UNIVERSIDADE FEDERAL DE JUIZ DE FORA
FACULDADE DE ECONOMIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ECONOMIA

Technology and Justice: Determinants and effects of implementing the Electronic Judicial Process in the court of justice of Minas Gerais

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Juiz de Fora – Minas Gerais
2025

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Costa, João Erick Alexandre Barbosa.
Technology and Justice: Determinants and Effects of Implementing the Electronic Judicial Process in the Court of Justice of Minas Gerais / João Erick Alexandre Barbosa Costa. -- 2025.
145 p. : il.

Orientador: Laura de Carvalho Schiavon
Coorientador: Flávia Lúcia Chein Feres
Tese (doutorado) - Universidade Federal de Juiz de Fora, Faculdade de Economia. Programa de Pós-Graduação em Economia, 2025.

1. Electronic Judicial Process. 2. Modernization. 3. Technology. 4. Justice. I. Schiavon, Laura de Carvalho , orient. II. Feres, Flávia Lúcia Chein , coorient. III. Título.

João Erick Alexandre Barbosa Costa

Technology and Justice: Determinants and effects of implementing the Electronic Judicial Process in the court of justice of Minas Gerais

Tese apresentada ao Programa de Pós-graduação em Economia da Universidade Federal de Juiz de Fora como requisito parcial à obtenção do título de Doutor em Economia. Área de concentração: Economia

Aprovada em 04 de julho de 2025.

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ACKNOWLEDGEMENTS

First and foremost, I thank my mother, father, and siblings for their unconditional support throughout my journey. To my fiancée, Thamyres Firmino, my eternal gratitude for all the love, patience, and support during every step of this journey.

I also thank my advisor, Laura Schiavon, and my co-advisor, Flávia Chein, for accepting the challenge of guiding me and for the invaluable knowledge and guidance they provided in the development of this thesis.

I would like to thank all the professors I had the opportunity to attend classes with during my Ph.D. program, whose teachings greatly enriched my knowledge and contributed to the formation of this research.

Finally, I would like to thank the friends I made during the Ph.D. program, who helped make this process easier and more enjoyable.

I am also deeply grateful for the financial support provided by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brazil (CAPES) - Financing Code 001.

ABSTRACT

This study examines the digitalization of the judiciary through the implementation of the Processo Judicial Eletrônico (PJe) in the first-instance courts of the Tribunal de Justiça de Minas Gerais (TJMG), focusing on the adoption of the system and its effects on judicial performance. The study is structured in two chapters. The first chapter analyzes the determinants of PJe adoption, while the second chapter evaluates its impact on judicial efficiency.

The digitalization of the judiciary, an initiative of the Conselho Nacional de Justiça (CNJ), aims to replace physical processes with electronic ones, increasing transparency and expediting case processing. However, the implementation of this initiative has not been uniform, with regional and institutional variations reflecting the state of implementation. The initial chapter explores the factors influencing PJe adoption across the TJMG courts from 2015 to 2021, emphasizing the digital infrastructure of municipalities, such as internet speed, as a salient factor. The results indicate that, in civil courts, digital infrastructure exhibits a positive correlation with adoption, while in criminal courts, the effect is unclear.

The second chapter examines the effects of the PJe system on court performance, considering its gradual implementation over the years. To do so, it employs a two-way fixed effects (TWFE) model and a multi-period difference-in-differences approach. The data analysis reveals that, in civil courts, there were no significant improvements in efficiency during the period under review. In contrast, criminal courts experienced an increase in both court's and judges' productivity, in the number of disposed cases, and in the efficiency of issuing judgments. However, there were no substantial changes in the backlog rate, the demand fulfillment index, or the number of pending cases.

The findings indicate that the digital transformation of the judiciary is not uniform, but rather exhibits variations based on the nature of the court and the availability of local infrastructure. Public policies aimed at fostering innovation in the public sector must take these regional and functional disparities into consideration, allocating resources not solely to infrastructure development but also to the training of personnel and the streamlining of processes.

Keywords: Electronic Judicial Process; Modernization; Technology; Justice.

RESUMO

Este estudo examina a digitalização do judiciário por meio da implementação do Processo Judicial Eletrônico (PJe) nas varas de primeira instância do Tribunal de Justiça de Minas Gerais (TJMG), focando na adoção do sistema e seus efeitos sobre a performance judicial. Estruturado em dois capítulos, o primeiro analisa os determinantes da adoção do PJe e o segundo avalia seus impactos na eficiência do Judiciário.

A digitalização do Judiciário, uma iniciativa do Conselho Nacional de Justiça (CNJ), visa substituir os processos físicos por eletrônicos, aumentando a transparência e agilidade na tramitação dos casos. Contudo, sua implementação não foi uniforme, com variações regionais e institucionais que refletem no estado. No primeiro capítulo, a pesquisa investiga os fatores que influenciam a adoção do PJe entre as varas do TJMG entre 2015 e 2021, destacando a infraestrutura digital dos municípios, como a velocidade da internet, como fator relevante. Os resultados revelam que, nas varas cíveis, a infraestrutura digital possui uma correlação positiva na adoção, enquanto nas varas criminais, o efeito não é claro.

O segundo capítulo examina os efeitos do PJe sobre o desempenho das varas, considerando que sua implementação ocorreu de forma gradual ao longo dos anos. Para isso, foi utilizado um modelo de efeitos fixos bidimensionais (TWFE) e de diferenças-em-diferenças com múltiplos períodos. A análise dos dados revelou que, nas varas cíveis, não houve melhorias significativas na eficiência no período analisado. Por outro lado, nas varas criminais, observou-se um aumento na produtividade dos tribunais e dos juízes, no número de processos baixados e na eficiência do julgamento de sentenças, embora não tenham ocorrido mudanças substanciais na taxa de congestionamento, no índice de atendimento à demanda ou casos pendentes.

Os resultados sugerem que a digitalização do Judiciário não ocorre de maneira homogênea, com variações dependendo do tipo de vara e da infraestrutura local. As políticas públicas voltadas para inovação no setor público devem considerar essas diferenças funcionais, investindo não apenas em infraestrutura, mas também na capacitação de servidores e no redesenho dos processos.

Palavras-chave: Processo Judicial Eletrônico; Modernização; Tecnologia; Justiça.

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1 Introduction

The performance of institutions plays a central role in the economic and social development of countries. Both classical and contemporary studies highlight that strong institutions are essential for ensuring contract enforcement, protecting property rights, and reducing uncertainty, which are fundamental elements for the efficient functioning of economies (Acemoglu and Johnson, 2005; North, 1994; Acemoglu et al., 2020). Within this institutional framework, the judiciary has gained increasing attention not only for its normative and regulatory roles, but also as a foundation for democratic stability and economic growth. In this sense, judicial performance is directly associated with the state's capacity to guarantee access to justice, protect fundamental rights, and promote an environment favorable to investment and citizenship (Lichand and Soares, 2014; Banerjee et al., 2020).

In recent decades, the incorporation of information and communication technologies into public institutions has been a recurring strategy to address historical challenges of inefficiency, delays, and lack of transparency (Gomes, 2014; Gomes et al., 2017; Ramos-Maqueda and Chen, 2021; Ніколенко, 2022). In the judiciary, several international experiences suggest that digitalizing legal procedures and automating workflows can help reduce the duration of cases, expand access to justice, and reduce operational costs (Ramos-Maqueda and Chen, 2021; Djamaludin et al., 2023). In Brazil, this movement gained momentum with the creation of the Electronic Judicial Process (PJe) in 2006, a system developed and coordinated by the Conselho Nacional de Justiça (CNJ) with the aim of modernizing the judiciary through the digital management of legal proceedings (Brasil, 2006; CNJ, 2013).

Despite these normative and technological advances, the adoption and effects of the PJe have not been uniform in the state of Minas Gerais. The implementation process was gradual and varied according to judicial area, court type, and institutional capacity. This raises important questions: what factors influenced the adoption of the PJe across different judicial districts? And once implemented, what impact did this technology have on the performance of civil and criminal courts in Minas Gerais? This dissertation aims to investigate both questions, using the Tribunal de Justiça de Minas Gerais (TJMG) as an empirical case. The TJMG is one of the largest and most representative courts in Brazil, both in terms of population served and volume of judicial activity (CNJ, 2021).

This thesis is divided into two main chapters. The first chapter analyzes the determinants of PJe implementation in first-instance civil and criminal courts in Minas Gerais between 2015 and 2021. The central hypothesis is that local characteristics—such as income levels, urbanization, digital infrastructure, and judicial size—affect the likelihood of adopting the electronic system. To test this, an original dataset was constructed, combining administrative data from the TJMG on PJe implementation, socioeconomic indicators from Instituto Brasileiro de Geografia e Estatística (IBGE) and the João Pinheiro Foundation, and judicial structure data from the CNJ's Justiça Aberta portal. This dataset supports descriptive and exploratory analysis, followed by linear and nonlinear probability models to identify correlations between socioeconomic conditions and system adoption.

The dependent variable in Chapter 1 is a binary indicator that equals 1 starting from the year of PJe implementation in each judicial unit, including the implementation year itself, and remains 1 in the following years. In prior years, the indicator remains 0. The main predictors include (i) demographic and economic variables, such as the natural logarithm of municipal GDP per capita, the logarithm of population density, and the municipal employment rate, measured as the share of formally employed individuals in the working-age population (16 to 64 years old); (ii) infrastructure indicators, including average internet speed in households, used as a proxy for digital infrastructure quality in the municipality; (iii) institutional characteristics, such as the number of judges and the number of courts operating in each judicial district; and (iv) regional variables, represented by microregion dummies that account for local geographic and institutional effects.

The empirical strategy combines two methods. The first is a linear probability model with fixed effects by microregion, which identifies the variables associated with the likelihood that a court adopts the system in year *t*. The second method applies logistic regression models to assess the robustness of results using a nonlinear specification (Wooldridge, 2016).

The findings from Chapter 1 show that the adoption of the PJe by judicial courts in Minas Gerais is strongly influenced by territorial and institutional inequalities. In civil courts, digital infrastructure—measured by average municipal internet speed—proved to be a significant factor, even after controlling for institutional and regional characteristics. In criminal courts, however, this association disappears when more robust controls are added, suggesting that organizational and regulatory factors play a larger role in the adoption process in this area. In addition, factors such as the number of courts in a district and the level of local socioeconomic development also influence the likelihood of adoption. These results indicate that the digital modernization of the judiciary tends to progress unevenly across regions. This reinforces the need for public policies that are more sensitive to regional disparities, especially if the goal is to promote a universal and equitable digital transformation of the Brazilian justice system.

Chapter 2 focuses on the effects of PJe implementation on the performance of first-instance courts within the TJMG. Both Brazilian and international literature suggest that digitalization may improve efficiency by automating routine procedures, reducing the need for physical movement, increasing transparency, and facilitating access to information (Djamaludin et al., 2023; Lima and Recuero, 2022). However, the effects of digital transformation on institutional performance remain underexplored in Brazil, especially considering the challenges faced by developing countries.

The econometric strategy in Chapter 2 takes advantage of the fact that PJe was implemented in different courts and years, allowing for the identification of its effects using difference-in-differences models. Treated courts are those that implemented the system in a given year, while control courts are those that had not yet done so. In the case of civil courts, implementation occurred gradually over time, which made it possible to use multiperiod difference-in-differences models (Callaway and Sant'Anna, 2021), as well as two-way fixed effects models that control for both year and court (Wooldridge, 2015; Bertrand, Duflo, and Mullainathan, 2004). In the criminal justice segment, however, implementation was more concentrated: in 2020, only a few courts adopted the PJe, while the majority remained in the control group. In 2021, the system was fully implemented across all criminal courts, making it impossible to use multiperiod models. Therefore, a canonical difference-in-differences model was used, along with two-way fixed effects. In both areas, the objective was to compare court performance before and after PJe adoption, isolating the policy's effect while controlling both observable and unobservable characteristics over time. Robustness tests were also conducted, including placebo tests with false treatment years, to verify the validity of the parallel trends assumption.

The main explanatory variable is a binary indicator equal to 1 for courts that implemented the PJe in a given year and in the following years, and 0 otherwise. The analysis considers two main groups of outcome variables, based on annual data from Justiça Aberta between 2015 and 2021. The first group includes indicators of judicial efficiency, such as judges' productivity, courts' productivity, the demand fulfillment index, and the backlog rate. The second group consists of workload variables, including the number of new cases, pending cases, disposed cases, and total judgments (CNJ, 2015, 2019, 2020, 2021). To isolate the effects of PJe adoption, the models include municipal socioeconomic controls such as GDP per capita, population density, internet speed, and employment rate. These variables help account for local structural characteristics that could simultaneously affect the probability of adoption and judicial performance.

The results from Chapter 2 show that the effects of PJe adoption vary significantly between civil and criminal courts. In civil courts, a temporary decline was observed in performance indicators such as the demand fulfillment index and the backlog rate, suggesting initial difficulties in adapting to the system. However, robustness checks reveal that some of these effects are sensitive to model specifications, which suggests caution in interpreting the findings. In criminal courts, the estimated effects indicate consistent productivity gains at both the court and judge levels. These results are robust across different model specifications and placebo tests. Nonetheless, the analysis is limited to the year 2020, when implementation was still recent, and criminal courts operate under a more standardized and less variable case structure.

By combining two dimensions of analysis—the factors that influence policy adoption and the effects of implementation on institutional performance—this thesis offers a comprehensive evaluation of judicial modernization in Minas Gerais. Using local data over time, this research aims to fill a relevant gap in the literature on justice and evidence-based public policy. While most studies on the Brazilian judiciary rely on qualitative approaches or aggregated data (Silva, 2018; Stollmeier Pandini and Dos Santos Pereira, 2021), this work contributes a rigorous quantitative analysis based on administrative microdata and appropriate econometric methods.

Judicial modernization involves the adoption of new technologies and administrative practices designed to increase transparency and efficiency in the justice system. Studies show that digitalization through electronic case management systems can reduce processing time and improve access to justice (Lima and Recuero, 2022; Ramos-Maqueda and Chen, 2021; Rotta et al., 2013). In Brazil, the implementation of the PJe represents a major step in addressing chronic judicial delays. In a comparative study, Djamaludin et al. (2023) analyze the effects of the E-court system on judicial efficiency in Indonesia's religious and district courts, finding positive results, especially in remote regions.

From a different perspective, Dahis, Schiavon, and Scot (2023) show that well-qualified public servants are essential to the proper functioning of public services. In Brazil, the recruitment of judges through transparent public examinations is associated with higher productivity in resolving cases. Bandiera, Best, Khan, and Prat (2023) add that bureaucratic autonomy improves performance, as shown in an experiment in Pakistan that reduced costs without compromising service quality.

Given the limited availability of empirical research, especially on the recent implementation of the PJe, this study contributes to the understanding of judicial performance and related public policies. It highlights the importance of rigorous empirical evaluations to support efforts aimed at building a more efficient, accessible, and high-quality justice system (Rosano-Peña and Gomes, 2018).

This thesis is organized into two chapters. Chapter 1 presents, in Section 1.1, the structure of the Brazilian Judiciary. Section 1.2 analyzes the judicial demand in the country, while Section 1.3 discusses innovation theory in the public sector. Section 1.4 details the methodology used to investigate the determinants of the implementation of the PJe, with subsections dedicated to data sources and the empirical strategy. Section 1.5 discusses the main results and presents robustness tests.

Chapter 2 begins with Section 2.1, which provides an overview of the modernization and implementation of the PJe in the TJMG. Section 2.2 then briefly reviews the literature on justice and judicial performance. Section 2.3 describes the methodology used, with subsections 2.3.1 and 2.3.2 presenting the data and the empirical strategy, respectively. Section 2.4 presents the results obtained for civil and criminal courts, as well as the robustness checks. Finally, Section 2.5 concludes the chapter.

Chapter 1 – Determinants of Processo Judicial Eletrônico Implementation in Judicial Courts of the Tribunal de Justiça de Minas Gerais

This chapter provides an overview of the Brazilian Judiciary, focusing on the Tribunal de Justiça do Estado de Minas Gerais (TJMG) and the factors influencing the adoption of the Processo Judicial Eletrônico (PJe) system.

It begins by outlining the structure of the Judiciary in Brazil and the role of the State Justice system, especially TJMG. Then, it discusses the judicial demand faced by civil and criminal courts, highlighting their distinct characteristics.

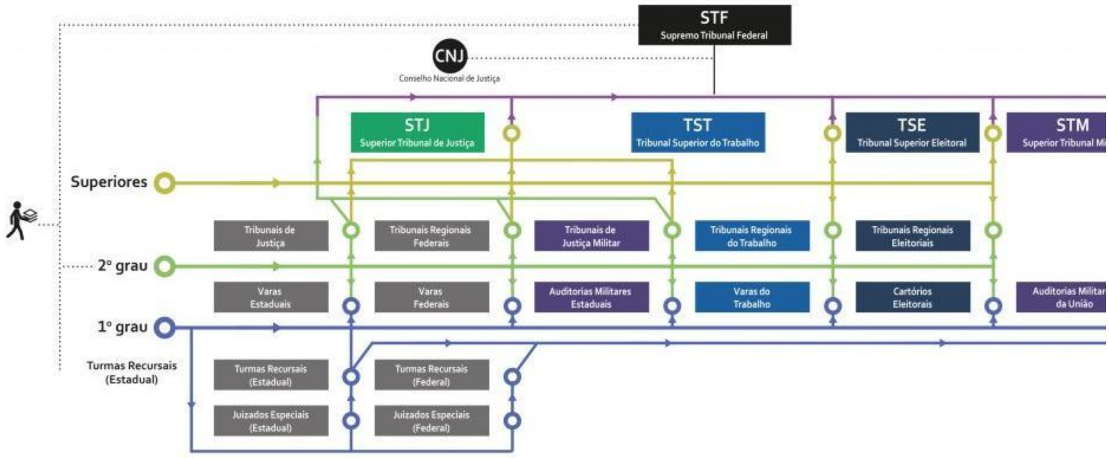
Next, the chapter explores innovation in public services, emphasizing how technological adoption can enhance judicial efficiency.

The methodology section describes the data and econometric models used to analyze determinants of PJe implementation in TJMG's courts. An exploratory data analysis follows, presenting key patterns and significant factors influencing adoption.
The chapter concludes by summarizing the findings, discussing their implications for judicial modernization policies, and suggesting directions for future research.

1.1 The Brazilian Judiciary

The Brazilian justice system is structured in a complex and hierarchical manner, with different levels and areas of specialization that define jurisdiction over various types of cases. This division allows for the distribution of legal demands across different branches of the Judiciary, according to the subject matter and the parties involved. The Federal Constitution of 1988 establishes five main branches of the Judiciary: The Supreme Federal Court (Supremo Tribunal Federal - STF) is the highest judicial authority in the country and is responsible for issuing rulings on matters pertaining to the interpretation of the Constitution and issues of significant national importance. In contrast, the Superior Court of Justice (STJ) serves as the court of last resort for cases that do not involve constitutional matters. In addition to the higher courts, the Brazilian judicial system comprises specialized courts, including the Superior Military Court (Superior Tribunal Militar - STM), the Superior Electoral Court (Tribunal Superior Eleitoral - TSE), and the Superior Labor Court (Tribunal Superior do Trabalho - TST). Each of these courts is responsible for specific functions and jurisdictions within the legal framework. In addition to these branches, the superior courts are responsible for ensuring consistent interpretation of the law and maintaining uniform legal standards throughout the country. Figure 1 below illustrates this structure in detail.

Figure 1 - Structure of the Brazilian Judiciary



Note: (CNJ, 2025).

The Supreme Federal Court (STF) is the highest body in the Brazilian judiciary, responsible for upholding the Constitution as outlined in Article 102. It is composed of 11 judges who have significant legal expertise. The primary functions of the STF include adjudicating issues of unconstitutionality and constitutionality, as well as addressing matters related to fundamental principles and extradition.

In criminal cases, the STF has the authority to judge high-ranking officials, such as the President of the Republic, members of Congress, and its own ministers. Regarding appeals, the STF reviews habeas corpus petitions, writs of mandamus, and extraordinary appeals when there is a violation of the Constitution.

The Conselho Nacional de Justiça (CNJ) was created by Constitutional Amendment No. 45/2004 and installed in 2005 as an agency of the judiciary responsible for overseeing the administrative and financial management of the Brazilian judicial system, ensuring transparency, efficiency and best practices (BRASIL, 2004). It is composed of 15 members with two-year terms, including ministers of the STF, STJ and TST, judges, members of the Public Prosecution Service, lawyers and citizens appointed by Congress. It is chaired by the President of the STF and is headed by a minister of the STJ. Its functions include supervising administrative acts within the judiciary, receiving complaints against judges, reviewing disciplinary proceedings, and preparing reports on the performance of the judiciary in Brazil.

The Superior Courts are the highest courts within their respective branches of the judiciary and are composed of the Superior Court of Justice (STJ), the Superior Military

Court (STM), the Superior Electoral Court (TSE), and the Superior Labor Court (TST). Its members, known as ministers, are responsible for making important decisions. The STJ, which operates within the framework of ordinary justice (both state and federal) and deals with matters not directly related to the Constitution (infra-constitutional matters), is composed of 33 ministers. Its main task is to ensure uniformity in the interpretation of federal legislation, except for matters involving specialized courts, such as electoral and labor courts. According to Article 105 of the Constitution, one of the STJ's powers is to rule, through special appeals, on cases decided in the last or only instance by the Tribunais Regionais Federais, Tribunais de Justiça or Tribunais de Justiça Militar, when a decision contradicts federal legislation.

The Superior Electoral Court, composed of ministers from the STF, STJ, and legal experts, ensures the integrity of the electoral process by hearing appeals from decisions made by the Tribunais Regionais Eleitorais. The Superior Military Court, composed of general officers of the Armed Forces and civilians appointed by the Presidency, has the authority to hear appeals from military justice and to try general officers, including the possibility of ordering the loss of rank. Superior Labor Court (TST), composed of 27 ministers, standardizes labor-related decisions and hears appeals from audits, collective disputes, and other labor actions, in accordance with the Constitution.

The Brazilian Judiciary is made up of several branches, with the State Courts (Justiça Estadual) responsible for handling cases that are not assigned to other branches, such as the Federal, Labor, Electoral, and Military Courts. The structure of the Judiciary consists of two levels: the first instance, which includes state judges, and the second instance, represented by the Courts of Justice (Tribunais de Justiça – TJs). In the Courts of Justice, appellate judges (desembargadores) review appeals and original jurisdiction cases.

The State Courts form the largest branch of the system, dealing with most cases involving both citizens and businesses. Additionally, the State Courts incorporate Special Civil and Criminal Courts (Juizados Especiais), which were established by Law No. 9,099/1995 to manage less complex cases, such as small civil claims and minor criminal offenses.

The State Courts of Justice play a fundamental role in reviewing first-instance decisions. In the case of Minas Gerais, the Court of Justice of Minas Gerais (Tribunal de Justiça de Minas Gerais – TJMG) is the highest body of the State Judiciary in the state, responsible for ruling on appeals and managing the judicial organization of Minas Gerais.

It has the authority to review judgments, resolve jurisdictional disputes between state judges, and perform administrative functions such as appointing judges and organizing the operation of the judiciary. Furthermore, the TJMG plays a key role in overseeing the activities of first- and second-instance judges and in formulating policies aimed at improving the efficiency and speed of rulings in the state's judicial districts and civil and criminal courts.

1.2 Analysis of Judicial Demand

The demand for justice in Brazil has become one of the main challenges facing the judicial system, especially in the state courts, which handle the majority of cases in progress (CNJ, C. N. de J., 2020; CNJ, 2021b). This increase in the number of cases reflects, on the one hand, the expansion of access to justice and the growing tendency of citizens to resolve their disputes through the judicial system. On the other hand, it places a significant burden on the courts, resulting in case backlogs and delays in legal proceedings. According to the Justice in Numbers reports (CNJ, 2022, 2015, 2019, 2020, 2021)[1], both the number of new cases and the number of pending cases have been steadily increasing over the years, highlighting the need for effective strategies to optimize judicial management and ensure greater procedural speed.

Judicial delays have been recognized as a significant issue since the colonial period (Sadek, 2004). However, the enactment of the 1988 Constitution marked a notable expansion of individual and social rights, leading to a previously suppressed demand for justice. The slow pace of Brazil's judicial system affects both civil and criminal cases, resulting in serious consequences for society. In the civil realm, this sluggishness is particularly evident when compared to other countries. For instance, the average duration of a first-instance case in Brazil is three times longer than in Europe, taking 600 days compared to 232 days. Additionally, cases in the second instance take 50% longer in Brazil, averaging 320 days as opposed to 215 days in Europe (Castelliano; Guimaraes, 2023).

In the criminal justice system, delays undermine the effectiveness of the judiciary, resulting in the statute of limitations on crimes and a pervasive sense of impunity. On average, it takes 4 years and 4 months (1,570 days) to complete a criminal case in the first

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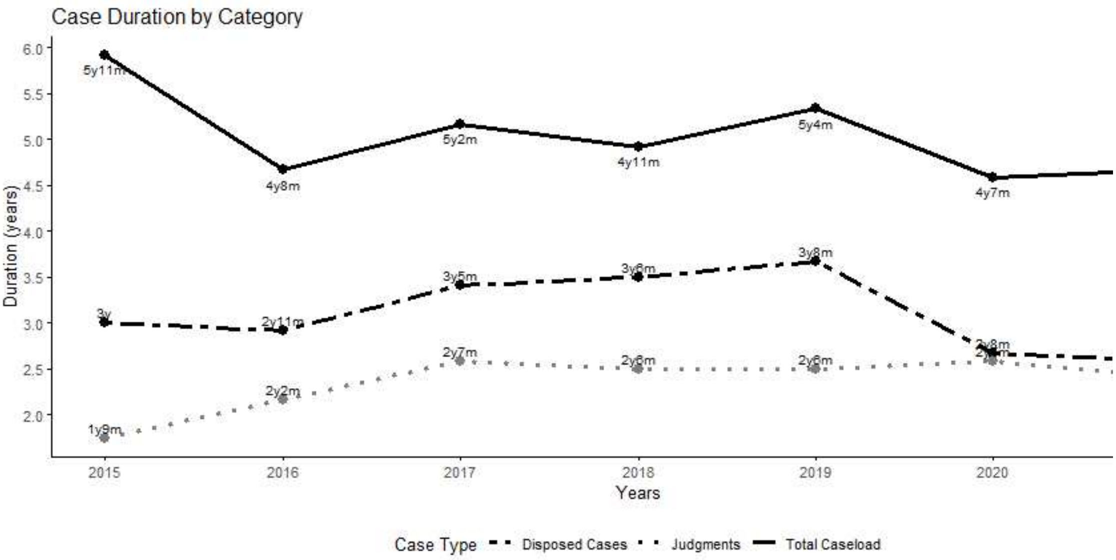
[1] Justice in Numbers reports available at: https://www.cnj.jus.br/pesquisas-judiciarias/justica-em-numeros/. Accessed on March 23, 2025.

instance of the state court system, and it can exceed 7 years (2,555 days) in cases of intentional homicide (CNJ, 2022). The problem of criminal delay is linked to the inability of the system to efficiently process the crimes brought before it, undermining its role in social control and fostering public distrust in the enforcement of the law (Ramos *et al.*, 2017).

Figure 2 shows the trend in case disposition times in the state court system between 2015 and 2021, based on data from the Justice in Numbers report. The number of cases resolved fluctuated over the period, ranging from 3 years in 2015 to 2 years and 7 months in 2021, with peaks in 2017 (3 years and 5 months) and 2019 (3 years and 8 months). The total case backlog, on the other hand, maintained higher processing times, reaching 5 years and 11 months in 2015 and ending the period at 4 years and 8 months, with intermediate increases and decreases. Sentences had shorter processing times than the other categories, ranging from 1 year and 9 months (2015) to 2 years and 7 months (2020), ending the period at 2 years and 5 months.

Figure 2 - Judicial Case Processing Time by Category in State Courts



Note: Author's elaboration based on the Justiça em Números report 2022.

Key factors contributing to this slowness include an excessive number of cases, judicial overload, and the complexity of the appellate system, which allows for multiple appeals and prolongs litigation. (Roque, 2011). Professional literature identifies two important concepts for analyzing judicial delay: legal delay, which pertains to the processing time defined by laws and procedural codes, and necessary delay, which represents the optimal timeframe needed to ensure both efficient case resolution and the protection of the rights of the parties involved.(Santos; Marques; Pedroso, 1995). A justice system is deemed more efficient when there is a smaller gap between the time a crime occurs and when justice is served. In criminal proceedings, a significant delay can hinder evidence collection and compromise the trial. Excessive time can weaken the reliability of witness testimony and may even lead to the expiration of the statute of limitations for the crime.

In addition to procedural and institutional obstacles, the culture of litigation remains prevalent in Brazil, and the adoption of alternative dispute resolution methods, such as conciliation and mediation, is low (Law No. 13,140/2015). Several initiatives have been and are being implemented to address this issue, including legislative reforms, increased investment in technology, and performance monitoring by the CNJ. However, despite these efforts, judicial delays persist, and a more comprehensive approach is needed to mitigate their impact and improve the efficiency of the system.

The growth in the demand for justice and the diversity of cases vary among the different courts in the country, considering factors such as social reality, population density and socio-economic conditions. To allow for a more equitable comparative analysis, the CNJ has adopted a segmentation that classifies courts as large, medium, and small, based on criteria such as total expenditures, number of new cases, pending cases, and number of judges and staff. This classification allows for a more accurate assessment of the structure and responsiveness of each court in the face of increasing demand.

Table 1 shows the ranking of the five largest state courts in Brazil, based on a score that considers variables such as total expenditures, number of new and pending cases, and number of judges and staff. The Tribunal de Justiça de São Paulo (TJSP) ranks first, with a score of 4.32, and stands out for its high volume of demands and allocated resources. It is followed by the Tribunal de Justiça de Minas Gerais (TJMG) with a score of 1.14, reflecting its large structure and the complexity of its jurisdiction. The Tribunal de Justiça do Rio de Janeiro (TJRJ) follows closely with a score of 1.09, followed by the Tribunal de Justiça do Paraná (TJPR) and the Tribunal de Justiça do Rio Grande do Sul (TJRS) with scores of 0.60 and 0.51, respectively.

Table 1 – Classification of State Judiciary Courts (Base Year 2020)

	Court	Score	Total Court Expenditure	New Cases	Pending Cases	Judges	Employees
1º	TJSP	4.32	12,088,192,307	4456839	19432935	2620	65179
2º	TJMG	1.14	6,396,561,674	1428480	3940277	1085	27334
3º	TJRJ	1.09	4,629,690,694	1461530	7897304	877	24629
4º	TJPR	0.6	2,723,588,046	1281624	3754090	929	18592
5º	TJRS	0.51	3,813,727,897	1095931	3035797	759	16603

Note: Author's elaboration based on the Justiça em Números report 2021.

These five courts manage the largest caseload in the state judiciary and play a significant role in the country's socio-economic landscape. Together, they serve 51% of Brazil's population and contribute to 64% of the nation’s gross domestic product (GDP). This illustrates the connection between judicial demand, economic development, and population density.(CNJ, 2021b).

In the specific case of the TJMG, in addition to the significant volume of cases, the territorial distribution of the state poses additional challenges to the administration of justice, as Minas Gerais has a high number of municipalities (853) and districts, spread across regions with different socio-economic characteristics. In this context, it is essential to adopt strategies to cope with the growing demand for justice, such as modernizing procedures, digitizing case files, and expanding the use of alternative dispute resolution methods. Measures such as these can help reduce case backlogs, making justice more efficient and accessible to the population.

1.3 Innovation in the Public Sector

Innovation in the public sector is generally understood as the introduction and application of new processes, products and services, as well as innovative methods and techniques in the delivery of public services (Criado *et al.*, 2021). These changes should lead to improvements in the efficiency, effectiveness and impact of the results delivered to society (Albury, 2005; Mulgan; Albury, 2003). According to Koch and Hauknes (2005), innovation is a new approach to social action implemented or led by an organization, unit, or department that departs from previous standards. The adoption of innovation in the public sector creates strategic opportunities for economic development, promoting social welfare, and even attracting investment (Acemoglu *et al.*, 2020; Avlonitis; Papastathopoulou; Gounaris, 2001; Banerjee *et al.*, 2020; Lichand; Soares, 2014).

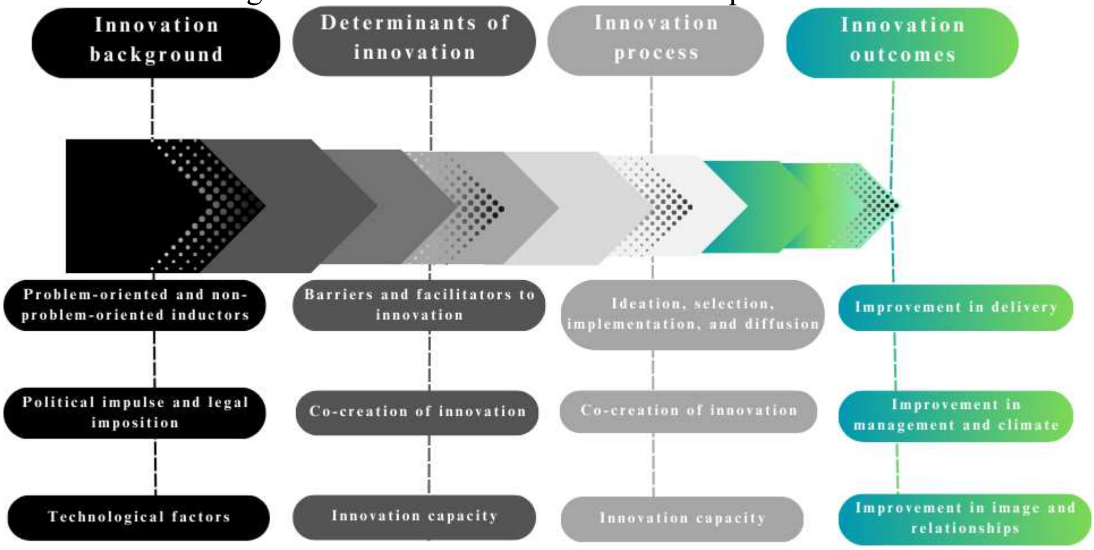
Studies such as Bloch and Bugge (2013), Bugge and Bloch (2016), and Arundel, Bloch and Ferguson (2016) have focused on deepening the understanding of innovation in the public sector, with an emphasis on creating indicators and analytical models to enable its measurement. One of the key challenges in this process is the creation of value through collaboration between the government and citizens. Crosby, t' Hart and Torfing (2017) emphasize that the complex problems of contemporary society, known as wicked problems, require collaborative approaches based on collaborative networks that involve multiple actors from both government and civil society. This perspective promotes the development of more sustainable solutions and increases the perception of public value.

Models and frameworks play a key role in structuring and classifying concepts related to innovation in the public sector (Isidro-Filho, 2017). According to the Organization for Economic Cooperation and Development (OECD, 2015), these tools help to organize and guide innovation strategies. Initiatives such as MEPIN in the Nordic countries, NESTA in the United Kingdom, and APSII in Australia exemplify efforts to develop conceptual and methodological approaches that enhance the understanding of innovation in the public sector.

The literature suggests that a broader theoretical framework on innovation can contribute to the consolidation of this topic in public administration (Djellal; Gallouj; Miles, 2013). In this context, the integrative approach to innovation, first proposed by Gallouj and Weinstein (1997), and later refined by Gallouj (2002), Gallouj *et al*. (2009), and Djellal *et al*. (2013), stands out. This model broadens the understanding of innovation in public services, especially in a scenario where the boundaries between the public and private sectors are increasingly blurred.

To analyze the implementation of the PJe system in the civil and criminal courts of the TJMG, it is essential to adopt a model that views innovation in the public sector as a dynamic process. The framework for the public sector innovation process is illustrated in Figure 3 below. This model serves as a reference for understanding how innovations such as PJe can be analyzed from a broad perspective, considering both the challenges and the factors that drive their adoption. The structure proposed by Bugge and Bloch (2016) provides a basis for this analysis by dividing innovation into four dimensions: innovation context, innovation determinants, innovation process, and innovation outcomes. However, the literature also highlights the influence of other factors, such as drivers, barriers, and facilitators, as well as co-production, co-creation, ideation, selection, implementation, and diffusion among the different actors involved.

Figure 3 - Innovation framework in the public sector



Note: Author's elaboration based on the model proposed by Isidro-Filho (2017).

According to the framework presented, innovation in the public sector is driven by a number of factors that precede its implementation, known as innovation drivers (Bloch, 2011). Studies such as those by Halvorsent *et al.* (2005), Koch and Hauknes (2005), Agolla and Lill (2013) classify these drivers into different categories. Problem-oriented drivers refer to the introduction of innovations in response to specific challenges, such as demographic changes or social crises. Non-problem drivers, on the other hand, are related to the continuous search for improvements even in the absence of a concrete problem. Finally, political drivers represent strategic changes in the public service that require firm decisions from top management, influenced by ideologies, critical events or institutional goals. Legal imposition also plays a key role in innovation, as norms, laws, or regulations can make the adoption of new public management practices mandatory. Finally, technological factors enable change by facilitating new ways of doing things, driven by the development and diffusion of information and communication technologies (ICTs).

In addition to the factors that drive innovation, Valladares *et al*. (2014) show that the organization's ability to translate these motivations into concrete actions is a central element of the process. Transformational leadership plays a crucial role in mobilizing employees beyond their individual interests and promoting a collective vision focused on innovation. The strategic intent to innovate reflects the organization's willingness to take risks and promote structural change, while people management for innovation aims to ensure autonomy, set challenging goals, and stimulate the engagement of public servants. Another fundamental aspect is knowledge of the user and the environment, so that innovations can be adapted to the real needs of society. Strategic management of technology enables effective planning for the creation and implementation of new solutions, complemented by the organic nature of the organizational structure, which promotes autonomy, flexibility and efficient communication. Finally, project management plays an essential role in the planning, execution and monitoring of innovative initiatives, ensuring their feasibility and positive impact.

The innovation process in the public sector involves the operationalization of these changes, from conception and planning to implementation and continuous improvement. This process is not linear, but rather involves experimentation, stakeholder involvement, and constant adaptation. Frequent evaluation and strategic adjustments are necessary to ensure that innovation achieves its goals and delivers the expected benefits.

The results of innovation can be observed at different levels within public administration (Bloch; Bugge, 2013; Bloch, 2011). One of the most important effects is the improvement of service delivery and quality, ensuring greater efficiency and user satisfaction. In addition, improvements in organizational management can be seen in increased productivity and progress in performance indicators. Another positive effect of innovation is the improvement of the organization's image and institutional relationships, strengthening its reputation and expanding its capacity to build partnerships and address social challenges. Finally, innovation can also have internal effects, promoting improvements in the organizational climate by providing better working conditions, increasing employee satisfaction, and strengthening an organizational culture focused on innovation (Ferreira *et al.*, 2015).

In the context of the TJMG, the implementation of PJe can be analyzed in light of this innovation framework. The implementation of PJe was driven by a number of factors, including political impetus, with the search for greater efficiency and modernization of the judiciary; technological factors, enabled by advances in information and communication technologies (ICTs); and legal imposition, with regulations that required the digitization of judicial processes (CNJ, 2013; Dewantoro; Busro; Priyono, 2023; Silva; Souza, 2015; TJMG, 2012). TJMG's innovation capacity was critical to the implementation of the system, which involved transformational leadership, strategic management of technology, and project management to ensure an efficient transition.

The change was not without challenges. The implementation of the PJe system faced resistance from various stakeholders in the justice system, including judges, clerks, and lawyers. These individuals had to adapt to new routines, modify their workflows, and navigate initial operational difficulties. (Tres; Ferretti, 2015). In addition, issues such as system instability, the need for continuous training, and disparities in access to and proficiency with new technologies were barriers to implementation (Barros, 2020).

Although challenges remain, the adaptation to PJe is gradually progressing, with training, technical support and system adjustments aimed at its consolidation (CNJ, 2020). The implementation of PJe also strengthens the institutional image of the TJMG, demonstrating its commitment to modernizing the judiciary and promoting new ways of working and collaborating. In this way, the digitization of the judicial process is an example of how innovation in the public sector can transform traditional structures, although its full functionality and acceptance are still evolving challenges.

The model adopted provides a structured view of digital transformation in the justice system, considering the actors involved, institutional practices and expected impacts. It is an approach that seeks to map the challenges and changes resulting from the digitization of processes, highlighting how modernization can redefine the functioning of the courts. Although there are limitations in evaluating the impact of PJe, the study of this innovation process contributes to the improvement of public management and deepens the discussion on innovation in the Brazilian justice sector.

1.4 Methodology

1.4.1 Data

To identify the determinants associated with the implementation of the PJe system in first-instance courts under the jurisdiction of the TJMG, a panel dataset was constructed at the court-year level. The data cover the period from 2015 to 2021 and include 293 municipalities in Minas Gerais with active judicial courts. The dependent variable is a binary indicator that takes the value 1 from the year in which a court adopts the PJe system—counting the year of implementation itself—and remains at 1 in all subsequent years. It takes the value 0 in all years prior to adoption. This variable was constructed based on official information released by the TJMG, which provides a detailed implementation schedule for the electronic system, including the name of each judicial unit and its respective activation date. These records made it possible to build a novel dataset tracing the annual digitalization trajectory of each court in the state.

Additionally, the data from TJMG and the Justiça Aberta platform classify first-instance courts according to their jurisdiction, distinguishing between criminal and non-criminal courts (CNJ, 2021). The criminal category refers to courts and cases that fall under the criminal sphere, while the non-criminal category primarily pertains to civil matters, including courts and cases related to family, inheritance, juvenile justice, public administration, among others. Based on this distinction, two dummy variables were created: one for the implementation of PJe in civil courts and another for criminal courts, derived from the name of the judicial unit. The records indicate that the implementation of PJe in civil courts began in 2012 with a pilot project in the judicial units of the Barreiro region in Belo Horizonte, and it was gradually expanded to cover all civil courts in the state by 2021. On the other hand, PJe in criminal courts started to be implemented only in 2020, and was also completed in 2021, with full coverage of criminal courts.

To investigate the factors associated with the adoption of PJe, a set of explanatory variables was selected based on hypotheses grounded in the literature and the CNJ's guidelines on resource allocation in the judiciary. As shown in Table 2, we used: (i) the average Internet speed in the municipality (in Mbps), obtained from the ANATEL database, as a proxy for the quality of the digital infrastructure - a crucial aspect for the operation of the electronic system; (ii) the logarithm of the real GDP per capita, obtained from the Instituto Brasileiro de Geografia e Estatística (IBGE), as an indicator of the level of local economic development; (iii) the logarithm of population density; and (iv) the formal employment rate, both derived from data from the João Pinheiro Foundation (FJP), used to capture the degree of urbanization and the dynamics of the local labor market - characteristics that may influence both the demand for judicial services and the institutional capacity to absorb technological innovations.

Table 2 - Data

Outcome	**Description**	**Source**
$\boldsymbol{PJe_{i,t}}$	A dummy variable equal to 1 if the Processo Judicial Eletrônico (PJe) was implemented in the court located in municipality i in year t, and 0 otherwise.	TJMG
Independent variables ($\mathbf{X_{i,t}}$)	**Description**	**Source**
ln(Average internet speed)	Proxy for the quality of internet infrastructure in the municipality where the court is located, with annual measurements in Mbps.	ANATEL
Number of court in the judicial district	Total number of courts within the judicial district, representing the yearly sum of courts (varas) in each comarca.	CNJ
Number of judges in the judicial district	Sum of all judges working in the courts within the judicial district	CNJ
ln(per capita GDP)	Natural logarithm of the annual per capita gross domestic product of each municipality.	IBGE
ln(Population density)	Natural logarithm of the population per square kilometer in each municipality, measured annually	FJP
Employment rate	Annual municipal employment rate, calculated as the percentage of formally employed individuals relative to the working-age population (16–64 years old)	FJP
Microregion dummy	Variable controlling for fixed effects of microregions in the state of Minas Gerais.	IBGE

Note: This table presents the description and data sources of the variables used in the analysis. All variables are based on secondary data and are measured annually at the municipal level. Some variables were constructed by the author using raw data from CNJ, TJM, IBGE, ANATEL, and FJP.

A logarithmic transformation was applied to some continuous variables - specifically, GDP per capita, average Internet speed, and population density - with the aim of reducing the influence of extreme values and improving the interpretation of the estimated coefficients in the model. By using the logarithm of these variables, it was possible to interpret the results in terms of percentage changes, which facilitated the analysis of the relative impact on the likelihood of PJe implementation. This approach also helped to linearize the relationships between the explanatory variables and the dependent variable, thus better satisfying the assumptions of the econometric model. On the other hand, the formal employment rate, as originally expressed in percentages, did not require any additional transformation, since its values are already on an appropriate scale for comparative analysis across municipalities.

In addition to the socio-economic variables, institutional factors were also considered. The number of courts and the number of judges in each jurisdiction were obtained from the CNJ's Justiça Aberta data, representing the institutional size of the local judicial structure. It is assumed that jurisdictions with a larger structure tend to have more conditions and incentives to promote the implementation of technological innovations such as the PJe. We also included dummy variables for micro-regions, as defined by the IBGE, to control for territorial fixed effects that may influence implementation independently of observable characteristics-such as centralized administrative decisions, regional priorities of the TJMG, or local logistical constraints.

The construction of this database involved integrating sources with varying levels of aggregation. While the data on the implementation of the PJe is at the judicial court level, the socio-economic variables are at the municipal level. Cross-referencing this information enabled an unprecedented analysis of the factors that may have influenced the dissemination of the PJe in the judicial courts of TJMG, particularly within a state context characterized by significant territorial and institutional diversity.

During the data processing, we excluded second-instance judicial units, offices, and courts that had duplicate identification codes from the dataset. As a result, the final dataset includes only civil, criminal, and special courts, which enhances the consistency and homogeneity of the analysis regarding the implementation of the PJe within the first instance of the TJMG. It is important to note that the resulting panel is unbalanced; not all courts are represented in every year of the analyzed period. This reflects the dynamics of the creation, dissolution, or lack of records for certain units over time.

For the analysis of the factors associated with the implementation of the PJe in civil courts, the period from 2015 to 2021 was examined, based on the annual implementation data provided by the TJMG. This timeframe allows us to observe the variations in the adoption of the system over time, as the expansion of the civil PJe occurred gradually and unevenly among different courts and municipalities.

In contrast, the implementation of the PJe in criminal courts happened more uniformly, with data indicating that all units within this jurisdiction began using the system between 2020 and 2021, and none adopted it before 2020. As a result, since all criminal courts had already implemented the system by 2021, the dependent variable only shows variation for the year 2020. Therefore, the analysis of the factors influencing PJe implementation in criminal courts was limited to a cross-sectional study for that year.

In the next section, the empirical strategy used to estimate the effects of these variables on the probability of PJe implementation in civil and criminal courts is presented.

1.4.2 Estimation

Wooldridge (2016) posits that when the dependent variable is binary — as is the case with the PJe — it is possible to employ both linear probability models (LPM) and nonlinear models, such as the Logit model, to estimate the effects of explanatory variables. Despite the limitations of the linear model, including the potential for predicting probabilities outside the [0,1] interval, it offers simple and easily interpretable estimates. Furthermore, the linear model demonstrates robustness under specific structural specifications, particularly in scenarios involving large samples with the incorporation of fixed effects and robust standard errors.

In this study, a linear probability model (LPM) was estimated to examine the relationship between municipalities' socioeconomic and institutional characteristics and the implementation of the Electronic Justice System (PJe) in first-instance courts of the Tribunal de Justiça de Minas Gerais (TJMG).The fundamental specification of the model is outlined in Equation (1), excluding the incorporation of fixed effects:

$$PJe_{i,t} = \beta_0 + \boldsymbol{\beta} \cdot \mathbf{X}_{i,t} + \varepsilon_{i,t} \qquad (1)$$

In this specification, the dependent variable $PJe_{i,t}$ is a binary indicator that equals 1 if court i (civil or criminal) implemented the PJe in year t, and 0 otherwise. The vector $\mathbf{X}_{i,t}$ represents the set of explanatory variables presented in Table 2, which includes municipalities' socioeconomic and institutional characteristics. The coefficient vector $\boldsymbol{\beta}$ captures the magnitude and the correlation between these variables and the probability of PJe implementation. Finally, $\varepsilon_{i,t}$ is the idiosyncratic error term, accounting for unobserved factors not controlled for in the model, which vary across units and over time.

We then refine the model by including two-way fixed effects (TWFE) for microregion θ_i and year λ_t, as shown in Equation (2). This approach aims to control unobservable factors that are time-invariant within each territory, as well as shocks that are common to all municipalities in specific years—such as centralized policies from the TJMG, guidelines issued by the CNJ, or external events like the COVID-19 pandemic:

$$PJe_{i,t} = \beta_0 + \boldsymbol{\beta} \cdot \mathbf{X}_{i,t} + \theta_i + \lambda_t + \varepsilon_{i,t} \qquad (2)$$

As a complementary and robustness analysis, we also estimate a Logit model, which accounts for the nonlinear nature of the dependent variable and models the probability of a court adopting the PJe as a logistic function of the covariates. The general specification with fixed effects is given by:

$$P(PJe_{i,t} = 1 | X_{i,t}, \theta_i, \lambda_t) = \frac{1}{1 + e^{-(\boldsymbol{\beta} \cdot \mathbf{X}_{i,t} + \theta_i + \lambda_t + \varepsilon_{i,t})}} \quad (3)$$

The coefficients of the Logit model are presented in terms of *odds ratios*, thereby facilitating a more direct interpretation of the proportional effect of each explanatory variable on the likelihood of PJe adoption. In all models, robust standard errors are employed to account for potential heteroskedasticity (Bertrand; Duflo; Mullainathan, 2004; Wooldridge, 2012, 2016).

1.5 Results

1.5.1 Descriptive Analysis

Table 3 displays the percentage of PJe implementation in the civil and criminal courts of the TJMG from 2015 to 2021 within the sample. Part A of the table pertains to the civil courts, while Part B exclusively addresses the criminal courts.

An examination of the civil courts shows a gradual expansion of the system over time. In 2015, the implementation of the PJe was observed in only 21.2% of the units, while 78.8% continued to rely on non-electronic systems.Subsequent years witnessed a steady rise in the proportion of courts adopting PJe, with a significant surge in 2018 and 2019, when the proportion of treated courts exceeded 40% and 85%, respectively. By 2021, the adoption of PJe by all civil courts had been completed, resulting in comprehensive coverage of the system for this category.

Table 3 - Summary

Year		Percent
Part A: Civil		
2015	Control	78,8%
	Treat	21,20%
2016	Control	70,41%
	Treat	29,59%
2017	Control	65,05%
	Treat	34,95%
2018	Control	59,39%
	Treat	40,61%
2019	Control	14,23%
	Treat	85,77%
2020	Control	14,88%
	Treat	85,12%
2021	Treat	100%
Part B: Criminal		
2020	Control	93,58%
	Treat	6,42%
2021	Treat	100%

Note: Data from the TJMG.

In criminal courts, the implementation pattern is markedly different. As previously mentioned, the adoption of PJe in this jurisdiction commenced in 2020 (TMJ, 2025). In that year, the utilization of PJe was minimal, with only 6.4% of criminal courts adopting the system. However, a notable surge occurred in 2021, with the adoption rate reaching 100%, indicating a more recent and concentrated implementation process within a brief time frame. This temporal dynamic highlights the phased implementation of public policy in civil courts, in contrast to its simultaneous implementation in criminal courts.

Furthermore, Table 4 presents the descriptive statistics of the independent variables utilized in the analysis. The data refers to the set of observations available between 2015 and 2021, totaling 5,574 observations in the unbalanced panel of first-instance judicial courts of the TJMG.

The average internet speed in the municipalities, measured in logarithmic form, has a mean of 9.18 with a standard deviation of 0.48, indicating a relative homogeneity in the digital infrastructure across the municipalities in the sample. The mean number of courts per jurisdiction is 15.52, with a high dispersion (standard deviation of 27.91), reflecting the heterogeneity in the institutional size of the judicial units. This variation is also observed in the number of judges per jurisdiction, with a mean of 30.93 and a standard deviation of 58.89.

Table 4 - Descriptive statistics of independent variables

Variables	Mean	Std. Dev.	N. of obs.
ln(Average internet speed)	9,18	0,48	5574
Number of court in the judicial district	15,52	27,91	5574
Number of judges in the judicial district	30,93	58,89	5574
ln(per capita GDP)	10,35	0,50	5574
ln(Population density)	4,96	1,99	5574
Employment rate	33,53	16,06	5574
Number of civil courts	723		
Number of criminal courts	412		
Number of comarcas	293		

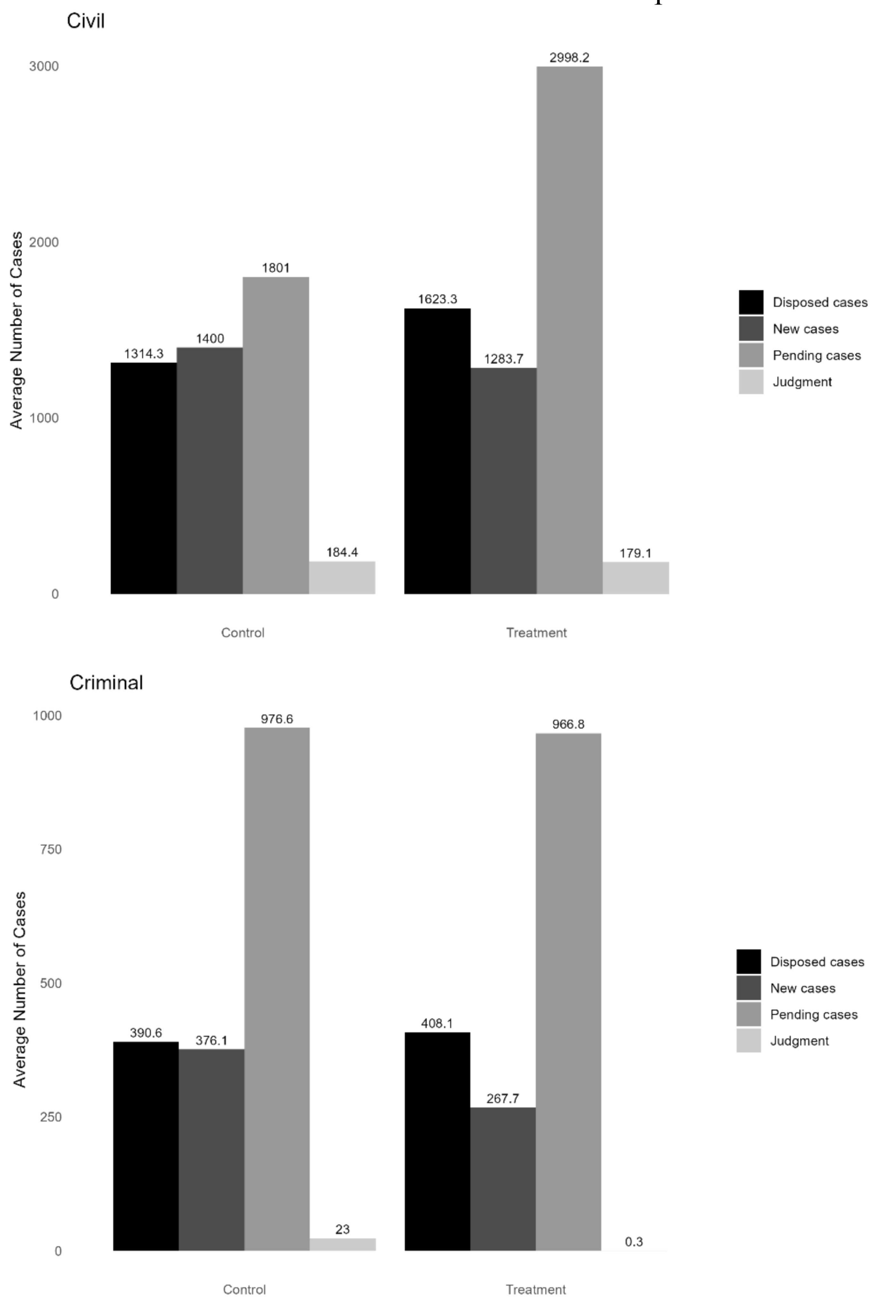
Note: Data from Agência Nacional de Telecomunicação (Anatel), Justiça Aberta (CNJ), Instituto Brasileiro de Geografia e Estatística (IBGE), and Fundação João Pinheiro (FJP).

The logarithm of GDP per capita has a mean of 10.35 and a standard deviation of 0.50, which captures moderate differences in the level of local economic development. The logarithm of population density, expressed in a similar fashion, has a mean of 4.96 and greater variation (standard deviation of 1.99), highlighting stark contrasts between municipalities with a more urban profile and those with a more rural profile. The average formal employment rate in the municipalities is 33.53%, with a standard deviation of 16.06, indicating disparities in the population's integration into the labor market.

A total of 723 civil courts and 412 criminal courts were subjected to analysis, dispersed across 293 jurisdictions. These data underscore the structural diversity of the judiciary in Minas Gerais and underscore the importance of controlling territorial and institutional characteristics when analyzing the factors associated with the implementation of PJe.

An exploratory analysis of the case load between the treated and control groups was conducted, and Figure 4 presents comparisons of the average number of disposed cases, new cases, pending cases, and judgment in the civil and criminal courts. A preliminary examination of the civil courts reveals that the average number of disposed cases increased after treatment, rising from 1,314.3 in the control group to 1,623.3 in the treated courts. This growth may be indicative of an augmented capacity to finalize cases. Conversely, the average number of new cases was lower in the treated courts (1,128.7) compared to the control courts (1,400), which could be indicative of a change in the volume of new filings or in the distribution of cases. Conversely, the average number of pending cases exhibited a substantial increase, rising from 1,801 in the control group to 2,998.2 in the treated group, suggesting the accumulation of ongoing cases. With regard to rulings, a slight decrease was observed in the treated courts, with an average of 179.1 compared to 184.4 in the control courts, suggesting stability or a modest decline in the number of decisions rendered.

Figure 4 - Comparison of Average Disposed, Pending, New Cases, and Judgments Between Treated and Control Groups



Note: Data from Justiça Aberta (CNJ). The graphs display the average number of new cases, pending cases, disposed cases, and judgments in the civil and criminal courts, comparing the control and treated groups before and after the adoption of PJe. The averages were calculated based on data per court and period.

As illustrated in the second graph of the figure, the average case load of criminal courts is typically lower compared to civil courts. This disparity can be attributed to the fact that criminal courts are primarily concerned with a more limited range of subjects, including criminal offenses, criminal execution, precautionary measures, and custody hearings. In contrast, civil courts encompass a broader array of subjects, frequently encompassing more intricate cases and a substantial volume of documentation. Notwithstanding, an intriguing trend is evident in the criminal courts: the average number of disposed cases exhibited a slight increase in the treated courts, from 390.6 to 408.1. Conversely, the entry of new cases was lower in the treated courts (267.7) compared to the control courts (376.1), suggesting a possible decrease in demand or operational changes. The average number of pending cases exhibited a modest decline, from 976.6 to 966.8.

The most notable difference between the two groups in the criminal courts is the average number of judgments rendered. The control group had an average of 23 judgments, while the treated courts experienced a significant decrease, with an average of only 0.3 judgments. This sharp decline may indicate operational challenges, changes in how decisions are documented, or variations in the implementation of the treatment in these courts. Comparing the civil and criminal areas shows that the treatment's impact varied considerably, which can be partially attributed to the unique characteristics of each branch of the judiciary and the types of cases they handle.

1.5.2 Empirical Results

1.5.2.1 Civil Courts

The main variable of interest is the logarithm of the average internet speed in the municipality where the court is located. The rationale for choosing this variable stems from the central hypothesis that local digital infrastructure is a crucial factor for enabling the adoption of technological solutions in the justice system, such as PJe (Gomes; Freitas, 2017; Silva; Souza, 2015). In this sense, municipalities with better connectivity tend to have more favorable conditions for the digitalization of public services, including judicial services.

Column 1 of Table 5 presents the results of the basic model, as specified in Equation 1. This model does not include additional controls or fixed effects, as it aims to capture the correlation between local internet quality and the implementation of the electronic system in civil courts. The estimated coefficient for the logarithm of internet speed is positive and statistically significant at the 1% level, with a value of 0.628. This suggests that a 1% increase in average internet speed is associated with a 0.628 percentage point increase in the likelihood of adopting the electronic system (PJe) in each civil court. Although this specification is relatively simple, it already indicates a strong positive relationship between digital infrastructure and judicial modernization.

In Column 2, relevant institutional controls are included, such as the number of courts and the number of judges in the judicial district where the unit is located. This inclusion aims to control for characteristics of the justice system itself that may influence the decision to implement PJe. The inclusion of these controls does not substantially alter the coefficient of the main variable, which remains virtually unchanged (0.622), reinforcing the robustness of the observed association. The number of courts per jurisdiction is positively associated with PJe adoption, suggesting that judicial districts with larger institutional size are more likely to modernize. On the other hand, the number of judges does not show a significant effect in this model, which may indicate that the number of magistrates alone is not a direct determinant of technological implementation, at least at this stage of the analysis.

Table 5 - LPM Results (Civil Courts)

	Model 1	Model 2	Model 3	Model 4	Model 5
ln(Average internet speed)	0.638***	0.622***	0.605***	0.626***	0.199***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Number of court in the judicial district		0.622***	0.605***	0.626***	0.199***
		(0.010)	(0.012)	(0.012)	(0.019)
Number of judges in the judicial district		0.00	-0.00	-0.00	-0.05***
		(0.00)	(0.00)	(0.00)	(0.00)
ln(per capita GDP)			0.147***	0.179***	0.080***
			(0.018)	(0.025)	(0.019)
ln(Population density)			0.004	0.030***	0.088***
			(0.005)	(0.008)	(0.007)
Employment rate			-0.01***	-0.01***	-0.003**
			(0.001)	(0.001)	(0.001)
Intercept	-5.11***	-5.06***	-6.17***	-6.85***	-2.76***
	(0.089)	(0.094)	(0.163)	(0.220)	(0.229)
Year	NO	NO	NO	NO	YES
Microregion	NO	NO	NO	YES	YES
R^2	0.407	0.407	0.420	0.455	0.606
R^2 Adj.	0.406	0.406	0.419	0.446	0.599
AIC	4134.1	4136.0	4035.7	3874.0	2314.8
BIC	4153.6	4168.5	4087.5	4373.3	2852.9
RMSE	0.37	0.37	0.37	0.36	0.30
Num.Obs.	4833	4833	4833	4833	4833

Note: Models 1 to 3 follow the specification of Equation (1), while Models 4 and 5 use the specification of Equation (2). The estimates were obtained using the Linear Probability Model (LPM), with robust standard errors in parentheses. *** denotes $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Model 3 enhances the analysis by incorporating socio-economic variables of the municipalities, including GDP per capita, population density, and employment rate. These variables are important for assessing the level of local development, which may indicate both a higher demand for judicial services and improved conditions for the implementation of new technologies. With these controls in place, the coefficient for Internet speed remains positive and significant (0.605), though slightly lower than in the previous model. Additionally, GDP per capita is positively associated with the likelihood of PJe adoption, aligning with the literature that connects greater municipal economic capacity to enhanced institutional and technological capabilities. (CNJ, 2021b). Population density, although having a positive coefficient, only becomes statistically significant in models with fixed effects. The employment rate, on the other hand, shows a negative association, which may reflect, among other things, different patterns in the municipal productive structure that do not necessarily translate into a greater capacity to absorb innovation in the public sector.

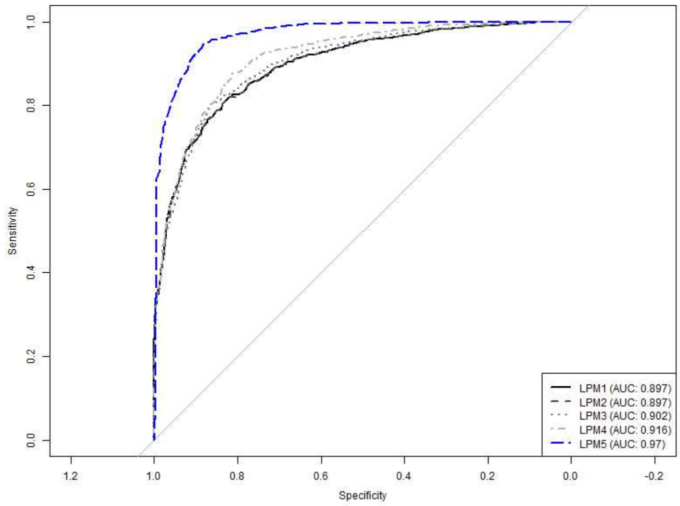
Starting in column 4, the model includes fixed effects for microregions to account for unobservable characteristics that remain constant over time within each microregion, such as legal culture, local judicial administration, and historical patterns of court operations. By including these effects, we can make more rigorous comparisons between civil courts located in similar territorial contexts. In this specification, the coefficient for the variable of interest stays virtually unchanged at 0.626, indicating that even within the same microregion, internet speed remains a significant factor correlated with the adoption of the PJe system. This reinforces the idea that digital infrastructure independently plays a crucial role in the diffusion of technology within the justice system.

Finally, column 5 presents the most complete model, which includes two-way fixed effects for microregion and year. This specification is particularly relevant because it simultaneously controls for unobservable and time-invariant factors within the area, as well as common shocks over time, such as normative changes promoted by the CNJ, centralized investments in infrastructure, or the COVID-19 pandemic itself, which may have accelerated digitization in various areas. In this specification, the coefficient on Internet speed is reduced to 0.199, although it remains statistically significant at the 1% level. This reduction in magnitude suggests that some of the initially observed association may be due to fixed factors in time and space. Nevertheless, the result reinforces the robustness of the relationship between local connectivity and technology adoption in civil courts, even after controlling for strict fixed effects.

Regarding the quality of the models, a progressive improvement in fit is observed as explanatory variables and fixed effects are added. The adjusted R^2 increases from 0.406 in Model 1 to 0.599 in Model 5, reflecting the greater explanatory power of the more complete models. Similarly, the Root Mean Square Error (RMSE) decreases significantly from 0.37 to 0.30, indicating an improvement in predictive accuracy. The AIC and BIC metrics also show a sharp decrease, especially in Model 5, confirming the superiority of the fixed effects models in terms of parsimony and statistical fit.

In addition to the analysis of the estimated coefficients and traditional model fit metrics, Figure 5 presents the Receiver Operating Characteristic (ROC) curves corresponding to each of the estimated specifications, allowing for a more precise evaluation of the discriminatory ability of the models, that is, their ability to correctly classify cases of PJe adoption and non-adoption in the civil courts.

Figure 5- Predictive performance (ROC Curves) of LPM specifications (Civil Courts)



Note: ROC curves were constructed based on the predicted probabilities generated by Linear Probability Models (LPM). Although LPMs do not impose a probabilistic functional form, the fitted values can be interpreted as predicted probabilities for binary outcomes. The ROC curve assesses the predictive accuracy of each model specification by plotting the true positive rate against the false positive rate across various thresholds. Higher AUC values indicate better model discrimination performance.

The area under the curve (AUC) values confirms the predictive quality of the models, even in the more parsimonious stages of the analysis. Model 1 already shows an AUC of 0.897, indicating a high degree of accuracy in the binary classification of outcomes, even without the inclusion of additional controls. The performance is maintained in model 2, with an AUC also equal to 0.897, suggesting that the inclusion of institutional variables, although theoretically relevant, does not substantially alter the classificatory ability of the model compared to the basic structure.

The introduction of socio-economic variables in Model 3 results in a slight improvement in accuracy, as evidenced by an increase in the AUC to 0.902. This modest increase signifies an enhancement in predictive capacity when considering the structural characteristics of the municipalities.

The most significant gains occur from model 4 onwards, with the introduction of fixed effects by microregion, which increases the AUC to 0.916. This improvement highlights the importance of controlling for fixed spatial heterogeneities, which can capture institutional, cultural, and historical aspects that influence the propensity to innovate in territories. Finally, Model 5, which simultaneously includes fixed effects by microregion and year, achieves an AUC of 0.970, indicating very high predictive accuracy. This result suggests that the combination of local digital infrastructure, institutional and socioeconomic variables, along with the control of fixed effects over time and space, is highly effective in predicting the adoption of PJe in Minas Gerais civil courts.

To verify the robustness of the results obtained with the LPM model, equation (3) was also estimated using the logit specification, which has the mainors constant. This effect increases to 139.01 in Model 2 and 154.11 in Model 3, when the institutional and socioeconomic variables are included.

The results are even more pronounced in Model 4, which controls for microregion fixed effects, with the odds ratio reaching 385.33, reflecting the high sensitivity of PJe adoption to improvements in digital infrastructure, even after controlling for regional heterogeneity. However, a sharp reduction in the odds ratio is observed in model 5, dropping to 5.66 when year fixed effects are also included. Although smaller in magnitude, this value remains statistically significant, reinforcing the interpretation that access to high-speed internet remains an important factor associated with the digitization of civil courts, even after controlling unobserved temporal shocks.

The other variables also show results consistent with those obtained in the previous estimations. The logarithm of GDP per capita shows significant positive effects, indicating that courts located in more economically developed municipalities are more likely to adopt PJe. Population density and the employment rate also show statistically significant effects in some models, although with fluctuations in the odds ratios and less consistency across specifications. The institutional variables (number of courts and number of judges in jurisdictions) are not statistically significant in most specifications, except in Model 5, where the number of judges is positively associated with adoption, with an odds ratio of 9.79.

These findings support the thesis that local digital infrastructure is a crucial element in modernizing the judiciary through the implementation of the PJe system. Additionally, the consistency between the LPM and logit models reinforces the robustness of the empirical results, further validating the conclusions drawn from the main analysis. The substantial estimated effects observed in both models indicate a clear pattern: access to high-quality internet plays a fundamental role in the digitization of civil justice from 2015 to 2021. This body of empirical evidence enhances our understanding of the structural factors that influence the capacity for technological adoption within the state judiciary.

This evidence carries significant implications for the design and implementation of public policies aimed at modernizing the justice system, particularly in large state courts like the TJMG. They suggest that expanding local digital connectivity can facilitate the adoption of technological solutions such as PJe, thereby contributing to the modernization of the justice system and potentially improving accessibility.

The next section discusses the findings in relation to criminal courts. This will allow us to assess whether this pattern is reproduced in another area of judicial activity or whether there are specific features to be considered.

1.5.2.2 Criminal Courts

The dynamics of PJe implementation in criminal courts differ significantly from those in civil courts. In civil courts, the adoption process occurred gradually from 2015 to 2021. In contrast, the implementation of the system in criminal courts was concentrated primarily in the last two years of the study period—2020 and 2021—culminating in full system adoption in 2021. Consequently, for the statistical analysis of the local factors influencing PJe adoption in criminal courts, only data from 2020 were utilized. This period allowed for the observation of variations in adoption, enabling the estimation of cross-sectional models.

Table 6 presents the estimation results for criminal courts based on equations (1) and (2), using the LPM model. Models 1, 2 and 3 are based on equation (1) and progressively include explanatory variables of an institutional and socio-economic nature. Model 4 introduces microregion fixed effects, as specified in equation (2), to control for unobservable area-specific characteristics that may simultaneously influence both the probability of system adoption and local conditions.

It is important to note that, unlike the findings related to civil courts, the Internet proxy variable does not have a statistically significant impact on the adoption of PJe in any of the models analyzed. While the coefficient does become positive starting from Model 3, the p-value remains above conventional levels of significance. This lack of significance may be attributed to the more uniform and top-down approach to PJe implementation within the criminal justice system, especially considering the institutional push for digitization during the COVID-19 pandemic.

Table 6 - LPM Results (Criminal Courts)

Criminal	Model 1	Model 2	Model 3	Model 4
ln(Average internet speed)	-0.081	-0.077	0.036	-0.004
	(0.052)	(0.060)	(0.070)	(0.060)
Number of court in the judicial district		0.001	0.005	0.000
		(0.004)	(0.004)	(0.004)
Number of judges in the judicial district		-0.001	-0.002	-0.000
		(0.002)	(0.002)	(0.002)
ln(per capita GDP)			-0.088**	0.018
			(0.034)	(0.031)
ln(Population density)			-0.013	0.008
			(0.012)	(0.011)
Employment rate			-0.002	-0.001
			(0.002)	(0.001)
Intercept	0.815	0.777	0.736	-0.114
	(0.483)	(0.553)	(0.666)	(0.610)
Microregion	NO	NO	NO	YES
R^2	0.009	0.009	0.067	0.542
R^2 Adj.	0.006	0.002	0.053	0.439
AIC	12.9	16.8	-1.8	-153.5
BIC	25.0	36.8	30.2	150.8
RMSE	0.24	0.24	0.24	0.17
Num.Obs.	405	405	405	405

Note: Models 1 to 3 follow the specification of Equation (1), while Model 4 use the specification of Equation (2). The estimates were obtained using the Linear Probability Model (LPM), with robust standard errors in parentheses. *** denotes $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

The adoption of PJe in criminal courts in 2020 seems to be influenced more by centralized administrative decisions than by local conditions. This conclusion is supported by the low adjusted R^2 values in the first three models, which range from 0.002 to 0.053. These values indicate that the institutional and socio-economic factors analyzed account for only a small portion of the variation in system adoption. However, Model 4, which incorporates microregion fixed effects, shows a significant increase in the adjusted R^2 to 0.439. This suggests that important structural differences between regions affect the likelihood of adoption, even if these differences are not directly represented by the included variables.

Among the control variables used, only the natural logarithm of GDP per capita (ln(GDP per capita)) showed a statistically significant coefficient in Model 3, and it has a negative sign. At first glance, this result may appear counterintuitive; however, it could suggest that poorer municipalities were prioritized in the implementation of the Electronic Judicial Process (PJe) in criminal courts. This prioritization could be based on need or as part of a policy aimed at technological equalization. Alternatively, this finding might reflect the inflexibility of the system's implementation policy, which did not necessarily follow a diffusion pattern aligned with local levels of development, as seen in civil courts.

As part of a robustness check, we estimated equation (3) using the logit model to verify whether the results obtained from the linear probability model (LPM) are consistent with a non-linear approach, which is more suitable for binary dependent variables. The results can be found in Appendix A, Table 8, and they follow the same incremental structure as the previous estimates. This includes institutional and socio-economic controls, as well as micro-regional fixed effects in Model 4.

Overall, the coefficients estimated in the logit model align with the effects identified in the LPM model. Specifically, the variable average internet speed, which showed a positive but statistically insignificant coefficient in the LPM, maintains this trend in the logit specification. However, the magnitude of the coefficients varies significantly between the models. This pattern indicates that the relationship between internet speed and the use of the PJe system in criminal courts may not be statistically robust, regardless of the methodology employed.

The introduction of institutional controls (number of courts and number of judges per district) and socio-economic controls (GDP per capita, population density and employment rate) does not significantly alter the results. Only a few coefficients reach statistical significance, the most notable being the natural logarithm of GDP per capita in model 3. However, the value of the odds ratio (5.99) indicates an overly sensitive relationship and is difficult to interpret in practice, given the associated standard error (8.70). This pattern suggests that the local determinants included in the models do not adequately explain the variation in the adoption of the PJe across criminal courts, confirming previous findings that the implementation policy was more uniform and centralized in this segment.

The introduction of microregion fixed effects in model 4 leads to a sharp decline in the quality of the fit, as indicated by the increase in AIC and BIC. In addition, the log-likelihood improves, but not enough to justify the added complexity of the model. This behavior may indicate over-parameterization or insufficient intra-regional variation, limiting the usefulness of the fixed effects in this specific context. The lack of statistically robust results in the logit model reinforces the hypothesis that the adoption of PJe in criminal courts in 2020 was less sensitive to local characteristics and more driven by broad institutional guidelines.

Taken together, the results from the logit model confirm the fragility of the relationship between local factors and the adoption of PJe in criminal courts, suggesting that the patterns observed in the linear models are not only statistically insignificant but also inconsistent across specifications. This evidence strengthens the argument that, unlike in civil courts, where local infrastructure and regional levels of development directly influenced the pace of digitization, in the criminal context, the adoption of PJe in 2020 seems to have followed a distinct institutional logic, less dependent on local conditions and more driven by universalization goals. This pattern may be directly related to the COVID-19 pandemic, which severely limited the judiciary's face-to-face operations and accelerated the need for digitization in all segments of the justice system, especially in criminal courts, where the continuity of case processing was crucial for protecting fundamental rights.

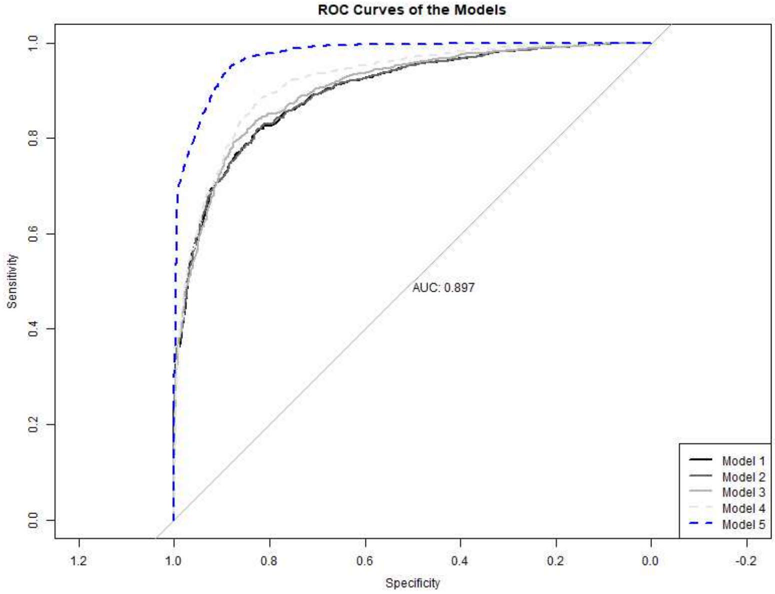
APPENDIX A – CHAPTER 1 RESULTS

Table 7 - Logistic regression estimates for civil court Adoption of PJe

	Model 1	Model 2	Model 3	Model 4	Model 5
ln(Average internet speed)	134.40***	139.01***	154.11***	385.334***	5.66***
	(19.63)	(22.19)	(26.30)	(79.08)	(2.18)
Number of court in the judicial district		0.98	1.09	1.03	1.03
		(0.01)	(0.01)	(0.02)	(2.30)
Number of judges in the judicial district		1.01	1.01	1.01	9.79*
		(0.01)	(0.01)	(0.00)	(1.00)
ln(per capita GDP)			2.583***	4.606***	1.94*
			(0.380)	(0.991)	(6.44)
ln(Population density)			1.045	1.178**	5.61***
			(0.040)	(0.072)	(7.14)
Employment rate			0.923***	0.892***	9.76
			(0.007)	(0.009)	(1.60)
Intercept	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	NO	NO	NO	NO	YES
Microregion	NO	NO	NO	YES	YES
F	1125.396	374.237	186.872	14.597	9.415
AIC	3827.5	3828.8	3717.8	3527.1	2127.9
BIC	3840.4	3854.8	3763.2	4019.8	2659.5
Log. Lik.	-1911.726	-1910.419	-1851.920	-1687.555	-981.948
RMSE	0.35	0.35	0.35	0.33	0.24
Num.Obs.	4833	4833	4833	4833	4833

Note: Models 1 to 3 follow the specification of Equation (1), while Models 4 and 5 use the specification of Equation (2). The estimates were obtained through a logistic regression model, with coefficients reported in terms of odds ratios, and robust standard errors in parentheses. *** denotes $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure 6 – Predictive performance (ROC Curves) of logit specifications (civil courts)



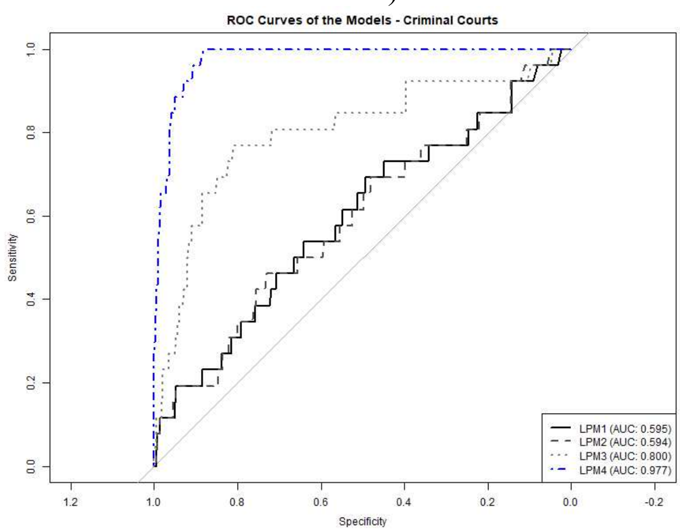
Note: ROC curves were constructed based on the predicted probabilities from the Logistic Regression Models. These curves evaluate the classification performance of each model by plotting the true positive rate (sensitivity) against the false positive rate (1 - specificity) at various probability thresholds. The area under the curve (AUC) summarizes the model's ability to discriminate between classes, with higher values indicating superior predictive accuracy.

Table 8 - Logistic regression estimates for criminal court Adoption of PJe

	Model 1	Model 2	Model 3	Model 4
ln(Average internet speed)	0.27	0.33	2.26	1.00
	(0.19)	(0.27)	(2.34)	(2.11)
Number of court in the judicial district		1.02	1.22	1.00
		(0.132)	(2.24)	(3.46)
Number of judges in the judicial district		0.98	0.91	1.01
		(0.06)	(8.10)	(1.60)
ln(per capita GDP)			0.074*	5.99
			(8.70)	(1.25)
ln(Population density)			0.811	1.40
			(1.93)	(9.78)
Employment rate			0.976	9.13
			(5.30)	(9.80)
Intercept	10835.92	2014.61	23369621.8	0.00
	(69775.22)	(14916.33)	(3.19)	(0.00)
Microregion	NO	NO	NO	YES
F	3.425	1.068	3.893	0.277
AIC	193.7	197.1	174.4	219.9
BIC	201.7	213.1	202.5	520.2
RMSE	0.24	0.24	0.23	0.17
Log. Lik.	-94.854	-94.535	-80.218	-34.945
Num. obs.	405	405	405	405

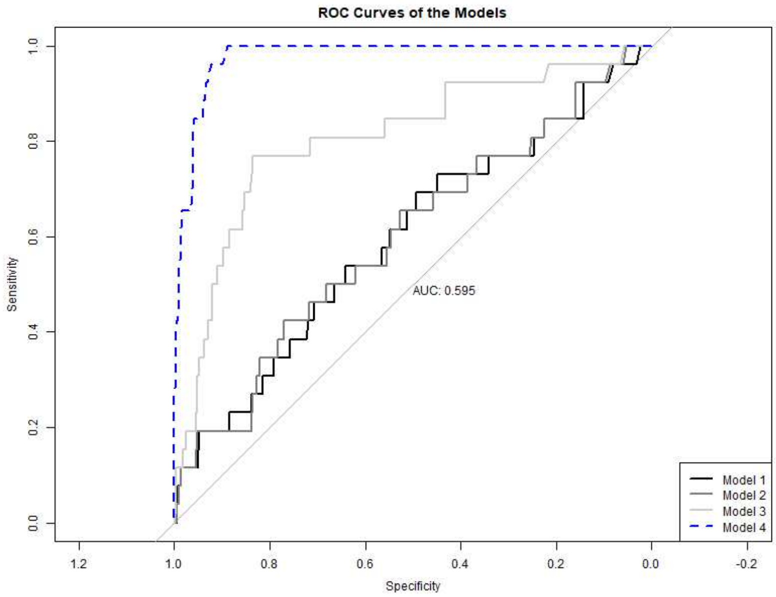
Note: Models 1 to 3 follow the specification of Equation (1), while Model 4 use the specification of Equation (2). The estimates were obtained through a logistic regression model, with coefficients reported in terms of odds ratios, and robust standard errors in parentheses. *** denotes $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure 7 - Predictive performance (ROC Curves) of LPM specifications (Criminal Courts)



Note: ROC curves were constructed based on the predicted probabilities generated by Linear Probability Models (LPM). Although LPMs do not impose a probabilistic functional form, the fitted values can be interpreted as predicted probabilities for binary outcomes. The ROC curve assesses the predictive accuracy of each model specification by plotting the true positive rate against the false positive rate across various thresholds. Higher AUC values indicate better model discrimination performance.

Figure 8 - Predictive performance (ROC Curves) of logit specifications (Criminal Courts)



Note: ROC curves were constructed based on the predicted probabilities from the Logistic Regression Models. These curves evaluate the classification performance of each model by plotting the true positive rate (sensitivity) against the false positive rate (1 - specificity) at various probability thresholds. The area under the curve (AUC) summarizes the model's ability to discriminate between classes, with higher values indicating superior predictive accuracy.

Chapter 2 – The Effects of Electronic Judicial Process (PJe) on Court Performance in Minas Gerais

This chapter undertakes an analysis of the impact of technological modernization on the performance of the judicial system. The analysis focuses on the implementation of the Electronic Judicial Process (PJe) in the Court of Justice of Minas Gerais (TJMG). The chapter commences with a presentation of the context of the modernization of the Judiciary in Minas Gerais and the adoption of PJe as a tool for digital transformation. Subsequently, a comprehensive review of extant theoretical and empirical literature on the relationship between judicial efficiency and economic development is conducted. The methodology section delineates the data used and the empirical strategy adopted to identify the effects of PJe on judicial performance indicators. The ensuing results are presented in two stages: an initial descriptive analysis, followed by empirical evidence for civil and criminal courts. Robustness checks are employed to corroborate the findings, thereby reinforcing the consistency of the estimates. Finally, the conclusion summarizes the main results and highlights implications for public policy aimed at the modernization of Judiciary.

2.1 Modernization and Implementation of the Processo Judicial Eletrônico (PJe)

Constitutional Amendment No. 45, enacted in Brazil in December 2004, was designed to increase transparency and efficiency in the judicial system. One of the most significant innovations of this amendment was the creation of the Conselho Nacional de Justiça (CNJ). The CNJ was established with the objective of implementing effective mechanisms for overseeing administrative activities and enforcing disciplinary measures, as well as addressing the challenges of modernization and correcting deficiencies caused by the fragmentation of administrative practices within the judicial system. In pursuit of these objectives, the CNJ has implemented a series of policies, including the digitization of judicial proceedings. The enactment of Law No. 11,419 on December 19, 2006, established a regulatory framework for the utilization of electronic means in the processing of lawsuits, communication of procedural acts, and transmission of documents, encompassing civil, criminal, and labor cases at all levels of jurisdiction, as delineated in Article 1 of the law (BRASIL, 2004).

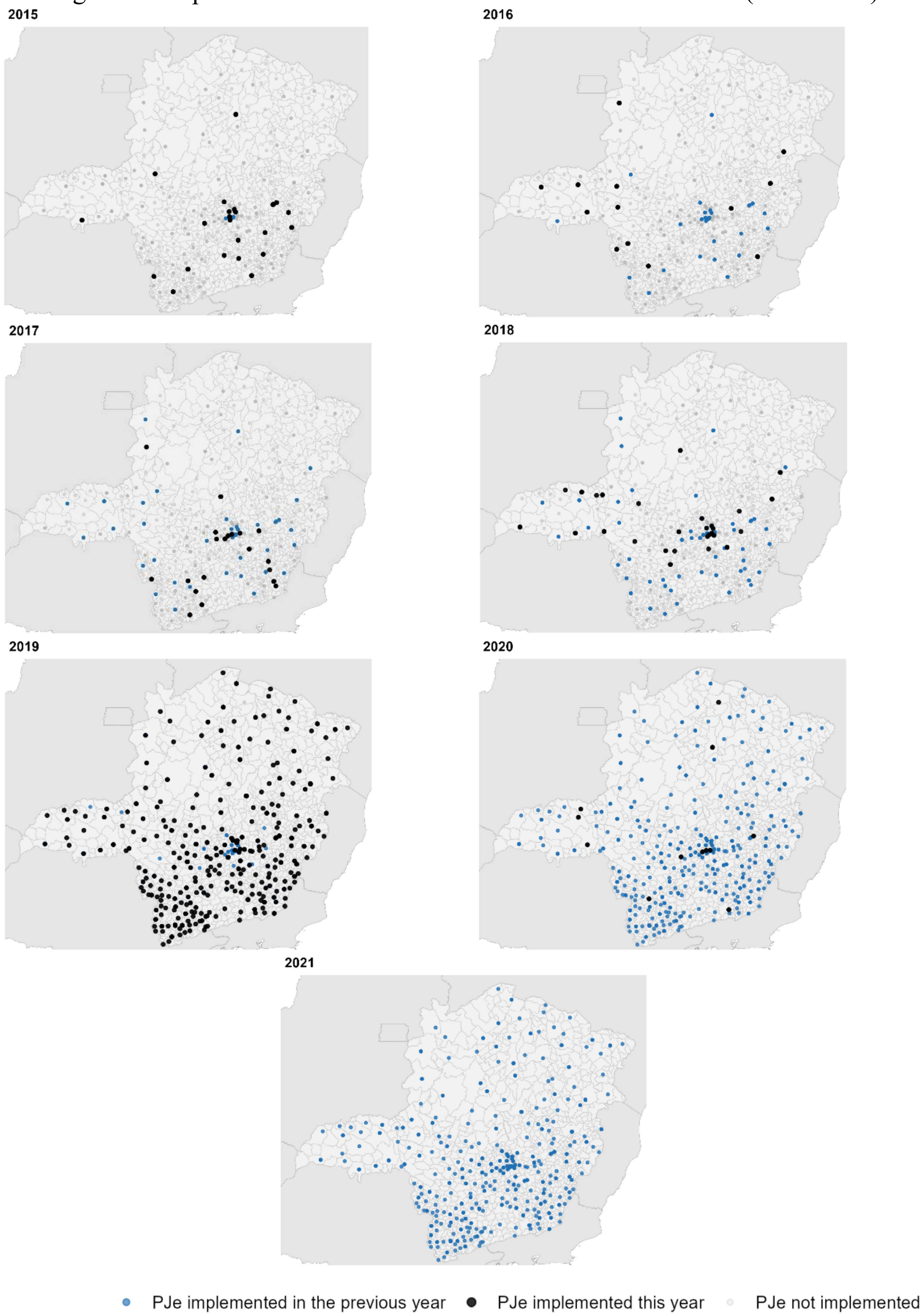
This legal advancement formalized the PJe, thereby creating conditions for delivering judicial services in a faster, more cost-effective, and paperless manner. The digitization of legal documents, statutes, and case law, in conjunction with search tools and internet access, has the potential to facilitate and streamline one of the fundamental stages of legal work (Brasil, 2006; Rotta *et al.*, 2013). The convenience of digital storage and retrieval of documents has been shown to reduce the time required to prepare legal opinions, decisions, and arguments (Rotta *et al.*, 2013). This, in turn, enables legal professionals to allocate more of their time and attention to activities such as legal analysis and the development of legal arguments.

In 2012, the TJMG began implementing the Electronic Judicial Process (PJe) in First Instance courts, which is the focus of this study. This initiative started with a pilot project in two courts located in the Barreiro district. The First Instance, also known as the First Level, represents the initial stage of judicial proceedings, where most cases are initiated. After this measure was approved, the tool was gradually rolled out across the state's courts, encompassing all civil, special, public finance, and criminal courts. (TJMG, 2012).

As illustrated in Figure 9, the implementation of the PJe in civil courts followed a specific timeline. The adoption process exhibited a gradual trend between 2015 and 2021. The blue dots in the figure denote courts that had implemented the PJe in the previous year, the black dots represent those that implemented it in the reference year, and the gray dots correspond to courts that had not yet adopted the system.

Over time, there has been a steady expansion of the PJe (Electronic Judicial Process). In 2015, only 21.2% of civil courts had implemented the PJe, while 78.8% were still in the control group and not yet using the system. In the following years, the system's coverage increased consistently. Significant advancements occurred in 2018 and 2019, when the percentage of courts utilizing the PJe rose to over 40% and 85%, respectively. By 2021, the implementation process was considered complete, with all civil courts operating through the PJe, thereby achieving full system coverage in this category.

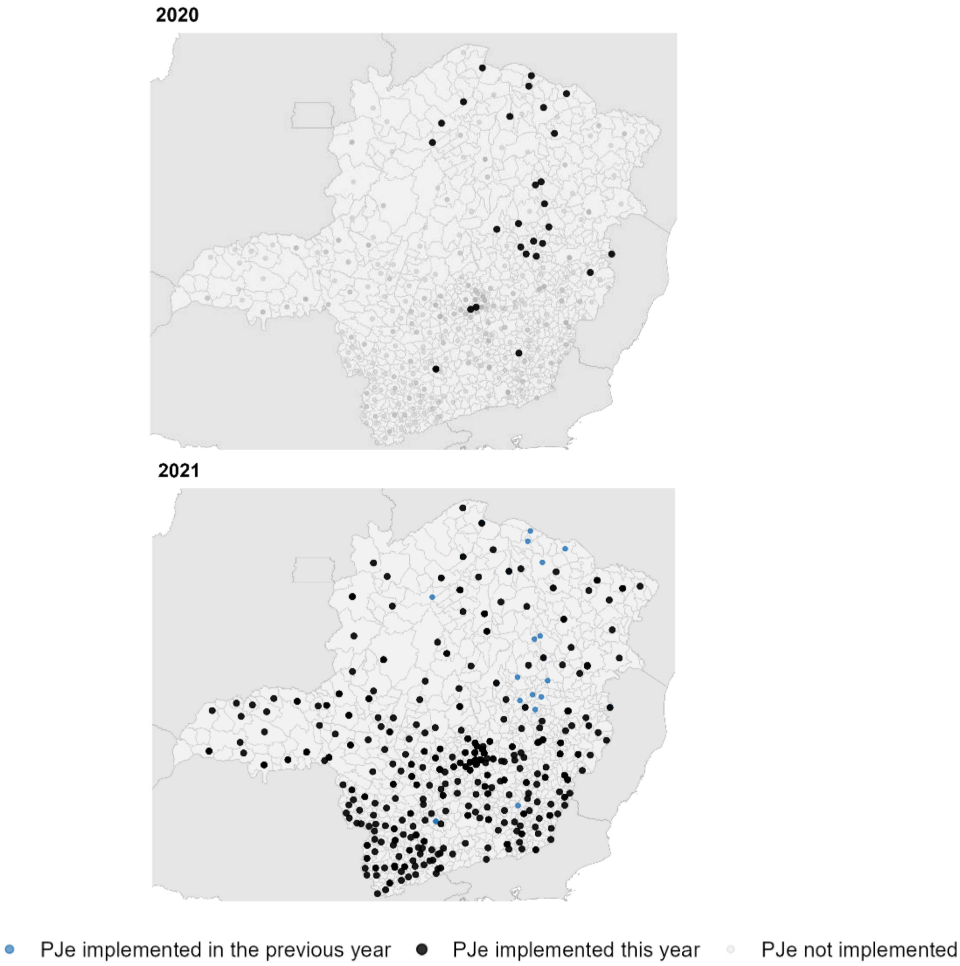
Figure 9 - Implementation of PJe in civil courts of Minas Gerais (2015-2021)



Note: The data presented in the maps are based on information provided by the TJMG regarding the implementation of the PJe. Light gray dots represent courts that had not yet implemented the system in the given year. Black dots indicate courts that adopted the PJe in that particular year, while blue dots correspond to those that had already implemented the system in the previous year.

In criminal courts, the implementation pattern is markedly different. The adoption of the PJe in this jurisdiction commenced in 2020 (TJMG, 2025). In that year, the adoption of the PJe was already in effect in only 6.4% of criminal courts. However, the following year, in 2021, the percentage of courts using the system increased dramatically to 100%, indicating a more recent implementation process concentrated within a short time frame (see Figure 10). This temporal dynamic of the treatment variable underscores the staggered nature of the public policy in civil courts, in contrast to the simultaneous implementation in criminal courts.

Figure 10 - Implementation of PJe in criminal courts of Minas Gerais (2015-2021)



Note: The data presented in the maps are based on information provided by the Tribunal de Justiça de Minas Gerais (TJMG) regarding the implementation of the Processo Judicial Eletrônico (PJe). Light gray dots represent courts that had not yet implemented the system in the given year. Black dots indicate courts that adopted the PJe in that particular year, while blue dots correspond to those that had already implemented the system in the previous year.

The staggered implementation of the PJe in first-instance courts serves as a significant source of variation for the present analysis. The staggered adoption of the PJe provides a unique opportunity to compare the effects of the system between courts that have adopted the PJe and those that have not yet done so. The variation in the implementation of the PJe over time allows us to create a treatment group, which consists of courts that have adopted the PJe, and a control group, made up of courts that have not yet adopted it. This methodological approach facilitates a systematic assessment of the impact of the PJe on court performance and the judicial system as a whole. By using the staggered adoption of the PJe as a basis for comparison, we can develop a comprehensive and nuanced understanding of its effects across different groups.

2.2 Literature Review

Empirical literature highlights that robust institutions play a fundamental role in economic growth and development by ensuring contract enforcement and protecting property rights (Acemoglu; Johnson; Robinson, 2001; Banerjee; Duflo, 2005; Blattman; Hartman; Blair, 2013; North, 1994; Rodrik; Subramanian; Trebbi, 2004; Sandefur; Siddiqi, 2013). In this context, access to justice, in conjunction with the assurance of property rights, functions as a catalyst for market transactions that engender positive externalities for society(Field, 2007; Galiani; Schargrodsky, 2010; Ponticelli; Alencar, 2016; Ramos-Maqueda; Chen, 2021). The effectiveness and efficiency of conflict resolution mechanisms, as well as the effective enforcement of the law, are therefore essential to sustain long-term economic progress.

Trust in judicial institutions is a crucial factor in the effectiveness of the legal system. A study conducted in Pakistan has highlighted that reforms designed to improve the efficiency of state courts have led to an increase in public trust. As a result, people were more willing to access and use the judiciary. These findings emphasize the essential role of institutional legitimacy in strengthening the rule of law.

Some studies have examined the use of data from judicial systems in developing countries as a foundation for evaluating the impact of institutional reforms. The extant literature, including the works of Ahsan (2013), Amirapu and Gechter (2020), Chakraborty (2016), and Chemin (2009), demonstrates that policies designed to curtail case delays, ensure the effective enforcement of contracts, and foster increased trust among economic agents have the potential to engender efficiency gains and enhance business competitiveness.

A notable illustration of this phenomenon is the "Access to Justice Program" in Pakistan, which was examined by Chemin (2009). The initiative involved training judges in contemporary case management practices and reducing case backlogs. The results of the program's implementation indicate a significant improvement in judicial efficiency and positive effects on local economic development, such as the promotion of entrepreneurship. It is noteworthy that the reform, which represented a mere 0.1% of GDP, yielded a 0.5% growth in gross domestic product.

In the context of India, Chemin (2012) assesses the repercussions of the 2002 Civil Procedure Code reform, which encompassed measures such as the limitation of delays, the imposition of deadlines, and the promotion of out-of-court settlements. The efficacy of these changes is evidenced by the acceleration in the resolution of cases and the positive impact on business investments, which increased by 7.5%. The study further suggests that judicial delays are associated with poorer outcomes in both the industrial and agricultural sectors.

In a similar vein, a study examined the correlation between judicial inefficiency and various economic and social indicators in India. The delays and unpredictability in case judgment times were linked to declines in per capita income, increased poverty, contractions in private economic activity, weaknesses in public infrastructure, rising crime rates, and greater industrial instability. These findings highlight the central role of an effective judiciary in promoting social welfare.

In addition to its macroeconomic impact, research indicates that access to justice also affects social equity. Research conducted in the United States, including studies by Seron *et al.* (2001) Greiner *et al.* (2012), demonstrates that legal assistance programs targeted at low-income tenants significantly reduce the likelihood of eviction and increase success in negotiations with landlords. These findings underscore the importance of legal interventions aimed at vulnerable populations.

The extant literature also highlights various strategies to promote more accessible and efficient justice. Blattman, Hartman and Blair (2013) underscore the pivotal role of educational campaigns in modifying behaviors concerning dispute resolution. Conversely, Sandefur and Siddiqi (2013) posit that progressive legal reforms are particularly efficacious in historically marginalized regions. The complementarity between educational approaches and structural reforms reinforces the need for multifaceted strategies.

In the domain of judicial management, Bray *et al.* (2016) examined the "first in, first out" (FIFO) policy implemented in Italy and demonstrated that this measure led to a substantial enhancement in the case resolution rate. In a similar vein, Kondylis and Stein

(2015) highlight the reduction of pre-trial phases and improvements in procedural efficiency as positive outcomes of well-designed interventions when evaluating a litigation resolution system reform in Senegal.

In the context of Brazil, Ponticelli and Alencar (2016) examined the impact of bankruptcy law reform on access to credit, investments, and business growth. The results of their study indicate that municipalities with lower extrajudicial potential experienced increases in secured loans, investments, and industrial production. This suggests that institutional reforms have the potential to drive economic development. Conversely, Dahis *et al.* (2023) demonstrate that the selection of judges through public competitions in Brazil, in addition to ensuring transparency, is positively associated with productivity in case resolution. This lends further credence to the notion that meritocratic processes are paramount in the composition of the Judiciary.

Recent international experiences have demonstrated a clear correlation between the presence of effective judicial institutions and economic development. The implementation of electronic justice in Ukraine, as examined by (Ніколенко, 2022), has been shown to facilitate procedures, reduce expenses and processing times, and enhance transparency. This analysis underscores the transformative impact of technology in enhancing judicial effectiveness.

The concept of judicial performance, measured through various indicators and methodologies, has gained prominence in research focused on development. (Ramos-Maqueda; Chen, 2021) emphasize that advancements in judicial data management and archiving systems, driven by innovations such as electronic management systems, have facilitated more precise analysis of the judiciary's operations and their impact on economic and institutional dynamics.

2.3 Methodology

2.3.1 Data

To assess the impact of the implementation of the PJe in the civil and criminal courts of TJMG, two main sources of data were utilized. The initial source comprises data furnished by TJMG itself, encompassing the dates of PJe implementation in the various judicial units of the state.

Using this information, we built a database that identified the year of electronic system adoption by each court, distinguishing between civil and criminal courts. The second data source is the Justiça Aberta system, provided by the CNJ, which offers standardized and detailed data on judicial activity in all courts across the country. From this database, we extracted information on the nature of the cases (criminal or non-criminal) and various types of procedural variables: number of new cases, pending cases, disposed cases, and judgments issued. The temporal scope of the analysis, from 2015 to 2021, is based on the availability of this information during that time period.

The classification of case types into "criminal" and "non-criminal" follows the standardization adopted in CNJ reports, such as "Justiça em Números". Criminal cases are those that proceed in the criminal sphere, related to the investigation and judgment of criminal offenses such as homicides, thefts, robberies, drug trafficking, and other crimes defined by criminal law. Conversely, non-criminal cases encompass all other areas of law, including civil, family, tax, business, and consumer law. For the sake of analytical coherence, the present study has adopted the convention of categorizing these non-criminal cases under the designation of civil cases. This distinction was imperative not only for the organization of the database but also for the construction of specific indicator variables regarding the use of PJe in both civil and criminal courts. Segmenting cases by type facilitates the identification of procedural variables, including new cases (cases filed in the system during the reference year), pending cases (cases in progress at the end of each year), disposed cases (cases that have been closed or archived), and judgments issued (the number of judicial decisions made).

The database also includes information about the judges working in each court, allowing us to determine the number of judges in each tribunal. After an exhaustive review of the available data, performance variables were created, including court productivity, judges' productivity, demand fulfillment index, and backlog rate. These variables align with the CNJ's methodology and facilitate an assessment of the impact of PJe on the courts' performance.

Tables 9 and 10 present the variables used. Table 9 shows the dependent variables, which are defined in the CNJ's Glossary of Performance Indicators (CNJ, 2021a). The court's productivity index and judges' productivity in resolving criminal cases are used as metrics to evaluate performance. This reflects the individual capabilities of the courts and judges in adjudicating cases. The demand fulfillment index indicates the ability of a court to handle the volume of cases received relative to its jurisdictional capacity, thus highlighting its performance in case management. The backlog rate is a measure of the proportion of disposed cases in relation to the total number of new and pending cases, thus indicating the judicial system's ability to promptly respond to the demand for its services. Disposed cases are those that have been legally concluded, demonstrating the effectiveness of the litigation resolution process and the reduction of delays in cases awaiting resolution. On the other hand, the volume of new cases each year directly influences the court's workload.

Pending cases represent those that have not yet been judged or finalized in court. They have a significant impact on the overall efficiency and responsiveness of the judiciary. These indicators are crucial for assessing judicial performance, providing vital insights that can be used to improve judicial management and effectively address societal demands.

Table 9 - Dependent Variables

Outcomes	Description	Variables	Source
Court's productivity	Index that measures the average productivity of disposed cases in court i, in year t.	$\boldsymbol{CP_{i,t}} = \frac{TDC_{i,t}}{TNJ_{i,t}}$ $TPD_{i,t}$ - Total disposed cases. $TNJ_{i,t}$ - Total number of judges.	CNJ
Judges' productivity	Index measuring average productivity per judge in court i, in year t.	$\boldsymbol{JP_{i,t}} = \frac{TJ_{i,t}}{TNJ_{i,t}}$ $TPD_{i,t}$ - Total Judgment. $TNJ_{i,t}$ - Total number of judges.	CNJ
Demand Fulfillment Index	Index measuring the ratio between the number of disposed cases and the number of new cases filed in court i in year t.	$\boldsymbol{DFI_{i,t}} = \left(\frac{DC_{i,t}}{NC_{i,t}}\right) \times 100$ $DC_{i,t}$ - Disposed cases in the period. $NC_{i,t}$ - New Cases in the period	CNJ
Backlog rate	Measures the court's backlog by evaluating the total number of disposed cases, divide at the number of new cases more the pending cases at the court i, and year t,.	$\boldsymbol{B_{i,t}} = 1 - \left(\frac{DC_{i,t}}{NC_{i,t} + PP_{i,t}}\right)$ $DC_{i,t}$ - Disposed cases in the period. $NC_{i,t}$ - New Cases in the period $PP_{i,t}$ - Process pending in the period	CNJ
Disposed cases	This figure represents the total number of legal disposed cases in court each year.	$\boldsymbol{DC_{i,t}}$	CNJ

New cases	The total number of new cases presented to the court i, in the year t.	$\boldsymbol{NC_{i,t}}$	CNJ
Pending cases	The total number of pending cases to the court i, in the year t.	$\boldsymbol{PC_{i,t}}$	CNJ
Judgment	Total number of final decisions issued by a judge, resolving the legal issues in dispute, which may result in a conviction, acquittal, or other legal resolution in court i, in year t.	$\boldsymbol{J_{i,t}}$	CNJ

Note: The indices used in this study were derived from the manual published by the CNJ (2021).

Table 10 presents the variable of interest along with the control variables used in this study. The control variables were obtained from the Brazilian Institute of Geography and Statistics (IBGE), the National Telecommunications Agency (ANATEL), and the João Pinheiro Foundation (FJP). The variable of interest is a dummy that indicates the adoption of the PJe system. It takes value 1 from year *t* onward, starting in the year in which the court implements the system—including the implementation year itself—and remains at 1 in subsequent years. It takes the value 0 in the years prior to adoption.

Table 10 - Independent Variables

Regressor	Description	Variable	Source
Electronic Judicial Process	Dummy variable = 1 if court has PJe, 0 otherwise, in year t	$\boldsymbol{PJe_{i,t}}$	TJMG
Controls	**Description**	**Variable**	**Source**
ln(Average internet speed) (Mbps)	Proxy for the quality of internet infrastructure in the municipality where the court is located, with annual measurements in Mbps.	$\boldsymbol{X_{i,t}}$	**ANATEL**
ln(per capita GDP)	Natural logarithm of the annual per capita gross domestic product of each municipality.		**IBGE**
ln(Population density)	Natural logarithm of the population per square kilometer in each municipality, measured annually		**FJP**
Employment rate	Annual municipal employment rate, calculated as the percentage of formally employed individuals relative to the working-age population (16–64 years old)		**FJP**

In order to ensure the robustness of the estimates and control for factors that may influence the implementation of PJe and the judicial performance indicators simultaneously, a set of socioeconomic and infrastructural variables is included in the model. One such variable is the average internet speed (Mbps), expressed in natural logarithm, which serves as a proxy for the quality of digital infrastructure in the municipalities where the courts are located. Additionally, the municipal Gross Domestic Product (GDP) per capita, also in natural logarithm, is employed as an indicator of the local economic development level.

In addition, we considered population density measured by the logarithm of population per square kilometer to capture demographic pressures that may influence judicial demand and the complexity of legal service delivery in different regions. Municipalities with higher population density have been observed to record higher cases volumes, which can impact both the productivity of the courts and the adoption of technological innovations. Finally, we incorporated the municipal employment rate, calculated as the proportion of formally employed individuals relative to the working-age population (16 to 64 years). This variable reflects the dynamism of the local labor market and may be associated with patterns of judicialization, as well as the administrative and institutional capacity of the municipalities.

Out of the 988 courts initially included in the dataset, 103 were deemed ineligible and were excluded, resulting in a total of 885 courts. This total includes 412 criminal courts and 473 civil courts, creating an unbalanced panel. This decision was made to reduce any potential interferences that could distort the results, allowing for a more robust evaluation of the specific impact we intend to investigate.

In the interest of obtaining a more accurate and representative assessment of the impact on the courts, the single-instance courts [2] were retained in the analysis. While single-instance courts do manage a range of case types, they facilitate a more comprehensive analysis within the same jurisdictional context. This allows for a clearer understanding of the procedural dynamics and the impact of the variables being investigated.

2.3.2 Estimation

In order to ascertain the mean effect of the implementation of PJe on the civil and criminal courts of TJMG, a Two-Way Fixed Effects (TWFE) Ordinary Least Squares model was initially employed for court and year. This methodological approach leverages the temporal variation in PJe adoption across distinct courts, thereby enabling a comparative analysis of the evolution of outcomes before and after the system's implementation. This methodology also incorporates a control for unobservable fixed characteristics of the courts and aggregate shocks common to all courts annually.

The econometric specification is represented by the following equation:

$$Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t} \tag{4}$$

$Y_{i,t}$ denotes the outcome of interest for court i at time t. $Year_t$ denotes year fixed effects, which are useful for capturing common shocks at time t; $Court_i$ denotes court fixed effects and controls for all time-invariant characteristics of court i; $Post\_Pje_{it}$ is a dummy variable equal to 1 if court i implemented PJe in year t or in a previous year (i.e.,

[2] Single-instance court refers to a "vara única," where a single judge is responsible for handling all cases within a specific jurisdiction. This term is used in judicial systems that do not make an explicit distinction between specialized courts or multiple judges for the same case, characterizing a structure where judicial authority is centralized in one judge for the management of the case.

t is greater than or equal to the implementation date); and $\varepsilon_{i,t}$ denotes the error term clustered at the court level. The coefficient of interest is δ, which captures the average effect of PJe implementation. We use clustered standard errors at the court level to allow for arbitrary dependence of $\varepsilon_{i,t}$ over time within court i (Bertrand; Duflo; Mullainathan, 2004; Wooldridge, 2012, 2016).

The identification strategy employed is predicated on two fundamental pillars. Firstly, we take advantage of the fact that courts are unaware of and not notified about future implementation actions. Consequently, the timing of PJe implementation is plausibly exogenous — an unexpected event — for the court. Secondly, we employ a strategy that contrasts the treated courts with those that have not yet been treated, while accounting for fixed differences across courts and common time effects.

Following the approach proposed by Callaway and Sant'Anna (2021), we adopt a difference-in-differences model with multiple time periods, combined with two-way fixed effects. To estimate the average treatment effect over time, we compare treated units to those that have not yet received the treatment in the same period—i.e., the not-yet-treated group—thereby preserving the validity of the parallel trends assumption in settings with staggered policy adoption. Specifically, we estimate the following equation:

$$Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t} \tag{5}$$

respectively, where α_t is a time fixed effect, α_g is a group fixed effect, $\mu_{i,t}$ denotes the error terms, $D_{i,t}^e = 1\,\{t - G_i = e\}$ is an indicator for unit i being e periods away from the initial treatment at time t, and K and L are positive constants. In this dynamic TWFE specification, we are interested in examining the effect of β_e for $e \geq 0$, which are commonly interpreted as estimates of the treatment impact across different exposure periods following its adoption.

For the estimate to genuinely reflect the effect of the implementation on the courts, it is necessary to ensure that the parallel trends assumption holds prior to the implementation. This entails the expectation that, prior to the implementation of the treatment, units exposed to the intervention and those not exposed should demonstrate parallel trends in the outcome variable under scrutiny.

In the case of civil courts (varas cíveis), the groups that implemented PJe in 2015 and 2016 were not included in the main analysis. This exclusion is justified by the limited availability of data prior to implementation, which compromises the verification of the parallel trends assumption between treated and control groups. Specifically, units treated in the early years of the policy have very few pre-treatment observations, making it impossible to construct a reliable trajectory before PJe adoption. Absent this trajectory, the accurate estimation of counterfactual effects becomes challenging, potentially compromising the validity of the results. While records exist after the implementation of the policy, the absence of sufficient pre-treatment data hinders the identification of the expected causal effects.

Consequently, the analysis focuses on the groups treated from 2017 onwards, when the policy was intensified and the number of courts with data both before and after the system's adoption became more adequate. The decision to concentrate on these groups guarantees greater temporal balance, respects the assumptions of the difference-in-differences methodology with multiple periods, and increases the reliability of the estimates produced.

In the case of criminal courts, the implementation dynamics of the PJe present a distinct configuration. Most units were treated within a short time frame, with some adopting the system in 2020 and all being treated by 2021 (TJMG, 2025). This substantially limits the temporal heterogeneity required for applying the difference-in-differences methodology with multiple periods, as proposed by Callaway & Sant'Anna (2021).

More specifically, the number of criminal courts remaining as a control group — that is, not yet treated — becomes nonexistent after 2020, making it difficult to compare treated and untreated trajectories over time. The presence of only one group treated in 2020, combined with the complete adoption of the system by all other units in 2021, creates a setting with very little variation in treatment timing across groups, which undermines the identification of heterogeneous effects.

Given this context, the empirical strategy for the criminal courts relies exclusively on the canonical Difference-in-Differences model, which estimates the average effect of PJe implementation by comparing units that adopted the system with those that had not yet adopted it at the time of implementation. The estimation is restricted to the years 2019 (pre-treatment) and 2020 (post-treatment). This specification allows a direct interpretation of the average treatment effect on the treated units (ATT) by comparing the changes in outcomes between courts that implemented PJe in 2020 (treatment group) and those that had not yet implemented it (control group). The model specification is given by Equation 6:

$$Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t} \quad (6)$$

where $Y_{i,t}$ s the dependent variable (described in Table 9) for court i in year t; $Treat_i$ is a dummy variable indicating whether court i belongs to the treated group; $Post_t$ is a dummy variable indicating the post-treatment period; $Treat_i \times Post_t$ is the interaction term capturing the treatment effect; δ is the coefficient of interest (the average treatment effect on the treated); $X'_{i,t}$ is the vector of control variables; and $\varepsilon_{i,t}$ is the error term clustered at the court level.

In the civil courts, as a robustness check, we conducted a randomization of the PJe implementation date among the courts to simulate a placebo treatment scenario. The objective of this test is to verify whether the model would detect statistically significant effects even when the treatment did not actually occur. If effects were identified in this scenario, it would indicate the possibility of spurious relationships, weakening the validity of the main results. Conversely, the absence of effects in the placebo test reinforces the robustness of the empirical approach adopted.

To assess the robustness of the criminal court analysis, we conducted a placebo test based on a fictitious treatment design with a fixed year. Specifically, we artificially assigned the treatment to a random subset of courts starting in 2018—that is, two years before the actual implementation of the PJe, which only occurred in 2020 for part of the units. Based on this setup, we estimated a canonical difference-in-differences model restricted to the 2015–2019 period, using only pre-treatment data.

The logic behind this exercise is straightforward: since no actual intervention occurred prior to 2020, any statistically significant effect found in this model would indicate potential issues such as differential trends between groups or flaws in the model specification.

2.4 Results

2.4.1 Descriptive Analysis

Table 11 presents the descriptive statistics for the variables of interest for the civil and criminal courts of TJMG, distinguishing between treated units (those that implemented the PJe) and control units (those that did not implement the system). The data refers to the period from 2015 to 2021, with the unit of observation being annual at the court level.

In civil courts, it is observed that the treated courts exhibit, on average, higher court's productivity (162.68) compared to the control courts (152.06), with a statistically significant difference at the 5% level. However, judges' productivity is lower in the treated courts (19.37) compared to the control courts (27.35), with a significant difference at the 1% level. Additionally, the demand fulfillment index is substantially higher in the treated courts (127.32) than in the control courts (97.16), with a statistically significant difference. Other indicators reinforce this pattern: treated courts report a higher average number of disposed cases (1591.66) and a higher stock of pending cases (2813.09), with both differences also significant. On the other hand, the average number of new cases is lower in the treated courts (1276.36), which could indicate a change in the demand profile. Finally, the average number of judgments is slightly lower in the treated courts, with a significant difference.

Table 11 - Summary statistics

	Control		Treatment		Difference		
	Mean	SD	Mean	SD	Mean	SD	
Civil							
Court's productivity	152.06	135.75	162.68	165.81	10.68	30.05	**
Judges' productivity	27.35	57.33	19.37	41.47	-7.99	-15.87	***
Demand fulfillment index	97.16	31.02	127.32	99.56	30.17	68.54	***
Backlog rate	52.72	28.32	52.24	40.73	-0.49	12.41	
Disposed cases	1314.01	1258	1591.66	1812.52	277.65	554.52	***
New cases	1400	1365	1276.36	1055.22	-123.48	-309.72	***
Pending cases	1801.12	1304.29	2813.09	1791	1011.97	486.71	***
Judgment	184.51	344.27	145.78	275.14	-38.73	-69.13	****
Criminal							
Court's productivity	48.41	68.16	58.41	79.11	10	10.95	**
Judges' productivity	3.58	14.98	0.03	0.11	-3.55	-14.86	***
Demand fulfillment index	199.02	3193.21	182.27	136.04	-16.75	-3057.17	
Backlog rate	60.40	34.61	64.11	17.34	3.72	-17.27	***
Disposed cases	389.73	462.35	412.24	327.85	22.51	-134.5	
New cases	375.40	424.63	272.79	254.40	-102.6	-170.23	***
Pending cases	976.20	889.72	968.81	729.07	-7.39	-160.65	
Judgment	23.09	99.29	0.31	1.14	-22.78	-98.15	***

Note: The unit of observation is annual at the level of judicial courts of the Tribunal de Justiça de Minas Gerais (TJMG) for the period 2015-2021. Court's productivity, judges' productivity, demand fulfillment index, and backlog rate are indicators used by the *Conselho Nacional de Justiça* to measure the performance of judicial courts. New cases, pending cases, disposed cases, and judgments are variables that allow the calculation of performance indicators. Statistically significant differences between treatment and control judicial courts are observed as follows: * 0.10 ** 0.05 *** 0.01.

In criminal courts, the pattern is similar in some aspects. The treated courts show slightly higher court's productivity (58.41) compared to the control courts (48.41), with a significant difference at the 5% level. However, judges' productivity is again lower in the treated courts (0.03) compared to the control courts (3.58), with a statistically significant difference at the 1% level. The demand fulfillment index and the number of judgments are also lower in the treated courts, with the latter showing a statistically significant difference. The backlog rate is slightly higher in the treated courts (64.11 vs. 60.40), with statistical significance. On the other hand, there is a lower entry of new cases in the treated courts (272.79), which could indicate a redistribution of demand or behavioral change after the implementation of the PJe.

A general review of the results indicates that the implementation of the PJe is associated with changes in various performance indicators in both civil and criminal courts, with distinct effects on the productivity of judges and courts. These observations form the basis for the empirical analysis that will be presented in the subsequent sections. The objective of this analysis is to identify and isolate the causal impact of the PJe.

Table 12 presents the descriptive statistics of the variables used as controls in the empirical models. The average internet speed, measured in Mbps, is 191.62 with a standard deviation of 462.38. The average GDP per capita is 31,441.64, while the logarithm of population density has a mean of 344.78 and a dispersion (standard deviation) of 1,283.18. The average employment rate is 27.64%, with a standard deviation of 12.44.

Table 12 - Controls: descriptive statistics

	Mean	**Std. dev.**
Average internet speed	191.62	462.38
per capita GPD	31441.64	22893.46
Population density	344.78	1283.18
Employment rate	27,64119	12,4386

Note: The data presented are sourced from the Instituto Brasileiro de Geografia e Estatística (IBGE), Agência Nacional de Telecomunicações (ANATEL) e Fundação João Pinheiro (FJP).

These controls are included to assess the robustness of the main results to the inclusion of socioeconomic and infrastructure characteristics, without the intention of interpreting them directly.

2.4.2 Empirical Results

2.4.2.1 Civil Courts

It is important to emphasize the need for caution when interpreting the results of this analysis. The focus is on civil courts, which handle a large volume of cases and a wide range of complex issues. Additionally, this investigation uses a quantitative and empirical approach, estimating the average effects on judicial performance related to the implementation of the PJe system. However, this method may not take into account specific institutional, operational, or contextual factors unique to each judicial unit. As a result, the findings represent a preliminary measure of impact, but they remain robust across various conditions.

Tables 13 and 14 present the primary results of the estimation of the average impact of the PJe on various performance metrics of civil courts in Minas Gerais, employing a strategy with time and court fixed effects. Table 13 focuses on indicators related to productivity and efficiency of the judicial system, while Table 14 considers raw variables of case processing.

According to Table 13, the implementation of the PJe system did not produce statistically significant effects on overall court productivity (column 1), judges' productivity (column 2), or the demand fulfillment index (column 3), considering the conventional 5 percent significance level. However, a statistically significant effect is observed on the backlog rate (column 4), with an estimated reduction of 6.2 percentage points following the adoption of the PJe system, significant at the 1 percent level. This result suggests a substantial improvement in the management of pending caseloads, indicating a greater ability of courts to address the stock of accumulated cases. Although the coefficient for the demand fulfillment index indicates a 6.3 percentage point decline—potentially reflecting a deterioration in the system's ability to respond to new demands—this result is not statistically significant at the 5 percent level and should therefore be interpreted with caution. Taken together, the findings suggest that, at least in the short term, the most evident impacts of digitalization occurred in the volume of pending cases, with positive effects in addressing structural delays.

Table 13 - Main results: Impact of PJe on civil performance metrics

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	-6.422	-3.534	-6.327*	-6.245***
	(4.728)	(4.495)	(3.054)	(1.869)
Observations	3159	3154	3156	3157
R-squared	0.823	0.369	0.375	0.524

Note: This table reports the results of the estimation of equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4). In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 14 complements this analysis by examining variables related to absolute case volume. The estimated coefficients for the number of resolved cases, new filings, and pending cases are all positive but statistically insignificant, suggesting that the adoption of the PJe had no robust impact on these variables. On the other hand, the number of judgments issued showed a slight decrease (-4.1), although this result was also not statistically significant.

Table 14 – Main results: Impact of PJe on civil performance variables

	Disposed cases	**New cases**	**Pending cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	163.784	144.889	115.972	-4.147
	(92.842)	(79.492)	(106.403)	(32.243)
Observations	3166	3173	2998	3168
R-squared	0.878	0.898	0.809	0.290

Note: This table reports results from estimating equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model in Columns (1) through (4). In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include court and year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.

Taken together, the findings indicate that, in civil courts, the introduction of the PJe was not accompanied by gains in productivity or increases in case resolution. On the contrary, the observed effects on efficiency indicators suggest a possible adverse impact during the years analyzed. This scenario may reflect the initial difficulties of the technological transition, particularly in an institutional context that requires the reorganization of routines, training of system operators, and technical stability. Thus, the results underscore the importance of considering the adaptation costs involved in implementing technologies in the public sector, even when the goals are focused on modernization and efficiency.

Additionally, estimations were conducted using the same variables but with different model specifications, including one analysis with only court fixed effects and another considering only year fixed effects. The results, presented in Appendix B (Tables 21 to 24), were largely consistent with those previously reported, reinforcing the robustness of the main findings. In some specifications, the coefficients lost statistical significance or even changed sign, which may reflect the model's greater sensitivity to the omission of relevant fixed effects, such as court-specific characteristics or conjunctural variations in certain years. Nevertheless, even with these variations, the overall direction of the effects and the observed patterns remain aligned with the main results: the implementation of the PJe is associated with a statistically significant reduction in the demand clearance rate and congestion rate in civil courts, with no robust impacts on the volume of new, resolved, or pending cases, nor on the number of rulings issued. This convergence across different specifications lends greater credibility to the findings, suggesting that they are not artifacts of a specific model but rather systematic reflections of the PJe's impact on civil court performance.

Considering that the implementation of the PJe in civil courts occurred gradually across different jurisdictions, we estimated equation (5), with the results presented in Appendix B, Figures 15 to 38. The estimates encompass the average treatment effects by group and period (group-time average treatment effects), as well as the average balanced and unbalanced effects.

Overall, the results do not indicate statistically significant impacts from the implementation of the PJe on the performance variables analyzed. Although the parallel trends assumption was verified, we did not identify robust and consistent effects on metrics such as court productivity, judges' productivity, demand fulfillment index, backlog rate, disposed cases, and judgments.

In some specifications without covariates, we observed point effects on these variables. However, when covariates were introduced, many of these effects lost significance. This suggests that part of the initial variation captured may be associated with other characteristics of the courts or specific trends during certain periods.

It is hypothesized that the current data structure, which includes annual observations and heterogeneity in the timing of PJe adoption across courts, may have constrained the precision in identifying the policy's effects. The difference-in-differences method, which relies on the presence of comparable control groups in terms of time and characteristics, may have been hindered by the limited number of courts that implemented PJe in the early years of the sample. This limitation could have reduced the statistical power necessary to detect significant effects. To address these limitations, future analyses could benefit from expanding the data set to include national-level cuts and finer temporal granularity, such as quarterly or monthly data. In addition, ancillary studies could delve into more discrete mechanisms within the civil court system, such as the nature of the cases or the profile of litigants. These supplementary analyses would contribute to a more comprehensive understanding of the effects of PJe on civil justice.

The absence of significant effects on volume and productivity variables, combined with a deterioration in relative performance indicators, suggests that digitalization through PJe, while neutral in terms of gross procedural movement, may have caused operational misalignments that temporarily compromised the ability of civil courts to handle demand efficiently. These findings underscore the necessity of contemplating not solely the prospective advantages of technological innovation within the judicial system, but also the institutional transition challenges and immediate costs that may emerge during its nascent implementation phase.

Tables 15 and 16 confirm the consistency of the main findings, even after the inclusion of control variables that capture the socioeconomic and infrastructure characteristics of the municipalities — such as average internet speed, GDP per capita, population density, and employment rate.

Table 15 shows that the introduction of the PJe is associated with a statistically significant reduction in the congestion rate (column 4) and the case clearance rate (column 3), suggesting that although the electronic system may help reduce the accumulation of cases, there may be initial challenges in keeping up with the inflow of new cases. The coefficients for court productivity (column 1) and judge productivity (column 2) remain negative but statistically insignificant, consistent with the main results.

Table 15 – Robustness: Impact of PJe on civil performance metrics with controls

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	-5.512	-3.356	-7.363*	-5.970**
	(4.677)	(4.485)	(3.104)	(1.873)
ln(Average internet speed)	-11.688	-1.505	9.759*	-0.800
	(7.996)	(4.744)	(4.282)	(1.771)
ln(per capita GPD)	10.079	-4.637	0.867	-4.262
	(19.571)	(7.932)	(6.940)	(2.812)
ln(Population density)	356.037**	-20.324	-130.896	45.097*
	(117.568)	(39.236)	(81.407)	(22.183)
Employment rate	1.147	-0.078	0.740	-0.131
	(0.796)	(0.421)	(0.420)	(0.185)
Observations	3159	3154	3156	3157
R-squared	0.824	0.369	0.379	0.525

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + X_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

Table 16 deepens the analysis by examining raw performance variables. Although the introduction of the PJe has no statistically significant effect on the number of judgments rendered (column 4), the results point to increases in the number of disposed cases (column 1), new cases (column 2), and pending cases (column 3), even though these effects are not statistically significant in most models.

Table 16 – Robustness: Impact of PJe on civil performance variables with controls

	Disposed cases (1)	**New cases (2)**	**Pending cases (3)**	**Judgment (4)**
PJe	152.025	130.673	125.388	-3.700
	(91.110)	(78.370)	(107.392)	(32.450)
ln(Average internet speed)	79.241	67.661	7.123	2.489
	(63.784)	(64.536)	(112.029)	(28.615)
ln(per capita GPD)	238.864*	377.169***	-149.295	12.500
	(100.037)	(105.025)	(121.593)	(39.103)
ln(Population density)	-130.995	-231.623	5281.499**	-370.364
	(966.363)	(1351.871)	(1696.844)	(275.778)
Employment rate	4.977	3.768	-6.960	-7.710*
	(5.247)		(11.030)	(3.099)
Observations	3173		2998	3168
R-squared	0.899		0.812	0.291

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = \alpha + \phi_t + \tau_i + \delta Post\_Pje_{it} + X_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include court and year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

In summary, these results reinforce the interpretation that the PJe has mixed effects on the performance of civil courts: on one hand, it reduces the backlog rate, indicating an improvement in case stock management; on the other hand, the average effect on the demand fulfillment index is more limited. The inclusion of controls does not substantially change the direction or magnitude of the estimated effects, which strengthens the empirical evidence of the main analysis.

In addition to the estimates with two-way fixed effects for court and year, separate estimations of Equation (4) were also performed, including only court fixed effects or only year fixed effects. The results of these additional specifications can be found in Appendix C, Tables 25 to 28. Overall, the coefficients follow the same pattern of sign and statistical significance observed in the main estimates. However, some isolated differences—such as changes in significance or the sign of certain coefficients—highlight the sensitivity of the results to the chosen specification, indicating inherent limitations of the available data and underscoring the importance of considering multiple approaches to more accurately capture the effects of the PJe on judicial performance in the civil area.

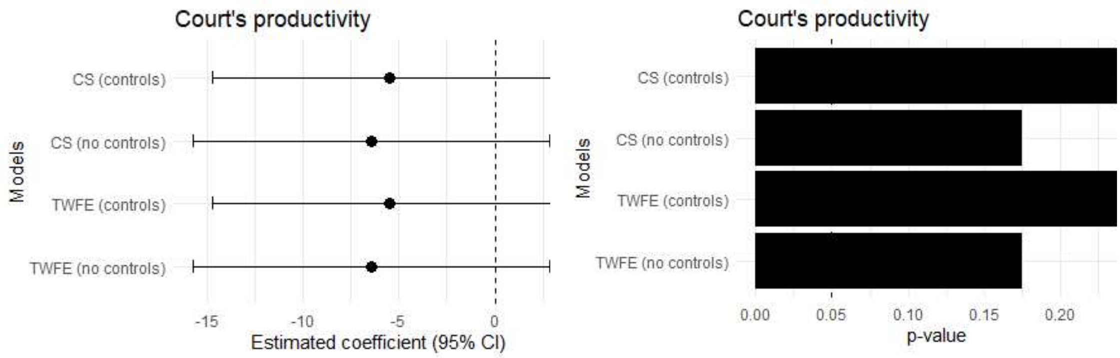
Figures 11 and 12 present a detailed comparison of the estimates obtained from the two econometric models applied to the civil domain. These are the two-way fixed effects model (TWFE) and the event study estimator developed by Callaway and Sant'Anna (CS). Both models were tested with and without the inclusion of control variables. The central purpose of this analysis is to assess the robustness and consistency of the estimated effects of the intervention on performance indicators, as well as to evaluate the statistical significance of the results produced.

Figure 11 is divided into two panels. The left panel, labeled (a), displays the graphs of the estimated coefficients of interest along with their respective 95% confidence intervals. The right panel, labeled (b), shows the p-values associated with these estimates, allowing for the assessment of the statistical significance of the coefficients. The dashed line positioned at 0.05 serves as a reference for the conventional five percent significance level.

The results reveal that, in the specifications evaluating court's productivity and judges' productivity, the effects estimated by both the TWFE and CS models, with and without control variables, do not reach statistical significance. On the other hand, when considering the indicators related to the demand fulfillment index and the backlog rate, both models produce statistically significant estimates, suggesting a possible effect of the intervention on these specific dimensions of judicial performance.

Figure 11 – Robustness for civil performance metrics

(a) **(b)**



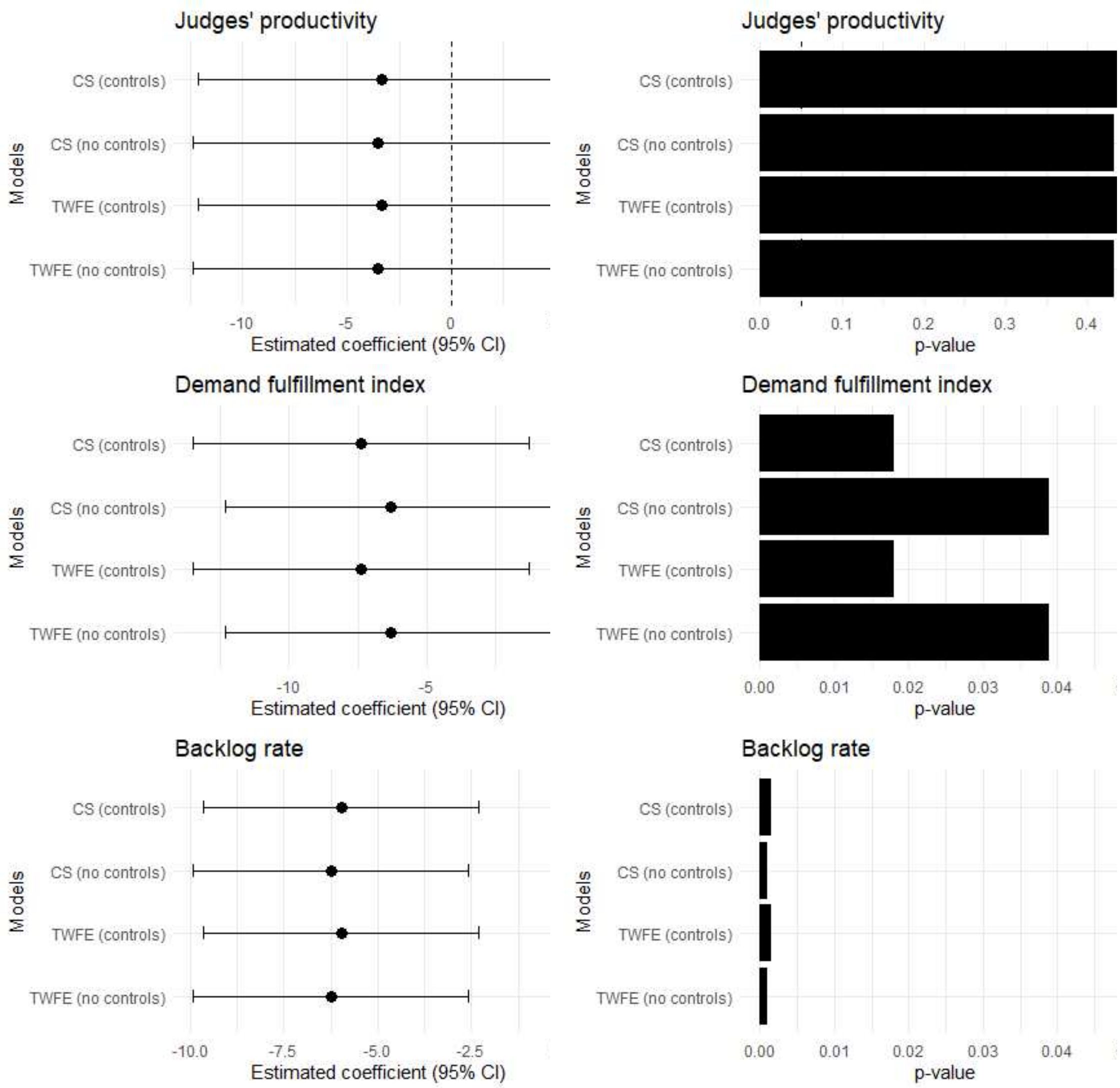
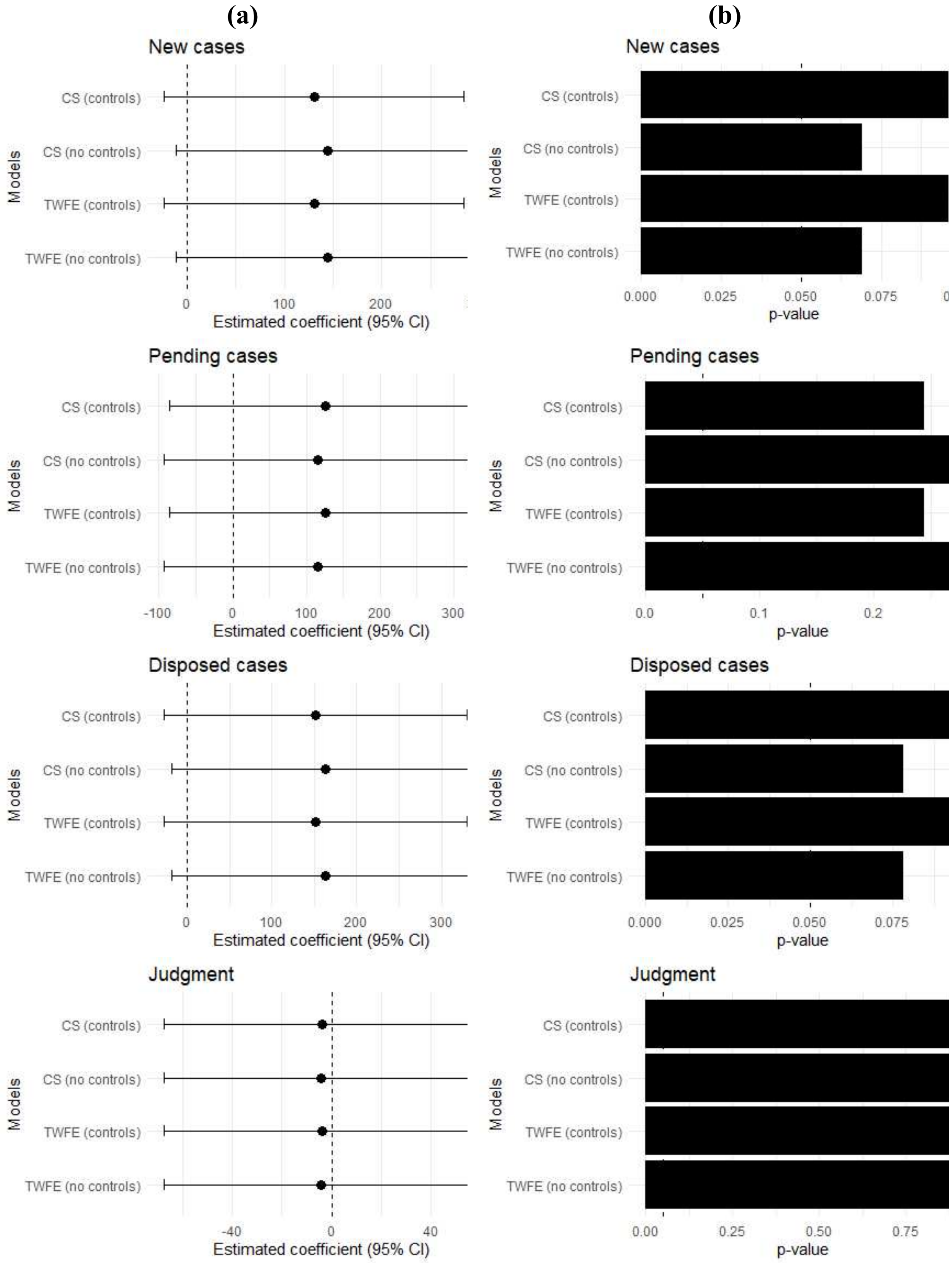


Figure 12 complements the analysis by presenting the results for the judiciary's raw operational variables, including the number of new cases, disposed cases, pending cases, and judgments. The graphs indicate that, across all these dimensions, the econometric models evaluated did not identify statistically significant effects of the intervention, regardless of whether control variables were included.

Figure 12 - Robustness for civil performance variables



Given the observed limitations, it is proposed that future research consider expanding the database to include judicial courts at the national level and adopt a finer temporal granularity, such as quarterly or monthly data. Additionally, complementary investigations could explore more specific internal mechanisms related to the functioning of civil courts, such as the typology of lawsuits or the socioeconomic profile of litigants.

Such approaches could enrich the understanding of the effects of the PJe on the efficiency of civil justice.

2.4.2.2 Criminal Court

When interpreting the results related to criminal courts, it is important to proceed with caution, especially given the specific characteristics of this branch of the judiciary. According to the 2021 Justice in Numbers report, criminal cases in the State Judiciary lasted, on average, four months less than non-criminal cases. This time difference is particularly relevant when comparing the impacts of PJe across civil and criminal courts. The shorter average duration of criminal proceedings may be linked to factors such as the legal priority for processing, distinct procedural rules, and the specific operation of criminal courts. Moreover, the caseload in these courts tends to be significantly lower than in civil courts — as shown in Figure 2 of Chapter 1 — which also influences their operational dynamics and the potential effects of digitalization. Therefore, it is essential to take these institutional and operational distinctions into account when assessing the impact of PJe on criminal courts, as the mechanisms driving gains in efficiency and productivity may operate differently in this context.

The results presented in Tables 17 and 18 suggest that the implementation of the PJe in criminal courts is associated with a statistically significant increase in both the court's productivity and the judges' productivity. As shown in Table 15, the court's productivity increased by approximately 13.5 cases per judge, while the individual productivity of judges grew by about 1.7 judgments per magistrate. These effects may indicate that the electronic system contributed to accelerating case adjudication, even in a more complex procedural context. This finding is consistent with the literature suggesting that digitalization can increase courts' capacity to process and resolve cases more rapidly. Bray et al. (2016) and Ramos-Maqueda and Chen (2021) show that electronic systems often facilitate case management and reduce processing time. However, no statistically significant changes were identified in the Demand fulfillment index or the Backlog rate, suggesting that despite the productivity increase, impacts on the overall flow of case intake and disposition may have been more limited.

Table 17 - Main results: Impact of PJe on criminal performance metrics

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	13.478*	1.734***	-4.402	-3.983
	(5.329)	(0.517)	(54.700)	(3.809)
Observations	2666	1679	2650	2660
R-squared	0.737	0.362	0.174	0.619

Note: This table reports the results of the estimation of equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4). In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

The data presented in Table 18 supports these findings by showing an increase in the number of disposed cases, with approximately 76 more cases per court, as well as a notable rise in the number of judgments issued, averaging about 9 additional decisions. However, the number of new cases and the backlog of pending cases did not exhibit statistically significant changes. These results can be seen as indicators of improved efficiency in criminal courts following the implementation of PJe. Nevertheless, it is important to note that these improvements did not necessarily lead to a clear reduction in case backlogs or a substantial enhancement in the overall performance of the system. Therefore, caution should be exercised when interpreting these results, taking into account the limitations of the dataset, the inherent complexity of criminal proceedings, and the need for more thorough analyses that include the qualitative aspects of the Criminal Justice system.

Table 18 - Main results: Impact of PJe on criminal performance variables

	Disposed cases	**New cases**	**Pending cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	75.930**	41.547	-83.946	9.295**
	(29.122)	(22.899)	(56.436)	(3.217)
Observations	2666	2666	2438	1679
R-squared	0.665	0.668	0.913	0.345

Note: This table reports results from estimating equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model in Columns (1) through (4). In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the defendant's conviction or acquittal. All estimates include court and year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.

Additionally, alternative estimates were conducted for criminal courts using the same variables but under different model specifications — one including only court fixed effects and another considering only year fixed effects. The results of these analyses, presented in Appendix D, in Tables 29 to 32, proved to be reasonably consistent with the main findings previously reported. In some specifications, there was a loss of statistical significance and, in certain cases, even a change in the sign of the coefficients, which may reflect the sensitivity of the results to the omission of relevant heterogeneities, such as institutional characteristics of the courts or year-specific shocks. Still, despite these limitations, the overall direction of the effects remains aligned with the main results: the PJe is associated with gains in both court's productivity and judges' productivity in criminal courts, with no robust effects on the Backlog rate, the Demand fulfillment index, or the volume of Pending cases. The convergence of the results, even under distinct specifications, reinforces the robustness of the evidence and suggests that the observed impacts are not artifacts of a specific model, but more broadly reflect the response pattern of criminal courts to the digitalization promoted by the PJe.

In addition to the TWFE estimates, we conducted a complementary analysis using the canonical difference-in-differences model, leveraging the fact that, for criminal courts, there are observations both before and after the implementation of the PJe, as well as the presence of both treated and control groups in the year 2020. The results of this approach are presented in Appendix D, in Figures 39 to 46. We did not identify statistically significant impacts of PJe adoption on the analyzed performance variables — such as court's productivity, judges' productivity, the Demand fulfillment index, and the Backlog rate — nor on raw operational variables such as the number of New cases, Disposed cases, Pending cases, or Judgments. These findings reinforce the evidence that, in the context of criminal courts, the effects of the digitalization brought about by PJe on judicial performance indicators appear to be limited. However, given the observational design of the study and the potential for uncontrolled sources of bias, it is not possible to establish a conclusive causal relationship between the implementation of the system and the observed changes in performance variables.

When analyzing the average effect of PJe implementation in the criminal courts of the TJMG, the results obtained through the two-way fixed effects (TWFE) model indicate a positive, albeit limited, association between digitalization and both court's productivity and judges' productivity. Although no substantial improvements were observed in key aggregate performance indicators, such as the Backlog rate and the Demand fulfillment index, there is evidence that PJe contributed to accelerating case processing, particularly through the increase in the number of Judgments and Disposed cases. The recurrence of these effects across different statistical specifications reinforces their robustness, although the magnitude of the impacts should be interpreted with appropriate caution.

On the other hand, when employing the difference-in-differences estimator, the results do not indicate statistically significant effects of the intervention. This divergence suggests that the effects captured by the TWFE model may reflect mere correlations, which underscores the limitation regarding causal inference. Additionally, the specific characteristics of the criminal court segment — such as the lower volume of cases, the greater legal speed required for proceedings, and its distinct procedural features — help explain why the impacts of digitalization may differ from those observed in civil courts.

Ultimately, the findings suggest that although the PJe represents a tool with potential to enhance judicial efficiency (Djamaludin et al., 2022; Ramos-Maqueda and Chen, 2021; Hikojekck, 2022), its effects on the performance of criminal courts remain limited and are likely conditioned by institutional, operational, and structural factors that warrant further investigation, including through qualitative approaches.

Tables 19 and 20 present the results with the inclusion of control variables. In Table 19, it is observed that the PJe had a positive and statistically significant impact on productivity, both at the court and judge levels. Specifically, the court's productivity index increased by 13.4 units ($p < 0.1$) following the adoption of the PJe, while judges' productivity increased by 1.56 judgments per magistrate ($p < 0.1$). These results indicate that the use of technology can contribute to greater efficiency in processing criminal cases, possibly by streamlining workflows and reducing bureaucratic steps.

However, the impact on the other performance indicators was not statistically significant. The demand fulfillment index, which relates resolved cases to new cases, showed an increase, but without statistical significance. The backlog rate decreased by approximately 3 percentage points, also without statistical significance. This may indicate that, despite gains in court's productivity, the effect of the PJe on the ability of criminal courts to keep up with case flow and reduce pending case stock remains limited in the short term.

Table 19 – Robustness: Impact of PJe on criminal performance metrics with controls

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	13.449*	1.563*	44.306	-2.985
	(5.420)	(0.631)	(68.624)	(3.798)
ln(Average internet speed)	-6.104	0.354	-83.643	-7.498***
	(5.849)	(1.080)	(74.984)	(2.160)
ln(per capita GPD)	1.348	-0.455	62.100	-3.470
	(5.011)	(2.177)	(100.777)	(3.166)
ln(Population density)	-127.796	-97.615**	10139.754	103.099***
	(100.881)	(30.317)	(7205.526)	(29.010)
Employment rate	0.264	0.137	-12.224	-0.058
	(0.352)	(0.124)	(14.386)	(0.264)
Observations	2666	1679	2650	2660
R-squared	0.738	0.371	0.176	0.622

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \theta X_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

Table 20 analyzes the raw variables related to the number of cases. After the introduction of the PJe, the number of disposed cases increased by approximately 71 cases per court ($p<0.1$), and the number of judgments increased by 8.3 decisions ($p<0.1$), confirming the findings of higher court's productivity. On the other hand, no statistically significant effects were identified for the number of new cases or the stock of pending cases, suggesting that the PJe has a greater impact on the internal performance of courts than on judicial demand or the ability to reduce accumulated case backlogs.

Table 20 –Robustness – Impact of PJe on criminal performance variables with controls

	Disposed cases	**New cases**	**Pending cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	71.304*	33.664	-81.222	8.276*
	(28.593)	(23.646)	(56.274)	(4.135)
ln(Average internet speed)	-14.192	29.804	-39.760	1.925
	(26.585)	(21.023)	(37.076)	(6.925)
ln(per capita GPD)	42.156	44.955	-35.229	5.735
	(37.600)	(29.184)	(58.546)	(8.945)
ln(Population density)	-1319.587	-1861.579*	904.795	-630.037**
	(860.129)	(741.369)	(586.891)	(206.382)
Employment rate	1.203	5.054*	-4.106	0.668
	(2.782)	(2.087)	(5.596)	(0.615)
Observations	2666	2666	2438	1679
R-squared	0.667	0.673	0.914	0.353

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = \alpha + \phi_t + \tau_i + \delta Post\_Pje_{it} + \theta X_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include court and year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.

Alternative specifications were estimated by separately considering either court fixed effects or year fixed effects only. The results of these models are presented in Appendix E, in Tables 33 to 36. Overall, the findings align with the logic of the main estimates, indicating positive effects of PJe on court's productivity in criminal courts. However, in some specifications, changes in the sign or statistical significance of the estimates were observed. These variations stem from the omission of one set of fixed effects—either court or year—which may introduce bias into the estimation by failing to adequately control for unobservable characteristics specific to each court or time period. The absence of full fixed effects may capture variations not directly attributable to the implementation of PJe, such as structural changes in the criminal justice system over time or persistent differences across courts, thereby affecting the robustness of the estimated coefficients.

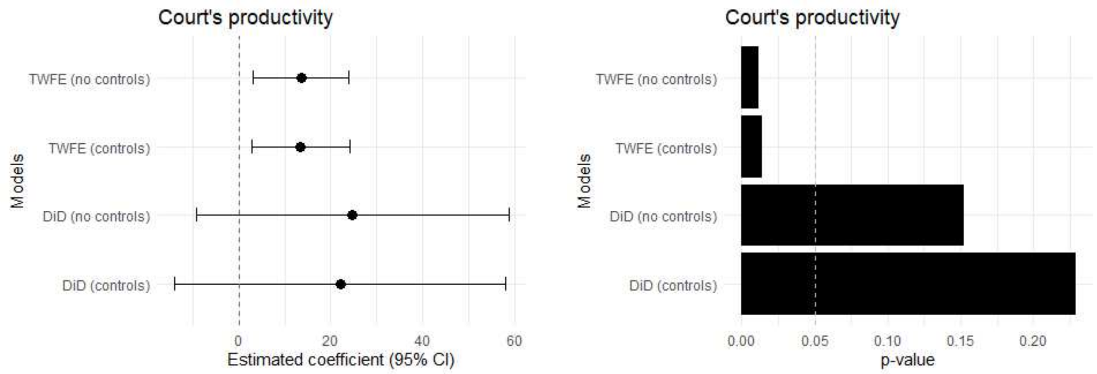
Figures 13 and 14 present a detailed comparison of the estimates obtained from the two econometric models applied to the criminal court context. As in the analysis of the civil courts, both the two-way fixed effects model (TWFE) and the canonical difference-in-differences model were used, each evaluated with and without the inclusion of control variables. The main objective of this analysis is to assess the robustness and consistency of the estimated effects of PJe implementation on performance indicators in criminal courts, as well as to evaluate the statistical significance of these results.

The figures are organized into two panels. The left panel, identified as (a), displays the estimated coefficients along with their respective 95% confidence intervals. The right panel, identified as (b), shows the corresponding p-values, allowing for the assessment of the statistical significance of the estimates. The reference line set at 0.05 marks the conventional threshold for statistical significance.

The results in Figure 13 reveal that, for the judicial performance metrics, the TWFE model presented statistically significant estimates for the court's productivity and judges' productivity, suggesting a possible positive association between digitalization and the increased capacity for judgment in criminal courts. On the other hand, the canonical difference-in-differences model indicated statistically significant effects only on the backlog rate, pointing out that the impacts of the intervention are not uniform and may be sensitive to the estimation methodology adopted. Regarding the demand fulfillment index, neither model showed statistical significance, suggesting that the PJe, by itself, did not substantially alter the balance between the inflow and outflow of cases in this sphere.

Figure 13 - Robustness for criminal performance metrics

(a) **(b)**



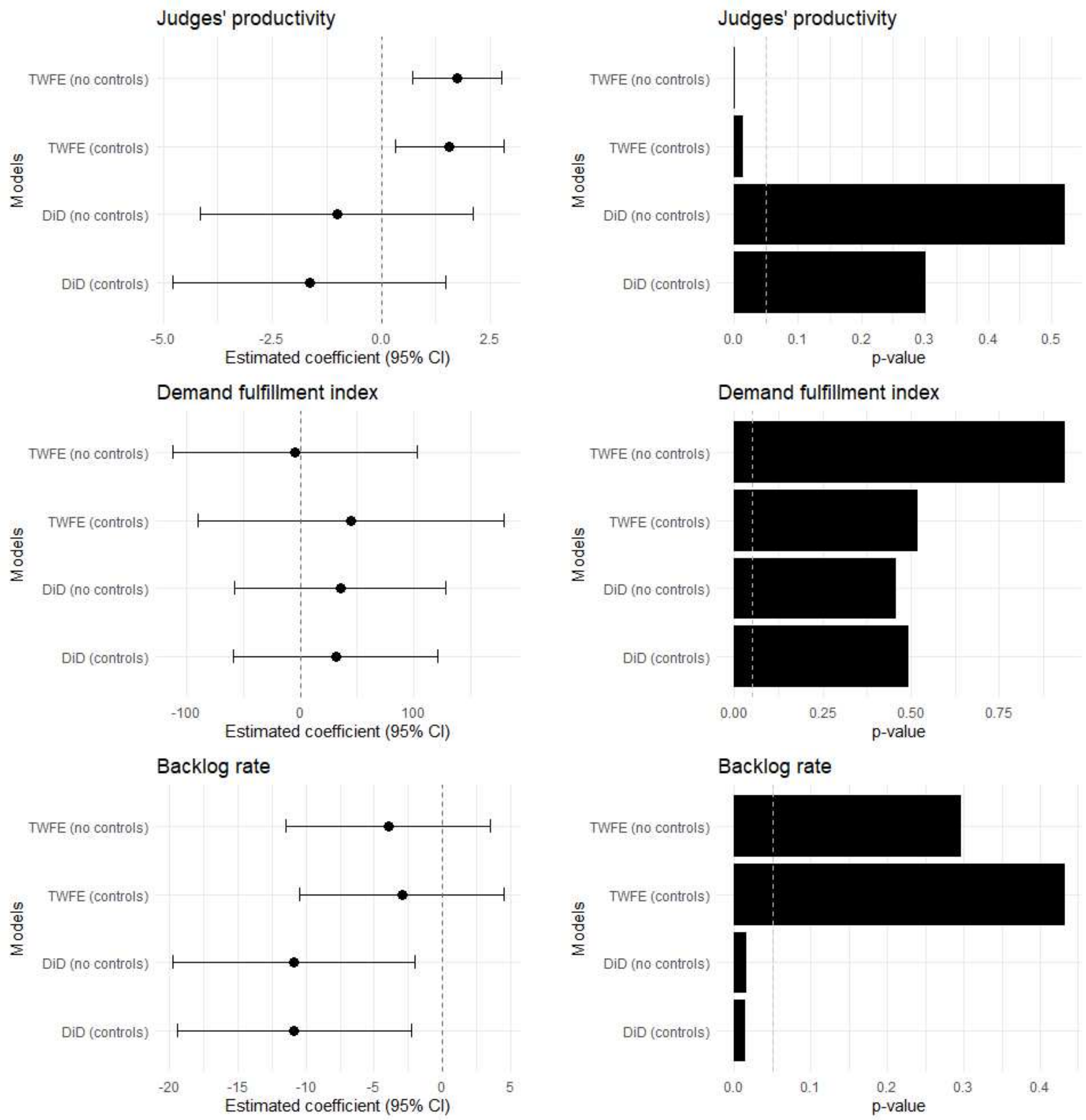
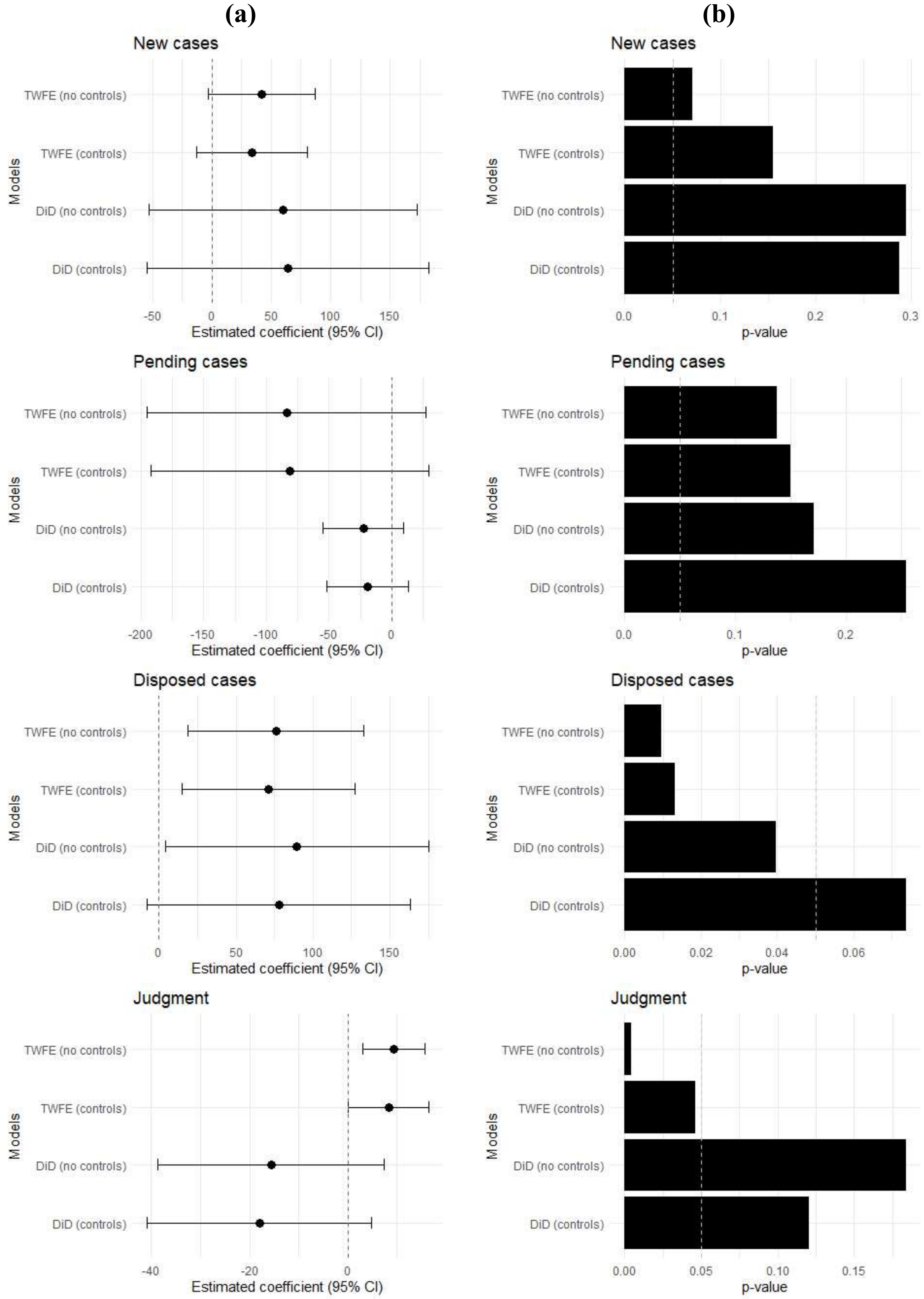


Figure 14 complements the analysis by presenting the results for the raw operational variables, namely: number of new cases, disposed cases, pending cases, and judgments. The results show that the TWFE model identified statistically significant effects on the numbers of disposed cases and judgments, which may indicate a punctual gain in efficiency following digitalization. In contrast, for new cases and pending cases, neither of the econometric models presented statistically significant effects, suggesting that the introduction of the PJe had no measurable impact on the inflow of demands or on the case backlog.

Figure 14 - Robustness for criminal performance variables



In summary, the results indicate that the adoption of the PJe in the criminal courts of Minas Gerais shows a positive correlation with the court's productivity and the judges' productivity, with positive effects also on the number of disposed cases and judgments.

Although no statistically significant impact was observed on the demand fulfillment index and the backlog rate, the estimated coefficients suggest a favorable direction toward improved performance.

These findings should be interpreted with caution. While the TWFE model points to positive associations between digitalization and some performance indicators, the absence of robust effects in the canonical differences-in-differences model indicates that it is not possible to confidently assert a causal relationship between the implementation of the PJe and the observed improvements. This methodological divergence suggests that the results may be influenced by unobserved trends or specific characteristics of the units analyzed. Furthermore, the particular context of the criminal courts—characterized by lower case volumes, faster legal proceedings, and more structured procedural rites—may limit the extent of the digitalization effects. For a more comprehensive understanding, it is recommended to deepen the investigation by including judicial courts from other federative units, increasing temporal data granularity, and adopting qualitative approaches that explore institutional and operational aspects of the criminal justice system's functioning.

2.4.3 Robustness

2.4.3.1 Civil Courts

With the objective of testing the consistency of the estimated results for the civil courts, robustness exercises were conducted using the two proposed econometric models: the two-way fixed effects model (TWFE) and the Event Study estimator. The test consisted of randomizing the implementation date of the PJe among the courts, creating a placebo treatment scenario. The purpose of this exercise was to verify whether the model would detect statistically significant effects even when the treatment, in fact, did not occur. The identification of spurious effects in this context would indicate potential fragility in the main results. Conversely, the absence of significant effects in the placebo test reinforces the validity of the empirical strategy employed.

The results of the placebo test for the TWFE model estimates, presented in Appendix F (Tables 37 to 40), reveal mixed evidence. In some specifications — especially for the demand fulfillment index, backlog rate, and the variables of new cases and pending cases — statistically significant coefficients were observed even under the random scenario, suggesting that the results in these dimensions should be interpreted with caution, as they may reflect spurious patterns or uncontrolled temporal trends. On the other hand, the effects on court's productivity, judgments, and disposed cases were not significant in the placebo tests, which confers greater robustness to the findings for these specific variables.

In the case of the Event Study estimator, the placebo test results are shown in Figures 47 to 62 (Appendix F). In all specifications evaluated for the eight outcomes analyzed, the coefficients associated with the fictitious adoption of the PJe remained statistically non-significant, both in the average treatment effect on the treated (ATT) and in the group- and period-specific effects ($ATT_{g,t}$). The absence of statistical significance in this exercise reinforces the empirical validity of the adopted approach and suggests that the model is not capturing spurious effects due to pre-existing trends or unobserved simultaneous shocks. This result helps strengthen the robustness of the main findings when estimated by this method.

2.4.3.2 Criminal Courts

To assess the robustness of the results obtained in the analysis of the criminal courts, a placebo test was conducted using a fictitious treatment design with a fixed year. In this exercise, the treatment was artificially assigned to a random subset of courts in 2018, that is, two years before the actual implementation of the PJe, which occurred only in 2020 in some units. The estimation was carried out using a canonical differences-in-differences model applied to a sample restricted to the period from 2015 to 2019, which includes exclusively pre-intervention data.

The logic of this test is based on the premise that, since no effective institutional change was implemented before 2020, statistically significant effects should not be observed. Otherwise, this would indicate possible differential trends between the treated and control groups or weaknesses in the model specification. The absence of significant effects in this exercise, therefore, reinforces the empirical validity of the main results and suggests that the findings are not the result of spurious relationships or methodological biases.

The results of the placebo test, presented in Appendix G (Tables 41 to 44), show that the estimated coefficients for the fictitious effect of the PJe on the performance variables of the courts and judges are statistically non-significant in virtually all evaluated specifications. Furthermore, when socioeconomic and technological controls were included (such as average internet speed, GDP per capita, population density, and employment rate), the results remained consistent, reinforcing the absence of bias due to omitted variables.

This absence of statistical significance in the placebo test indicates that there is no evidence of effects prior to the actual implementation of the PJe, suggesting that the differences observed in the real data do not stem from pre-existing trends or unobserved simultaneous shocks. Thus, the main findings of the study, which indicate positive and statistically significant impacts of the PJe on court's productivity, judges' productivity, and other performance metrics (as shown in Tables 17, 19, and 20), are robust and reliable.

Moreover, the graphs of the average treatment effect (ATT) estimates for the different outcomes, shown in Appendix G (Figures 63 to 70), both without controls (panel a) and with controls (panel b), corroborate these results, showing coefficients close to zero and statistically non-significant.

Therefore, the results of the placebo test, supported by the graphical analyses of the average treatment effects (ATT) for the various outcomes, demonstrate the absence of spurious effects prior to the implementation of the PJe. This finding reinforces the validity of the parallel trends assumption and the adopted model specification. Consequently, the findings observed in the analysis of the real data for the criminal courts demonstrate econometric robustness, providing greater confidence in the inferences about the impacts of the PJe in this context.

2.5 Conclusions

This thesis analyzed the digitalization of the Electronic Judicial Process (PJe) system in the state of Minas Gerais, focusing on first-instance courts within the TJMG, across two complementary chapters. The aim was to understand both the factors that influence the adoption of digital technology and the effects of this transformation on institutional performance. The results reveal a landscape marked by structural inequalities and heterogeneous impacts, which must be taken into account when formulating public policies aimed at modernizing the judiciary.

The first chapter showed that the digital infrastructure of municipalities is a relevant determinant of PJe adoption, particularly in civil courts. Average internet speed was positively and statistically significantly associated with the likelihood of adoption, even after controlling for institutional and regional characteristics. This finding suggests that technological modernization tends to concentrate in regions with better socioeconomic conditions and greater technical capacity, reinforcing preexisting inequalities among judicial districts in the state. In criminal courts, by contrast, the influence of local infrastructure was less pronounced, indicating that centralized administrative decisions and organizational factors play a more significant role. The analysis also revealed that more complex districts—with a higher number of judicial units—were more likely to adopt the system, reinforcing the idea that digitalization has been driven by institutional strategic criteria rather than merely local operational conditions.

The second chapter assessed the effects of digitalization on court performance, revealing distinct outcomes between civil and criminal jurisdictions. In criminal courts, PJe adoption was associated with consistent gains in both court and judges' productivity, with robust and statistically significant estimates even after the inclusion of controls and validity checks (placebo and pre-trend tests). These findings suggest that digitalization contributed to speeding up case processing in this segment, possibly due to greater procedural standardization and lower variability in case types. In civil courts, on the other hand, results were more ambiguous. No statistically significant effects were identified for the main productivity indicators, and the observed coefficients pointed to a possible initial decline in responsiveness to new demand. Nonetheless, a statistically significant reduction in the backlog rate was observed, suggesting that despite short-term adaptation challenges, the PJe system helped reduce the stock of pending cases, signaling medium-term structural gains.

These findings indicate that the digital transformation of the judiciary is neither a uniform nor an automatic process. Its effects depend on institutional, operational, and territorial factors, which call for implementation policies that are more responsive to local specificities. Moreover, the research highlights that the benefits of digitalization can coexist with short-term frictions, reinforcing the importance of well-planned transition strategies, including adequate training, technical support, and continuous monitoring.

From a methodological standpoint, this thesis contributes by applying Differences-in-Differences models with multiple periods and fixed effects, based on the approach proposed by Callaway and Sant'Anna (2021), along with robustness checks that enhance the empirical credibility of the findings. Nonetheless, some limitations must be acknowledged, such as the focus on a single state (Minas Gerais) and the temporal constraint of estimating treatment effects primarily for 2020—a year significantly affected by the disruptions caused by the COVID-19 pandemic.

In summary, this thesis reinforces the notion that judicial digitalization is shaped by territorial asymmetries and institutional disparities, and its effects cannot be fully understood without rigorous empirical analysis that is sensitive to local specificities. To build a more equitable, responsive, and efficient digital justice system, modernization efforts must account for these heterogeneities and promote technological integration alongside structural and organizational equity. Future research may deepen these findings by exploring other states, different levels of the judiciary, and qualitative dimensions of digital transformation, such as the degree of system usage, stakeholder perceptions, and impacts on access to justice.

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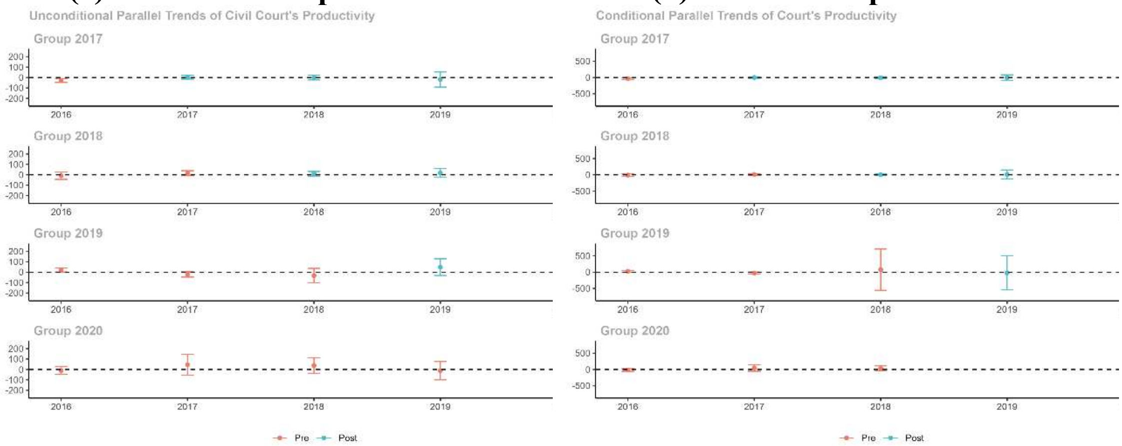
APPENDIX B – MAIN RESULTS: CIVIL COURTS

Figure 15 - Court's productivity group-time average treatment effects

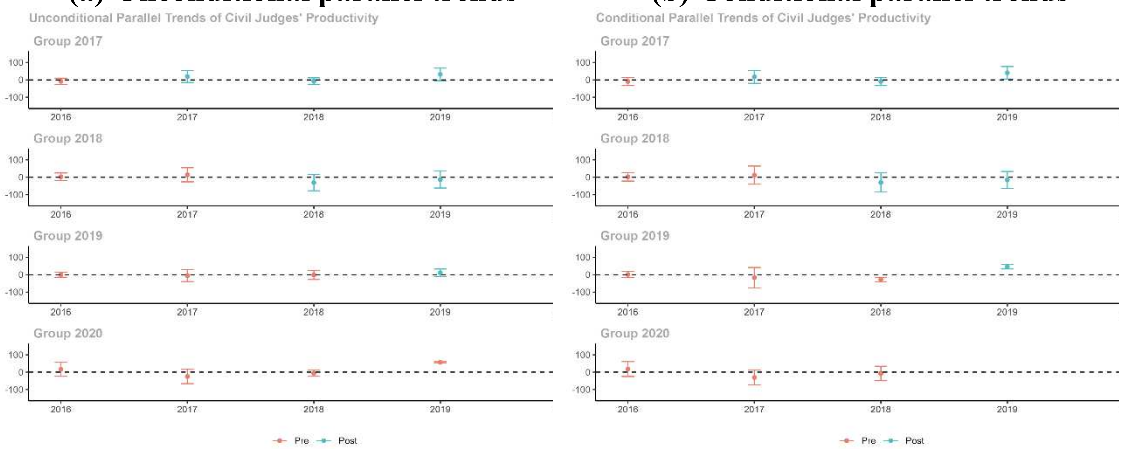
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 16 - Judges's productivity group-time average treatment effects

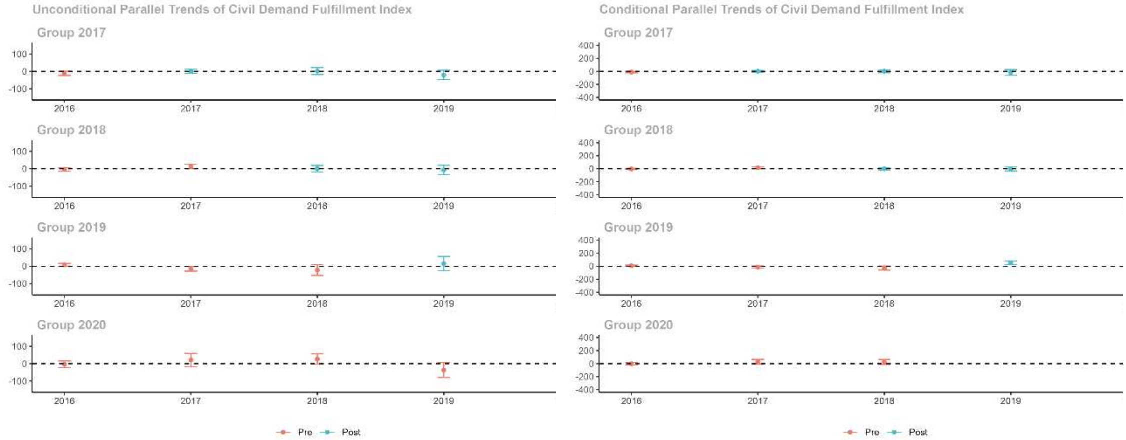
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 17 - Demand fulfillment index group-time average treatment effects

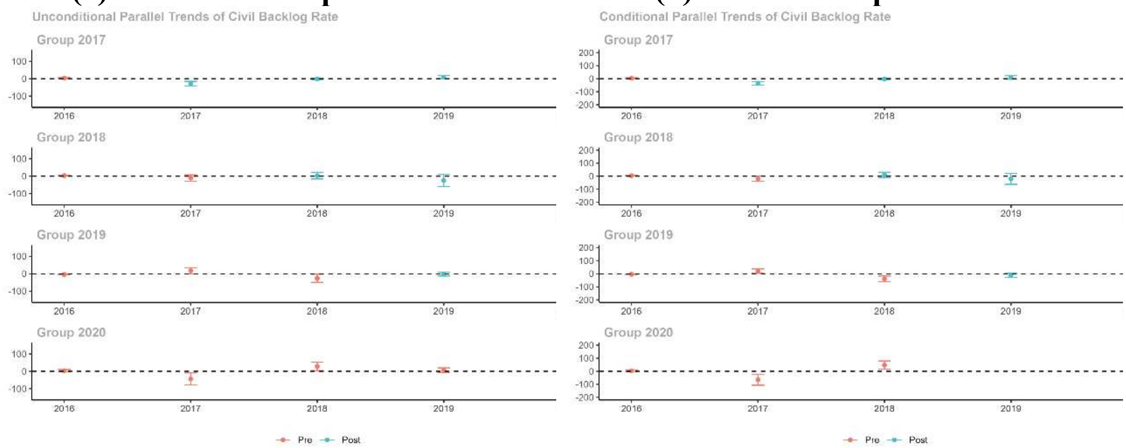
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil demand fulfillment index is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 18 - Backlog rate group-time average treatment effects

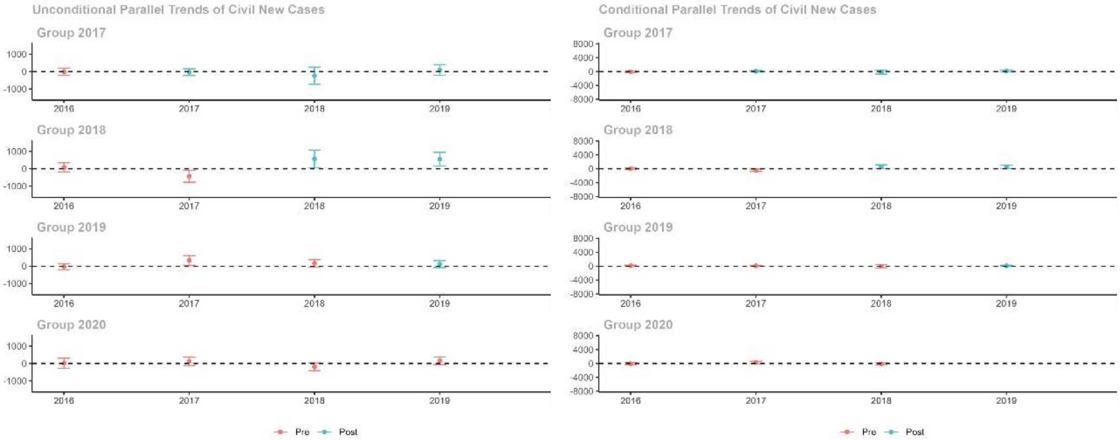
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil backlog rate is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 19 - New cases group-time average treatment effects

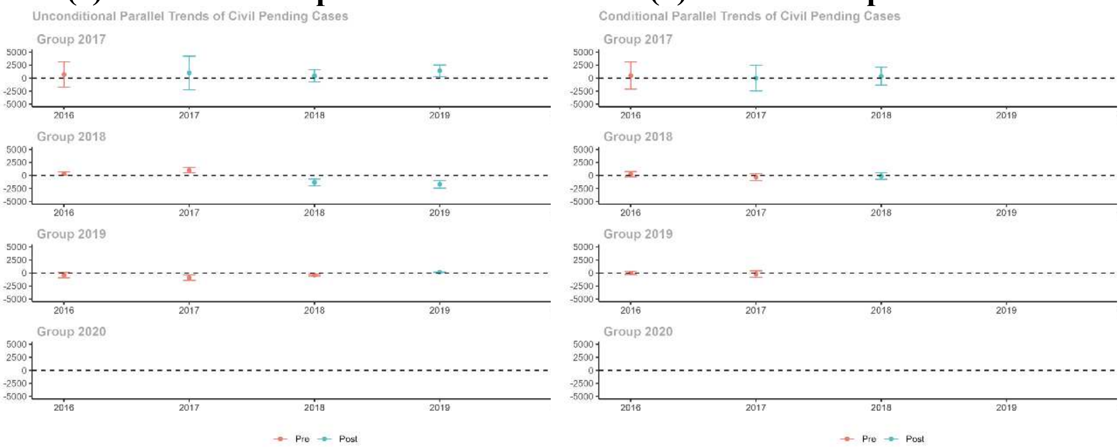
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil new cases is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 20 - Pending cases group-time average treatment effects

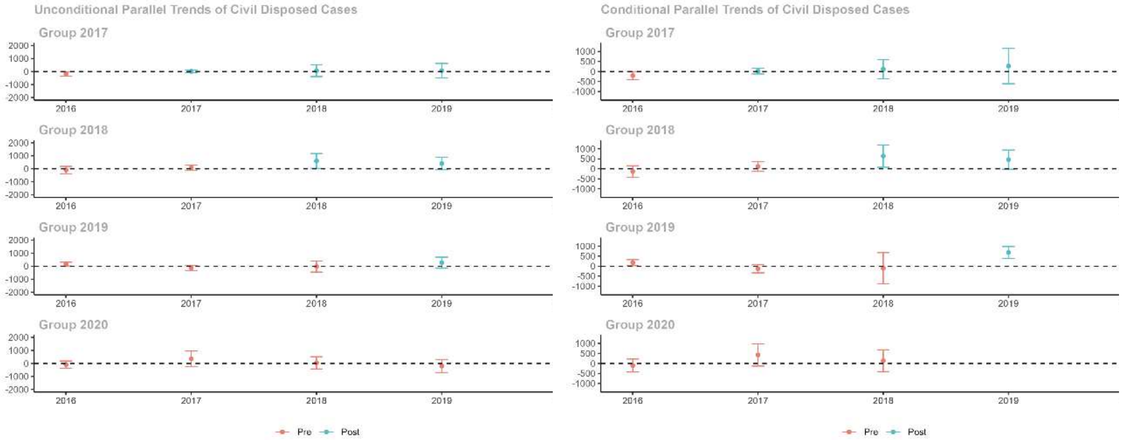
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on pending cases is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 21 - Disposed cases group-time average treatment effects

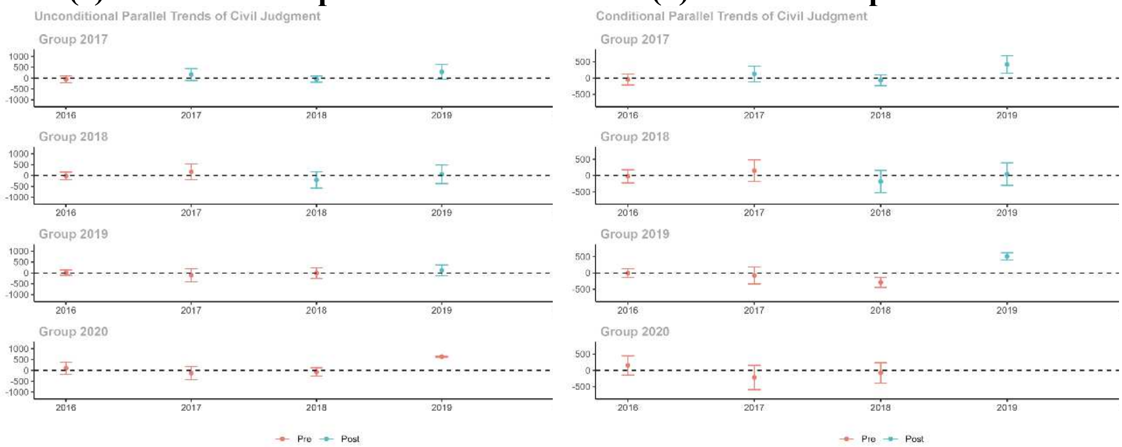
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil disposed cases is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 22 - Judgment group-time average treatment effects

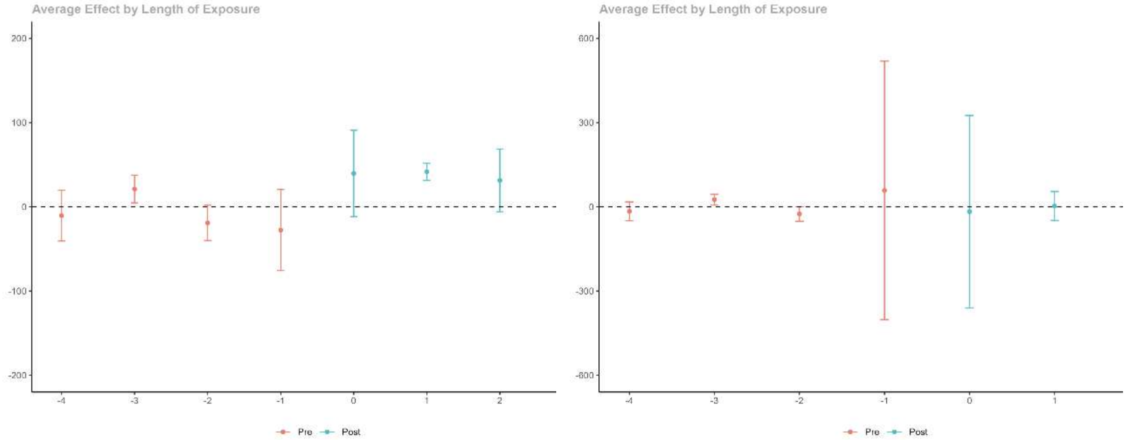
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report the estimates from Equation (5). The effect of the PJe on civil judgment is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2029, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text.

Figure 23 - Average effect of PJe on court productivity (Unbalanced)

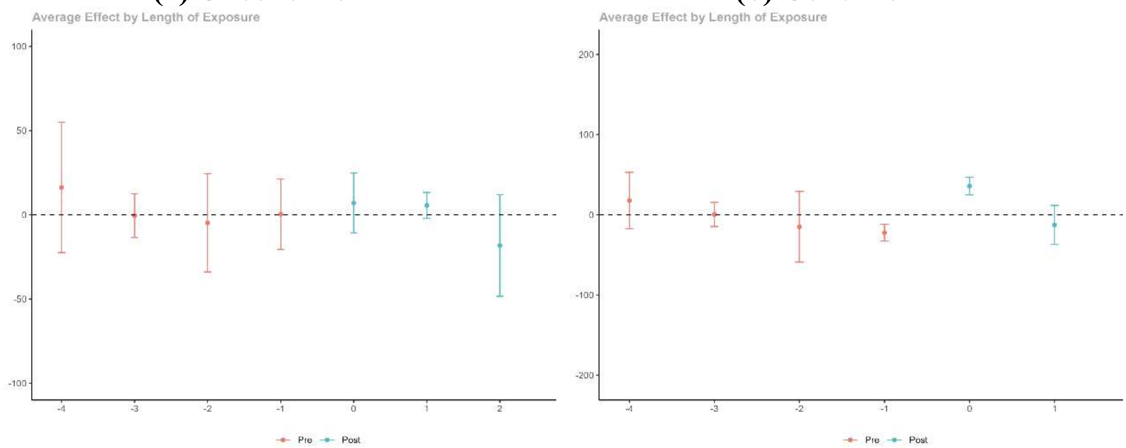
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 24 - Average effect of PJe on judges' productivity (Unbalanced)

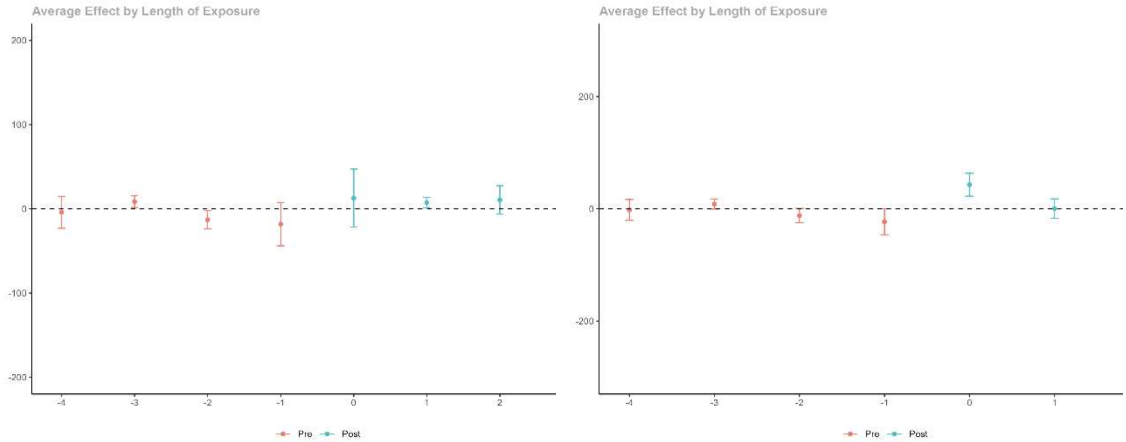
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 25 - Average effect of demand fulfillment index (Unbalanced)

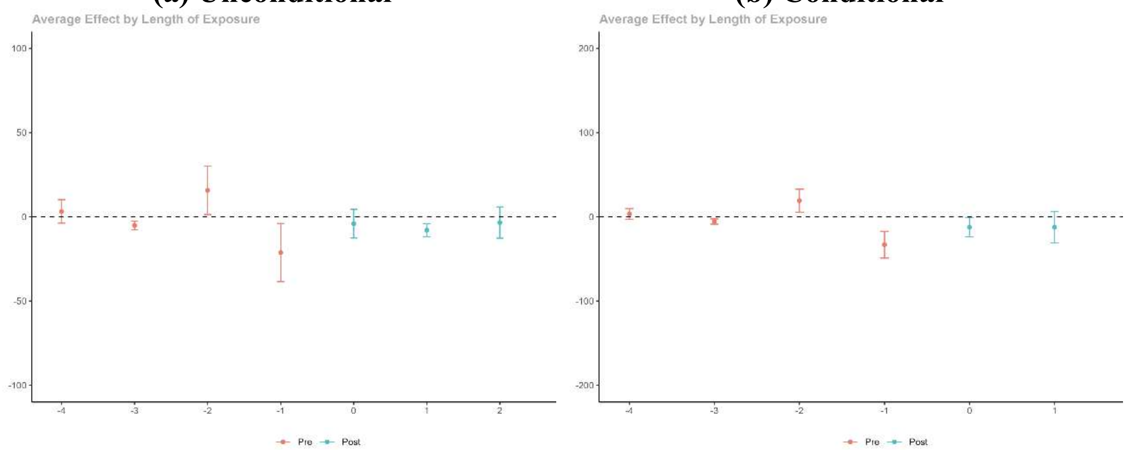
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 26 - Average effect of backlog rate (Unbalanced)

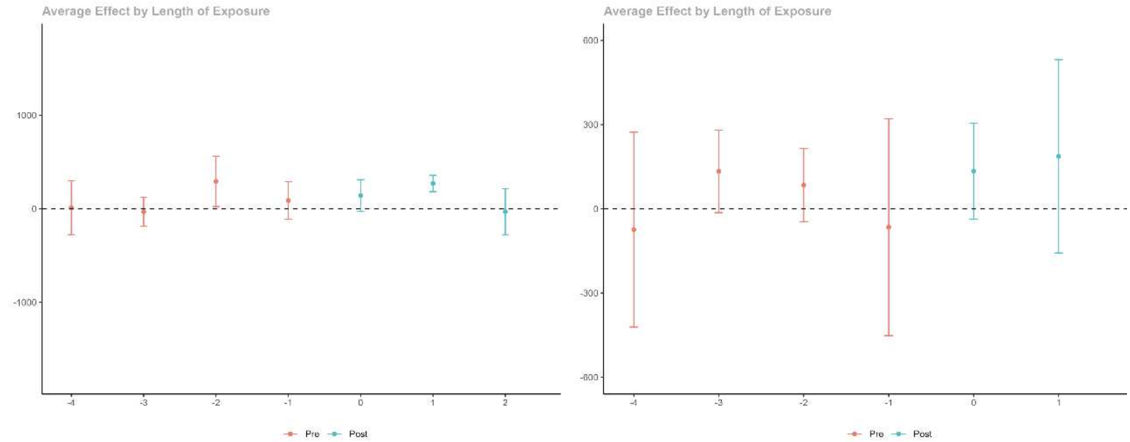
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 27 - Average effect of new cases (Unbalanced)

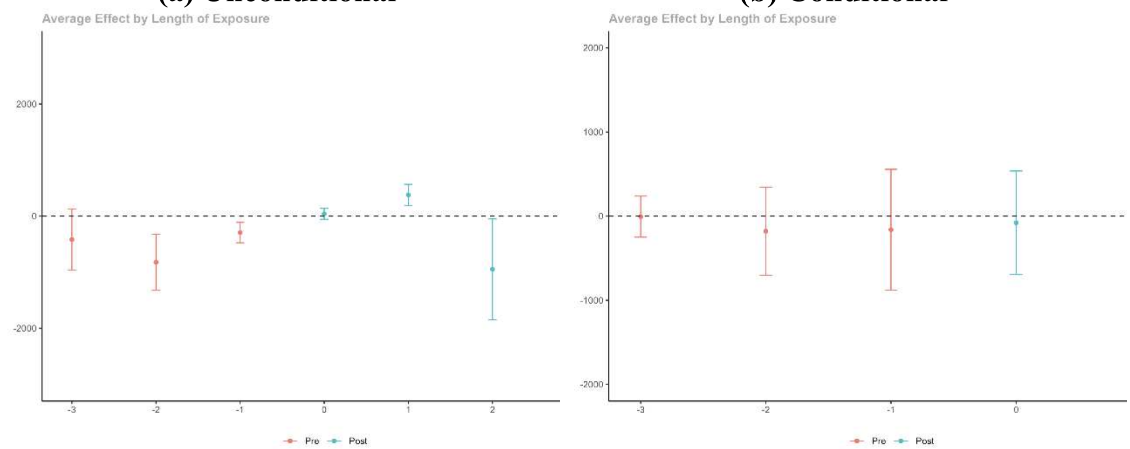
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 28 - Average effect of pending cases (Unbalanced)

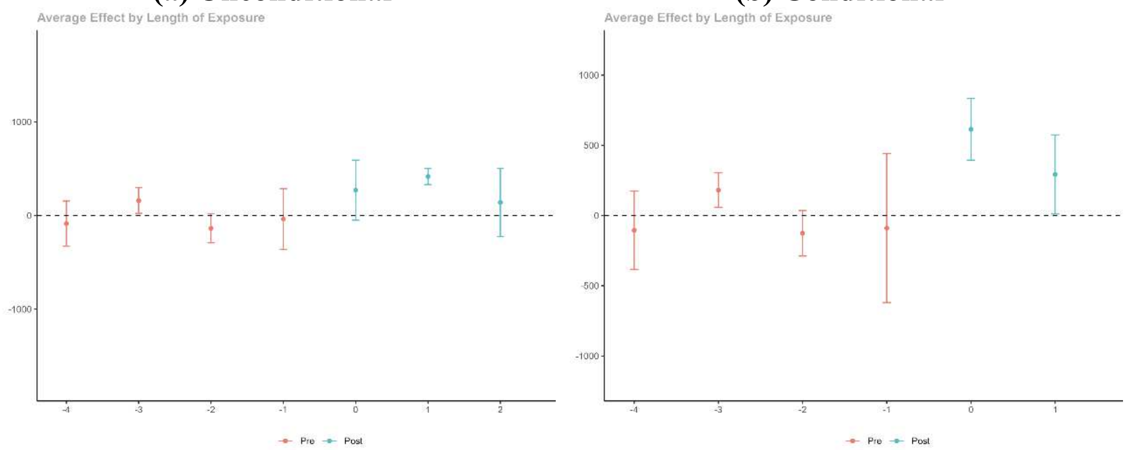
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 29 - Average effect of disposed cases (Unbalanced)

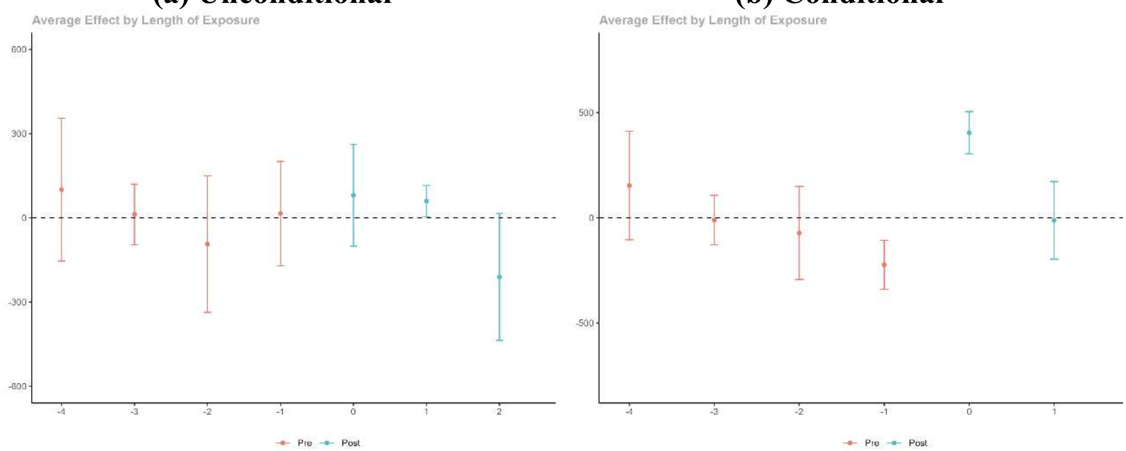
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 30 - Average effect of judgment (Unbalanced)

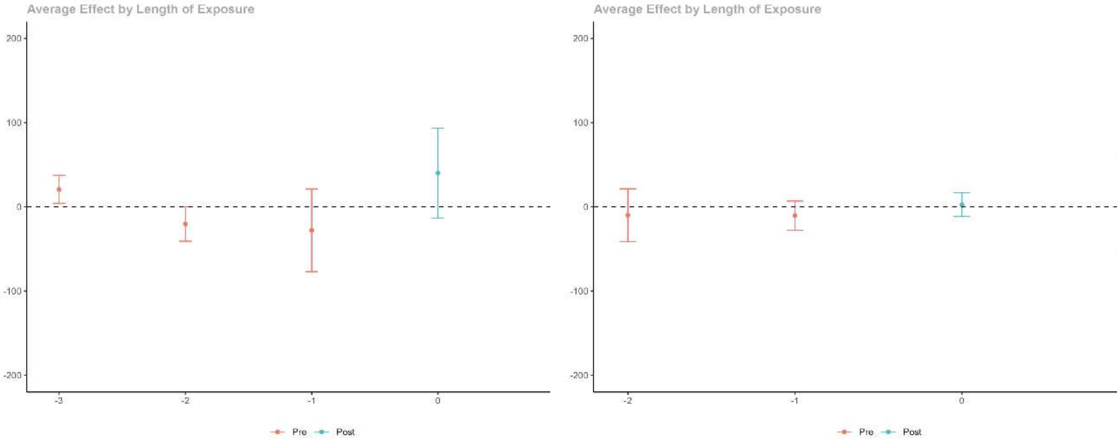
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (unbalanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 31 - Average effect of court's productivity (Balanced)

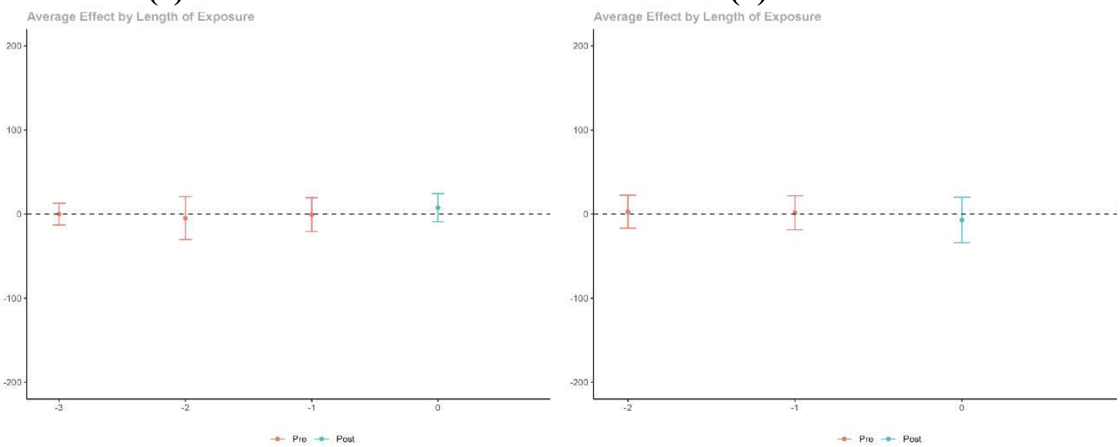
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 32 - Average effect of PJe on judges' productivity (Balanced)

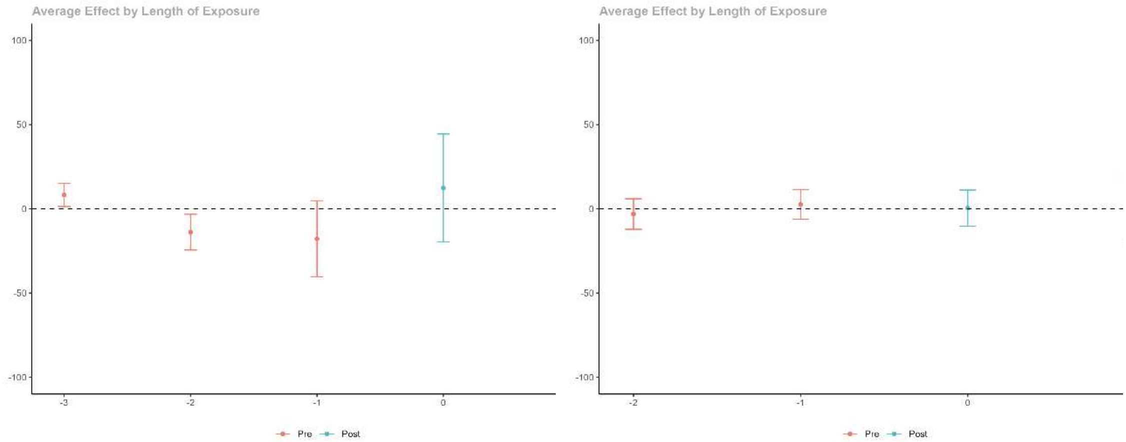
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 33 - Average effect of demand fulfillment index (Balanced)

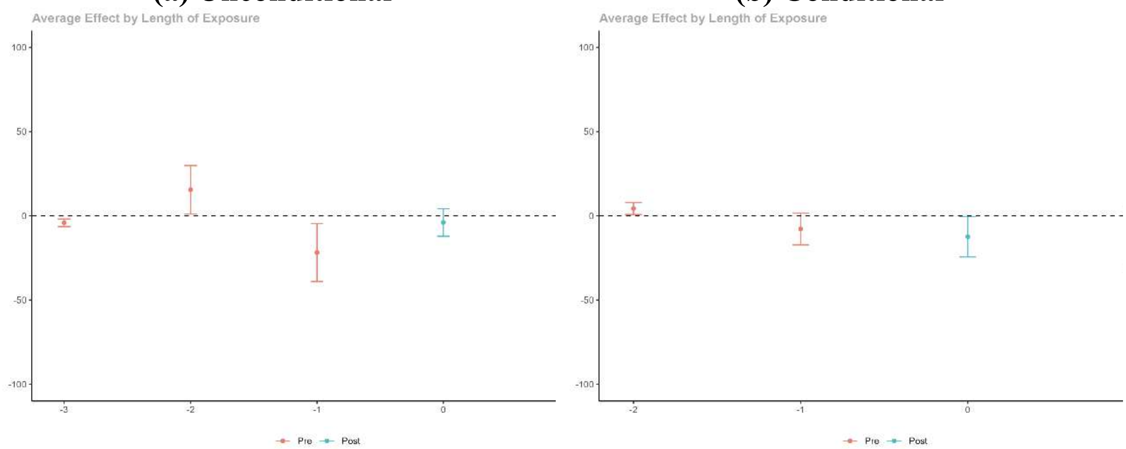
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 34 - Average effect of backlog rate (Balanced)

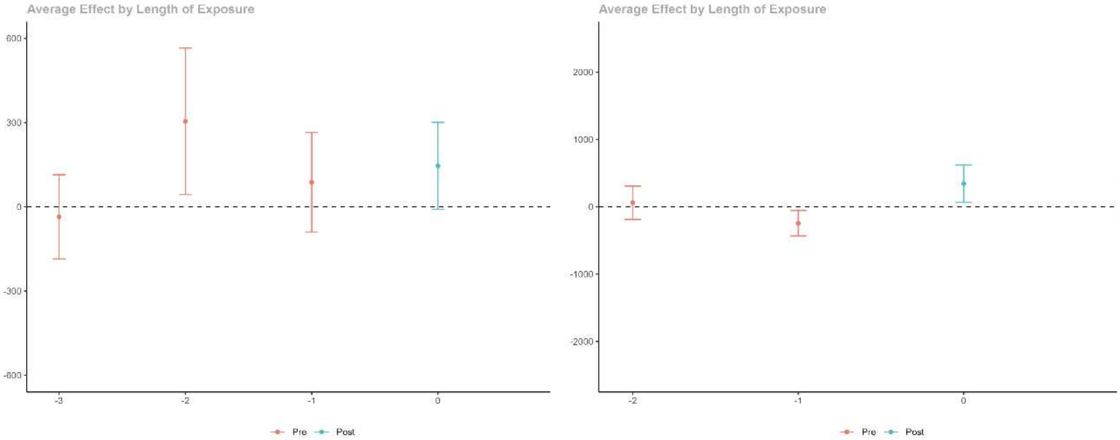
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 35 - Average effect of new cases (Balanced)

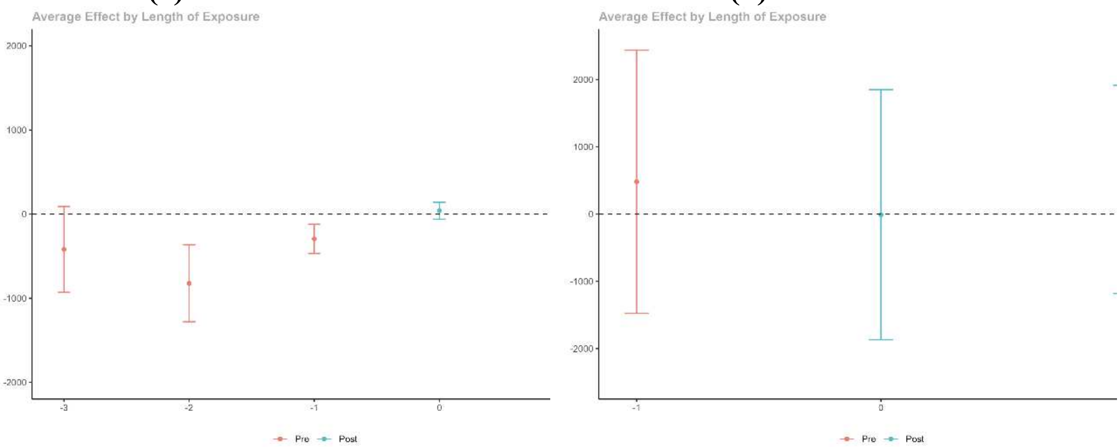
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 36 - Average effect of pending cases (Balanced)

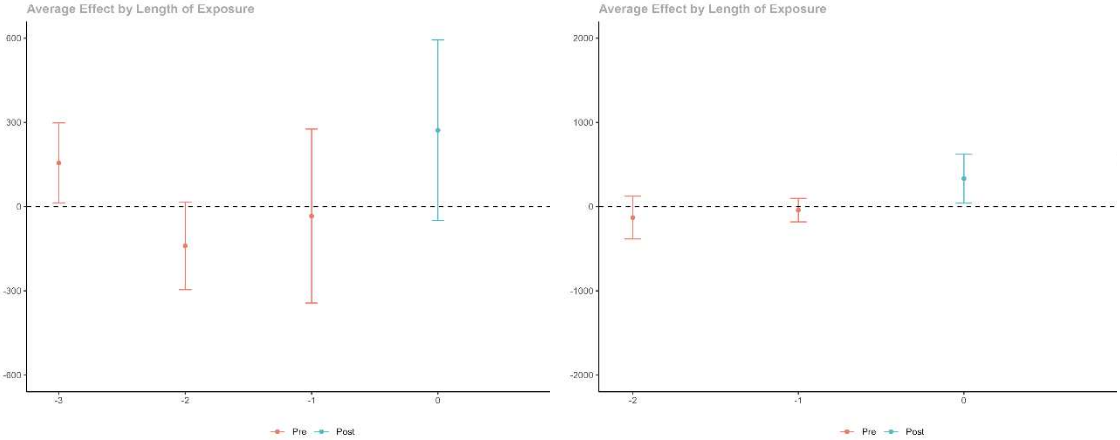
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 37 - Average effect of disposed cases (Balanced)

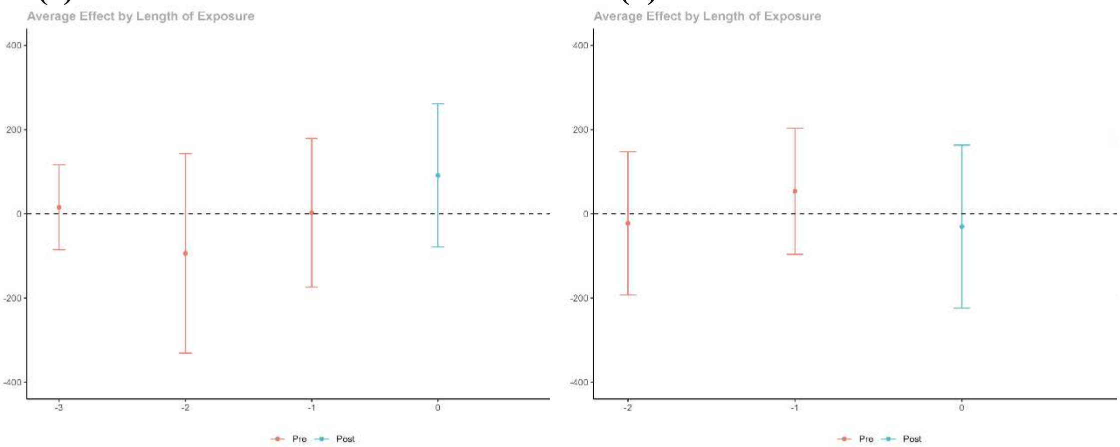
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 38 - Average effect of judgment (Balanced)

(a) Unconditional Parallel Trends **(b) Conditional Parallel Trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5 (balanced). The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Table 21 - Main results: Impact of PJe on civil performance metrics with court fixed effects

	Court's productivity (1)	Judges' productivity (2)	Demand fulfillment index (3)	Backlog rate (4)
PJe	3.895	-7.203***	14.244***	7.680***
	(3.033)	(1.746)	(1.504)	(0.865)
Observations	3159	3154	3156	3157
R-squared	0.785	0.345	0.207	0.222

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 22- Main results: Impact of PJe on performance variables with court fixed effects

	Disposed cases (1)	New cases (2)	Pending cases (3)	Judgment (4)
PJe	99.756***	-114.676***	530.489***	-29.463**
	(22.498)	(23.508)	(44.090)	(10.644)
Observations	3166	3173	2998	3168
R-squared	0.851	0.894	0.773	0.264

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 23 - Main results: Impact of PJe on civil performance metrics with year fixed effects

	Court's productivity	Judges' productivity	Demand fulfillment index	Backlog rate
	(1)	(2)	(3)	(4)
PJe	4.551	-3.405	1.948	-6.788**
	(11.349)	(4.869)	(2.953)	(2.064)
Observations	3159	3154	3156	3157
R-squared	0.046	0.028	0.200	0.325

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 24 - Main results: Impact of PJe on civil performance variables with year fixed effects

	Disposed cases	New cases	Pending cases	Judgment
	(1)	(2)	(3)	(4)
PJe	712.192**	567.771**	1025.215**	19.694
	(235.369)	(204.651)	(315.606)	(36.146)
Observations	3166	3173	2998	3168
R-squared	0.042	0.013	0.083	0.028

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

APPENDIX C – ADDITIONAL RESULTS: CIVIL COURTS

Table 25 – Robustness: Impact of PJe on civil metrics with controls and court fixed effects

	Court's productivity (1)	Judges' productivity (2)	Demand fulfillment index (3)	Backlog rate (4)
PJe	-38.041***	-6.455*	-14.696***	17.277***
	(3.530)	(2.813)	(2.278)	(1.405)
ln(Average internet speed)	63.013***	-3.296	50.445***	-14.999***
	(5.673)	(2.952)	(2.964)	(1.494)
ln(per capita GPD)	35.234	-1.122	14.740*	-11.285**
	(20.692)	(8.052)	(7.051)	(3.515)
ln(Population density)	276.161*	2.497	-109.551	16.444
	(120.876)	(40.963)	(79.521)	(23.301)
Employment rate	1.905*	-1.456***	0.478	0.095
	(0.740)	(0.422)	(0.348)	(0.197)
Observations	3159	3154	3156	3157
R-squared	0.801	0.348	0.321	0.247

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand satisfaction index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court fixed effects, as well as controls for urbanization rate and population density. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 26- Robustness: Impact of PJe on civil variables with controls and court fixed effects

	Disposed cases (1)	New cases (2)	Pending cases (3)	Judgment (4)
PJe	-238.627***	-128.318***	409.047***	-20.001
	(26.830)	(24.831)	(49.376)	(17.837)
ln(Average internet speed)	557.090***	16.590	166.728**	-37.184
	(39.978)	(36.485)	(54.599)	(18.960)
ln(per capita GPD)	397.371***	367.712***	-210.950	26.944
	(106.994)	(97.840)	(127.489)	(40.753)
ln(Population density)	-889.618	-1337.863	4411.286*	-294.646
	(993.295)	(1316.592)	(1784.185)	(288.366)
Employment rate	11.008+	10.069*	23.218*	-16.377***
	(5.751)	(4.660)	(9.248)	(3.397)
Observations	3166	3173	2998	3168
R-squared	0.864	0.895	0.777	0.273

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include court fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 27 – Robustness: Impact of PJe on civil metrics with controls and year fixed effects

	Court's productivity (1)	**Judges' productivity (2)**	**Demand fulfillment index (3)**	**Backlog rate (4)**
PJe	-33.304*	-7.958	0.999	-2.800
	(12.957)	(5.209)	(3.137)	(2.029)
ln(Average internet speed)	40.160**	2.298	4.829*	-3.318*
	(15.246)	(4.730)	(2.386)	(1.617)
ln(per capita GPD)	33.770*	7.962*	-0.715	1.436
	(15.841)	(3.835)	(2.487)	(1.653)
ln(Population density)	22.032***	2.899*	-0.042	-2.006***
	(5.413)	(1.233)	(0.746)	(0.469)
Employment rate	-0.861	-0.203	-0.005	-0.179
	(0.844)	(0.196)	(0.122)	(0.103)
Observations	3173	2998	3166	3168
R-squared	0.316	0.158	0.359	0.047

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Years_t + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 28 - Robustness: Impact of PJe on civil variables with controls and year fixed effects

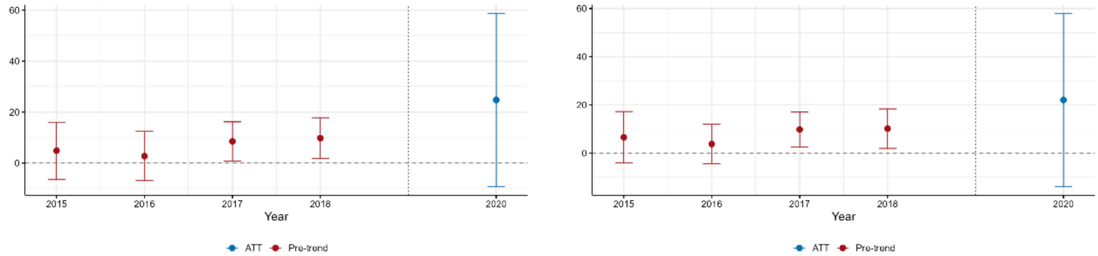
	Disposed cases	**New cases**	**Pending cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	126.008	15.606	675.264**	-18.066
	(161.225)	(149.577)	(254.321)	(37.696)
ln(Average internet speed)	90.317	122.321	260.825+	12.622
	(117.992)	(124.966)	(141.990)	(24.038)
ln(per capita GPD)	-344.481	-250.080	86.261	40.307
	(192.734)	(193.804)	(197.855)	(22.265)
ln(Population density)	369.564***	352.068***	210.550**	28.588***
	(59.597)	(56.965)	(73.377)	(7.795)
Employment rate	34.925**	29.135*	3.766	-1.068
	(11.350)	(11.567)	(10.187)	(1.170)
Observations	3166	3173	2998	3168
R-squared	0.359	0.316	0.158	0.047

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

APPENDIX D – MAIN RESULTS: CRIMINAL COURTS

Figure 39 - Average effect of PJe on court productivity (Criminal)

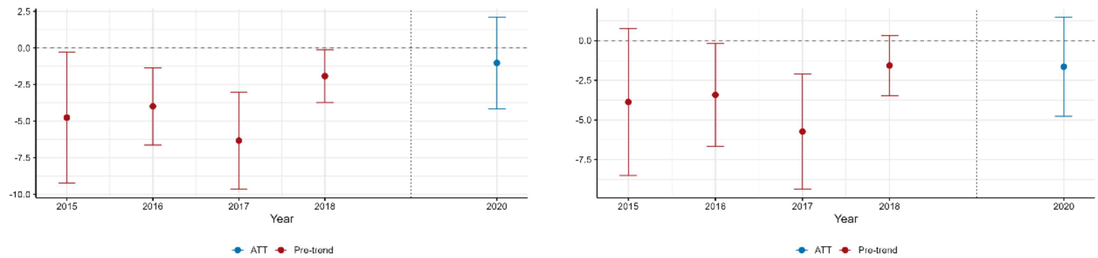
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 40 - Average effect of PJe on judges' productivity (Criminal)

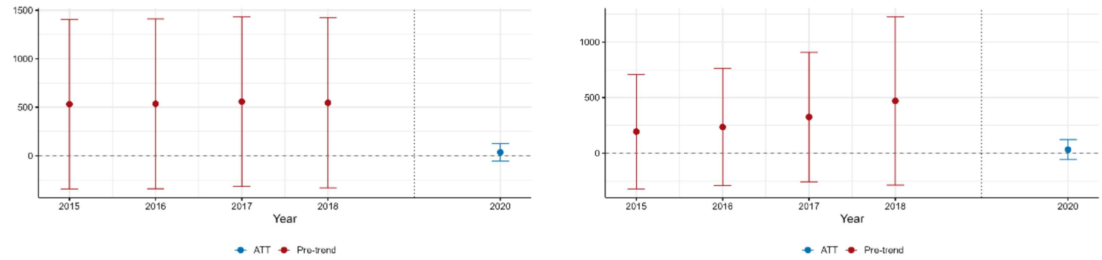
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 41 - Average effect of demand fulfillment index (Criminal)

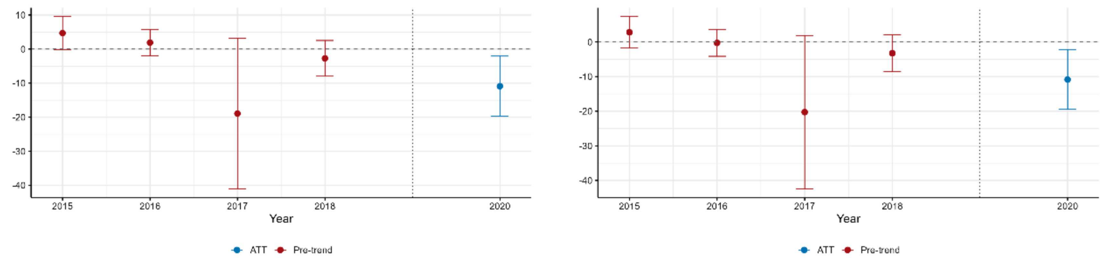
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 42 - Average effect of backlog rate (Criminal)

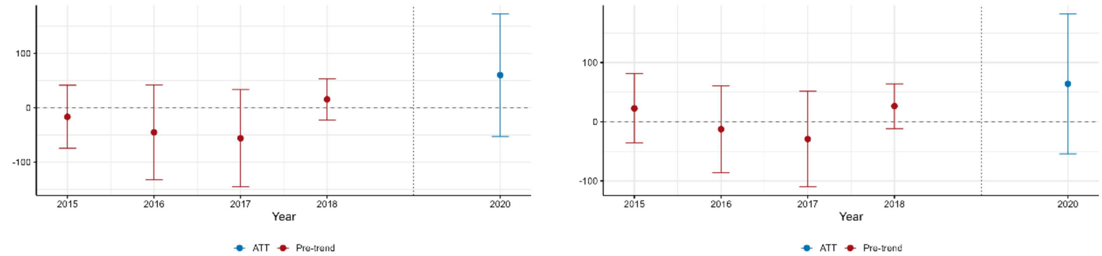
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 43 - Average effect of new cases (Criminal)

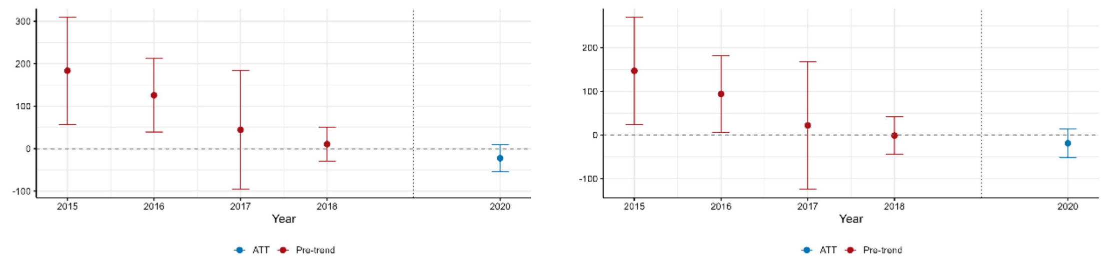
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 44 - Average effect of pending cases (Criminal)

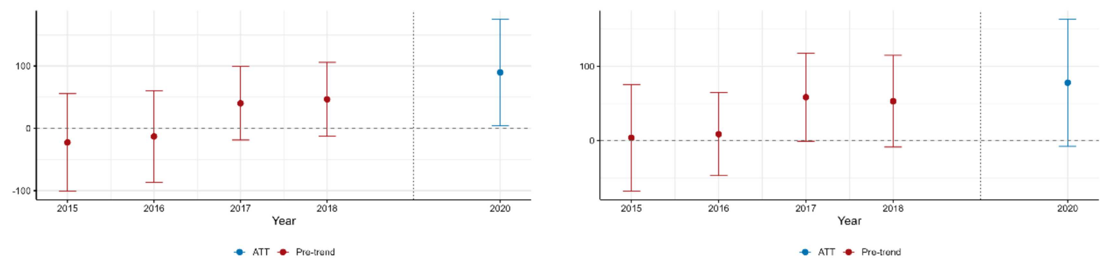
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 45 - Average effect of disposed cases (Criminal)

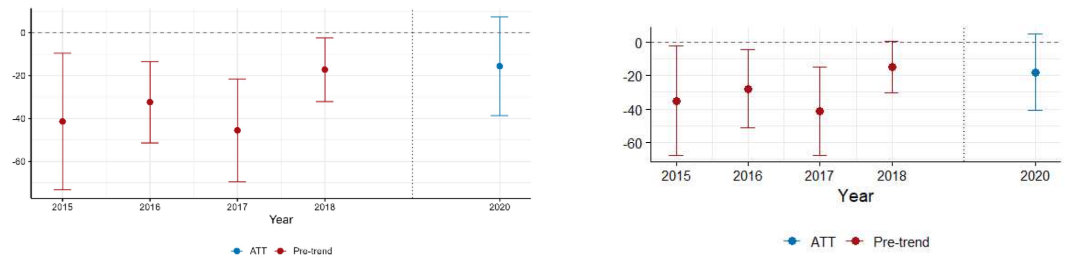
(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Figure 46 - Average effect of judgment (Criminal)

(a) Unconditional **(b) Conditional**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level.

Table 29 - Main results: Impact of PJe on criminal performance metrics with court fixed effects

	Court's productivity (1)	**Judges' productivity (2)**	**Demand fulfillment index (3)**	**Backlog rate (4)**
PJe	4.840*	-2.829***	2.573	5.351***
	(1.945)	(0.348)	(69.612)	(1.069)
Observations	2666	1679	2650	2660
R-squared	0.725	0.347	0.169	0.120

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 30 - Main results: Impact of PJe on criminal performance variables with court fixed effects

	Disposed cases (1)	**New cases (2)**	**Pending cases (3)**	**Judgment (4)**
PJe	39.955***	-89.015***	-42.949*	-17.748***
	(11.293)	(8.492)	(18.902)	(1.741)
Observations	2666	2666	2438	1679
R-squared	0.652	0.642	0.871	0.332

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 31 - Main results: Impact of PJe on criminal performance metrics with year fixed effects

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	14.349	-0.810	-19.799	-3.835
	(15.868)	(0.493)	(57.891)	(3.939)
Observations	2666	1679	2650	2660
R-squared	0.011	0.025	0.005	0.490

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 32 - Main results: Impact of PJe on criminal performance variables with year fixed effects

	Disposed cases	**New cases**	**Pending cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	31.680	14.469	-230.791	-4.322
	(76.135)	(80.628)	(145.477)	(3.081)
Observations	2666	2666	2438	1679
R-squared	0.017	0.037	0.102	0.023

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

APPENDIX E – ADDITIONAL RESULTS: CRIMINAL COURTS

Table 33 - Robustness: Impact of PJe on criminal metrics with controls and court fixed effects

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	17.462***	0.349	-183.347	0.382
	(3.805)	(0.961)	(179.614)	(1.608)
ln(Average internet speed)	-14.059***	-2.534*	48.167	5.118**
	(3.964)	(1.018)	(39.028)	(1.600)
ln(per capita GPD)	2.081	-1.644	251.357	-0.329
	(5.008)	(2.061)	(211.859)	(3.786)
ln(Population density)	-166.932	-97.956**	9906.762	88.075**
	(101.931)	(31.120)	(6981.966)	(32.467)
Employment rate	-0.657	0.143	-52.786	0.018
	(0.344)	(0.105)	(40.294)	(0.279)
Observations	2666	1679	2650	2660
R-squared	0.730	0.363	0.173	0.125

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand satisfaction index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court fixed effects, as well as controls for urbanization rate and population density. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 34 - Robustness: Impact of PJe on criminal variables with controls and court fixed effects

	Disposed cases	**New cases**	**Pending cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	80.065***	13.879	-240.718***	3.657
	(23.049)	(15.739)	(27.505)	(6.624)
ln(Average internet speed)	-38.238	-97.967***	238.799***	-18.698**
	(21.132)	(14.493)	(27.324)	(6.754)
ln(per capita GPD)	64.056	-15.715	90.248	-2.505
	(38.550)	(29.849)	(59.506)	(8.151)
ln(Population density)	-1518.841	-2129.059**	68.468	-642.266**
	(845.555)	(732.694)	(654.562)	(213.199)
Employment rate	-7.544**	10.375***	-15.544**	0.761
	(2.641)	(2.026)	(5.448)	(0.573)
Observations	2666	2666	2438	1679
R-squared	0.655	0.660	0.879	0.348

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Court_i + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include court fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 35 - Robustness: Impact of PJe on criminal metrics with controls and year fixed effects

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	20.091	0.605	35.871	-3.536
	(12.509)	(1.660)	(72.450)	(3.904)
ln(Average internet speed)	15.339*	1.155	-40.757	-4.213**
	(7.788)	(0.985)	(95.454)	(1.553)
ln(per capita GPD)	32.917***	1.711	424.375	-2.821*
	(6.840)	(0.985)	(408.668)	(1.390)
ln(Population density)	15.917***	2.793*	135.819	-1.204
	(4.153)	(1.104)	(102.239)	(0.666)
Employment rate	-1.681**	-0.036	-21.076	0.249*
	(0.549)	(0.098)	(18.461)	(0.098)
Observations	2666	1679	2650	2660
R-squared	0.150	0.093	0.010	0.496

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Years_t + \delta Post\_Pje_{it} + \mathbf{X}_{\mathrm{i,t}} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 36 - Robustness: Impact of PJe on criminal variables with controls and year fixed effects

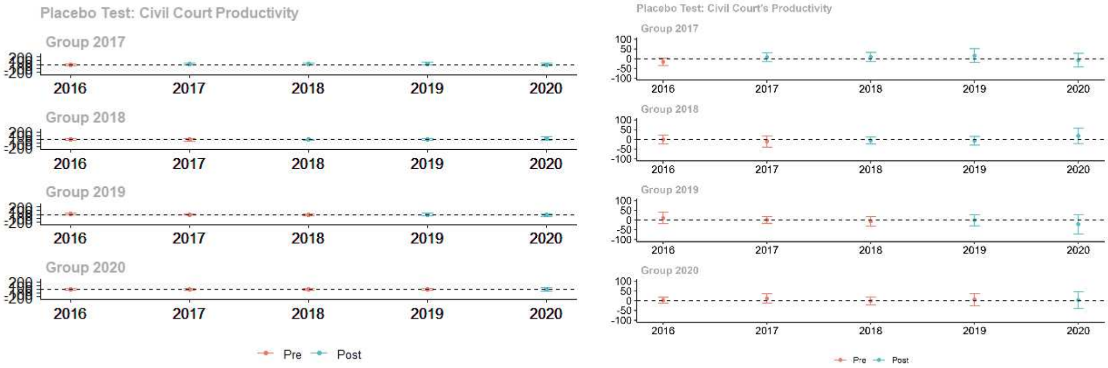
	Disposed cases (1)	New cases (2)	Pending cases (3)	Judgment (4)
PJe	61.813	42.970	-109.677	3.250
	(64.257)	(61.945)	(124.385)	(10.285)
ln(Average internet speed)	176.793***	190.611***	514.259***	9.778
	(46.694)	(41.224)	(105.648)	(6.982)
ln(per capita GPD)	131.176***	110.798***	89.210	9.991
	(36.196)	(29.694)	(81.660)	(5.834)
ln(Population density)	94.177***	77.775***	162.226***	18.025*
	(27.293)	(23.389)	(36.284)	(7.682)
Employment rate	-6.930*	-5.323	1.573	-0.378
	(3.165)	(2.718)	(4.652)	(0.637)
Observations	2666	2666	2438	1679
R-squared	0.176	0.197	0.336	0.087

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + \delta Post\_Pje_{it} + \mathbf{X}_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais criminal courts. In Column 1, disposed cases refers to the total number of lawsuits that were closed or resolved through various means, including judgment, dismissal, settlement, withdrawal, or any other method that concludes the case. In Column 2, the variable new cases represent the total number of new cases filed in the court during the year. In Column 3, the variable pending cases refers to the total number of cases pending in the court during the year. Judgment refers to the final decision issued by a judge at the end of a lawsuit. This decision resolves the legal issues in dispute, determining the rights and obligations of the parties involved, and may result in either the conviction or acquittal of the defendant. All estimates include year fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

APPENDIX F – PLACEBO TEST: CIVIL COURTS

Figure 47 - Placebo test: Court's productivity group-time average treatment effects

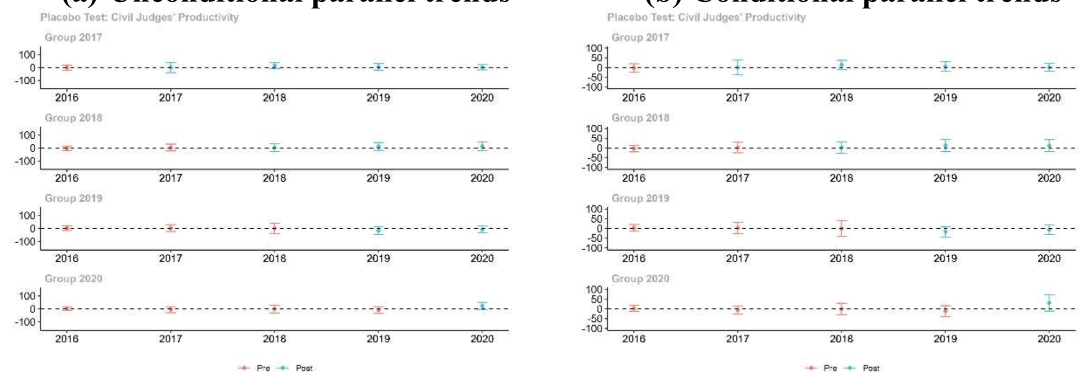
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 48 - Placebo test: Judges's productivity group-time average treatment effects

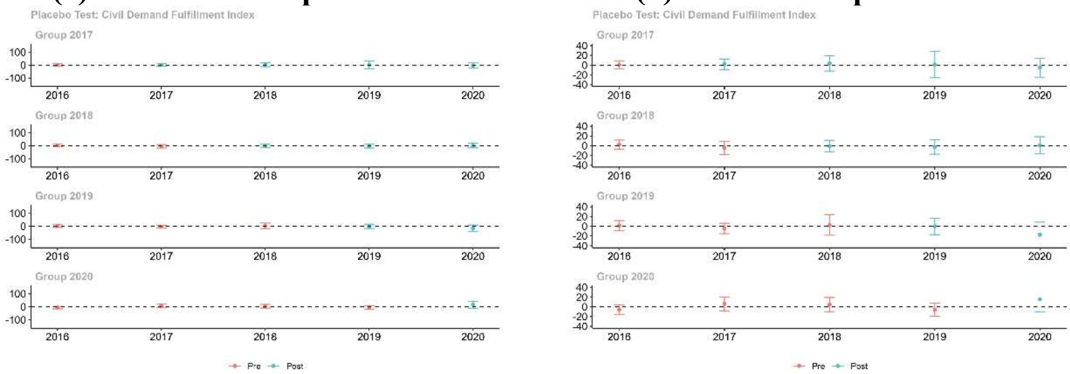
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 49 - Placebo test: Demand fulfillment index group-time average treatment effects

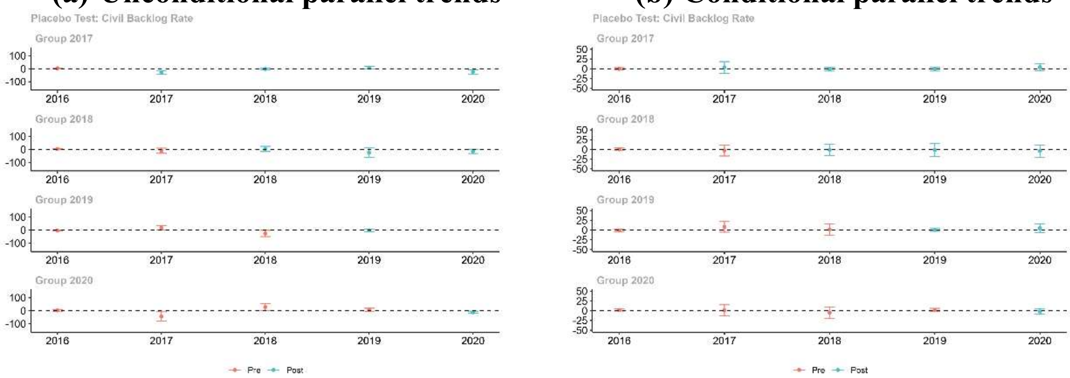
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 50 - Placebo test: Backlog rate group-time average treatment effects

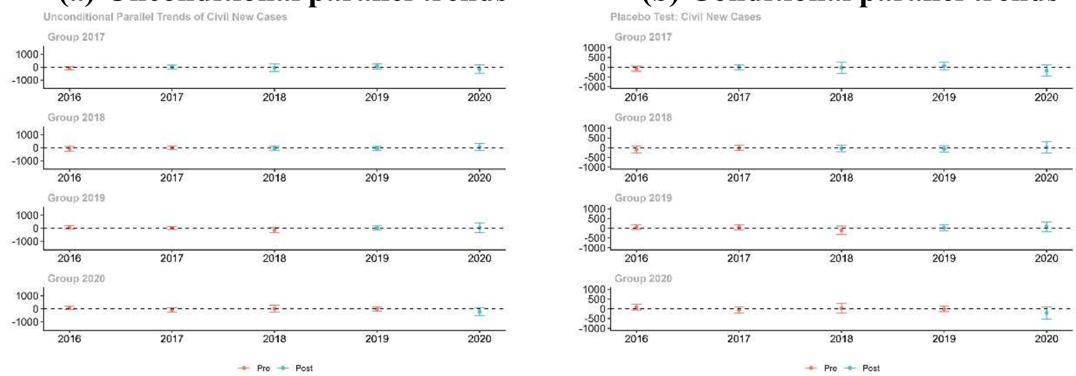
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 51 - Placebo test: New cases group-time average treatment effects

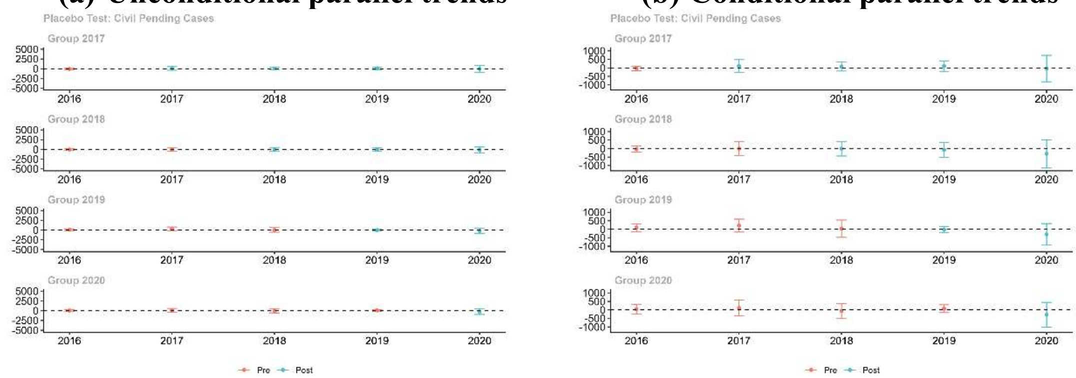
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 52 - Placebo test: Pending cases group-time average treatment effects

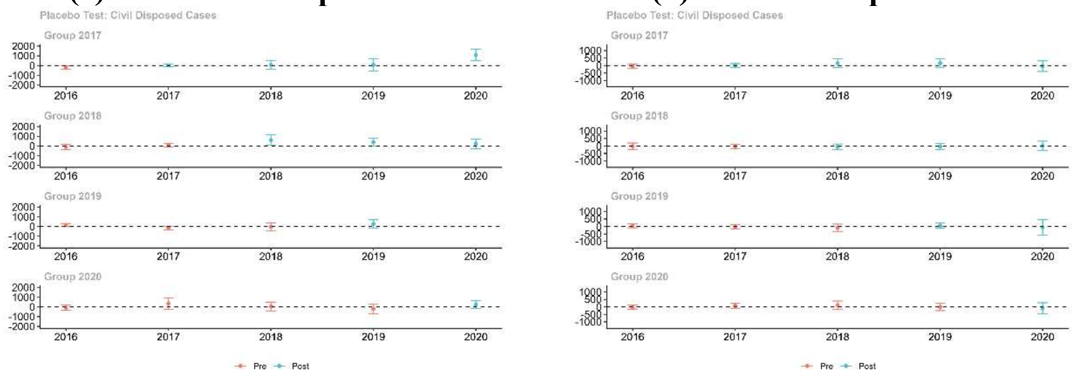
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 53 - Placebo test: Disposed cases group-time average treatment effects

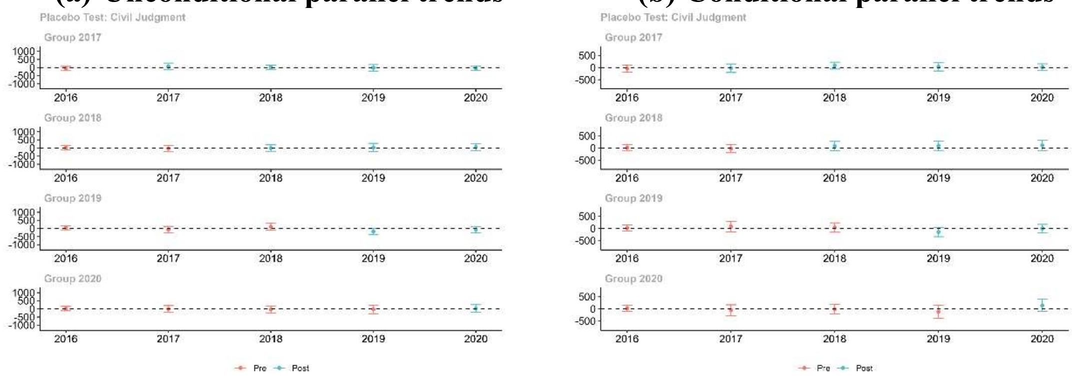
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 54 - Placebo test: Judgment group-time average treatment effects

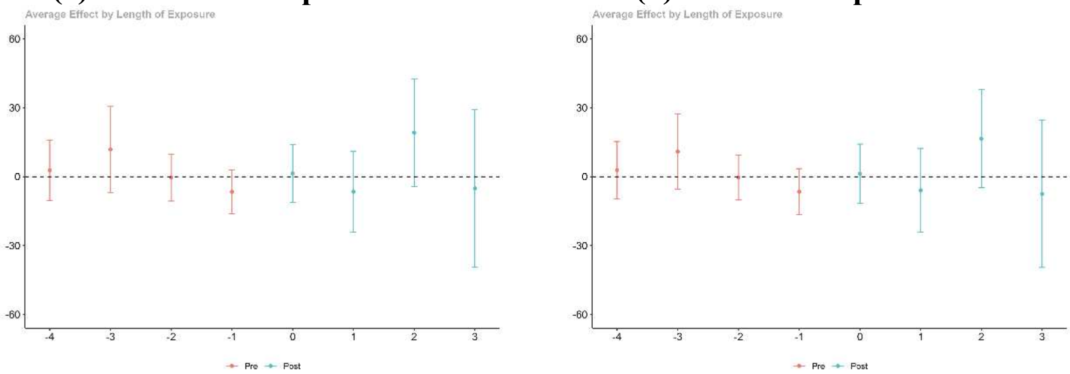
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: These figures report estimates from Equation (5): $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The effect of the PJe on civil court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and the assumption of conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. The top line includes courts that implemented PJe in 2017, the second line includes courts that implemented PJe starting in 2018, the third line shows courts that implemented starting in 2019, and the bottom line includes courts that implemented PJe in 2020. The estimates in Panel (b) use the doubly robust estimator discussed in the text. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 55 - Placebo test: Average effect of PJe on court productivity (Civil)

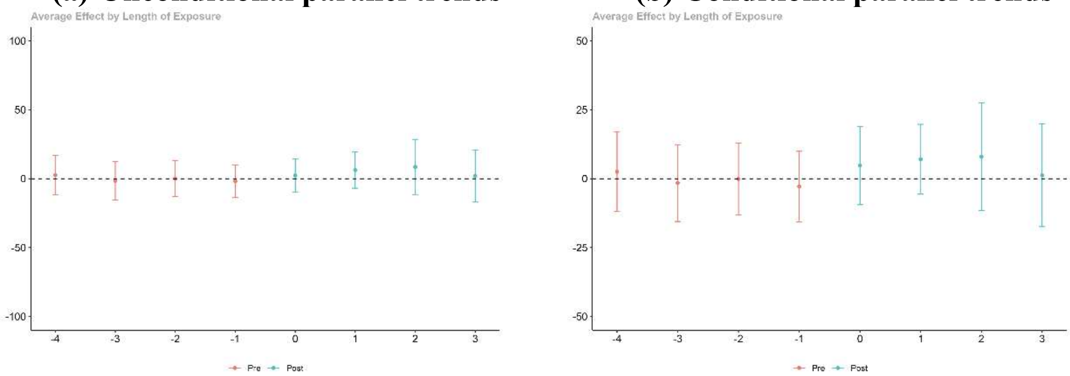
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 56 - Placebo test: Average effect of PJe on judges' productivity (Civil)

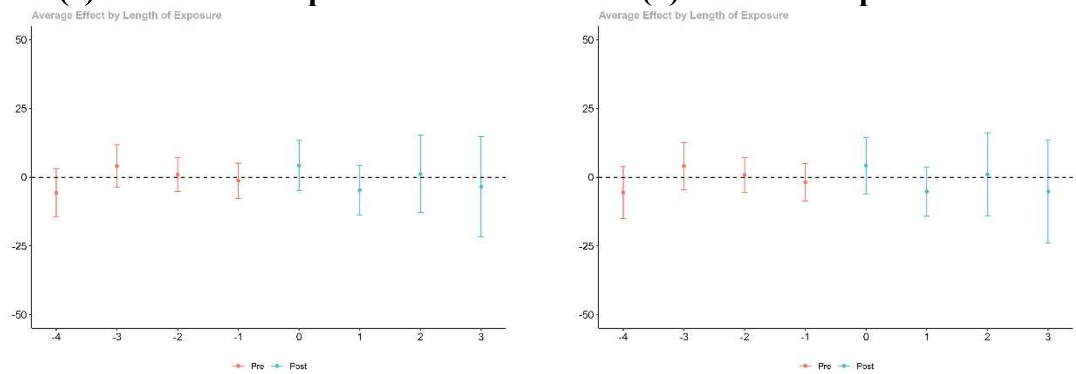
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 57 - Placebo test: Average effect of demand fulfillment index (Civil)

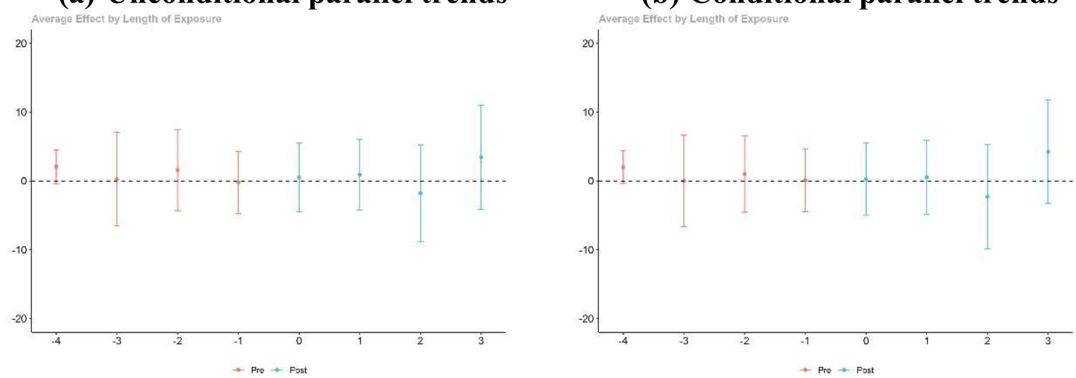
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 58 - Placebo test: Average effect of backlog rate (Civil)

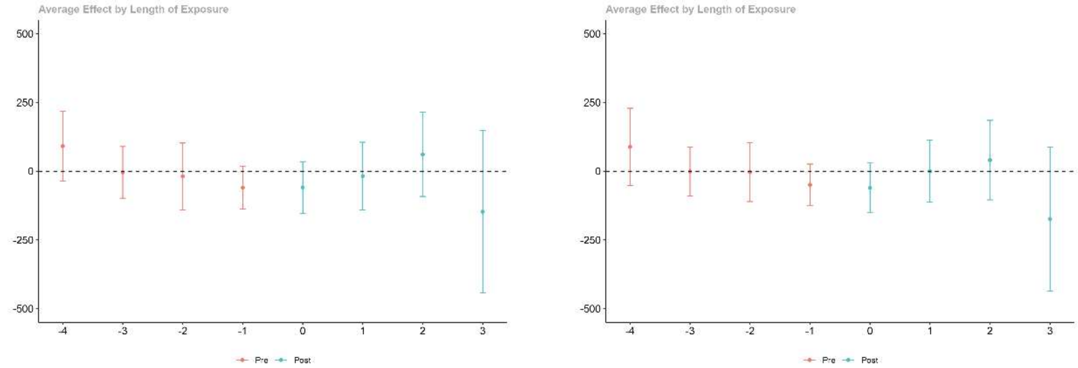
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 59 - Placebo test: Average effect of new cases (Civil)

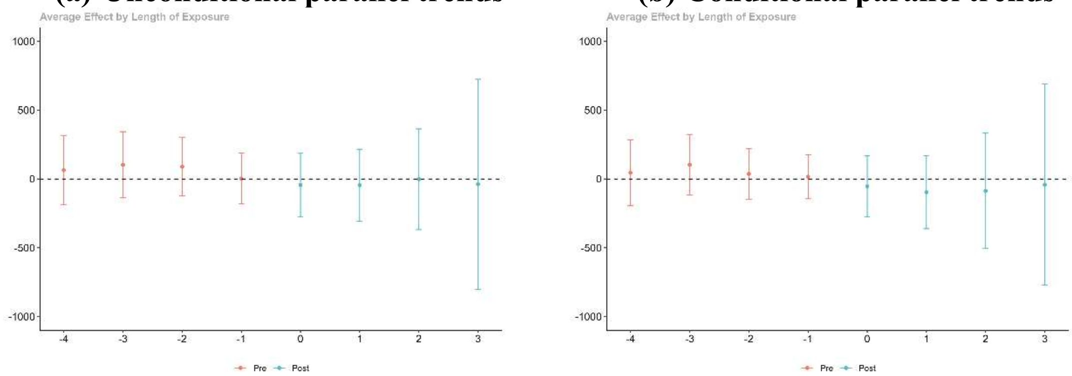
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 60 - Placebo test: Average effect of pending cases (Civil)

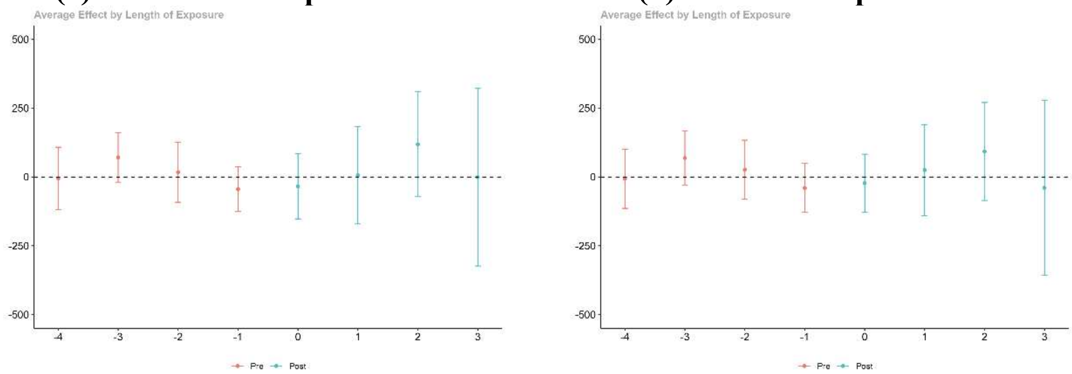
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 61 - Placebo test: Average effect of disposed cases (Civil)

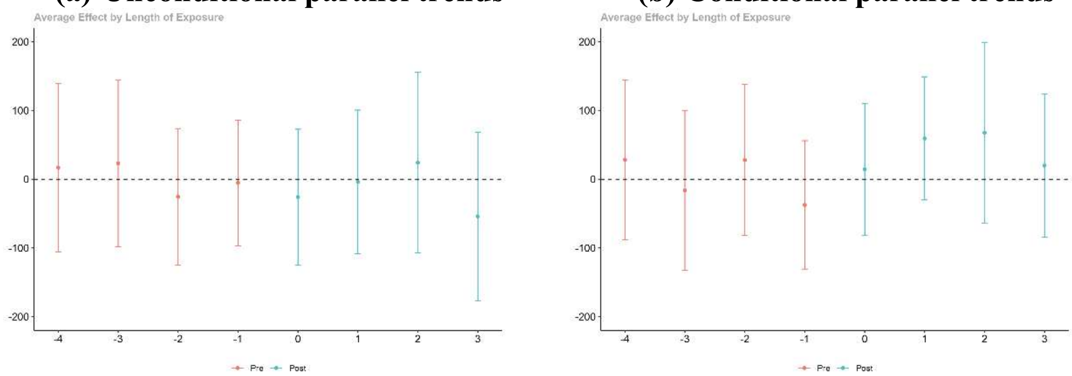
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Figure 62 - Placebo test: Average effect of judgment (Civil)

(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated β_e coefficients from a regression of the form given in Equation 5: $Y_{i,t} = \alpha_t + \alpha_g + \sum_{e=-K}^{-2} \delta_e^{anticip} \cdot D_{i,t}^e + \sum_{e=0}^{L} \beta_e \cdot D_{i,t}^e + \mu_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. As a robustness check, the figures display a placebo test based on randomly assigned PJe implementation years across courts. The lack of significant effects in this placebo scenario supports the validity of the main results.

Table 37 - Placebo test of the PJe's impact on civil court performance metrics (unconditional)

	Court's productivity (1)	Judges' productivity (2)	Demand fulfillment index (3)	Backlog rate (4)
PJe	-5.540	0.477	-7.338*	10.512***
	(6.601)	(3.534)	(3.489)	(1.723)
Observations	3159	3154	3156	3157
R-squared	0.823	0.368	0.375	0.527

Note: This table reports the results of the estimation of equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4). In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 38 – Placebo test of the PJe's impact on civil court performance variables (unconditional)

	New cases (1)	Pending cases (2)	Disposed cases (3)	Judgment (4)
PJe	179.415**	294.174**	-78.646	-32.161
	(65.872)	(98.473)	(75.404)	(24.075)
Observations	3173	2998	3166	3168
R-squared	0.899	0.810	0.878	0.290

Note: This table reports the results of the estimation of equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + \varepsilon_{i,t}$ in each model across Columns (1) to (4). In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. The backlog rate measures court congestion by evaluating the total number of disposed cases, divided by the number of new cases plus the number of pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, and * denotes p < 0.1.

Table 39 - Placebo test of the PJe's impact on civil court performance metrics (conditional)

	Court's productivity (1)	**Judges' productivity (2)**	**Demand fulfillment index (3)**	**Backlog rate (4)**
PJe	-3.953	0.299	-8.282*	11.068***
	(6.606)	(3.545)	(3.454)	(1.718)
ln(Average internet speed)	-12.327	-1.734	8.726*	-0.584
	(7.975)	(4.703)	(4.267)	(1.743)
ln(per capita GPD)	9.763	-4.806	0.417	-4.474
	(19.605)	(7.936)	(6.953)	(2.792)
ln(Population density)	353.096**	-18.646	-138.651	61.478**
	(118.007)	(40.152)	(81.207)	(22.049)
Employment rate	1.157	-0.084	0.765+	-0.189
	(0.793)	(0.423)	(0.422)	(0.187)
Observations	3159	3154	3156	3157
R-squared	0.824	0.369	0.379	0.529

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + X_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

Table 40 - Placebo test of the PJe's impact on civil court performance variables (conditional)

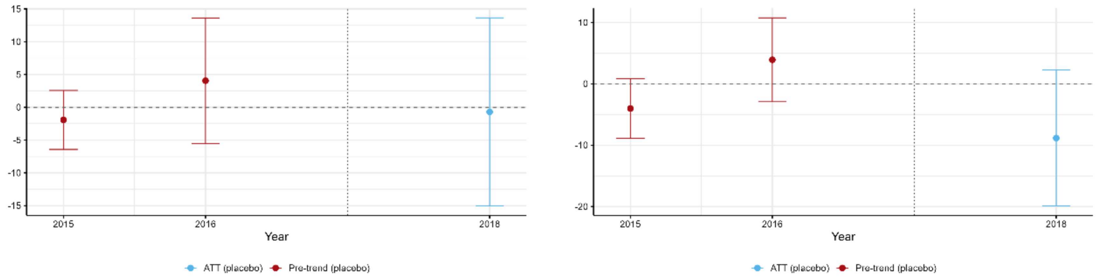
	New cases	**Pending cases**	**Disposed cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	181.032**	360.187***	-79.511	-32.621
	(65.560)	(100.523)	(73.189)	(24.156)
ln(Average internet speed)	88.807	26.905	85.878	0.214
	(67.768)	(110.585)	(67.337)	(28.457)
ln(per capita GPD)	385.326***	-143.461	245.749*	12.099
	(106.520)	(119.334)	(102.252)	(39.184)
ln(Population density)	-48.413	5815.999***	-292.702	-411.515
	(1350.864)	(1718.362)	(921.596)	(278.384)
Employment rate	3.193	-8.600	5.526	-7.582*
	(5.221)	(10.910)	(6.003)	(3.102)
Observations	3173	2998	3166	3168
R-squared	0.900	0.813	0.878	0.292

Note: This table reports the estimation results of the equation (4): $Y_{i,t} = Year_t + Court_i + \delta Post\_Pje_{it} + X_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

APPENDIX G – PLACEBO TEST: CRIMINAL COURTS

Figure 63 - Placebo test: Average effect of PJe on court productivity (Criminal)

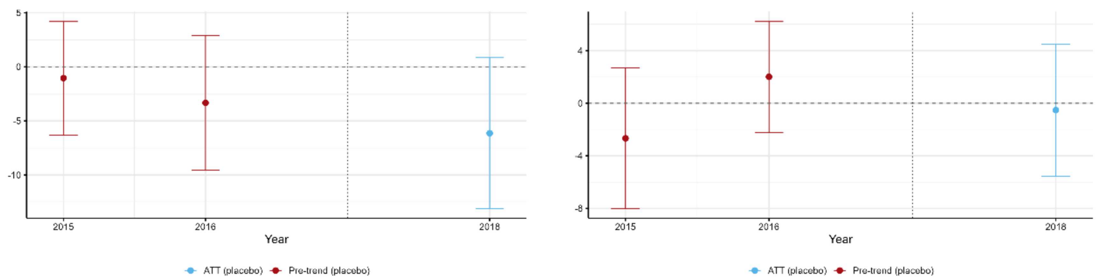
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 64 - Placebo test: Average effect of PJe on judges' productivity (Criminal)

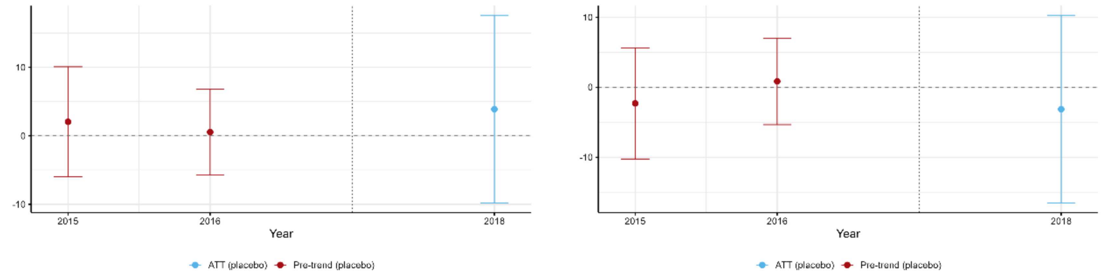
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 65 - Placebo test: Average effect of demand fulfillment index (Criminal)

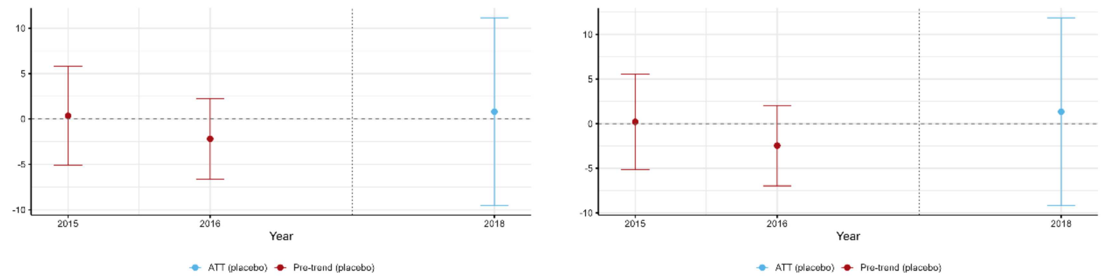
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 66 - Placebo test: Average effect of backlog rate (Criminal)

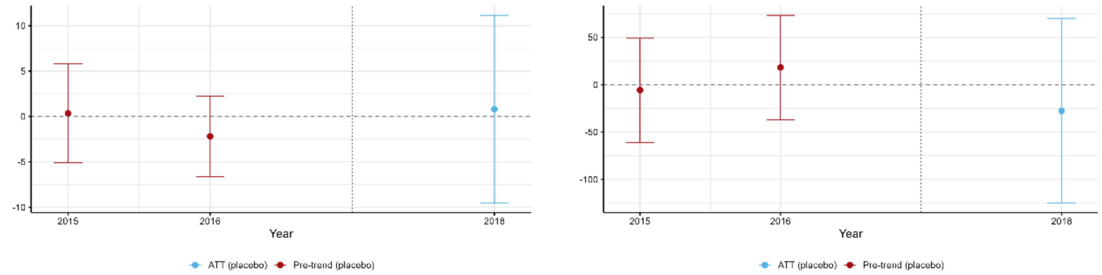
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 67 - Placebo test: Average effect of new cases (Criminal)

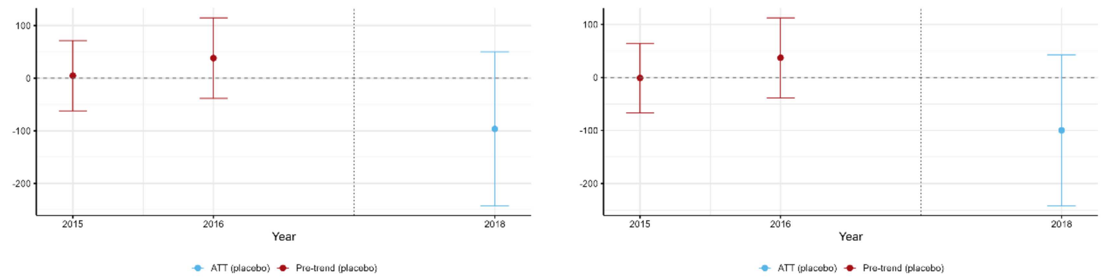
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 68 - Placebo test: Average effect of pending cases (Criminal)

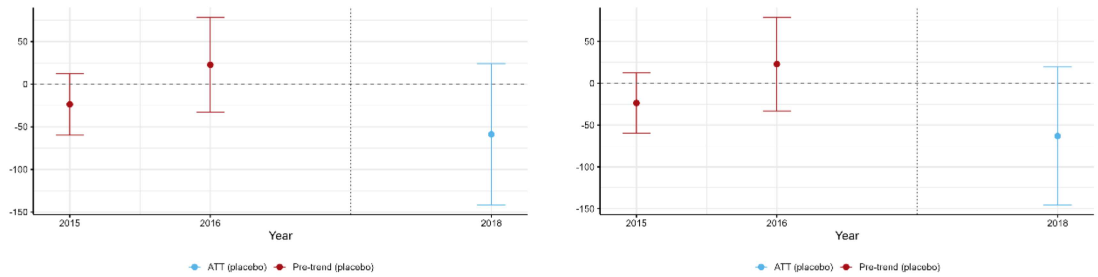
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 69 - Placebo test: Average effect of disposed cases (Criminal)

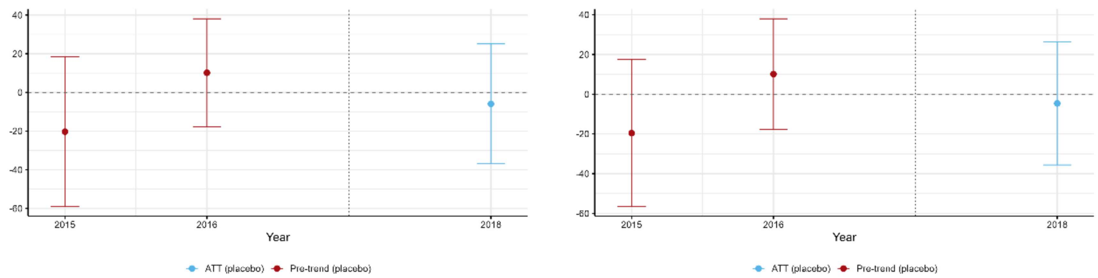
(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Figure 70 - Placebo test: Average effect of judgment (Criminal)

(a) Unconditional parallel trends **(b) Conditional parallel trends**



Note: The figure plots the estimated δ coefficients from a regression of the form given in Equation 6: $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. The average effect of PJe on court productivity is estimated under the assumption of unconditional parallel trends (Panel (a)) and conditional parallel trends (Panel (b)). The red lines provide point estimates and uniform 95% confidence intervals for pre-treatment periods, allowing for clustering at the court level. Under the null hypothesis that the parallel trends assumption holds across all periods, these should be equal to 0. The blue lines provide point estimates and uniform 95% confidence intervals for the treatment effect of PJe implementation, allowing for clustering at the court level. This is a placebo test based on a fictitious treatment design with a fixed year: treatment is randomly assigned to a subset of courts starting in 2018, two years before the actual PJe implementation (2020).

Table 41 - Placebo test of the PJe's impact on criminal court performance metrics (unconditional)

	Court's productivity (1)	**Judges' productivity (2)**	**Demand fulfillment index (3)**	**Backlog rate (4)**
PJe	4.147	1.271	-52.651	-0.166
	(6.064)	(1.773)	(354.353)	(2.111)
Observations	1858	1234	1847	1854
R-squared	0.741	0.391	0.204	0.700

Note: This table reports the estimation results of the equation (6): $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

Table 42 - Placebo test of the PJe's impact on criminal court performance variables (unconditional)

	New cases (1)	**Pending cases (2)**	**Disposed cases (3)**	**Judgment (4)**
PJe	11.798	1.338	27.848	7.719
	(51.582)	(40.172)	(53.222)	(12.016)
Observations	1858	1648	1858	1234
R-squared	0.667	0.932	0.679	0.357

Note: This table reports the estimation results of the equation (6): $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

Table 43 - Placebo test of the PJe's impact on criminal court performance metrics (conditional)

	Court's productivity	**Judges' productivity**	**Demand fulfillment index**	**Backlog rate**
	(1)	**(2)**	**(3)**	**(4)**
PJe	4.397	1.291	-102.476	-0.532
	(6.019)	(1.731)	(370.225)	(2.042)
ln(Average internet speed)	-6.039	-1.041	-358.556	-10.186**
	(7.656)	(1.733)	(347.228)	(3.263)
ln(per capita GPD)	6.715	1.947	-295.234	-2.885
	(8.268)	(3.375)	(296.577)	(3.854)
ln(Population density)	-181.622	-108.048	29309.234	122.682**
	(210.363)	(59.350)	(21504.605)	(40.248)
Employment rate	-0.068	0.177	2.265	0.098
	(0.391)	(0.184)	(18.630)	(0.299)
Observations	1858	1234	1847	1854
R-squared	0.742	0.397	0.211	0.703

Note: This table reports the estimation results of the equation (6): $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.

Table 44 - Placebo test of the PJe's impact on criminal court performance variables (conditional)

	New cases	**Pending cases**	**Disposed cases**	**Judgment**
	(1)	**(2)**	**(3)**	**(4)**
PJe	16.629	-4.626	31.358	7.720
	(50.043)	(39.738)	(51.619)	(11.721)
ln(Average internet speed)	24.879	-73.849+	4.356	-4.541
	(27.901)	(44.627)	(35.621)	(11.844)
ln(per capita GPD)	17.694	-41.973	24.777	11.663
	(41.787)	(62.697)	(52.639)	(16.639)
ln(Population density)	-3094.406*	2540.533**	-2305.089	-846.653*
	(1560.661)	(869.917)	(1876.946)	(409.136)
Employment rate	3.093	-5.383	0.562	0.648
	(2.385)	(7.257)	(3.226)	(1.059)
Observations	1858	1648	1858	1234
R-squared	0.672	0.933	0.681	0.364

Note: This table reports the estimation results of the equation (6): $Y_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \delta(Treat_i \times Post_t) + \theta X'_{i,t} + \varepsilon_{i,t}$, including controls (ln(average internet speed) , ln(per capita GPD), ln(population density) and employment rate) in each model across Columns (1) to (4), considering Minas Gerais civil courts. In Column 1, the court productivity index measures the number of disposed cases divided by the total number of judges in the court. In Column 2, judge productivity measures the total number of judgments divided by the total number of judges in the court. In Column 3, the demand fulfillment index calculates the number of disposed cases divided by the number of new cases, multiplied by 100. In Column 4, the backlog rate measures court congestion by evaluating the total number of disposed cases divided by the sum of new cases and pending cases. All estimates include court and time fixed effects. Standard errors are clustered at the court level and reported in parentheses. *** denotes p<0.01p < 0.01p<0.01, ** denotes p<0.05p < 0.05p<0.05, and * denotes p<0.1p < 0.1p<0.1.