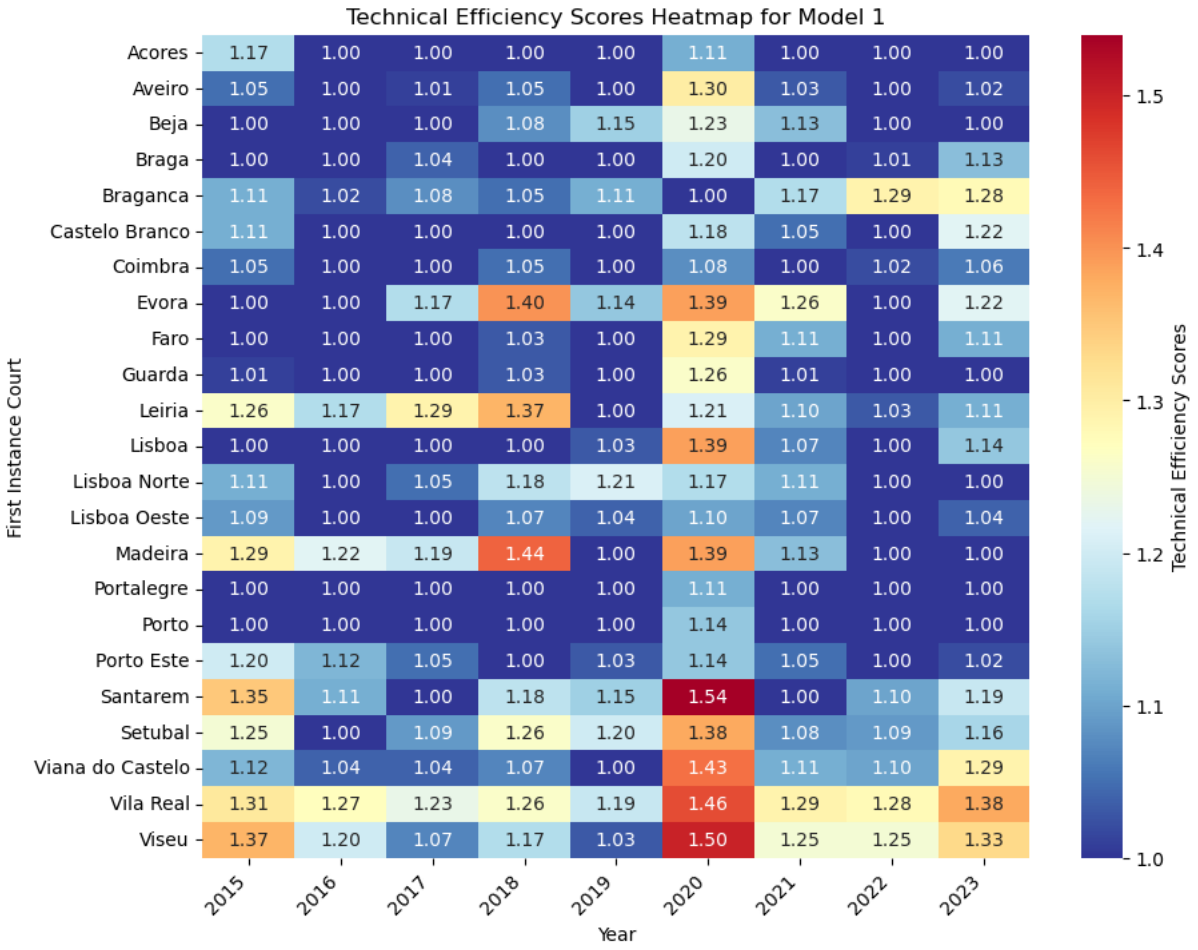

Figure 5.1: Technical efficiency scores for model 1 from 2015 to 2023. Values closer to red indicate higher technical efficiency scores, signifying poorer technical efficiency. Courts in these ranges have greater room for improvement in their efficiency. In contrast, values closer to blue suggest lower technical efficiency scores, representing better technical efficiency. Courts with these scores are more efficient.

Each cell represents a score reflecting the technical efficiency of a court for a given year, with a higher score indicating room for improvement. The color gradient represents the efficiency scores: blue for relatively efficient courts, transitioning to red for relatively inefficient courts. Across the heatmap, technical efficiency scores generally fluctuate year by year for each region. However, some regions show consistent efficiency over time, while others fluctuate significantly. Our technical efficiency scores range from 1.00 to 1.54.

By analysing the big picture of model 1, it is possible to make the following observations. After the 2014 reform of the FICs, technical efficiency scores exhibited relatively minor fluctuations, indicating a period of general stability and efficiency. However, the scores above 1 across all courts pointed to ongoing inefficiencies. Across all regions, the pandemic's impact is evident, with a marked increase in efficiency scores during the 2020-2021 period. On 2020, there was only one court, *Bragança*, which was able to reach full efficiency. This timeframe consistently shows the highest inefficiency levels, un-

derscoring the disruptive effect of COVID-19 on the judicial system. Despite these challenges, there is a general trend of improvement in scores after 2021, with many regions moving closer to scores of 1.0. This suggests a recovery phase, where courts have been adapting to new processes or technologies to enhance productivity. In 2022 and 2023, the technical efficiency scores show a continued improvement trend for many courts, although some still face challenges. Courts such as *Portalegre* and *Porto* managed to return to full efficiency, demonstrating resilience and effective adaptation post-pandemic. Other courts, like *Viana do Castelo*, *Vila Real* and *Viseu*, while showing some improvement, still have higher efficiency scores indicating areas that need further attention. This suggests that while there has been significant progress in recovering from the disruptions caused by COVID-19, ongoing efforts are required to achieve and maintain full efficiency across all courts. Moving forward, the analysis will focus on identifying patterns of judicial efficiency across regions.

Área Metropolitana de Lisboa **Region**

The *Área Metropolitana de Lisboa*, encompassing the courts of *Lisboa*, *Lisboa Norte*, and *Lisboa Oeste*, exhibits a pattern of persistent inefficiencies as reflected by efficiency scores that frequently exceed 1.0. This trend is particularly evident in the years 2019 and 2020, where *Lisboa* displayed an efficiency score of approximately 1.18, while *Lisboa Norte* and *Lisboa Oeste* reached 1.21 and 1.23, respectively. These elevated scores highlight underlying challenges despite the region's significant resources and ability to handle high caseloads.

The data suggests that, in this region, consistent efficiency has been difficult to achieve, with variations observed year by year. For instance, *Lisboa Norte* showed some improvement in 2021, dropping to a score of 1.14, but remained above the ideal threshold, indicating lingering inefficiencies. Similarly, *Lisboa* experienced slight fluctuation, with scores oscillating around 1.15 over multiple years. Such trends emphasize an ongoing need for productivity improvements and resource optimization, particularly given the high demands placed on these courts.

In 2020, the overall efficiency scores in *Lisboa Oeste* peaked at 1.26, reflecting substantial challenges likely exacerbated by the COVID-19 pandemic. This value represents one of the highest levels of inefficiency recorded in the *Área Metropolitana de Lisboa*, suggesting that the pandemic may have significantly impacted operational stability. This pattern persisted, though to a lesser degree, into 2021, as scores began to decline but still remained above 1.0.

The fluctuations in these efficiency scores not only underscore the difficulties in achieving consistent performance but also reflect a broader need for systematic resource management within the region. Despite significant investments and the presence of modernization initiatives, the courts in *Lisboa*, *Lisboa Norte*, and *Lisboa Oeste* face persistent challenges. Addressing these issues would require targeted interventions, such as enhancing technological infrastructure, optimizing case processing workflows, and reallocating resources based on specific demands. By focusing on these areas, it may be possible to promote greater consistency in efficiency scores and ultimately improve productivity in the *Área Metropolitana de Lisboa*.

***Norte* Region**

In terms of overall efficiency from 2015 to 2023, the courts in the *Norte region* can be order in terms of performance, with *Porto* leading in terms of consistent efficiency, followed by *Braga*, *Porto Este*, *Bragança*, *Viana do Castelo* and finally *Vila Real*. This ranking reflects a gradient in efficiency, with Porto displaying the most stable and optimal scores, while other courts show varying degrees of inefficiency and fluctuation over the years. *Vila Real* was the only court of *Norte* region which never reached a efficiency score of 1.00 in any of the years.

Porto maintained full efficiency with scores of 1.00 consistently from 2015 to 2019, suggesting highly effective resource management and case handling practices. This stability underscores Porto as the benchmark for efficiency within the region.

Braga generally performed well, with efficiency scores close to 1.00 across most years. However, slight inefficiencies began to emerge, culminating in a score of 1.20 in 2020 and of 1.13 in 2023. This indicates occasional challenges, though *Braga* remained relatively efficient overall.

Porto Este showed minor fluctuations with scores ranging from 1.00 to 1.20. These scores indicate a relatively stable performance, albeit with occasional inefficiencies, particularly during the pandemic. *Bragança* exhibited more pronounced fluctuations, with scores peaking at 1.29 in 2022. Despite showing values closer to full efficiency in earlier years, this pattern suggests periods of instability and room for improvement.

Viana do Castelo displayed significant inefficiencies, particularly in 2020, where the score reached 1.43. While there was some recovery, scores remained above 1.10, indicating persistent operational challenges.

Vila Real consistently showed inefficiencies, with scores rising to 1.26 in 2018 and reaching 1.38 in 2023, with a peak of 1.46 in 2020. This places *Vila Real* as one of the courts facing the greatest efficiency challenges within the*Norte* region and overall Portugal country, with significant scope for operational improvements.

***Centro* Region**

The *Centro* region, which includes courts in *Aveiro*, *Castelo Branco*, *Coimbra*, *Guarda*, *Leiria*, *Santarém*, and *Viseu*, presents a varied landscape of efficiency across different courts from 2015 to 2023.

Aveiro generally maintained stable efficiency scores, with minor inefficiencies peaking at 1.30 in 2020. This stability suggests effective management practices, particularly as *Aveiro* quickly returned to near-optimal scores in subsequent years, reaching 1.02 in 2023. The court's overall performance indicates adaptability and a strong capacity to manage caseloads effectively.

The efficiency scores for *Castelo Branco* remained fairly stable, though the court experienced minor fluctuations, reaching 1.18 in 2021 and 1.22 in 2023. These scores indicate occasional inefficiencies but suggest a general capacity to maintain performance. However, the recent upward trend suggests a need to monitor resource utilization and address emerging inefficiencies.

Coimbra displayed a strong and stable efficiency profile, with minor inefficiencies surfacing primarily in 2020 (1.08) and 2023 (1.06). These minor deviations suggest resilience, as *Coimbra* was able to

maintain efficiency close to 1.0 for most years. This performance reflects effective resource management and adaptability, especially in recovering quickly from pandemic-related disruptions.

Guarda has consistently operated close to full efficiency, with scores mostly around 1.00. Minor inefficiencies are noted in 2020, with scores of 1.26. Overall, the court has demonstrated a high level of stability and efficiency, showing limited vulnerability to external disruptions. Although the atypical year, *Guarda* reflects successful management strategies that ensure optimal use of resources.

Leiria showed considerable fluctuations in the begining of the period of analysis, with scores reaching 1.37 in 2018 and maintaining higher levels (above 1.0) in several years. The 2023 score of 1.11 indicates some improvement, but the persistent inefficiencies suggest underlying challenges in managing resources and maintaining consistent efficiency.

Santarém exhibited substantial inefficiencies, with a peak score of 1.54 in 2020, the highest in the *Centro* region and all Portugal courts. Although there has been gradual improvement, the court's scores remained above 1.10 in 2022 and 2023, indicating persistent challenges in resource management and operational stability. *Santarém* would benefit from enhanced support and process improvements to address these efficiency issues effectively.

Viseu, although geographically part of the *Centro* region, faced persistent inefficiencies similar to some courts in the *Norte* region. The court reached a score of 1.50 in 2020 and has remained above 1.20 on the following years, reflecting significant operational challenges. *Viseu* consistently demonstrates a need for substantial intervention to address resource allocation and improve efficiency.

Overall, the *Centro* region shows a mixed pattern of efficiency, with *Aveiro* and *Coimbra* displaying resilience and adaptability, while *Leiria*, *Santarém*, and *Viseu* face persistent challenges. Targeted measures aimed at resource optimization and process improvements would benefit courts experiencing ongoing inefficiencies, such as *Santarém* and *Viseu*. Addressing these issues can help stabilize and enhance overall efficiency within the *Centro* region.

Algarve **Region**

In the *Algarve* region, which is represented by the *Faro* court, there is a notable trend of sustained efficiency, with scores consistently equal or close to 1.0 from 2015 to 2023. This indicates that Faro has been able to effectively manage its resources and caseloads, demonstrating a high level of operational stability.

Minor inefficiencies are observed in a few years, such as 2020 and 2021, where scores reached 1.29 and 1.11, respectively. These slight deviations likely reflect the broader impacts of the COVID-19 pandemic, which disrupted court operations across Portugal. Despite this, *Faro* quickly returned to full efficiency in subsequent years, with scores returning to 1.00 in 2022, but didn't remain stable after, reaching to a score of 1.11 in 2023.

The overall performance of the *Faro* court suggests that it has robust systems in place for handling its caseload and maintaining resource optimization. This consistency reflects well on the court's management practices, which have allowed it to avoid the more significant fluctuations and inefficiencies seen in other regions. The relative stability in Faro indicates a court system that is adaptable and resilient,

capable of maintaining near-optimal efficiency even during challenging periods.

***Alentejo* Region**

The *Alentejo* region, which includes the courts in *Évora*, *Portalegre*, *Setúbal*, and *Beja*, displays a varied efficiency profile, reflecting a mixture of stability and persistent challenges across different courts.

Évora shows significant inefficiencies, especially around 2019 and 2020, with efficiency scores peaking at 1.40 in 2018 and 1.39 in 2020. These elevated scores suggest that the court may have faced resource constraints or increased caseloads during the pandemic, which likely strained its ability to maintain efficient operations. Although there was some improvement post-2020, with efficiency on 1.22 in 2023, the court has not fully returned to optimal levels, indicating an ongoing need for resource support and process optimization to achieve consistent efficiency.

In contrast, *Portalegre* demonstrates remarkable stability, with efficiency scores at 1.00 across all years except for 2020, when the score rose slightly to 1.11. This one-time deviation may reflect temporary disruptions caused by the pandemic, but *Portalegre* quickly recovered, returning to full efficiency by 2021. The court's consistent performance suggests effective management and resource utilization, making it an outlier of stability within the *Alentejo* region.

Setúbal has experienced fluctuations in efficiency, with scores rising to 1.20 in 2019 and peaking at 1.38 in 2020, followed by an improvement in subsequent years, reaching 1.09 in 2022 and 1.16 in 2023. This pattern points to recurring challenges, possibly related to resource allocation and case management, which the court has struggled to address fully. While there have been efforts to stabilize, *Setúbal* continues to show room for improvement.

Similarly, *Beja* exhibits inefficiencies, particularly around 2019, when it reached a score of 1.15, and in 2020, with a score of 1.23. These values reflect a period of difficulty, likely impacted by pandemic-related pressures. However, *Beja* has shown gradual improvement, returning to a score of 1.00 by 2022, suggesting that it has started to recover. Yet, the occasional higher scores indicate the need for sustained focus on maintaining efficiency, particularly under fluctuating demands.

Overall, the *Alentejo* region presents a mixed efficiency profile. While *Portalegre* stands out for its stability and resilience, other courts like *Évora*, *Setúbal*, and *Beja* demonstrate fluctuating scores and persistent inefficiencies. To promote more consistent performance across the region, targeted process enhancements and resource allocation strategies will be crucial. This could help courts like *Évora* and *Setúbal* to better handle external pressures and sustain efficiency improvements over time.

Região Autónoma dos Açores

The *Açores* region demonstrates a generally stable efficiency profile, with scores consistently at 1.0 for most of the period from 2015 to 2023. This indicates that, overall, the court system in *Açores* has been effective at managing resources and maintaining operational stability.

There are two exceptions, with slight inefficiencies observed in 2015 and 2021, where scores rose to 1.17 and 1.11, respectively. The higher score in 2015 may suggest initial inefficiencies that were quickly addressed, as the region returned to full efficiency from 2016 onwards. The temporary increase to 1.11

in 2021 likely reflects the lingering effects of the COVID-19 pandemic, which disrupted operations across many regions.

Despite these brief deviations, *Açores* has shown resilience and a strong capacity to maintain efficiency over time. The quick return to a score of 1.0 in the years following each deviation highlights effective management practices and adaptability to changing circumstances. This consistent performance underscores the court system's ability to handle caseloads and utilize resources effectively, positioning Açores as a region with a solid foundation for operational efficiency.

Região Autónoma da Madeira

The *Madeira* region provides an encouraging example of improvement in judicial efficiency over time. Initially, *Madeira* exhibited significant inefficiencies, with scores above 1.0 from 2015 onwards. Starting with a score of 1.29 in 2015, the region experienced fluctuations, peaking at 1.44 in 2018, which likely reflected pandemic-related disruptions and challenges specific to its geographic location.

However, *Madeira* showed a notable recovery trajectory post-2020, with efficiency scores steadily improving. By 2022, the region achieved full efficiency, with a score of 1.0, demonstrating successful adaptation and resilience. This marked improvement suggests that *Madeira* effectively implemented strategies to optimize resource utilization, perhaps through digitalization efforts and enhanced management practices, which enabled the court system to overcome prior inefficiencies.

The *Madeira* region's performance highlights the potential for targeted reforms to yield significant results. By addressing inefficiencies through tailored interventions, Madeira has been able to stabilize its operations and achieve a more consistent level of efficiency, positioning itself as a model for other regions facing similar challenges. This positive trend reflects the benefits of sustained focus on process improvements and resource optimization, which have allowed Madeira to reach full efficiency and maintain it.

Overall, these observations highlight the dynamic nature of court efficiency and the impact of external factors like the COVID-19 pandemic. They also underscore the importance of continued reforms and modernization initiatives to ensure a responsive and efficient judicial system in Portugal.

Another aspect is the similarity of the technical efficiency scores between both models, despite the second model including additional context variables such as the number of lawyers, solicitors, and enforcement agents, several conclusions can be drawn:

- Minimal impact of context variables: The similarity in results suggests that the additional context variables (lawyers, solicitors, and enforcement agents) may have minimal impact on the overall efficiency and productivity measures. This indicates that these factors might not significantly influence the efficiency of the judicial system in this dataset.

- Robustness of the traditional model: The traditional model, which includes judges, justice officials, and caseload as inputs, appears to capture the primary factors affecting efficiency and productivity. The robustness of this model is reinforced by the fact that adding more variables does not significantly alter the results.

- Redundancy of additional variables: The context variables included in the second model could be redundant or correlated with the variables already present in the traditional model. For instance, the presence of more lawyers, solicitors, and enforcement agents might not independently contribute to the efficiency measures if their effects are already captured through the caseload and the number of judges and justice officials.
- Complexity without added value: Adding more variables increases the complexity of the model but does not necessarily provide additional explanatory power. In this case, the traditional model is simpler yet equally effective, indicating that simpler models can sometimes be as powerful as more complex ones.
- Possible data homogeneity: If the data across the regions or time periods are relatively homogeneous, the additional variables might not show significant variation to affect the results. This homogeneity can result in similar outcomes for both models.

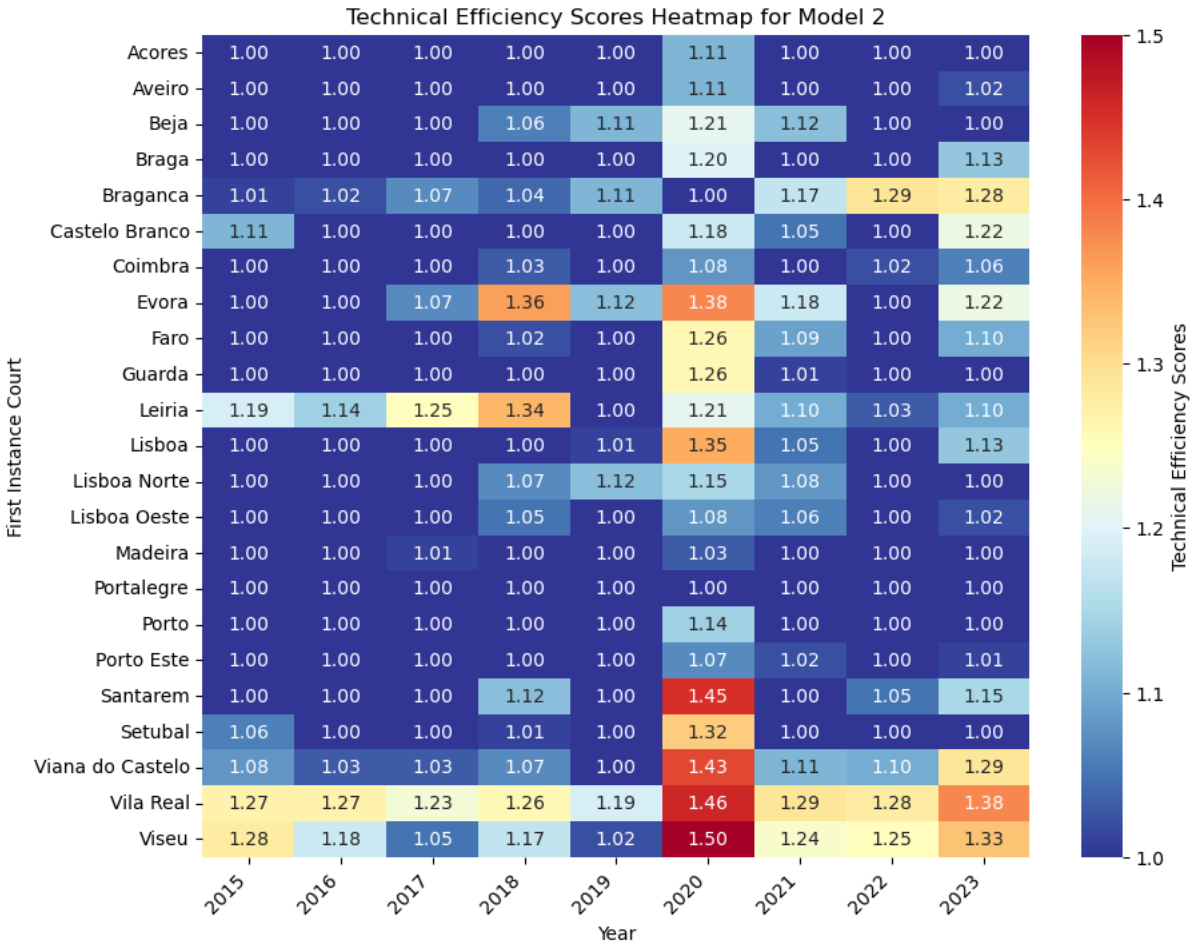

Figure 5.2: Technical efficiency scores for model 2 from 2015 to 2023. Values closer to red indicate higher technical efficiency scores, signifying poorer technical efficiency. Courts in these ranges have greater room for improvement in their efficiency. In contrast, values closer to blue suggest lower technical efficiency scores, representing better technical efficiency. Courts with these scores are more efficient.

Kruskal-Wallis Rank Sum Test

The evaluation of technical efficiency scores of FICs across different regions NUTS II in Portugal is a crucial aspect of understanding regional disparities and identifying areas for improvement in the judicial system. To conduct this evaluation, it was employed the Kruskal-Wallis test, a non-parametric statistical test that assesses whether there are statistically significant differences between the medians of three or more independent groups. This method is particularly suitable for our analysis due to its robustness against non-normal distributions and its ability to handle ordinal data effectively.

Before applying the Kruskal-Wallis Rank Sum Test, it is important to examine the differences in inputs and outputs across the NUTS II regions. In Table 5.1, it is possible to observe the distribution of FICs across the different regions classified under the NUTS II territorial units in Portugal. This table provides a clear breakdown of how the courts are allocated within each region, offering a view of the judicial infrastructure across the country. By examining the number of courts per region, one can gain insights into the geographical spread of judicial resources and how they correlate with regional populations and caseloads.

Table 5.1: Number of First Instance Courts per Region(s) NUTS II.

Region(s) NUTS II	**# First Instance Courts**	**First Instance Courts**
Alentejo	4	*Beja, Évora, Portalegre, Setúbal*
Algarve	1	*Faro*
Área Metropolitana de Lisboa	3	*Lisboa, Lisboa Norte, Lisboa Oeste*
Centro	6	*Aveiro, Castelo Branco, Coimbra, Guarda, Leiria, Santarém, Viseu*
Norte	7	*Braga, Bragança, Porto, Porto Este, Viana do Castelo, Vila Real*
Região Autonóma da Madeira	1	*Madeira*
Região Autonóma dos Açores	1	*Açores*

Table 5.2 presents the mean values of key input variables across the Region(s) NUTS II of Portugal for judicial FICs. These inputs include justice officials, judges, caseload, enforcement agents, lawyers, and solicitors, providing an overview of how resources are distributed across regions. The *Área Metropolitana de Lisboa* stands out, having the highest values across almost all inputs. The means of this region are 413.59 for justice officials, 114.93 for judges, and 160,641.33 for caseload. Additionally, it has the highest number of enforcement agents (111.22), lawyers (4,981.04), and solicitors (319.85), reflecting the region's higher judicial demand and population density. Other regions like *Algarve* and *Norte* also show relatively high inputs, with *Algarve* having a mean of 247 justice officials and 67.89 judges. However, despite *Algarve*'s smaller size, its mean caseload (66,559.22) and number of lawyers (1,088.22) are notable.

Regions like *Alentejo*, *Região Autónoma da Madeira*, and *Região Autónoma dos Açores* have lower means across most inputs, indicating fewer resources and likely smaller court systems. For instance, on *Alentejo* the mean of judges is 21.61, and the caseload is considerably smaller at 19,935.67.

Table 5.2: Mean of inputs per Region(s) NUTS II.

Region(s) NUTS II	μ **(Justice Officials)**	μ **(Judges)**	μ **(caseload)**	μ **(Enforcement Agents)**	μ **Lawyers**	μ **Solicitors**
Alentejo	79.03	21.61	19,935.67	8.94	265.17	35.75
Algarve	247.00	67.89	66,559.22	27.78	1,088.22	183.11
Area Metropolitana de Lisboa	413.59	114.93	160,641.33	111.22	4,981.04	319.85
Centro	190.14	44.52	39,449.48	38.87	764.48	150.92
Norte	271.70	64.52	63,578.09	79.57	1,631.56	239.30
Região Autonóma da Madeira	113.11	27.44	32,562.00	9.22	443.89	18.22
Região Autonóma dos Açores	132.33	32.11	22,498.44	9.11	243.89	38.67

Table 5.3 presents the mean values of outputs (i.e., completed cases) for civil cases, criminal cases, criminal labour cases, labour cases, and tutelar cases across the NUTS II regions of Portugal.

The *Área Metropolitana de Lisboa* once again stands out, with the highest mean of CC in almost every category. Courts in this region solve about 42,512.30 civil cases, 7,902.26 criminal cases, and 148.96 criminal labor cases, which are significantly higher compared to other regions. This region also handles the largest volume of labor cases (3,700.78) and tutelar cases (6,031.30), reflecting the high demand on its court system. The *Algarve* region follows, especially in civil and criminal cases, with means of 20,729.78 civil cases and 5,392.33 criminal cases resolved. However, the *Norte* region also shows strong performance in labor cases (3,621.37) and tutelar cases (2,847.74), suggesting a high specialization in these areas. Regions like *Alentejo*, *Região Autónoma da Madeira*, and *Região Autónoma dos Açores* have significantly lower outputs across all categories. For instance, Alentejo has a mean of 5,812.31 civil cases and 1,401.58 criminal cases resolved, indicating lower overall judicial output in comparison to larger regions. The *Região Autónoma dos Açores* and *Região Autónoma da Madeira* have smaller case volumes across the board, with outputs reflective of their smaller populations and judicial demands.

Table 5.3: Mean of outputs per Region(s) NUTS II.

Regions NUTS II	μ **(Civil Cases)**	μ **(Criminal Cases)**	μ **(Criminal Labour Cases)**	μ **(Labour Cases)**	μ **(Tutelar Cases)**
Alentejo	5,812.31	1401.58	62.00	650.81	968.94
Algarve	20,729.78	5,392.33	124.44	1,177.00	2,546.22
Área Metropolitana de Lisboa	42,512.30	7,902.26	148.96	3,700.78	6,031.30
Centro	13,685.40	2,678.41	98.87	1,631.60	1,931.11
Norte	21,992.76	3,576.83	66.35	3,621.37	2,847.74
Região Autonóma da Madeira	11,561.33	1,990.56	26.78	577.89	1,485.89
Região Autonóma dos Açores	8,846.33	2,325.33	8.89	760.11	1,887.22

The Kruskal-Wallis test operates under the following hypotheses, where i and j are indices of different regions, η_i and η_j are the median technical efficiency scores of those regions:

1. Null hypothesis (H_0): The distributions of technical efficiency scores are the same across all regions (NUTS II) of Portugal.

$$H_0 : \eta_1 = \eta_2 = \cdots = \eta_k$$

2. Alternative hypothesis (H_1): There is at least one region where the distribution of technical efficiency scores is different from the others.

$$H_1 : \exists\, i, j \text{ such that } \eta_i \neq \eta_j$$

By testing these hypotheses, the objective is to determine whether the observed differences in technical efficiency scores among the regions are statistically significant or if they could have occurred by random chance. The technical efficiency scores were calculated using DEA, which provides a comparative measure of the efficiency of FICs. These scores serve as the input data for the Kruskal-Wallis test. Given that the DEA scores may not follow a normal distribution and considering the ordinal nature of efficiency rankings, the Kruskal-Wallis test is appropriate for this analysis. It allows us to compare the median efficiency scores across multiple regions without assuming any specific distribution for the data. It ranks all data points from different groups together in a single list, regardless of their original groupings. Each value is assigned a rank based on its magnitude, with the smallest value receiving the lowest rank. In cases where multiple values are tied, they are given an average rank. After ranking, the sum of ranks is calculated for each group. This rank-sum approach allows the Kruskal-Wallis test to compare the distribution of values across groups without assuming a normal distribution. By analyzing the rank

sums, the test evaluates whether the differences between groups are statistically significant, providing insight into whether group medians differ. The Kruskal-Wallis test statistic follows a chi-square distribution with $k-1$ degrees of freedom, where k is the number of groups. A significant *p*-value indicates that at least one group differs significantly from the others in terms of median efficiency scores.

Table 5.4 shows the results of Kruskal-Wallis Rank Sum Test for both models. For model 1, the *p*-value is 0.10. Since this is greater than the significance level of 0.05, it is not possible to reject the null hypothesis. This suggests that there is no statistically significant difference in efficiency scores across the regions NUTS II for model 1. For model 2, the *p*-value is 0.01. Since this is less than the significance level of 0.05, it is possible to reject the null hypothesis. This indicates that there is a statistically significant difference in efficiency scores across the regions NUTS II for model 2.

The rejection of the null hypothesis in model 2 but not in model 1 is expected, as model 2 includes context variables that naturally differ across regions. For instance, it is normal that *Área Metropolitana de Lisboa* has a higher number of legal professionals compared to regions like *Algarve* or *Alentejo*. These regional disparities in resources, such as enforcement agents, lawyers and solicitors, are context factors that influence efficiency and are not uniformly distributed across the country. Therefore, it makes sense that model 2 shows significant differences in efficiency scores across the NUTS II regions, reflecting these inherent variations.

In model 1, which includes caseload, judges, and justice officials as inputs, the failure to reject the null hypothesis (*p*-value = 0.108) suggests that there are no statistically significant differences in efficiency scores across the regions for these variables. This implies that, despite regional variations in the number of judges, justice officials, and caseloads, these factors do not lead to significant differences in the overall efficiency of the courts. In other words, courts across different regions may be using these inputs similarly, and variations in caseload or staffing levels do not substantially affect their relative efficiency. This contrasts with model 2, where context factors like the number of lawyers do result in significant differences, highlighting that core operational inputs alone may not fully explain efficiency disparities.

Table 5.4: Results of Kruskal-Wallis rank sum test for model 1 and for model 2.

Kruskal-Wallis Rank Sum Test	**Model 1 Efficiency scores ∼Region(s) NUTS II**	**Model 2 Efficiency scores ∼Region(s) NUTS II**
χ^2	10.51	15.75
df	6	6
p-value	0.105	0.015

5.2 Meta-Malmquist Index

Table 5.5 presents the geometric mean of MMI results, along with EC and TC for both Models 1 and 2 over the periods from 2015/2016 to 2022/2023. As it was mentioned before, MMI is a comprehensive measure used to assess productivity change over time. It is calculated by decomposing productivity into two main components: EC and TC. The EC component captures the variation in performance relative to a given production frontier, reflecting improvements or declines in the ability of decision-making units to convert inputs into outputs. A value greater than one indicates an improvement in efficiency, while a value less than one signifies a decline. The TC component measures shifts in the production frontier itself, representing innovations or advancements in technology. Similar to EC, a value greater than one denotes technological progress, and a value less than one indicates technological regression. MMI is obtained by multiplying these two components, providing a holistic view of productivity dynamics that considers both improvements in operational efficiency and technological advancements.

For Model 1, the period 2015/2016 shows a decline in overall productivity, with an MMI of 0.937. The TC value of 0.936 indicates that the decline was primarily driven by technological regress, while the EC remained neutral at 1.000. This period might correspond to the aftermath of reforms in the public sector, which could have temporarily hindered productivity. In 2016/2017, the MMI of 1.006 indicates a slight improvement in productivity, primarily driven by a technological improvement (TC = 1.014), despite a small drop in efficiency (EC = 0.993). The stabilization of public policies and gradual reforms likely played a role in this minor recovery. The period 2017/2018 shows a more substantial productivity increase, with an MMI of 1.053. Both efficiency (EC = 1.000) and technology (TC = 1.054) improved, possibly reflecting the benefits of continued digital transformation in the public sector, particularly with initiatives like *Justiça + Próxima*. In 2018/2019, there is a slight decline in productivity, as reflected by the MMI of 0.948. Although efficiency slightly improved (EC = 1.003), a technological regression (TC = 0.946) led to the overall decline in productivity. This could be linked to disruptions from political instability and policy shifts. The period 2019/2020 marks a significant productivity improvement, with an MMI of 1.190. Both efficiency (EC = 0.998) and technology (TC = 1.192) made notable gains, reflecting strong economic performance and advancements in public sector digitalization just before the COVID-19 pandemic. However, 2020/2021 shows a substantial decline in productivity, with an MMI of 0.865. The impacts of the pandemic are evident, with declines in both efficiency (EC = 1.000) and technology (TC = 0.865), as courts faced severe disruptions and struggled to adapt quickly to the changing landscape. In 2021/2022, there is a slight recovery in productivity, with an MMI of 0.966. While efficiency (EC = 0.998) remained relatively stable, technological change (TC = 0.968) continued to improve, albeit slowly, as courts adapted to the challenges posed by the pandemic. Finally, 2022/2023 shows a stronger recovery with an MMI of 1.062, driven by improvements in both efficiency (EC = 1.005) and technology (TC = 1.056), as courts likely embraced digital solutions and remote work, helping to boost productivity post-pandemic.

For Model 2, the period 2015/2016 shows a modest decline in productivity, with an MMI of 0.985, driven by a slight regression in technology (TC = 0.979) and a minor reduction in efficiency (EC = 1.006).

This aligns with the public sector's adjustment to post-crisis conditions. In 2016/2017, the MMI of 1.003 reflects a small productivity improvement, with modest gains in technology (TC = 1.008) and a slight drop in efficiency (EC = 0.996), likely tied to gradual economic stabilization. The period 2017/2018 shows a more significant increase in productivity, as indicated by an MMI of 1.035. Both efficiency (EC = 0.998) and technology (TC = 1.037) improved, reflecting continued progress in digital transformation and economic growth. In 2018/2019, there is a slight decline in productivity, with an MMI of 0.965. This drop is driven by reductions in both efficiency (EC = 1.005) and technology (TC = 0.961), possibly linked to political changes and policy shifts. The period 2019/2020 marks a substantial productivity increase, with an MMI of 1.175. Significant gains in both efficiency (EC = 0.994) and technology (TC = 1.182) reflect strong performance prior to the pandemic. However, 2020/2021 shows a noticeable decline in productivity, with an MMI of 0.882, primarily due to technological regress (TC = 0.881) as the pandemic caused widespread disruptions in operations, although efficiency (EC = 1.002) remained stable. In 2021/2022, the MMI of 0.977 indicates a slight decrease in productivity, with small declines in both efficiency (EC = 1.000) and technology (TC = 0.976), continuing the trend of slow recovery post-pandemic. Finally, 2022/2023 shows a notable improvement in productivity, with an MMI of 1.056, driven by gains in both efficiency (EC = 1.003) and technology (TC = 1.053), as courts adapted to the new digital reality and remote work solutions.

Table 5.5: Geometric mean of Meta Malmquist Index results.

	Model 1			**Model 2**		
Years	**Meta Malmquist Index**	**Efficiency Change**	**Technological Change**	**Meta Malmquist Index**	**Efficiency Change**	**Technological Change**
2015/2016	0.937	1.000	0.936	0.985	1.006	0.979
2016/2017	1.006	0.993	1.014	1.003	0.996	1.008
2017/2018	1.053	1.000	1.054	1.035	0.998	1.037
2018/2019	0.948	1.003	0.946	0.965	1.005	0.961
2019/2020	1.190	0.998	1.192	1.175	0.994	1.182
2020/2021	0.865	1.000	0.865	0.882	1.002	0.881
2021/2022	0.966	0.998	0.968	0.977	1.000	0.976
2022/2023	1.062	1.005	1.056	1.056	1.003	1.053

Figures 5.3, 5.4 and 5.5 graphically represent the geometric means of the MMI, TC, and EC for both model 1 and model 2 over the analysis period from 2015/2016 to 2022/2023, respectively.

As observed in Figure 5.3, the trend of the MMI closely follows the pattern of TC shown in Figure 5.4. This indicates that the MMI is heavily influenced by technological improvements or regressions over the years. Notably, in periods such as 2019/2020, both models show a significant spike in MMI

and TC, while 2020/2021 shows a sharp decline in both, likely reflecting the impact of the COVID-19 pandemic on technological adoption and operational capacity within the courts. These results suggest that technological advancements or setbacks are the primary drivers of productivity fluctuations over this period, as indicated by the strong correlation between MMI and TC.

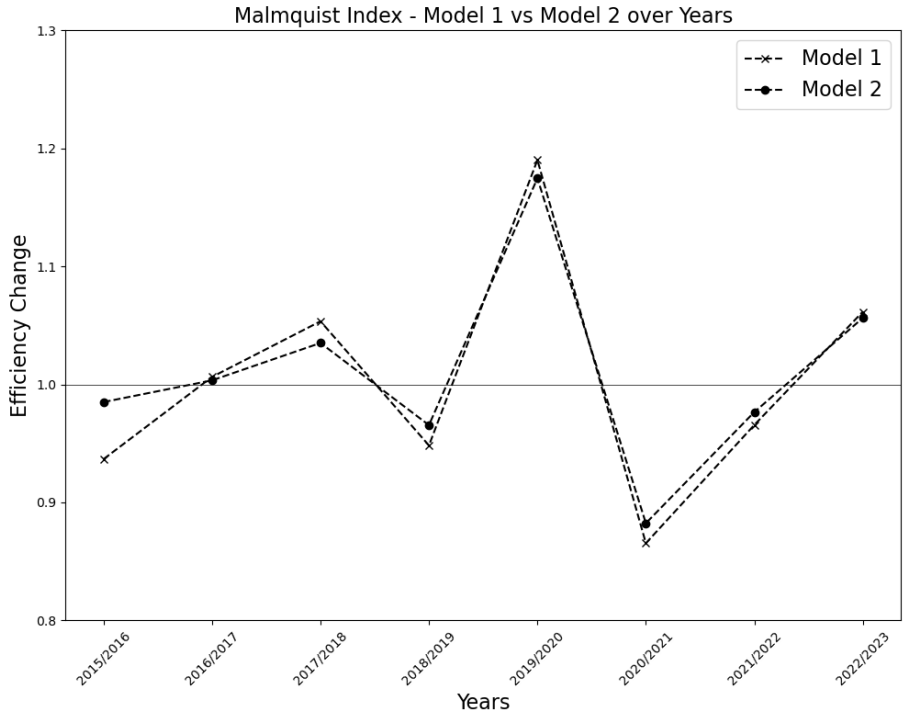

Figure 5.3: Meta Malmquist Index for Model 1 and Model 2 from 2015/2016 to 2022/2023.

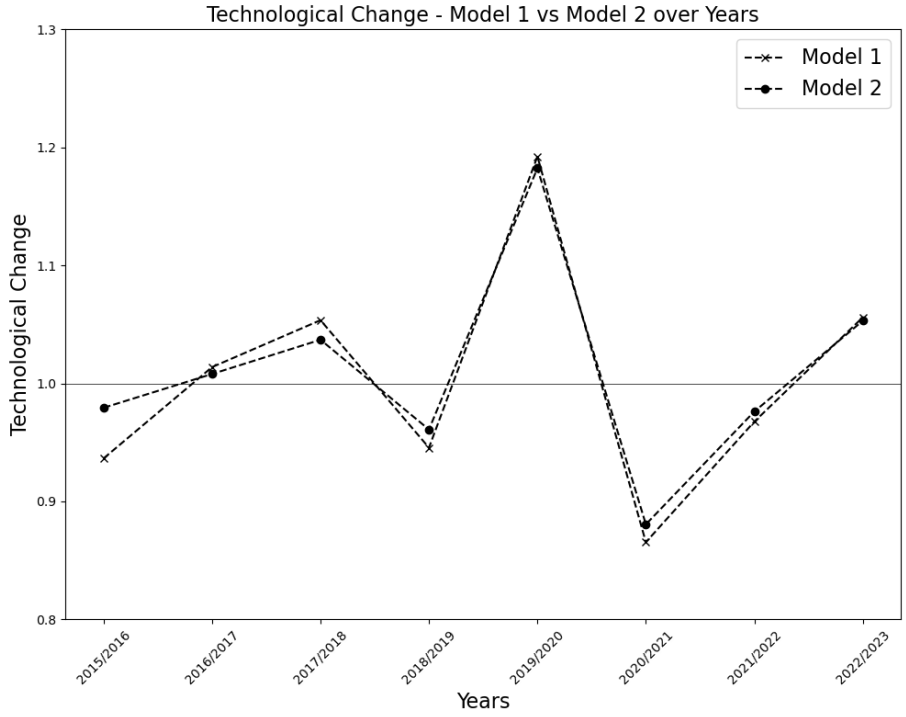

Figure 5.4: Technology Change for Model 1 and Model 2 from 2015/2016 to 2022/2023.

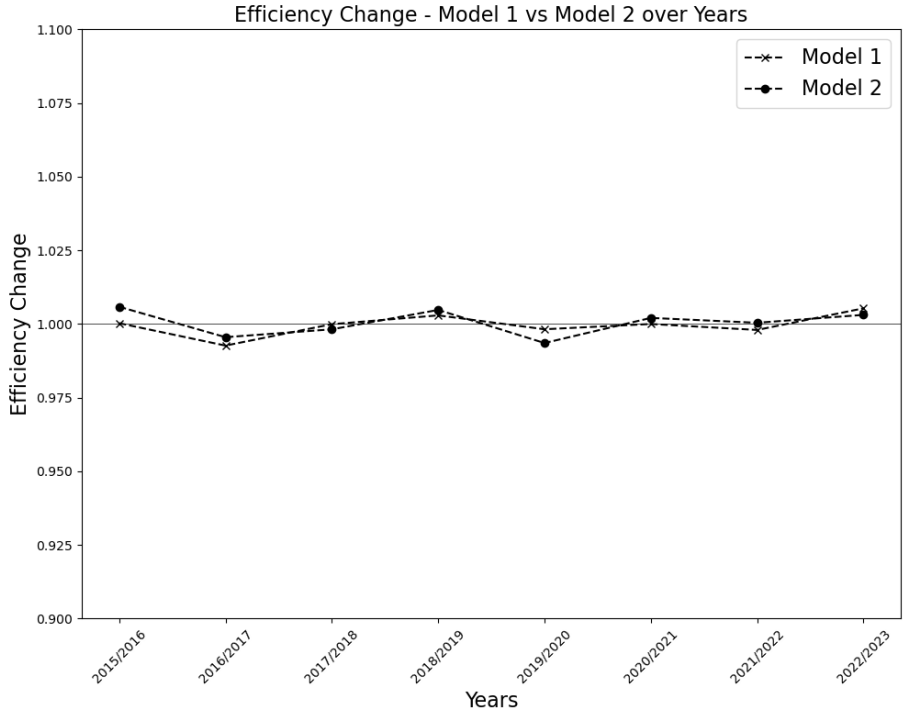

Figure 5.5: Efficiency Change for Model 1 and Model 2 from 2015/2016 to 2022/2023.

In contrast, the EC component, depicted in Figure 5.5, remains relatively stable throughout the entire period, with values closer to 1 in both models. This stability in EC highlights that efficiency improvements are less volatile and contribute much less to the variations in productivity compared to technological changes. This suggests that the efficiency of resource use within the courts (e.g., caseload management, staffing) has been relatively constant, and the major shifts in productivity, as seen in the MMI, are largely due to changes in technology rather than how efficiently the courts manage their existing resources.

The atypical years, specifically 2019/2020 and 2020/2021, likely correspond to the pandemic, which disrupted operations and forced a rapid shift toward digital solutions. This further underscores that the MMI, especially in these years, was more influenced by technological change than by efficiency adjustments. In sum, the graphical analysis emphasizes the important role of technology in shaping the productivity of the judicial FICs, particularly in response to external shocks like the pandemic. Furthermore, it is important to note that the improvements observed in the years following 2020/2021, particularly in 2022/2023, suggest that the courts were able to leverage technological innovations to recover from the pandemic-induced disruptions. This recovery, reflected in the upward trend of both MMI and TC, indicates that the integration of new technologies became more effective over time, allowing for enhanced operational capacity and case management. The relatively stable EC component during these periods reinforces the notion that while efficiency remained consistent, it was the courts' ability to adopt and implement technological advancements that drove productivity gains. Thus, the technological transformation of the judicial system played a crucial role in the observed fluctuations in performance across the analyzed years.

5.3 Implications and Recommendations

The analysis of Portuguese judicial FICs reveals significant insights into judicial efficiency, particularly when budget allocation, resource density, technological integration, and overall performance metrics. Portugal allocates around €60 per inhabitant to its judiciary, which represents 0.29% of the GDP, positioning it in the mid-range among European countries. This relatively stable funding level from 2018 to 2020, with only slight increases, suggests a consistent but conservative investment approach (CEPEJ, 2022a). In 2018, the judicial budget stood at approximately €484.7 million, covering salaries, ICT infrastructure, and other expenses (CEPEJ, 2018). By 2020, the budget rose to €562 million, reflecting enhanced investments in IT and training, aimed at bolstering digital capabilities and staff competencies across the judiciary (CEPEJ, 2022b). To boost judicial performance, especially in high-demand regions, Portugal may benefit from incremental budget increases. These additional funds could support further adoption of technology and ensure adequate resources for courts with high caseloads and notable efficiency challenges.

Portugal has made considerable strides in technological integration within the judiciary, reflecting a strong commitment to modernizing court operations. The country shows high levels of both regulation and deployment, underscoring the importance of these advancements. Initiatives like *Justiça + Próxima* demonstrate Portugal's proactive stance in streamlining processes through technology, which has proven to be essential in enhancing case management and transparency. While the regulatory framework supports technological adoption, aligning deployment speed with legislative standards remains a key area for improvement. This alignment could be achieved by establishing mandatory technology training for judicial staff, creating a baseline digital literacy standard, and regularly assessing technology adoption levels across various courts to ensure uniform progress.

The CR and DT are essential indicators of judicial performance. Portugal's CR has hovered around 100%, reflecting a generally balanced caseload. However, occasional dips below this mark indicate challenges in managing incoming cases efficiently. To maintain and surpass the 100% CR consistently, Portugal could adopt strategies aimed at increasing the throughput of FICs. This might involve expanding the judicial roster during peak periods or implementing alternative dispute resolution mechanisms to expedite simpler cases, allowing courts to focus resources on more complex matters. Despite a generally stable DT, it remains longer than the European median, highlighting potential for improvement (CEPEJ, 2022a). Establishing target DTs for various case types and conducting regular audits to identify bottlenecks could help streamline processes and enhance timeliness.

According to CEPEJ report around 18.9% of cases have been pending for over two years, a clear sign that more effective backlog management strategies are needed(CEPEJ, 2022a). Implementing a case triage system could help prioritize cases based on complexity and urgency, enabling quicker resolution for simpler matters and gradually reducing the proportion of long-pending cases. Additionally, expanding digital case tracking and making backlog metrics publicly accessible could increase accountability and drive sustained focus on reducing case backlogs.

Addressing the substantial backlog of cases older than two years will require specific interventions. A

significant portion of these cases strains the judicial system and delays justice, impacting public perception. One approach to tackling this issue could involve establishing dedicated backlog clearance teams, which focus on older cases, accelerating their review and resolution. Alternatively, task forces could conduct expedited reviews or recommend dismissals where appropriate, thus reducing the backlog. Regular reporting on case metrics and integrating advanced technologies, such as AI for case prioritization, can further enhance these efforts.

Considering the insights from the DEA analysis, there are several strategic actions that Portugal's judiciary could take to address regional disparities and optimize court performance. A more balanced allocation of judicial resources is essential. By deploying judges and staff proportionally to regions with higher caseloads or prolonged disposition times, Portugal can improve efficiency across the board. Investing part of the judicial budget specifically for continuous technological upgrades would ensure uniform digital capabilities across all courts. Establishing national digital benchmarks could further facilitate consistent technology deployment, thereby reducing regional disparities in judicial performance.

DGPJ currently provides key metrics such as the CR, DT, and case flow data. These metrics are essential for monitoring court performance and workload management. However, both CR and DT provide useful information about a court's case management and timeliness but they do not account for the inputs (e.g., judges, justice officials) or outputs (e.g., number of CC) relative to each other. They measure performance but not necessarily efficiency in resource utilization. For example, a court could have a high CR but still be inefficient if it consumes an excessive amount of resources relative to the cases it handles. DEA can complement these existing metrics by offering a comparative efficiency evaluation across courts. This approach enables a more detailed understanding of how efficiently courts utilize their resources, helping to identify specific areas for targeted improvements and ensuring that courts operate at their optimal potential. Transparency and public reporting are equally crucial. Regularly publishing clearance rates, disposition times, and backlog statistics, alongside DEA-derived efficiency metrics, could enhance accountability. Publicly accessible efficiency metrics grounded in DEA would not only provide insights into court performance but also offer real-time data for policymakers and the public. This transparency could foster a culture of continuous improvement and allow for prompt interventions when performance issues arise.

To maximize the benefits of technological integration, Portugal should invest in targeted training and professional development for judicial staff. Technological proficiency is vital, and staff should be well-equipped to leverage digital tools effectively. Specialization in different case types could further improve operational efficiency, enabling staff to handle specific cases more adeptly.

A people-centered approach in judicial reforms would also enhance public trust and access to justice. Extended disposition times, particularly in high-demand regions, can impede timely legal resolution. By expanding digital services, such as case tracking, remote hearings, and alternative dispute resolution methods, Portugal can provide flexible options that alleviate pressure on physical courtrooms while improving public access. This aligns with OECD's emphasis on user-centered justice, promoting a more responsive and accessible judiciary (OECD, 2024).

Finally, ensuring resilience against future disruptions is paramount. The pandemic revealed vul-

nerabilities in traditional court operations, emphasizing the need for adaptable digital tools and flexible frameworks. Investing in technologies that support digital resilience will prepare the courts to function effectively in various scenarios. This adaptability not only enhances efficiency but also fortifies the judicial system against potential future challenges. By building on these strategies, Portugal can strengthen its judiciary, ensuring a responsive, equitable, and modernized system that meets the demands of a contemporary society.

Chapter 6

Conclusions

The objective of this study was to assess the efficiency and productivity of Portuguese judicial FICs, focusing on regional differences and the underlying factors driving them. Using DEA and the MMI, the research provided a detailed comparison of court performance across Portugal's regions. Two DEA models were applied: Model 1, which considered the number of justice officials, judges, and caseload as inputs, and Model 2, which added context variables such as lawyers, solicitors, and enforcement agents. Both models used completed cases in various categories (e.g., civil, criminal, criminal labor, labor and tutelar) as outputs, allowing for a comprehensive evaluation of efficiency across courts.

Key findings reveal that both models produced similar technical efficiency scores, indicating that the core inputs—justice officials, judges, and caseload—are primary determinants of court efficiency, while additional context variables had a limited impact on overall efficiency outcomes. The study further illustrated that the TC component of MMI played a more significant role in productivity fluctuations than EC. Technological advancements, particularly during periods following reforms, were associated with increased productivity, while regressions in technology corresponded to declines. This pattern emphasizes the critical role of digital transformation in improving judicial performance.

The analysis also highlighted how external factors, such as the COVID-19 pandemic, substantially impacted court operations. Efficiency scores showed an increase in 2020 and 2021, reflecting the operational disruptions caused by the pandemic. Yet, recovery in subsequent years indicated the adaptability of the judicial system, mabye reinforced by reform initiatives like *Justiça + Próxima* and *Tribunal +*. These reforms, aimed at digital transformation and administrative streamlining, have shown positive effects, particularly in reducing pending caseloads and enhancing procedural efficiency.

The examination of regional disparities underscored the need for targeted resource allocation to address specific challenges in different regions. While some areas exhibited stable performance, others, particularly in high-demand regions like the *Área Metropolitana de Lisboa*, faced persistent efficiency challenges. These findings suggest that a more balanced distribution of judicial resources, supported by continuous investment in technology, is essential for optimizing court performance and maintaining consistent efficiency across the country.

In conclusion, this study provides a comprehensive evaluation of the efficiency and productivity dy-

namics within the Portuguese judicial system. By combining DEA and MMI methodologies, it offers insights into how regional disparities, technological advancements, and external shocks influence court performance. The study underscores the need for ongoing reform, emphasizing technological integration, improved resource allocation, and transparency to foster a responsive and efficient judiciary. Recommendations include the continuous monitoring of performance indicators, strategic investments in digital infrastructure, and addressing regional disparities through tailored interventions.

For future research, there are several avenues to explore that could enhance our understanding of judicial efficiency further. Incorporating additional environmental variables—such as socio-economic factors, regional economic conditions, and legal complexities—could provide a more nuanced view of the determinants of court efficiency. Employing more sophisticated DEA models, such as network DEA models that account for intermediate factors, may also capture the multifaceted aspects of judicial operations more effectively. Longitudinal studies extending beyond the current timeframe would offer insights into the long-term effects of judicial reforms and external shocks like the COVID-19 pandemic. Additionally, applying advanced machine learning techniques to predict efficiency trends and identify key drivers of productivity changes could add another layer of insight. Finally, qualitative research, including interviews with key stakeholders, could provide context and enrich the quantitative findings, helping to align future reforms with the practical needs of the judiciary and the public it serves. Moreover, it would be particularly valuable to explore civil cases in greater depth, as these cases not only constitute a significant portion of the judicial workload but also tend to have longer resolution times, making them crucial for understanding and improving overall court efficiency.

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