

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

MARIANA MOURA DO NASCIMENTO

**Does Transportation Infrastructure Growth Improve Women's Labor
Market Outcomes? Evidence from Rio de Janeiro**

Juiz de Fora
2023

MARIANA MOURA DO NASCIMENTO

**Does Transportation Infrastructure Growth Improve Women's Labor
Market Outcomes? Evidence from Rio de Janeiro**

Dissertação apresentada ao Programa de Pós-Graduação em Economia, da Universidade Federal de Juiz de Fora como requisito parcial à obtenção do título de Mestra em Economia Aplicada. Área de concentração: Economia.

Orientadora: Prof. Dra. Laura de Carvalho Schiavon

Juiz de Fora

2023

Ficha catalográfica elaborada através do programa de geração automática da Biblioteca Universitária da UFJF, com os dados fornecidos pelo(a) autor(a)

do Nascimento , Mariana Moura.

Does Transportation Infrastructure Growth Improve Women's Labor Market Outcomes? Evidence from Rio de Janeiro / Mariana Moura do Nascimento . -- 2023.

100 p.

Orientadora: Laura de Carvalho Schiavon

Dissertação (mestrado acadêmico) - Universidade Federal de Juiz de Fora, Faculdade de Economia. Programa de Pós-Graduação em Economia, 2023.

1. Política de Transporte. 2. Resultados do Mercado de Trabalho. 3. Gênero. 4. Diferenças em Diferenças. I. Schiavon, Laura de Carvalho, orient. II. Título.

Mariana Moura do Nascimento

Does Transportation Infrastructure Growth Improve Women's Labor Market Outcomes? Evidence from Rio de Janeiro

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

Aprovada em 31 de agosto de 2023.

BANCA EXAMINADORA

Dr^a. Laura de Carvalho Schiavon - Orientadora

Universidade Federal de Juiz de Fora

Dr^a. Flavia Lúcia Chein Feres

Universidade Federal de Juiz de Fora

Dr. Ricardo da Silva Freguglia

Universidade Federal de Juiz de Fora

Dr^a. Maína Celidônio de Campos

Instituto de Estudos do Trabalho e Sociedade

Juiz de Fora, 15/08/2023.



Documento assinado eletronicamente por **Laura de Carvalho Schiavon, Professor(a)**, em 31/08/2023, às 15:08, conforme horário oficial de Brasília, com fundamento no § 3º do art. 4º do [Decreto nº 10.543, de 13 de novembro de 2020](#).



Documento assinado eletronicamente por **Flavia Lucia Chein Feres, Professor(a)**, em 01/09/2023, às 08:31, conforme horário oficial de Brasília, com fundamento no § 3º do art. 4º do [Decreto nº 10.543, de 13 de novembro de 2020](#).



Documento assinado eletronicamente por **Ricardo da Silva Freguglia, Professor(a)**, em 11/09/2023, às 11:26, conforme horário oficial de Brasília, com fundamento no § 3º do art. 4º do [Decreto nº 10.543, de 13 de novembro de 2020](#).



Documento assinado eletronicamente por **Maína Celidonio de Campos, Usuário Externo**, em 15/09/2023, às 14:22, conforme horário oficial de Brasília, com fundamento no § 3º do art. 4º do [Decreto nº 10.543, de 13 de novembro de 2020](#).



A autenticidade deste documento pode ser conferida no Portal do SEI-Uffj (www2.ufff.br/SEI) através do ícone Conferência de Documentos, informando o código verificador **1407467** e o código CRC **0604D8D7**.

ABSTRACT

This dissertation examines the causal effects of transportation infrastructure expansion on female labor market outcomes using the case study of the 2014 World Cup in Rio de Janeiro and the 2016 Olympics. We utilize an employer-employee dataset from RAIS, spanning from 2010 to 2018, to analyze changes in employment, unemployment, employer-initiated dismissals, employee-initiated resignations, mutual agreement terminations, weekly hours worked, and weekly wages in firms located near transportation stations. Employing a dynamic differences-in-differences design, we find a substantial increase of 1.86% in female employment in firms located within 2 km of transportation stations post-expansion, with highly skilled women experiencing a larger increase of 2.65%. Despite this positive effect on female employment, the transportation expansion policy does not mitigate employee-initiated separations or mutual agreement terminations, suggesting that additional factors influence women's long-term job tenure.

Keywords: Transportation Policy; Labor Market Outcomes; Gender

RESUMO

Essa dissertação examina os efeitos causais da expansão da infraestrutura de transporte nos resultados do mercado de trabalho feminino usando o estudo de caso da Copa do Mundo de 2014 no Rio de Janeiro e dos Jogos Olímpicos de 2016. Utilizamos um conjunto de dados empregador-empregado da RAIS, entre 2010 e 2018, para analisar mudanças nas variáveis de emprego, desemprego, demissão por iniciativa do empregador, demissão por iniciativa do trabalhador, demissão por acordo, horas semanais trabalhadas e salário semanal em empresas localizadas próximas às estações de transporte. Empregando um design dinâmico de diferenças em diferenças, encontramos um aumento substancial de 1,86% no emprego feminino em empresas localizadas a até 2 km das estações de transporte após a expansão, sendo que mulheres altamente qualificadas experimentaram um aumento maior de 2,65%. Apesar desse efeito positivo sobre o emprego feminino, a política de expansão do transporte não mitiga as separações por iniciativa do trabalhador nem por acordo entre trabalhadores e empregados, sugerindo que existem fatores adicionais que influenciam a permanência de mulheres no emprego a longo prazo.

Palavras-chave: Política de Transporte; Resultados do Mercado de Trabalho; Gênero

LIST OF FIGURES

Figure 1: Business Density	14
Figure 2: Transportation Infrastructure and Business Density	16
Figure 3: Total of Firms Treated.....	20
Figure 4: Effects on Employment	25
Figure 11: Effects on Employment by Race.....	31
Figure 12: Effects on Unemployment by Race.....	33
Figure 18: Effects on Employment by Education Level	38
Figure 19: Effects on Unemployment by Education Level	39
Figure 6: Effects on Resignations	49
Figure 7: Effects on Terminations	50
Figure 8: Effects on Mutual Agreement Unemployment.....	51
Figure 10: Effects on Weekly Wage	53
Figure 13: Effects on Resignations by Race	54
Figure 14: Effects on Terminations by Race	55
Figure 15: Effects on Unemployment by Mutual Agreement by Race.....	56
Figure 16: Effects on Weekly Hours Worked by Race	57
Figure 17: Effects on Weekly Wage by Race.....	58
Figure 20: Effects on Resignations by Education Level	59
Figure 21: Effects on Terminations by Education Level.....	60
Figure 22: Effects on Unemployment by Mutual Agreement by Education Level	61
Figure 23: Effects on Weekly Hours Worked by Education Level	62
Figure 24: Effects on Weekly Wage by Education Level	63
Figure 25: Effects on Employment – Alternative Fixed Effects.....	64
Figure 26: Effects on Terminations – Alternative Fixed Effects	65
Figure 27: Effects on Resignations – Alternative Fixed Effects.....	66
Figure 28: Effects on Terminations – Alternative Fixed Effects	67
Figure 29: Effects on Unemployment by Mutual Agreement – Alternative Fixed Effects	68
Figure 30: Effects on Weekly Hours Worked – Alternative Fixed Effects	69
Figure 31: Effects on Weekly Wage - Alternative Fixed Effects	70
Figure 32: Effects on Employment – 1km	73
Figure 33: Effects on Unemployment – 1km	74
Figure 34: Effects on Resignations – 1km	75
Figure 35: Effects on Terminations – 1km	76

Figure 36: Effects on Mutual Agreement Unemployment – 1km	77
Figure 37: Effects on Weekly Hours Worked – 1km.....	78
Figure 38: Effects on Weekly Wage – 1km	79
Figure 39: Effects on Employment – 3km	80
Figure 40: Effects on Unemployment – 3km	81
Figure 41: Effects on Resignations – 3km	82
Figure 42: Effects on Terminations – 3km.....	83
Figure 43: Effects on Mutual Agreement Unemployment – 3km	84
Figure 44: Effects on Weekly Hours Worked – 3km.....	85
Figure 45: Effects on Weekly Wage – 3km	86
Figure 46: Effects on Employment – 4km	87
Figure 47: Effects on Unemployment – 4km	88
Figure 48: Effects on Resignations – 4km	89
Figure 49: Effects on Terminations – 4km.....	90
Figure 50: Effects on Mutual Agreement Unemployment – 4km	91
Figure 51: Effects on Weekly Hours Worked – 4km.....	92
Figure 52: Effects on Weekly Wage – 4km	93

LIST OF TABLES

Table 1: Descriptive Statistics - Treatment and Control	21
Table 2: Effects on Firms Outcomes - Geral	29
Table 3: Effects on Firms Outcomes - Women and Men	30
Table 4: Heterogeneous Effects by Race - Geral	34
Table 5: Heterogeneous Effects by Race - Women	36
Table 6: Heterogeneous Effects by Race – Men.....	37
Table 7: Heterogeneous Effects by Education Level - Geral	40
Table 8: Heterogeneous Effects by Education Level - Women	41
Table 9: Heterogeneous Effects by Education Level - Men.....	42
Table 10: Effects on Firm Outcomes - Alternative Fixed Effects - Geral.....	71
Table 11: Effects on Firms Outcomes – Alternative Fixed Effects – Women and Men.....	72
Table 12: Effects on Firms Outcomes - Alternative Treatment and Control (1km) - Geral.....	94
Table 13: Effects on Firms Outcomes - Alternative Treatment and Control (1km) – Women and Men	95
Table 14: Effects on Firms Outcomes - Alternative Treatment and Control (3km) - Geral.....	96
Table 15: Effects on Firms Outcomes - Alternative Treatment and Control (3km) – Women and Men	98
Table 16: Effects on Firms Outcomes - Alternative Treatment and Control (4km) - Geral.....	99
Table 17: Effects on Firms Outcomes - Alternative Treatment and Control (4km) – Women and Men	99

CONTENTS

1.	INTRODUCTION.....	9
2.	INSTITUTIONAL CONTEXT.....	13
2.2	Transportation infrastructure in Rio de Janeiro.....	14
3	DATA AND DESCRIPTIVE STATISTICS.....	17
3.1	Transportation Stations Data.....	17
3.2	Employer-Employee Data.....	17
3.3	Exposure to transportation station.....	18
3.4	Sample Selection	18
4	EMPIRICAL STRATEGY.....	22
5	MAIN RESULTS.....	24
5.1	Effects on Employment, Unemployment, Terminations, Resignations, Mutual Agreement, Hours Worked and Wages by Gender.....	24
5.1.1	Heterogeneities by Race.....	31
5.1.2	Heterogeneities by Education Level	38
6	Conclusion	44
7	References.....	46
	Additional Results.....	49

1. INTRODUCTION

Improvements in transportation infrastructure expansion can have a substantial effect on labor market, generating greater accessibility to jobs opportunities (FAN, GUTHRIE AND LEVINSON (2012); MARTINEZ et. al, 2018; BÜTIKOFER et. al, 2020), agglomeration gains (OVERMAN; PUGA, 2010; AHLFELDT; FEDDERSEN, 2018), and reducing the negative impacts of spatial mismatch (PATACCHINI; ZENOU, 2005). However, worker groups tend to benefit differently from these improvements. In the case of women, recent literature shows that women's labor market outcomes tend to be more impacted by improvements in transportation infrastructure, both on the supply side - where transportation infrastructure plays the role of promoting greater permanence and also greater participation of women in the labor market (MARTINEZ et. al, 2020; LEI; DESAI ;VANNEMAN, 2019;) In addition, on the demand side, where there is evidence that the arrival of transportation generates a local increase in the provision of labor-intensive female jobs (KWON, 2022).

As a result of being the most responsible for performing unpaid care work and due to their lower bargaining power in the housing market - where the choice of place of residence seems to be driven more by the professional possibilities of men (husbands) than the employment possibilities of women (wives) (MADDEN, 1981; WHITE, 1986) -, labor costs for women are greater than men, which tends to limit their job search horizon (FLUCHTMANN et. al, 2020). Furthermore, women are more likely to search for jobs that are more flexible (BERTRAND; GOLDIN; KATZ, 2010; GOLDIN, 2014) and have shorter commute times (BLACK et. al, 2014), especially married women with young children (LE BARBANCHON et. al, 2019) and less-educated women (CALDWELL; DANIELI, 2018). Moreover, poor safety during daily commuting seems to be a determining factor in women's participation in the labor market, especially in developing countries, where female participation can be affected by up to 15.5% as a result of lack of access to safe public transportation (ILO, 2017).

Given the potential solutions to the limitations to labor market participation that women face, transportation policy can play an important role in this issue. Improvements in transportation infrastructure tend to decrease the daily commute time to work, which can therefore be an important element in reducing the cost of female labor supply¹.

¹ BLACK et. al (2014) uses labor supply theory to argue the cost of commuting in a two-person family model

In contrast, with poor public transportation infrastructure, commuting time tends to be higher, which in a household dynamic can induce the partner (traditionally the wife) to leave the labor force while inducing the other partner (the husband) to increase the amount of hours worked (BLACK et. al, 2014; FARRE; JOFRE-MONSENY; TORRECILLAS, 2020).

Besides the influence of transportation on the reduction of daily commuting time, improvements in the connectivity and safety of the public transportation system can also have positive effects on labor outcomes. Evidence shows that women make labor market participation decisions also based on their perceived risk of experiencing violence in public spaces (JAYACHANDRAN, 2020). In this context, expansion of high-capacity transportation that offers safer bus stops (spaces with increased lighting, camera systems, and personal security) compared to conventional buses and informal transportation, can lower women's perception of risk, encouraging them to engage in the labor market (MARTINEZ et. al, 2020; SEKI; YAMADA, 2020).

This paper seeks to document the short-run effects of transportation infrastructure improvements on women's labor market outcomes. In particular, we use as a case study the transportation expansion triggered by the 2014 World Cup and the 2016 Olympic Games in Rio de Janeiro, Brazil, to quantify causal effects of infrastructure policy. Given that these transportation infrastructure improvements have increased accessibility by connecting several areas of the city that previously lacked high-capacity transportation infrastructure, thereby reducing average commute times², our main objective is to assess the impact of this transit shock as a natural experiment on the female labor market.

(husband and wife). In this case, increases in commuting time generate more labor supply costs, which can induce one of the partners (traditionally the wife) to leave the workforce and induce

² Campos (2019) showed that in the absence of the infrastructure expansion investments the average commuting time within the city might increase by 45 minutes.

To generate these estimations, we utilize an employer-employee dataset encompassing comprehensive details regarding all formal sector workers. This dataset offers insights into both labor demand and supply concurrently, enabling us to examine two key aspects: (a) the dynamics of employment, resignations, terminations and unemployment by mutual agreement³, and (b) information at dual levels - company specifics (such as economic sector and company size) and individual worker attributes (gender, race, education). By geo-coding the precise location of both establishments and transportation stations and calculating distances between those coordinates, we are able to define a measure of firms and employees' exposure to stations based on geographic proximity. Then, using a dynamic difference-in-differences design we are able to explore variation in the location and timing of each station's inauguration and compare female labor market changes over time between firms located near the stations and far from stations.

In addition to comparing labor market outcomes for women in firms close to transport stations compared to those located a distance away from these stations, we introduced heterogeneities to assess the validity of our conclusions in relation to women. To achieve this, we split women's labor market outcomes into subsamples, taking into account differences in educational background and racial attributes.

Due to the power of transport policies to promote spatial reorganization by encouraging the self-selection of firms to treated areas as a result of lower commuting costs and agglomeration gains, we also need to deal with possible endogeneity in our estimates. To this end, we restricted our panel to contain only firms that were already operating and remained at the same address before and after the expansion of transportation infrastructure. Thus, in addition to avoiding the inclusion of firms that opened after the expansion of transportation in our estimates, we are removing firms that moved to locations close to transportation stations from our sample.

This paper presents two remarkable results. Firstly, it reveals a substantial increase in the total number of women employed within a 2 km radius of transport stations. After the expansion of the transport network, there was a significant increase of 1.86% in the

³ The terms "terminations" and "resignations" are commonly employed to delineate the motivations behind professional disengagement. "terminations" pertain to the involuntary separation of an employee from their position, often instigated by the employer due to factors such as performance issues, restructuring, or downsizing. Conversely, "resignations" signify the voluntary act of an employee departing from their job role by personal choice, typically driven by personal or professional reasons, and initiated by the employee themselves and "unemployment by mutual agreement" refers to a situation in which both parties, typically an employer and an employee, come to a shared agreement to end the employment relationship.

number of women employed by firms located near the stations, compared to those located further away. In addition, further analysis of the impact of transport on distinct subgroups of women, categorized according to their educational background and racial attributes, revealed a more pronounced effect on the subset of high skilled women who work closer to stations. Specifically, a notable increase of 2.65% in the total of high skilled women employed by firms located closer to transport stations, in contrast to the corresponding results for high skilled women employed in more distant firms.

The second result concerns resignations and terminations by mutual agreement. Our observations indicate a consistent upward trajectory in the total number of women who voluntarily quit their jobs in the areas treated before the implementation of transport. Interestingly, our results show that even after the introduction of transport in these regions, the propensity of women to voluntarily leave their jobs remains, which suggests that the policy of expanding transport has failed to reverse this phenomenon. On the other hand, there has also been an increase in women leaving jobs through mutual agreements.

These two results underline that the transportation policy was effective in increasing the total number of women employed during the period of transport expansion. However, it seems insufficient to maintain their employment for prolonged periods in these regions, due to the costs women face to remain in the labor market. Furthermore, when analyzing the results related to terminations - dismissals initiated by the employer - we found no positive effects, further reinforcing the argument that this dismissal effect is predominantly driven by women's individual decisions.

Taken together, these results highlights that transportation policy can be effective in increasing the total number of women employed in areas adjacent to transport stations. However, it may be insufficient to maintain their employment for long periods, considering the presence of additional costs, in addition to commuting time, which have a significant influence on women's decision to participate in the labor force.

By addressing the issue of gender and the labor market, this paper contributes to a growing literature that investigates the costs of women's labor supply (BERTRAND; GOLDIN; KATZ, 2010; BERTRAND, 2011; GOLDIN, 2011; OLIVETTI; PETRONGOLO, 2016; KLEVEN ET. AL, 2018), specifically studies that investigate the cost of commuting (BLACK et. al, 2014; LE BARBANCHON et. al, 2019; FLUCHTMAN et. al, 2020)

Our paper also contributes to the literature that assesses the effects of transportation on the labor market (HEUERMANN; SCHMIEDER, 2018; TSIVANIDIS, 2018; CAMPOS,

2019; MARTINEZ et. al, 2020; ZARÁTE, 2019), especially the effects of transport expansion and improvements on the female labor market (MARTINEZ et. al, 2020; KWON, 2022). In addition to confirming some previous findings, such as the significant effect for women in the labor market through transport policy, we contribute to this literature in the following ways.

First, contrasting to other papers where post-transport expansion labor market outcomes are analyzed for women residing in the area of influence of the improved infrastructure, especially with regard to the greater likelihood of women residing in these regions being employed after the arrival of transport stations (MARTINEZ et. al, 2020), we estimate transportation effects through women's labor market outcomes in firms that are in transportation regions. This empirical approach allowed us to investigate the influence of transport policy on business regions and effectively address self-selection bias. Our sample exclusively includes firms that already operated in the treated areas before the announcement of the implementation of the transport station, which allows us to mitigate possible biases.

Secondly, in addition to examining how transport policy can effectively increase the overall number of women employed in firms located near transport stations, we also explored the patterns of women leaving their jobs after the expansion of transportation networks. This approach allows us to determine whether the reasons behind job terminations originate from employers or employees, a factor of particular importance when considering women's labor market costs.

The paper is organized as follows. In section 2, we provide an institutional context of Rio de Janeiro and the transport expansion policy. In Sections 3 and 4, we present, respectively, database, the proximity metric between firms and transportation stations, and the empirical strategy for estimating the causal effect of transportation policy on women's labor market outcomes. The results are presented in Section 5, along with the robustness tests. Our final remarks are in Section 6.

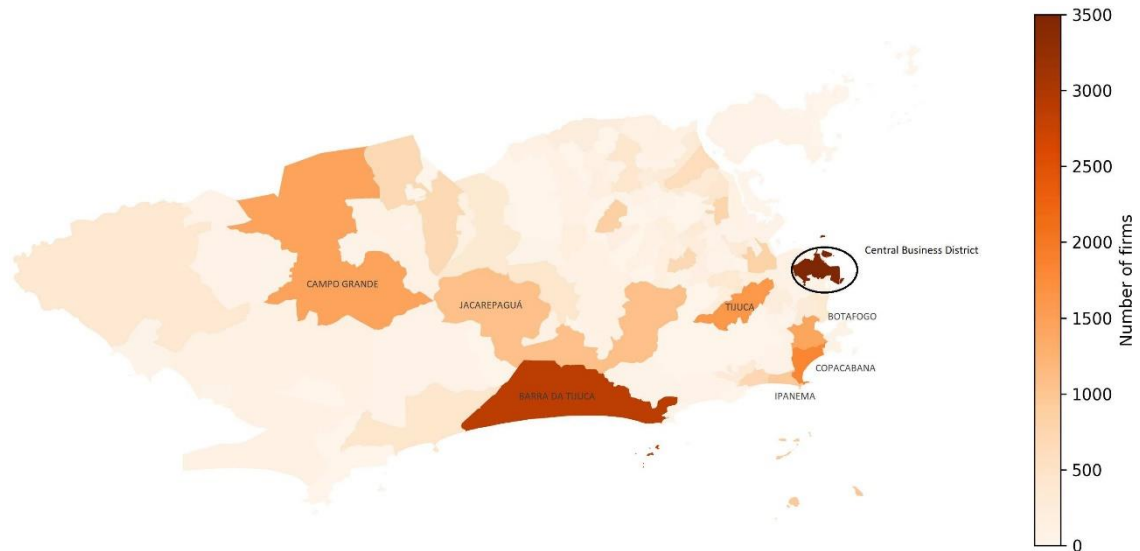
2. INSTITUTIONAL CONTEXT

2.1 Rio de Janeiro City

With more than 6 million inhabitants, the city of Rio de Janeiro is home to more than 40% of the state's population. Characterized as the second most populous city in the country, Rio is part of the Brazilian metropolitan area with the highest urbanization rate

where about 99.3% of the population lives in urban areas. (IBGE, 2022).

Figure 1: Business Density



Note: The figure shows the spatial distribution of firms across neighborhoods in 2009, one year before the announcement of Rio's transportation infrastructure expansion. Highlighted are neighborhoods within the West Zone that exhibit a heightened concentration of business: Campo Grande, Jacarepaguá and Barra da Tijuca. Meanwhile, in the South Zone, the neighborhoods boasting the most pronounced business density include Botafogo, Copacabana and Ipanema. Data is from Rais 2009 and the shapefile of the neighborhoods is from Instituto Pereira Passos.

Regarding firm density, prior to the expansion of transportation infrastructure, business concentration primarily existed in two areas. Firstly, in the Central Business District region and the neighborhoods of the South Zone, where approximately 35% of the city's firms were situated. Secondly, in the West Zone neighborhoods, where business concentration reached 24% (See Figure 1).

2.2 Transportation infrastructure in Rio de Janeiro

Selected as the host city for both 2014 World Cup and 2016 Olympic Games, Rio de Janeiro invested more than \$4.5 billion in its public transportation system between 2012 and 2016. These initiatives mainly included the extension of a metro line, the construction of

a light rail transit (LRT) system and three BRT (Bus Rapid Transit) corridors stretching approximately 122 kilometers (CAMPOS, 2019).

Planning for the expansion of the municipal public transport system achieved two main objectives. First, it aimed to improve public transport accessibility in the Olympic zones (Deodoro, Barra, Copacabana, Maracanã and the port area). Second, the public transport system improvement plan aimed to provide a transportation infrastructure legacy for the city of Rio de Janeiro (CAMPOS, 2019).

Figures 2 describe the evolution of the transportation network. In 2006, before being chosen as the host city for the Olympic Games and the World Cup, Rio had 36 train stations¹ and 32 subway stations.

The railway lines aim to connect different areas of the Rio de Janeiro Metropolitan Region to the central business area. On the other hand, the metro stations are concentrated only in the city of Rio de Janeiro and connect zones of the city to the central business area and to coastal locations. Between 2006 and 2010 three subway stations were inaugurated, but since construction of these stations began in the 1980s, they cannot be considered part of the expansion of transport infrastructure triggered by World Cup and Olympics.

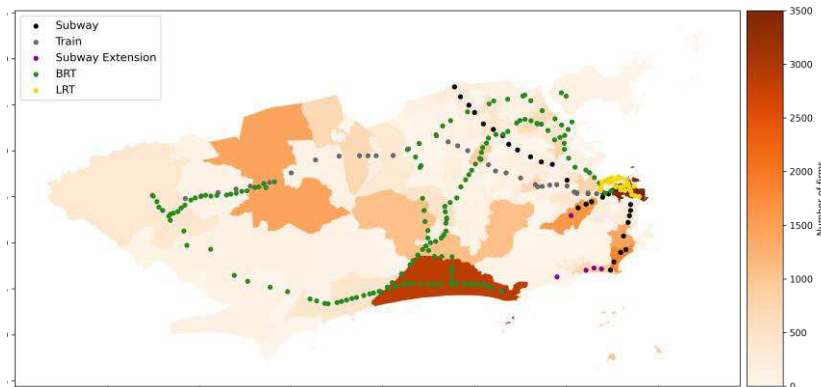
In 2010, Rio de Janeiro was elected as host city for the 2016 Olympic Games. Between 2012 and 2016, directly linked to the Olympic Games infrastructure expansion plan, 135 BRT stations distributed in three corridors were inaugurated: BRT Transoeste (2012), BRT Transcarioca (2014) and BRT Transolímpica (2016).

Figure 2: Transportation Infrastructure and Business Density

(a) Transportation infrastructure (2010)



(a) Transportation infrastructure (2018)



Note: The figure shows the distribution of transport stations before and after the policy expansion of the transport infrastructure. Black and gray symbols represent the infrastructure that already existed before 2016 Olympics. Symbols in the other colors represent transportation infrastructure that was created between 2012 and 2018, triggered by 2014 World Cup and 2016 Olympics. Data is from Rais 2009 and stations' shapefile is from Instituto Municipal Pereira Passos.

In addition to the construction of the BRT corridors, in 2016, the subway line 4 was inaugurated. The line is composed of five stations and connects the southern zone neighborhoods to Barra da Tijuca. On the other hand, the LRT construction, which began in 2014 and was completed between 2016 and 2017², aims to connect the port neighborhoods of Rio's central business area.

¹The metropolitan region of Rio de Janeiro has 104 train stations in total, but as we are considering only the city of Rio, the number drops to 36 ²The LRT system consists in two lines: first was inaugurated at the beginning of the Olympic Games in Rio (2016) and the other line in 2017.

3 DATA AND DESCRIPTIVE STATISTICS

3.1 Transportation Stations Data

Transport stations data came from *Instituto Pereira Passos* (IPP). For each station, we were able to obtain information regarding the inauguration date, transportation line it belongs to, if it has a connection to other stations of other modes of transportation, and the most important: the geographical coordinates that provide us the exact location of each station.

3.2 Employer-Employee Data

Our employer-employee data came from from RAIS (Annual Social Information Report). One of the main objectives of RAIS is to provide statistics regarding the Brazilian formal labor market, containing a set of variables on both firm and worker characteristics.

At the employee level, the data includes demographics such as gender, ethnicity and education. In addition, the data includes detailed information about the individual's work: occupation, type of work contract, duration, wage, and hours worked - RAIS also contains data on the exact date when the employee started and stopped working at a particular establishment, as well as information regarding the initiative for termination (by employee or employer). This information, combined with the unique identifiers of employees and establishments, allows us to study the labor flow of workers.

Finally, the data includes establishment level information, including the type of economic activity, information on the legal nature, total employees of the firm, and whether the firm is still active and the date of closure. In addition, we also have information on the address of these establishments, which allows us to geo-reference this information in order to calculate our measure of exposure to transport stations.

3.3 Exposure to transportation station

To calculate the exposure to transportation stations, we geo-coded the location of each transportation station and firms and then calculate the Euclidean distance between these two points. In our primary specification, we classify firms as exposed if they were situated between up to 2km from a transportation infrastructure.

The empirical justification for selecting this exposure to transportation stations is rooted on the fact that after 2km, the coefficients of the estimates drops consistently. This patterns is observed by the findings of the robustness tests presents in Additional Results Section. Nonetheless, in order to prevent any potential spillover effects on the control group, we choose to exclude from sample firms located beyond 2km and up to 3km from transportation stations.

This exposure measure is linked to the work of CAMPOS (2019), who studies the effect of transportation expansion in Rio de Janeiro on the increase in economic activity around transportation stations. CAMPOS (2019) finds positive and significant effects on total firms opened and total employees hired within 2km of stations.

3.4 Sample Selection

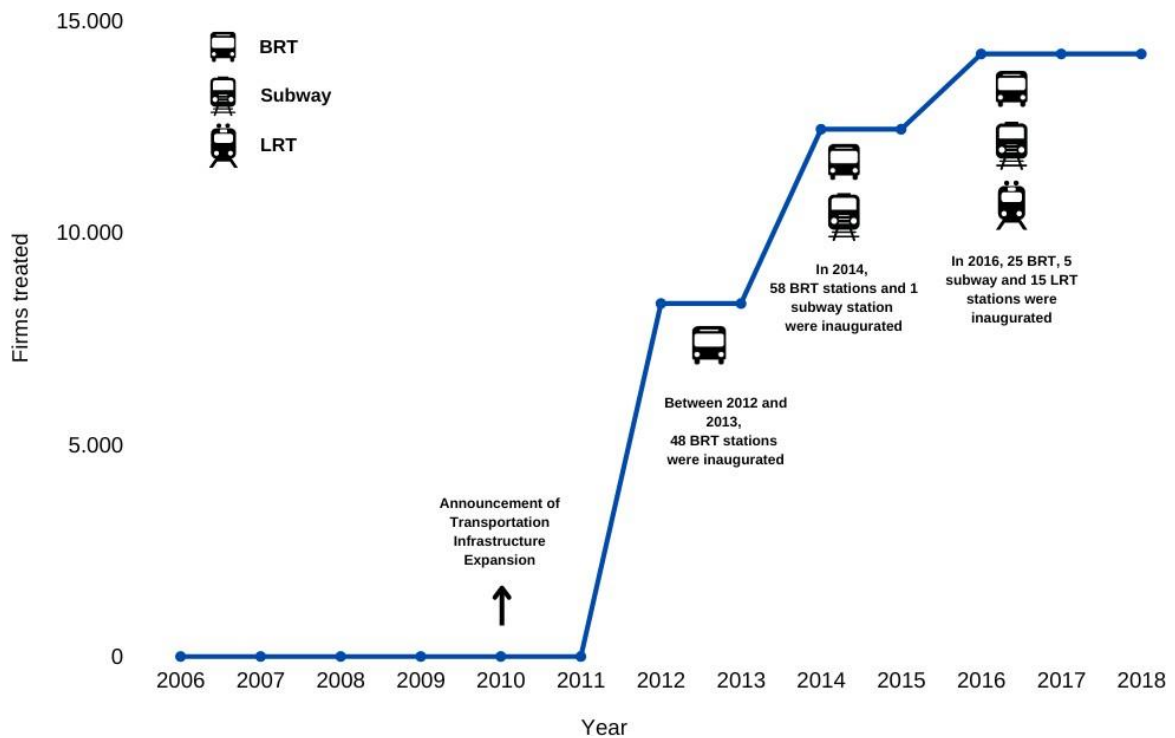
Given the issue of spatial reorganization promoted by transportation expansion and the possible self-selection of firms to be in locations near new stations, which could lead to firms in the control group becoming part of the treatment group, we restricted our estimation sample to only those firms that existed before the opening of the transportation stations and remained at the same address from 2010 to 2018. In this way, we were able to analyze labor market outcomes over six years after the first stations opened, using a balanced panel. In addition, we restricted the employer-employee data for the years 2009 to 2018 (i.e., from three years before and six years after the opening of the first stations).

Our second restriction is with respect to the age range of workers. Since our main objective is to estimate the heterogeneous effects of the transportation expansion between men and women, we restrict our sample to workers between the ages of 18 and 40. Thus, we investigate the effects of transportation taking into account the reproductive age group of women.¹

In total, my sample contains 23,471 firms, being 14,370 treated firms and 9,101 in control group. Figure 3 shows the total number of firms treated and the total number of lines and transport stations inaugurated per year. Before 2012, no lines or transport stations had been inaugurated. Between 2012 and 2013, the BRT line called *BRT Transoeste* is inaugurated with 43 stations and the total number of treated firms was 8,410. In 2014, with the arrival of the *BRT Transcarioca* and subway line 4, 58 more BRT stations were inaugurated in addition to 1 subway station, for a total of 12,545 treated firms. In 2016, with the arrival of the *BRT Transolímpica*, 25 more BRT stations were inaugurated, in addition to 4 more subway stations. Finally, the inauguration of LRT lines 1 and 2 provided 15 more stations. In 2018, the total number of firms treated was 14,370.

¹Specification proposed by Kleven et. al (2018) where female reproductive age is used to estimate the effect of a child on the labor market outcomes of women relative to men

Figure 3: Total of Firms Treated



Note: The figure shows the distribution of treated firms by year. In addition, it provides information regarding the transport lines and the total number of stations inaugurated in each year. Data is from Rais and the transport information is from Instituto Pereira Passos.

Table 1 presents descriptive statistics for both groups - treatment and control. Treated firms, on average, have 14 employees, a similar average to the control firms. Averages for total separation, separation by employer, separation by employee, and separation by agreement are also similar in both groups. On average, 66% of the workers are men and 60% are white. More than half of the employees in my sample have completed high school or college as their highest level of education. Firms and employees in treatment and control group have similar characteristics, which suggests that firms and employees working in establishments within 2km of the stations is an effective control group.

Table 1: Descriptive Statistics - Treatment and Control

	Treatment (<=2km)			Control (>2km)		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Main Variables						
Employees	14.226	14.43	28.18	9.063	13.19	24.64
Separation	14.226	6.15	11.36	9.063	6.00	10.61
By employer's initiative	14.226	2.80	4.23	9.063	2.67	3.99
By employee's initiative	14.226	1.29	2.65	9.063	1.31	2.63
By agreement	14.226	0.43	1.17	9.063	0.48	1.27
Weekly working hours	14.226	42.8	3.78	9.063	42.55	4.45
Weekly wage (R\$)	14.226	270.56	180.22	9.063	269.85	179.40
Workers' characteristics						
Gender (=1 if women)	14.226	0.44	0.33	9.063	0.44	0.34
Racial minority	14.226	0.38	0.33	9.063	0.40	0.34
High skilled (= 1 if high school or college)	14.226	0.57	0.37	9.063	0.57	0.37
Firms' characteristics						
Transformation Industry	14.226	0.07	0.27	9.063	0.07	0.26
Trade	14.226	0.45	0.49	9.063	0.44	0.49
Service	14.226	0.13	0.34	9.063	0.10	0.29
Construction	14.226	0.03	0.17	9.063	0.02	0.14
Others sectors	14.226	0.32	0.23	9.063	0.37	0.29
Firms' sizes						
up to 5 employees	14.226	0.42	0.49	9.063	0.44	0.49
more than 5 to 10 employees	14.226	0.25	0.43	9.063	0.25	0.43
more than 5 to 10 employees	14.226	0.13	0.11	9.063	0.11	0.10
more than 10 to 15 employees	14.226	0.12	0.09	9.063	0.13	0.12
20 or more employees	14.226	0.08	0.11	9.063	0.07	0.05

Note: This table provides summary statistics for the sample of firms, disaggregated by those that were near/far from a transportation station before 2012. In columns (1), (2) and (3) we have the results for treatment, while in columns (4), (5) and (6) results are for control. We classified racial minority for employees who are black, asian or indigenous. Data frequency is yearly.

4 EMPIRICAL STRATEGY

To identify the causal impacts of transportation infrastructure expansion on women's labor market outcomes, we exploit the variation in the timing of treatment using the difference-in-differences (DD) estimator. If women's labor market outcomes begin to differ between regions affected by the new transport infrastructure and those who did not, then we can link this change in trend to transport infrastructure policy.

Our empirical strategy assumes that treated units (firms in locations near transportation infrastructure) and untreated units (firms in locations far from transportation infrastructure) had parallel trends before treatment with respect to a given outcome Y . This allows us to estimate the causal effect of the inauguration of transportation infrastructure on variable Y , considering the following specification:

$$Y_{i,t} = \alpha + Date_t + Firm_i + \beta X_{i,t} + \sum_{k=r_{min}}^{k=r_{max}} \gamma_k \mathbf{1}(t_i = t^* + k) + \epsilon_{it} \quad (4.1)$$

Where $Y_{i,t}$ denotes the outcome of interest (i.e, total of employees) for firm in the date t . $Date_t$ denotes date fixed effects which captures common shocks to firms in date t ; $Firm_i$ denotes date fixed effects which captures common shocks to firms in date t ; $Firm_i$ denotes fixed effects which captures the firm's characteristics invariant in the period; $X_{i,t}$ is a vector of control variables; $\mathbf{1}(t_i = t^* + k)$ are dummies equal 1 if firm i was within 2km of a transport station while t^* is the treatment year; and ϵ_{it} denotes the error term.

The coefficients of interests are γ_k , which represents the effect of opening transportation stations on date t^* on outcomes, given by the difference between control and treated, k year later treatment (or previously, for $k < 0$). These effects are measured relative the year before the event ($k = -1$), because we expect responses to begin in the year of the inauguration of the transport stations, t^* (HOYNES; SCHANZENBACH, 2012).

In terms of the choice of controls, most of the firm-level variables could be impacted by the arrival of the transport station, which makes them for bad controls (ANGRIST; PISCHKE, 2009). So, we decided to control for interactions of their baselines values with time dummies, instead of directly controlling for their contemporaneous values (CHIMELI; SOARES, 2017). The variables used on baseline are the following: firm size (number of employees), economic activity sector and subdistrict.

To assess the average impact after the arrival of the transport station, we estimate the follow equation using difference-in-difference model:

$$Y_{i,t} = \alpha + Date_t + Firm_i + \beta X_{i,t} + \sigma Post_Transportation_{it} + \epsilon_{it} \quad (4.2)$$

Where $Y_{i,t}$ denotes the outcome of interest (i.e, total of employees) for firm in the date t . $Date_t$ denotes date fixed effects which captures common shocks to firms in date t ; $Firm_i$ denotes date fixed effects which captures common shocks to firms in date t ; $Firm_i$ denotes fixed effects which captures the firm's characteristics invariant in the period; $X_{i,t}$ is a vector of control variables; $Post_Transportation_{it}$ is a dummy equals 1 if the firm is within 2km of the station on date t and ϵ_{it} denotes the error term. The coefficient of interest is σ , which capture the average effect of transportation.

The models are estimated using weighted least squares. We weight for total of work-ers in the firm in the baseline (first year in the data). The goal is to approximate the average partial effect for the whole population in the potential presence of heterogeneous effects and heteroskedastic error terms (SOLON; HAIDER; WOOLDRIDGE, 2015).

In a traditional difference-in-differences or event study, in the presence of heterogeneous effects over time and among units, the model may have negative weights, as discussed by GOODMAN-BACON (2021) and CALLAWAY AND SANT'ANNA (2020). By adopting a weighted specification, we avoid this problem (BARTIK ET. AL, 2020).

We use standard errors that are clustered at the firm level to allow for arbitrary dependence of ϵ_{it} across t within i (BERTRAND; DUFLO; MULLAINATHAN, 2004).

5 MAIN RESULTS

In this section, we first analyze estimations for employment, unemployment, resignations, terminations, hours worked and wage variables for women. We compare these findings with the overall results as well as outcomes observed for men. In the next subsections, we will enhance our analysis by incorporating heterogeneities based on race and education level.

5.1 Effects on Employment, Unemployment, Terminations, Resignations, Mutual Agreement, Hours Worked and Wages by Gender

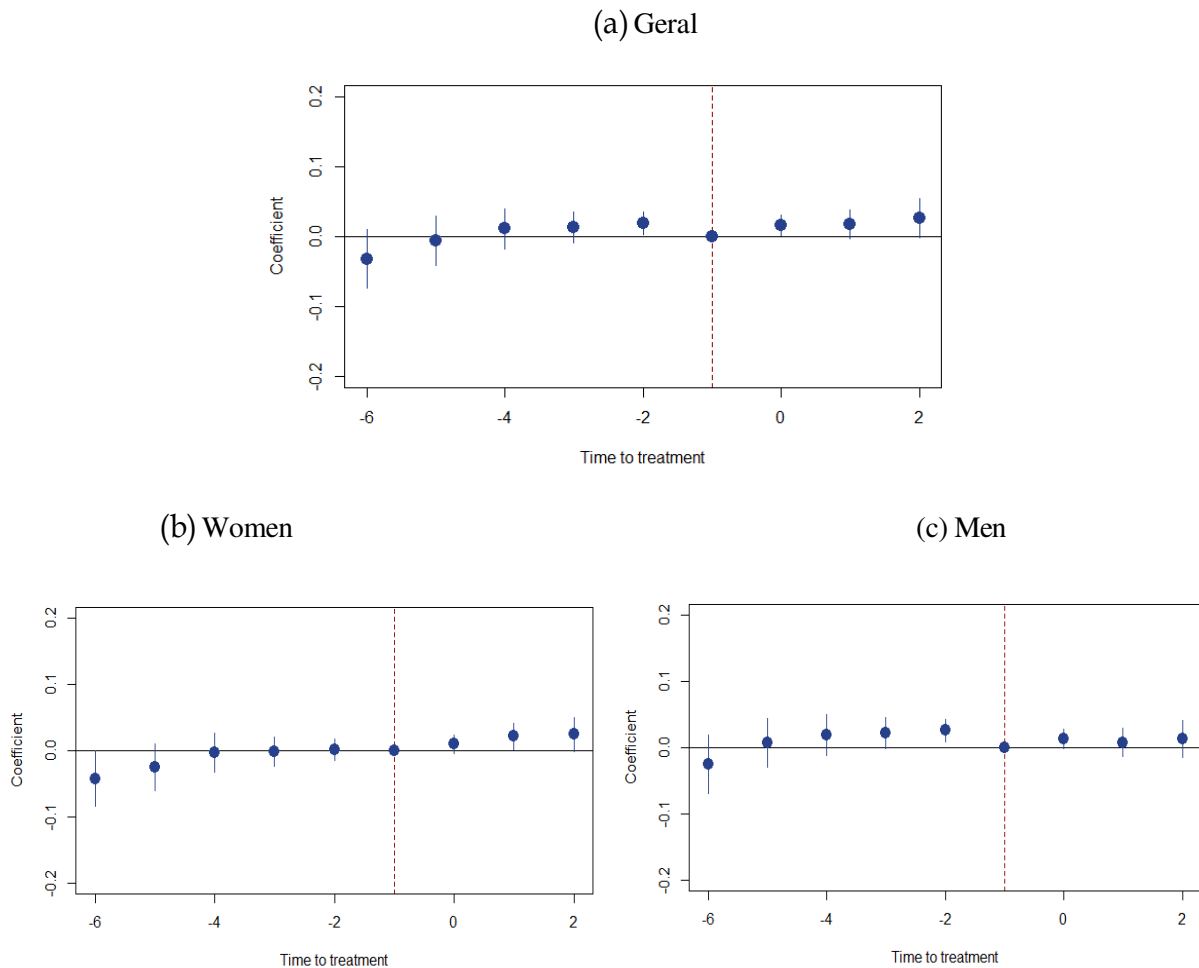
Figures 4-11 display γ_k for selected labor market variables. For employment, terminations, hours worked and wage, pre-event coefficients are statistically equal to zero for women. For unemployment and resignations, coefficients are not statistically equal to zero.

Figure 4 and Tables 2 and 3 illustrates the effect of the opening of transportation stations on total workers, as well as for male and female workers separately. In Panel (b) we see that change in total female employees is significant and positive. After treatment, we have a positive and significant variation of 1.86% (0.0184 in log terms) more women employed in the areas that received transport stations. For men (panel c), we not notice significant effects on employment variable.

As far as separation is concerned, we analyze the results from the point of view of general separation (Figure 5) and also of resignations (separation at the employee's initiative, Figure 6), terminations (separation at the employer's initiative, Figure 7), and mutual agreement (separation at the initiative of both the employee and the employer, Figure 8). Figures are in Additional Results section.

For women, we observe a positive and significant variation for the resignations and mutual termination variables. For the first, the variation is 3.13% (0.0298 in log terms), while for the second it is 2.07% (0.0205). It is important to highlight that this increase in resignations for women was already happening in the pre-treatment areas. Thus, we cannot attribute this effect to the expansion of transportation.

Figure 4: Effects on Employment



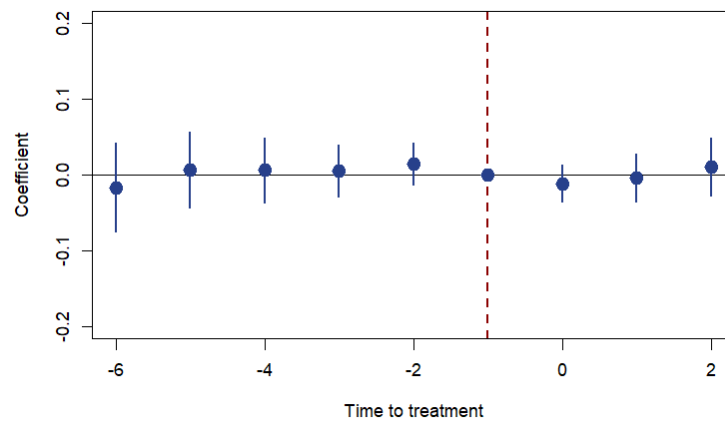
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln(\text{total of employees})$ (b) $1 + \ln(\text{total of female employees})$, (c) $1 + \ln(\text{total of male employees})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

In addition to the employment and separation variables, we analyze the effects of transportation stations on weekly wages and hours worked (Figures 9 and 10). For both genders, women and men, the effect of treatment on these variables is zero.

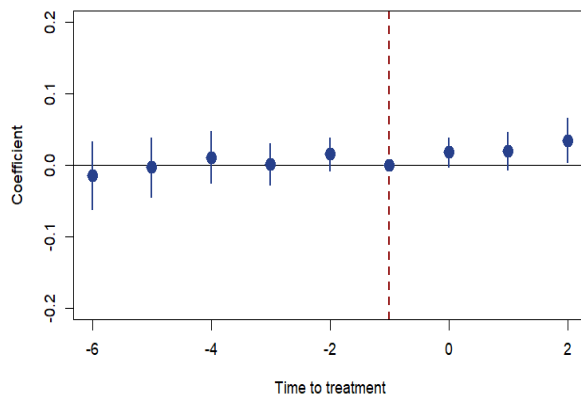
To test the robustness of our estimates, we include sector \times date and firm size \times date effects to control for unobserved time-varying shocks to sectors and firm sizes. Figures 25 to 31 and Tables 10 and 11 in Additional Results section shows the results from event study and difference-in-differences. We obtain similar results with and without the inclusion of specific fixed effects.

Figure 5: Effects on Unemployment

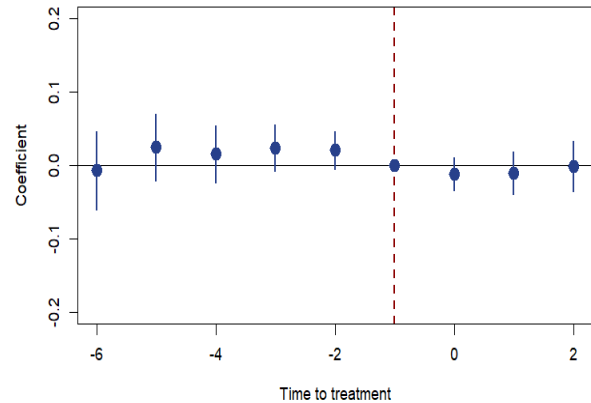
(a) Geral



(b) Women



(c) Men



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed})$ (b) $\ln(1 + \text{total of unemployed women})$, (c) $\ln(1 + \text{total of unemployed men})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

In addition to the employment and separation variables, we analyze the effects of transportation stations on weekly wages and hours worked. For both genders, women and

men, the effect of treatment on these variables is zero.

We also conducted an analysis with different control and treatment distances. As we can see in Figures 32 to 38 and Tables 12 to 17, in Additional Results Section, we observe no variation in the total number of women employed in firms located within 1km of the stations. When we analyze firms located up to 3km away, we also observe no significant effects on the employment of women (Figures 39 to 45). Finally, we set the treatment to a radius of up to 4km away, and the effects on the employment variable remain null (Figures 46 to 52). These results bring us evidence that it is in the treatment radius of up to 2km distance and control above 2km, that we observe the significant effects for women's employment.

Regarding the findings, we have observed positive effects on female employment as a result of transportation infrastructure improvement, effects that are in line with those documented in the literature. In situations where there is an expansion of transportation infrastructure, women tend to benefit more than men (MARTINEZ et. al, 2020; LEI; DESAI; VANNEMAN, 2019). This effect can be observed both because of the increase in supply and demand for female labor.

On the supply side, we have an extensive literature showing the higher labor supply costs for women (FLUCHTMANN et. AL, 2020; BERTRAND; GOLDIN; KATZ, 2010; GOLDIN, 2014, BLACK et. al, 2014). Women, being more responsible for the care of the home and children, face higher costs to participate in the labor market. In this context, transportation plays a crucial role in reducing these costs, as it not only affects the time women spend at the workplace but also the commuting time to work, which directly impacts the costs of female labor supply.

It is important to mention that for women, besides the cost of commuting time itself, transportation policies can also significantly influence in women's perception of safety in public spaces. In this sense, policies to expand and improve transportation, along with the creation of safer transportation systems, tend to increase women's accessibility to formal jobs and the feeling of safety while commuting. These effects become even more relevant in the context of a city like Rio de Janeiro, where, in addition to having one of the highest commuting times in the world⁴, in Rio there is a high perception of violence against women in transportation and public spaces (KONDILYS et. al, 2020). Consequently, the cost of transportation for women in the city tends to be even higher than for men.

On the other hand, there is an increased demand for female labor in situations where

⁴ According to data from Moovit, the average commuting time in the city of Rio de Janeiro is 67 minutes, the 4th longest among the world's major metropolises.

there is an expansion of transportation. This increase in demand occurs because of the impact that transportation expansion has on firms in the service and trade sectors (KWON, 2022). Since these sectors are labor intensive for women, in a situation of increasing firm size, it is expected that there will be a proportional increase in the demand for women employed in these areas.

Although we found positive effects on the variable of women's employment in the treated areas, we also observed a positive effect with regard to the variables of resignations and mutual terminations. With regard to resignations, as mentioned earlier, there was already a positive variance trend pre-treatment. However, this effect persists even after the arrival of transportation, which indicates that the greater accessibility promoted by transportation was not able to reverse the trend of resignations. On the other hand, there is a positive variation in the variable of mutual termination. In this sense, it is important to take up again the discussion regarding the issues that impact the permanence of women in the labor market.

Despite the transportation policy having a fundamental role in reducing commuting time and consequently in a greater supply of female labor, there are other gender issues that have an impact on this decision, such as domestic chores and childcare. In addition, there is the issue of women's perception of risk in relation to public spaces, thus including the perception of risk in the transportation system. Thus, it is possible that in the short term the arrival of transport stations in locations with a high density of firms in the trade and services sectors has encouraged the hiring of women, but that in the long term, the transport policy has not been enough to increase the permanence of these women in the labor market, given that there are other gender issues that play a significant role in this decision. This assumption gains strength when we analyze both the reasons for leaving and also when we consider these effects with men. With regard to dismissal motivation, we found no significant effects in dismissals by employer's initiative, only by worker's initiative and by mutual agreement. With regard to the results found for men, we found no significant effects for the employment variable, but also no significant effects for separation variables.

Table 2: Effects on Firms Outcomes - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Post_Transportation	0.0195** (0.0098)	0.0063 (0.0114)	0.0349*** (0.0098)	-0.0103 (0.0107)	0.0090 (0.0091)	0.0006 (0.0015)	0.1802 (3.131)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 2, Panel (A), presents the results of differences-in-differences estimation for selected labor market variables for workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 3: Effects on Firms Outcomes - Women and Men

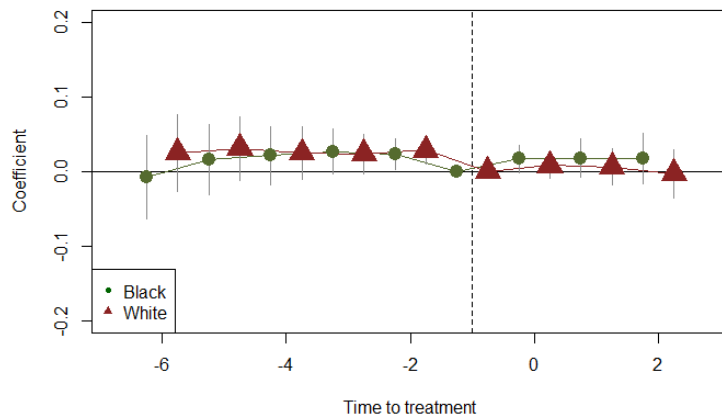
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel B: Women							
Post_Transportation	0.0184** (0.0094)	0.0168 (0.0101)	0.0298*** (0.0079)	-0.0036 (0.0087)	0.0205** (0.0066)	0.0004 (0.0017)	5.441 (4.101)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Panel C: Men							
Post_Transportation	0.0110 (0.0101)	-0.0006 (0.0109)	0.0222*** (0.0084)	-0.0105 (0.0101)	-0.0024 (0.0077)	0.0003 (0.0020)	-2.568 (4.612)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 3 presents the results of differences-in-differences estimation for selected labor market variables. In Panel (B), estimations are for female workers, (C) for male workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

5.1.1 Heterogeneities by Race

To investigate how transportation stations may impact different groups of women workers, we analyze the labor market variables in this subsection by focusing on two characteristics: race and education level. Our goal is to understand how transportation expansion policy can impact in different ways based on heterogeneities beyond gender.

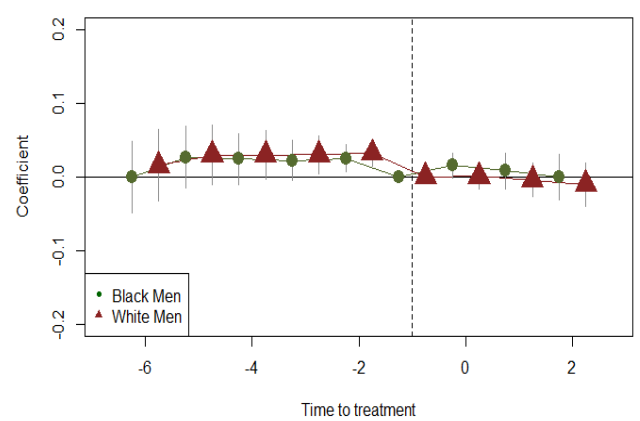
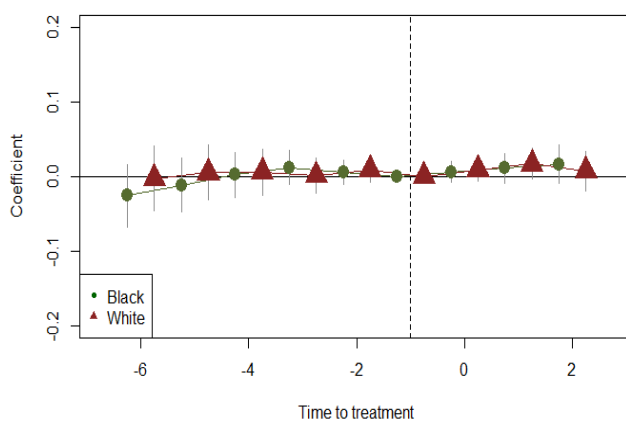
Figure 5: Effects on Employment by Race



(a) Geral

(b) Black/White Women

(c) Black/White Men



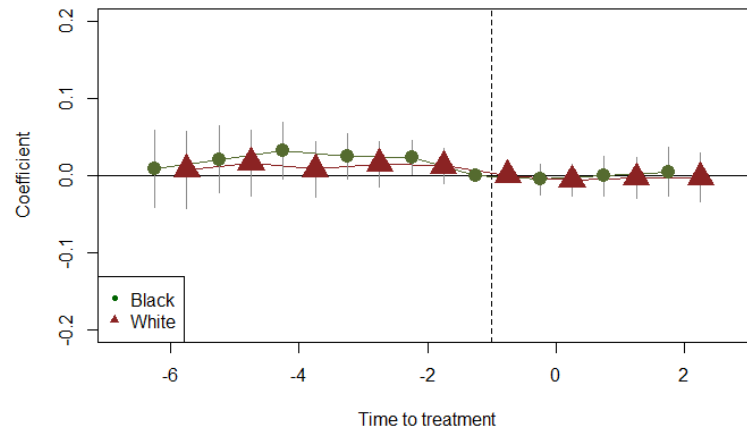
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient by race. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln$ (total of black/white employees) (b) $1 + \ln$ (total of black/white female employees), (c) $1 + \ln$ (total of black/whitmale employees). Data is from 2010 to 2018. Red vertical line represents time of treatment.

To begin, we explore how the impact of transportation may differ between black and white female workers. When including the racial dimension, we observe no significant effects between these two groups on the variance of employed women (Figure 11 and Table 5).

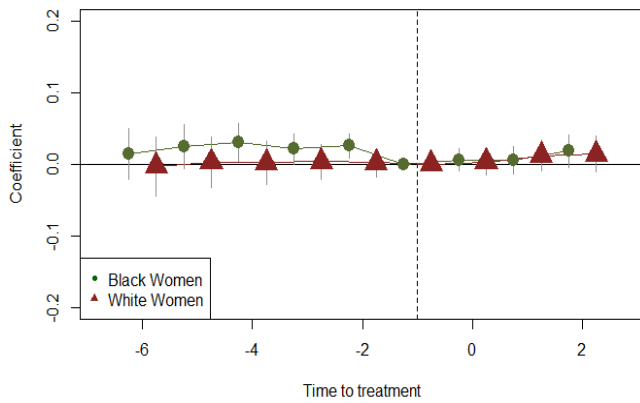
In terms of unemployment, regarding resignations, we observe that white women have a greater variation compared to black women, of 2.20% (0.0218 in log terms) versus 1.52% (0.0151 in log terms) (see Figure 13). As far as separation by mutual agreement is concerned, black women show a higher variation compared to white women - about 1.32% (0.0052 in log terms), while white women show a variation of 0.97% (0.0132 in log terms) (see Figure 15). We find no significant effects between white and black women regarding terminations (see Figure 14). Also, we did not report significant effects that distinguish black and white women in terms of hours worked per week and weekly wage (see Figures 16 and 17).

Figure 6: Effects on Unemployment by Race

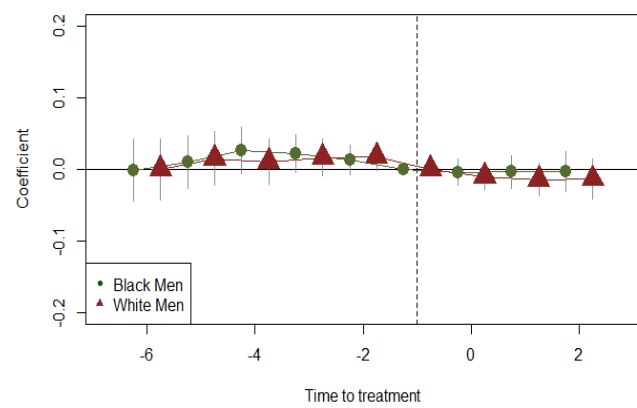
(a) Geral



(b) Black/White Women



(c) Black/White Men



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed})$ (b) $\ln(1 + \text{total black/white unemployed women})$, (c) $\ln(1 + \text{total black/white unemployed men})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Table 4: Heterogeneous Effects by Race - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Black							
Post_Transportation	0.0177 (0.0125)	-0.0044 (0.0117)	0.0125 (0.0083)	-0.0042 (0.0102)	0.0079 (0.0075)	0.0001 (0.0020)	-5.291 (5.875)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
White							
Post_Transportation	0.0034 (0.0118)	-0.0008 (0.0118)	0.0280*** (0.0085)	-0.0203 (0.0103)	-0.0039 (0.0068)	0.0011 (0.0021)	-1.879 (4.244)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 4, Panel (A), presents the results of differences-in-differences estimation for selected labor market variables for black/white workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 5: Heterogeneous Effects by Race - Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Women							
Black							
Post_Transportation	0.0111	0.0098	0.0151***	-0.0065	0.00132*	0.0052	1.741
	(0.0093)	(0.0086)	(0.0066)	(0.0076)	(0.0052)	(0.0104)	(1.551)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
White							
Post_Transportation	0.0110	0.0094	0.0218**	0.0014	0.0097**	0.0181	1.455
	(0.0098)	(0.0094)	(0.061)	(0.0069)	(0.0047)	(0.0106)	(2.177)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 5 presents the results of differences-in-differences estimation for selected labor market variable. In Panel (a), estimations are for black/white female. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 6: Heterogeneous Effects by Race – Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Men							
Black							
Post_Transportation	0.0027 (0.0110)	0.0038 (0.0105)	0.0050 (0.0069)	-0.0001 (0.0090)	0.0019 (0.0064)	0.0034 (0.0027)	0.4938 (6.469)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
White							
Post_Transportation	0.0049 (0.0115)	-0.0128 (0.0103)	0.0162** (0.0069)	0.0187** (0.0092)	0.0068 (0.0056)	0.0002 (0.0027)	-6.208 (7.439)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

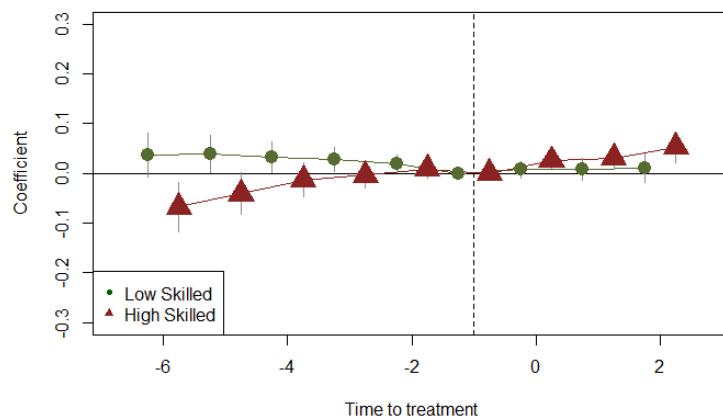
Note: Table 6 presents the results of differences-in-differences estimation for selected labor market variable. In Panel (a), estimations are for black/white male. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

5.1.2 Heterogeneities by Education Level

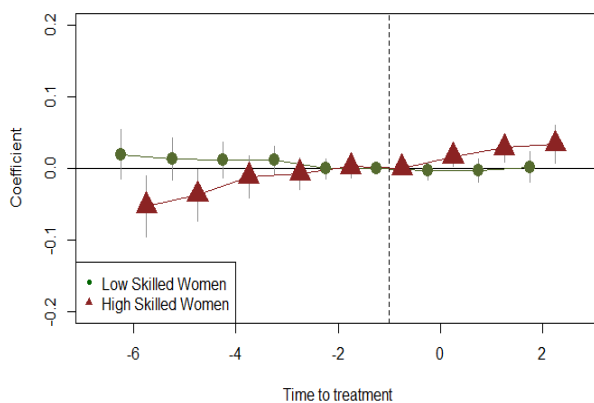
Next, we analyze the heterogeneous effects of transportation between women with low and high education. With regard to the employment variable, we observe that only high skilled women experienced a positive and significant change in total employment, of about 2.65% (0.0261 in log terms) (Figure 18 and Table 8). This increase in the change in employees also observed for high skilled men, about 2.3% (0.0231 in log terms) (Figure 18 and Table 9).

Figure 7: Effects on Employment by Education Level

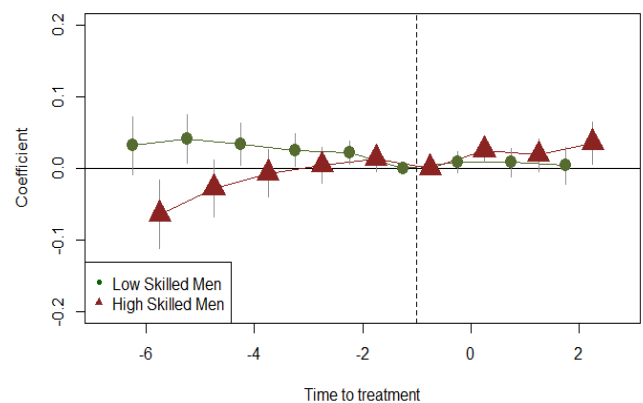
(a) Geral



(b) Low/High Skilled Women



(c) Low/High Skilled Men

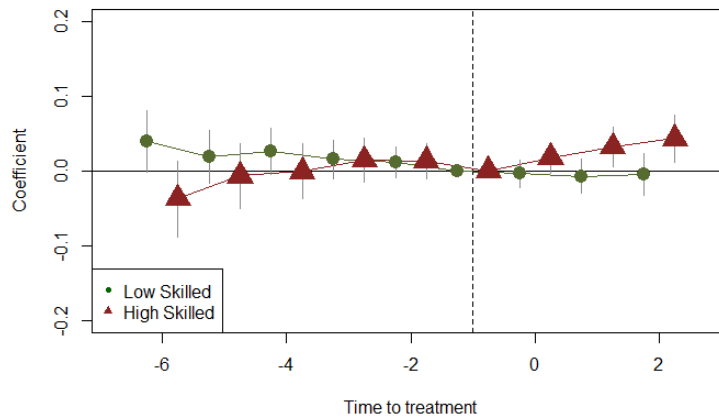


Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient by race. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln(\text{total of low/high skilled employees})$ (b) $1 + \ln(\text{total of low/high skilled female employees})$, (c) $1 + \ln(\text{total of low/high skilled male employees})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

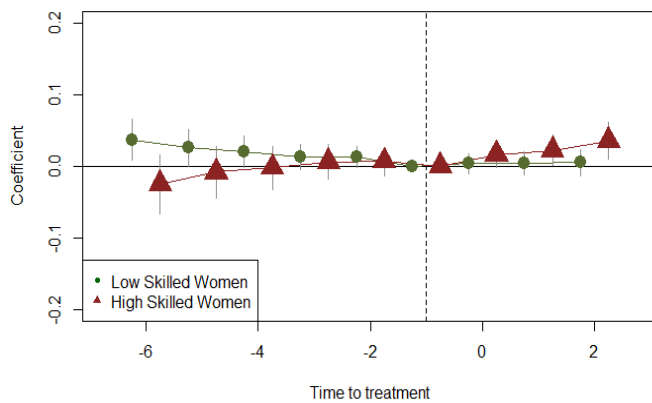
With regard to unemployment, high skilled women also have a positive variation in total resignations, of about 3% (0.0297 in log terms). We also observe a positive and significant change in mutual termination variable. In this case, high skilled women present a variation of 1.83% (0.0181 in log terms). Figures are in Additional Results.

Figure 8: Effects on Unemployment by Education Level

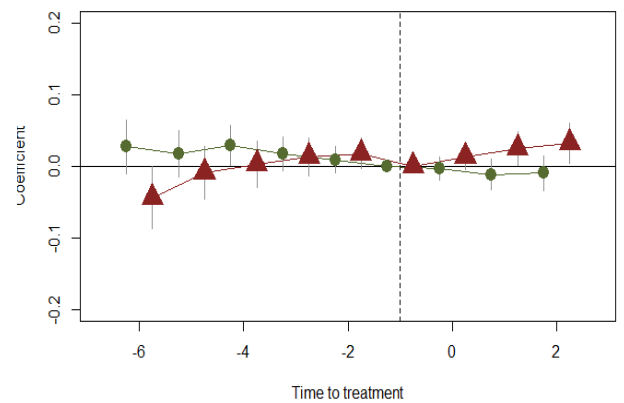
(a) Geral



(b) Low/High Skilled Women



(c) Low/High Skilled Men



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total low/high skilled unemployed})$ (b) $\ln(1 + \text{total low/high skilled unemployed women})$, (c) $\ln(1 + \text{total low/high skilled unemployed men})$. Data is from 2010 to 2018. Red vertical line represents time of treatment

Table 7: Heterogeneous Effects by Education Level - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Low Skilled							
Post_Transportation	0.0085	-0.0054	0.0088	-0.0154	0.0077	0.0022	6.243
	(0.0106)	(0.0103)	(0.0073)	(0.0091)	(0.0068)	(0.0017)	(3.346)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
High Skilled							
Post_Transportation	0.0362***	0.0307***	0.0424***	0.0147	0.0123	-0.0010	-2.370
	(0.0112)	(0.0117)	(0.0090)	(0.0105)	(0.0075)	(0.0020)	(3.841)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 7, Panel (A), presents the results of differences-in-differences estimation for selected labor market variables for low/high skilled workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 8: Heterogeneous Effects by Education Level - Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Women							
Low Skilled							
Post_Transportation	-0.0021 (0.0018)	0.0039 (0.0073)	0.0084 (0.0049)	-0.0060 (0.0058)	0.0095 (0.0040)	0.0059* (0.0030)	6.927 (4.863)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
High Skilled							
Post_Transportation	0.0260*** (0.0094)	0.0245** (0.0096)	0.0297*** (0.0073)	0.0057 (0.0081)	0.0181** (0.0058)	0.0039 (0.0020)	5.836 (4.750)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 8 presents the results of differences-in-differences estimation for selected labor market variable. In Panel (a), estimations are for low/high skilled female. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 9: Heterogeneous Effects by Education Level - Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Men							
Low Skilled							
Post_Transportation	0.0069 (0.0096)	-0.0084 (0.0093)	0.0050 (0.0063)	0.0130 (0.0087)	0.0019 (0.0059)	0.0022 (0.0015)	8.716 (4.233)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
High Skilled							
Post_Transportation	0.0261** (0.0108)	0.0232** (0.0103)	0.0282** * (0.0072)	0.0143 (0.0092)	0.0020 (0.0062)	0.0025 (0.0028)	-7.679 (6.654)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 9 presents the results of differences-in-differences estimation for selected labor market variable. In Panel (a), estimations are for low/high skilled male. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. * denotes $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

For remaining variables, weekly hours worked and weekly wage, we observe no significant effects that differentiate women by educational level heterogeneity.

Findings show a higher positive variance for high skilled women, which converges with the results that are found in the transportation literature (TSIVANIDIS, 2018; CAMPOS, 2019; BUTIKOFER et. al, 2020). In situations where firms are in transportation influence areas, there is a trend towards a concentration of economic activity around the stations, which can lead to an increase in agglomeration gains, both by the interaction between firms and by workers (ANDERSSON et. al, 2007; HERVAS-OLIVER et. al, 2017; TSIVANIDIS, 2018). This concentration of spatial activity leads to productivity gains for the firm, making it more specialized, added to the fact that the proximity to transport stations reduces commuting costs. All these factors combined may explain the increase in the variation of more educated workers in these areas to the detriment of areas more distant from transportation stations.

6 Conclusion

This dissertation aims to examine how transportation infrastructure improvements impacts women's outcomes in the labor market. We focus on the transportation expansion resulting from the 2014 World Cup and the 2016 Olympic Games in Rio de Janeiro, Brazil. Our goal is to assess the direct effects of this infrastructure policy on female employment. By utilizing a dataset covering formal female workers and employing an empirical differences-in-differences approach, we contribute to the existing literature on the relationship between gender and the labor market.

Our study addresses the challenges related to women's labor participation and the influence of commuting, building upon prior research. Additionally, we contribute to the discussion on the impact of transportation on the labor market, particularly its effect on the female workforce (MARTINEZ et. al, 2020; KWON, 2022). Our distinct empirical approach enables us to analyze the transportation effects on women's labor market outcomes within specific transportation regions, offering valuable insights into the influence of transportation policy on business sectors. Moreover, by mitigating self-selection bias, our study provides a comprehensive understanding of how transport policy affects women's employment dynamics.

Our findings reveal two main results. Firstly, we observe a significant increase in female employment within a 2 km radius of transport stations following the expansion of the transport network. Businesses located closer to these stations experience a notable rise of 1.86% in female employment compared to those farther away. Furthermore, when examining the impact on different groups of women based on education and race, we note a more pronounced effect among highly educated women. This subgroup experiences a noteworthy employment increase of 2.65%, in contrast to their counterparts at more distant firms. These results align with previous literature that highlights the disproportionate impact of transport policies on women (MARTINEZ et. al., 2018; KWON, 2022).

Our second significant finding pertains to resignations and terminations through mutual agreement. We observe a consistent upward trend in the number of women voluntarily leaving their jobs in the areas affected by the transportation expansion even before its implementation. Surprisingly, this trend persists even after the introduction of the expanded transportation network, indicating that the policy did not alter this process. Furthermore, we notice an uptick in the number of women leaving jobs through mutual agreements. This finding suggests that, although the transport policy increased the employability of women in

these areas in the first moment, it was not able to guarantee a longer stay of women in jobs when compared to areas that did not receive transport stations.

7 References

ADDA, J., DUSTMANN, C. AND STEVENS, K., (2017), The Career Costs of Children, *Journal of Political Economy*, 125, issue 2, p. 293 - 337

ADUKIA, A., ASHER, S. AND NOVOSAD, P. (2020). "Educational Investment Responses to Economic Opportunity: Evidence from Indian Road Construction." *American Economic Journal: Applied Economics*, 12 (1): 348-76.

ANDERSSON, F., BURGESS, S., & LANE, J. I. (2007). *Cities, matching and the productivity gains of agglomeration. Journal of Urban Economics*, 61(1), 112–128.

ANGELOV, N. AND JOHANSSON, P. AND LINDAHL, E. (2016), Parenthood and the Gender Gap in Pay, *Journal of Labor Economics*, 34, issue 3, p. 545 - 579.

AHLFELDT, G. AND FEDDERSEN, A., (2018), From periphery to core: measuring agglomeration effects using high-speed rail, *Journal of Economic Geography*, 18, issue 2, p. 355-390.

BARTIK, A. W., BERTRAND, M., CULLEN, Z., GLAESER, E. L., LUCA, M., & STANTON, C. (2020). *The impact of COVID-19 on small business outcomes and expectations. Proceedings of the National Academy of Sciences*, 202006991.

BERTRAND, M., DUFLO, E., & MULLAINATHAN, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, 119(1), 249–275.

BERTRAND, M. AND GOLDIN, C. AND KATZ, L. (2010). Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics*. 2. 228-55. 10.1257/app.2.3.228.

BLACK, D. AND KOLESNIKOVA, N. AND TAYLOR, LOWELL J., (2014), Why do so few women work in New York (and so many in Minneapolis)? Labor supply of married women across US cities, *Journal of Urban Economics*, 79, issue C, p. 59-71

BÜTIKOFER, A. AND LØKEN, V. AND WILLEN, A., (2019). "Building Bridges and Widening Gaps: Efficiency Gains and Equity Concerns of Labor Market Expansions," Discussion Paper Series in Economics 19/2019, *Norwegian School of Economics, Department of Economics*.

CALLAWAY, B., & SANT'ANNA, P. H. C. (2020). *Difference-in-Differences with multiple time periods. Journal of Econometrics*.

CAMPOS, M. (2016) *Urban Mobility, Inequality and Welfare in Developing Countries: Evidence from 2016 Olympics in Rio de Janeiro*. Phd Thesis. *Pontificia Universidade Catolica do Rio de Janeiro, Departamento de Economia*, 2019.

DANIELI, O. AND CALDWELL, S., Working Paper. Outside Options in the Labor Market.

FAN, Y., GUTHRIE, A. E., & LEVINSON, D. M. (2012). Impact of light rail

implementation on labor market accessibility: A transportation equity perspective. *Journal of Transport and Land Use*, 5(3). <https://doi.org/10.5198/jtlu.v5i3.240>

FARRÉ, L. , JOFRE-MONSENY, J. AND TORRECILLAS, J. (2020). "Commuting time and the gender gap in labor market participation," Working Papers 2020/03, Institut d'Economia de Barcelona (IEB).

FLUCHTMANN, J. AND GLENNY, A. AND HARMON, N. AND MAIBOM, J. (2020). The Gender Application Gap: Do men and women apply for the same jobs?

GOODMAN-BACON, A. (2021). *Difference-in-differences with variation in treatment timing. Journal of Econometrics.*

GOLDIN, C. (2014). "A Grand Gender Convergence: Its Last Chapter." *American Economic Review*, 104 (4): 1091-1119.

HERVAS-OLIVER, J.-L., SEMPERE-RIPOLL, F., ROJAS ALVARADO, R., & ESTELLES-MIGUEL, S. (2017). *Agglomerations and firm performance: who benefits and how much? Regional Studies*, 52(3), 338–349.

HEUERMANN, D. AND SCHMIEDER, J. (2019), The effect of infrastructure on worker mobility: evidence from high-speed rail expansion in Germany, *Journal of Economic Geography*, 19, issue 2, p. 335-372.

JAYACHANDRAN, S. (2020). Social Norms as a Barrier to Women's Employment in Developing Countries. *NBER Working Paper No. w27449*

KWON, E. (2020). Why Do Improvements in Transportation Infrastructure Reduce the Gender Gap in South Korea? (*Job Market Paper*)

LE BARBANCHON, T. AND RATHELOT, R. AND ROULET, A., (2021) Gender Differences in Job Search: Trading off Commute against Wage *Quarterly Journal of Economics*, 136.

LEI, L., DESAI, S., & VANNEMAN, R. (2019). The Impact of Transportation Infrastructure on Women's Employment in India. *Feminist economics*, 25(4), 94–125. <https://doi.org/10.1080/13545701.2019.1655162>

KLEVEN, H. AND LANDAIS, C. AND POSCH, J. AND STEINHAEUER, A. AND ZWEIMUF, (2019), Child Penalties across Countries: Evidence and Explanations, *AEA Papers and Proceedings*, 109, issue , p. 122-26

MADDEN, J. (1981). Why Women Work Closer to Home. *Urban Studies*. 18. 181-194.

MATAS, A. AND JOSEP-LLUIS ROIG. "Job Accessibility and Female Employment

Probability: The Cases of Barcelona and Madrid." *Urban Studies* 47, no. 4 (2010): 769–87.

MARTINEZ, D. AND MITNIK, O. AND SALGADO, E. AND SCHOLL, L. AND YAÑEZ-PAGANS, P. (2020). Connecting to Economic Opportunity: the Role of Public Transport in Promoting Women's Employment in Lima. *Journal of Economics, Race, and Policy*.

OLIVETTI, C., & PETRONGOLO, B. (2016). The Evolution of Gender Gaps in Industrialized Countries. *Annual Review of Economics*, 8(1), 405–434.

OVERMAN, H. AND PUGA, D., (2010), Labor Pooling as a Source of Agglomeration: An Empirical Investigation, p. 133-150 in , Agglomeration Economics, *National Bureau of Economic Research*

PATACCHINI, E. AND ZENOU, Y. (2005), Spatial mismatch, transport mode and search decisions in England, *Journal of Urban Economics*, 58, issue 1, p. 62-90.

SMALL, K. (2012): “Valuation of travel time,” *Economics of Transportation*, 1, 2–14.

SEKI, M. AND YAMADA, E. (2020), “Heterogeneous Effects of Urban Public Transportation on Employment by Gender: Evidence from the Delhi Metro”, No 207, Working Papers, JICA Research Institute.

SOLON, G., HAIDER, S., & WOOLDRIDGE, J. (2013). *What Are We Weighting For?*

STUART S. ROSENTHAL and WILLIAM C.S, (2012). "Female Entrepreneurship, Agglomeration, and a New Spatial Mismatch," *The Review of Economics and Statistics*, MIT Press, vol. 94(3), pages 764-788.

TSIVANIDIS, N. (2018). The aggregate and distributional effects of urban transit infrastructure: Evidence from Bogotá’s transmilenio. Technical report, Working Paper, University of Chicago Booth School of Business.

TYNDALL, J. (2017). Waiting for the R train: Public transportation and employment. *Urban studies*, 54(2):520–537.

WHITE, M. (1986). Sex Differences in Urban Commuting Patterns. *The American Economic Review*, 76(2), 368-372.

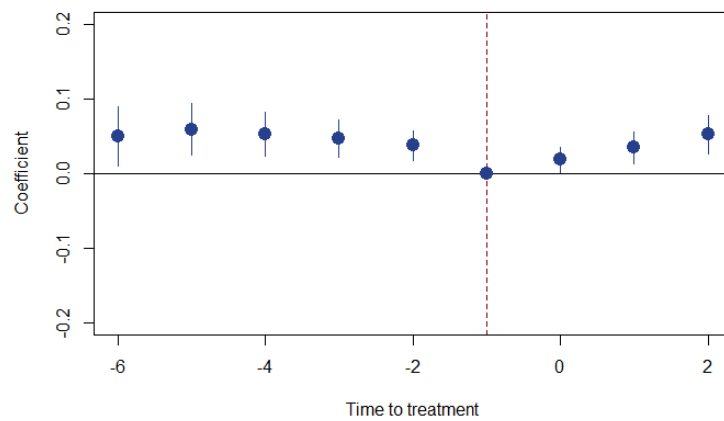
YAÑEZ-PAGANS, P. AND MARTÍNEZ, D. AND MITNIK, O. AND SCHOLL, L. AND VAZQUEZ, A. (2019). Urban transport systems in Latin America and the Caribbean: lessons and challenges. *Latin American Economic Review*.

ZÁRATE, ROMÁN D. (2019). “Factor Allocation, Informality, and Transit Improvements: Evidence from Mexico Ciudad”

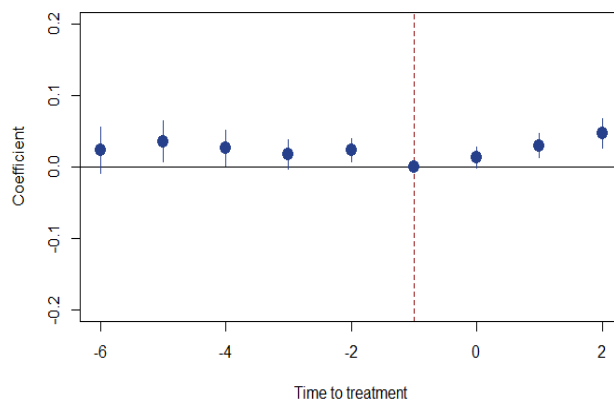
Additional Results

Figure 9: Effects on Resignations

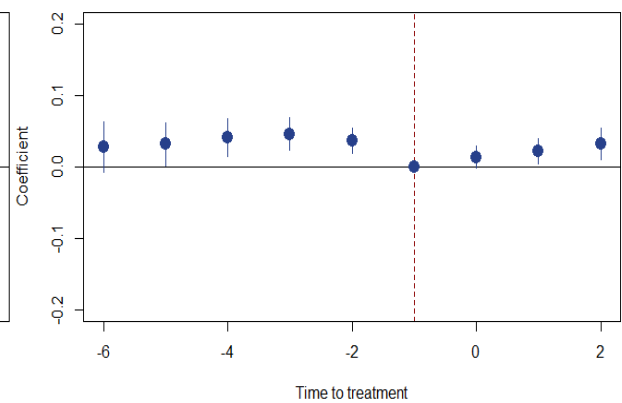
(a) Geral



(b) Women

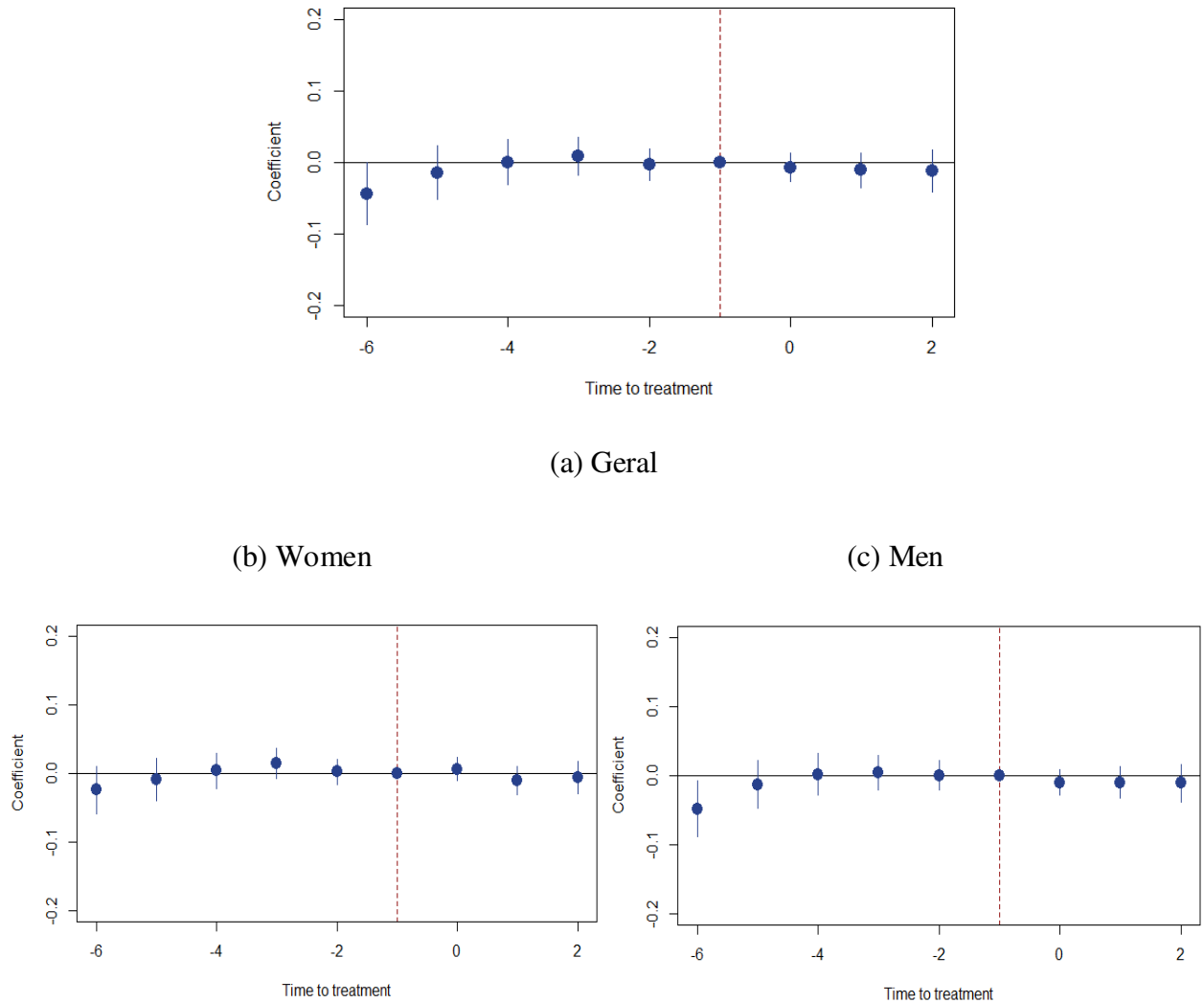


(c) Men



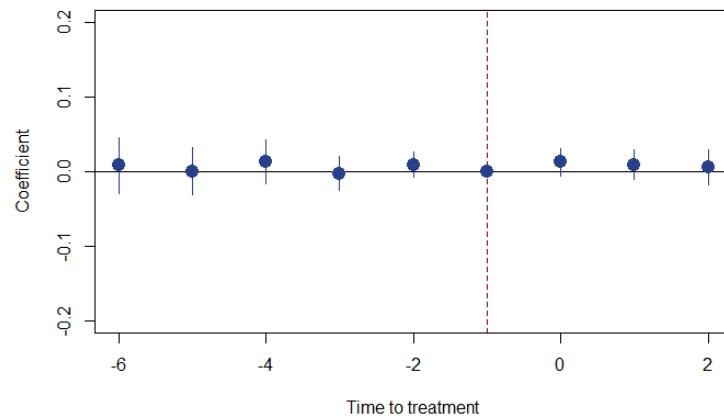
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employee's initiative})$ (b) $\ln(1 + \text{total unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 10: Effects on Terminations



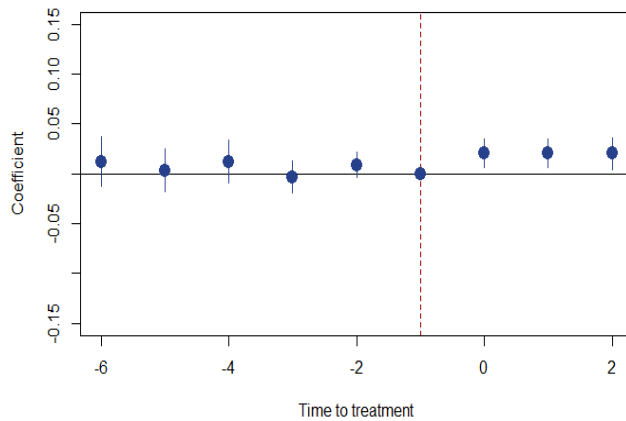
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employer's initiative})$ (b) $\ln(1 + \text{total unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 11: Effects on Mutual Agreement Unemployment

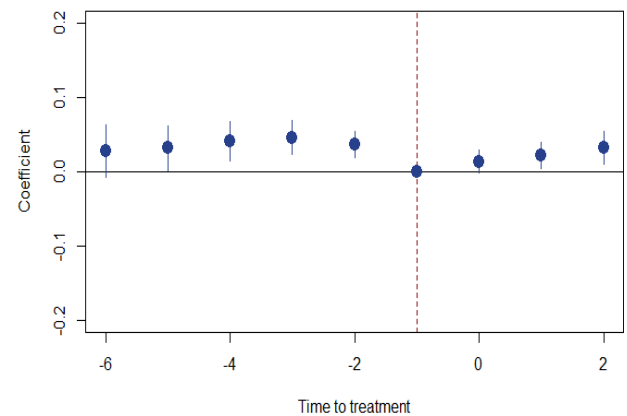


(a) Geral

(b) Women

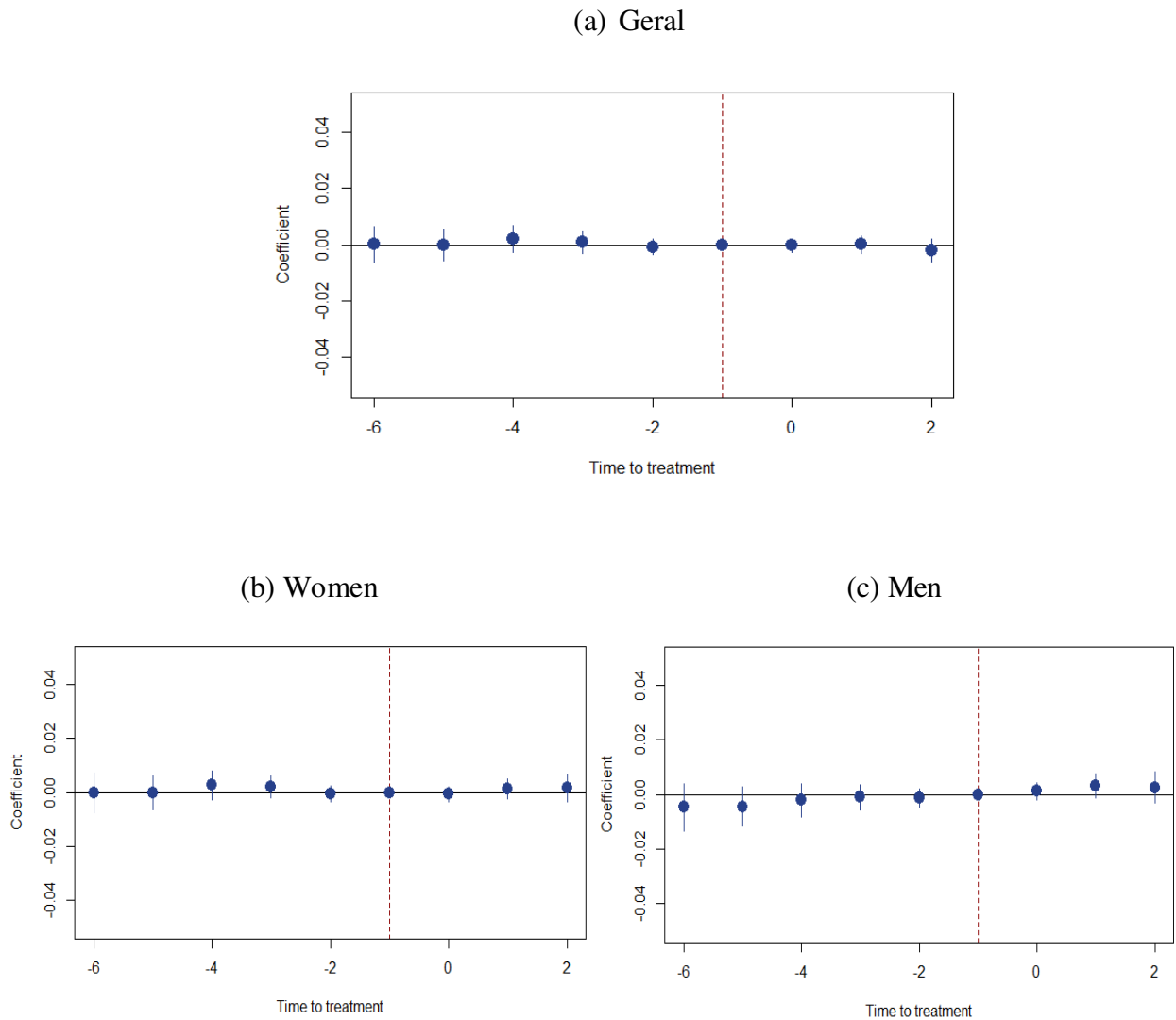


(c) Men



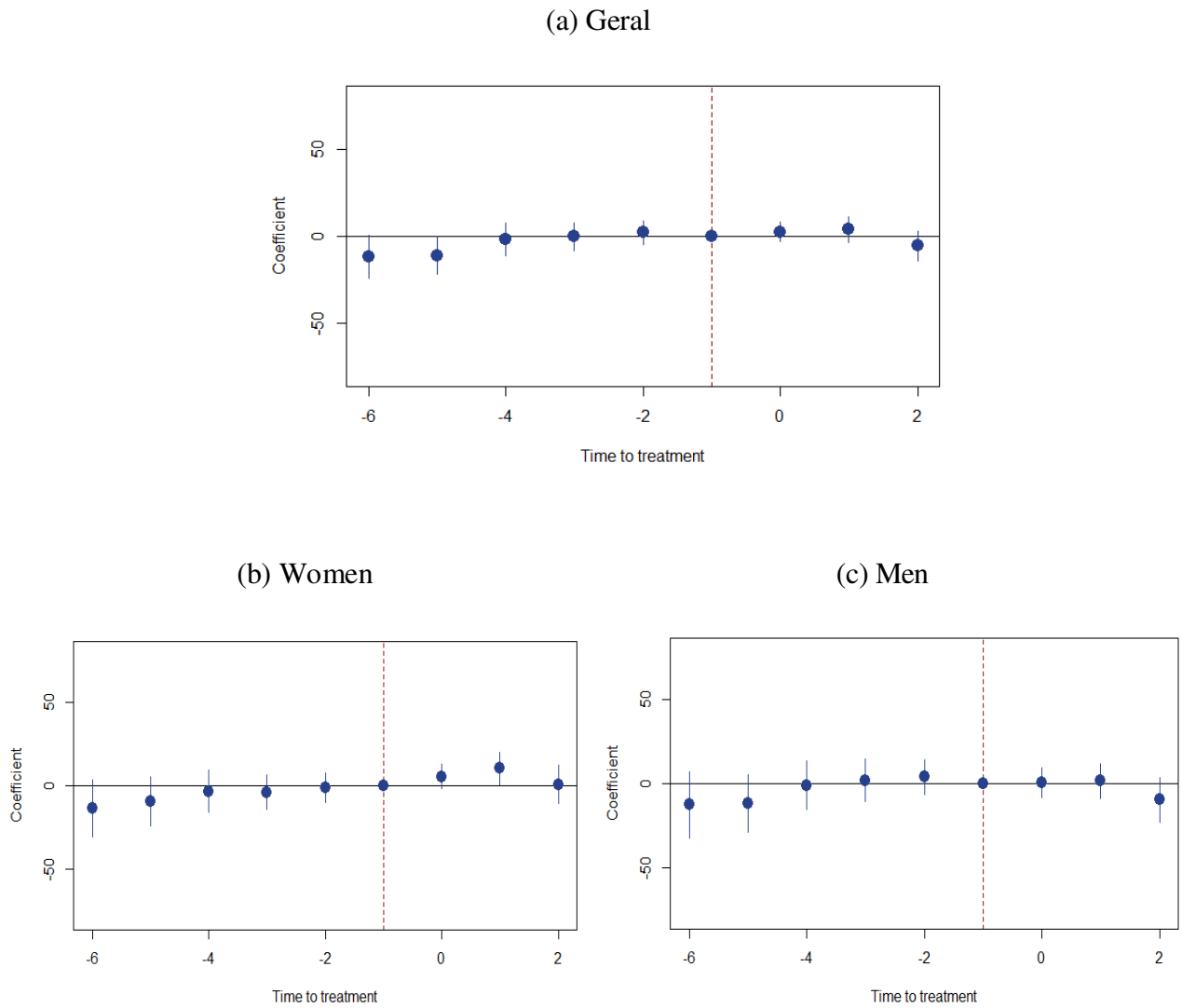
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by mutual agreement})$ (b) $\ln(1 + \text{total unemployed women by mutual agreement})$, (c) $\ln(1 + \text{total unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 9: Effects on Weekly Hours Worked by Race



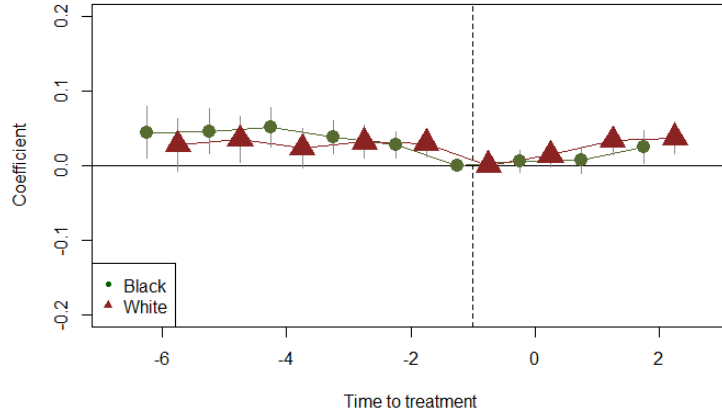
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{weekly hours worked})$ (b) $\ln(1 + \text{weekly female hours worked})$, (c) $\ln(1 + \text{weekly male hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 12: Effects on Weekly Wage



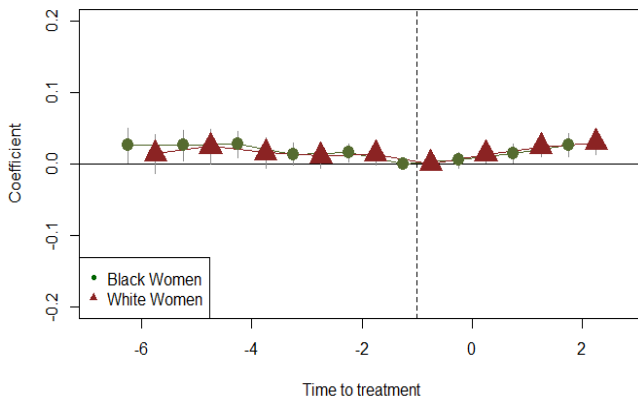
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) weekly wage (in R\$) (b) weekly female wage (in R\$) (c) weekly male wage (in R\$). Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 13: Effects on Resignations by Race

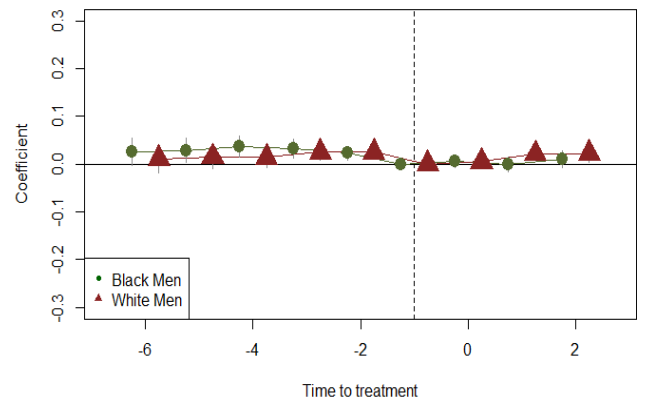


(a) Geral

(b) Black/White Women



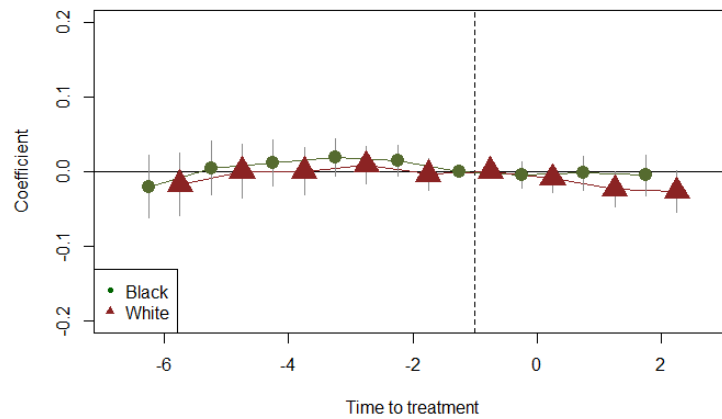
(c) Black/White Men



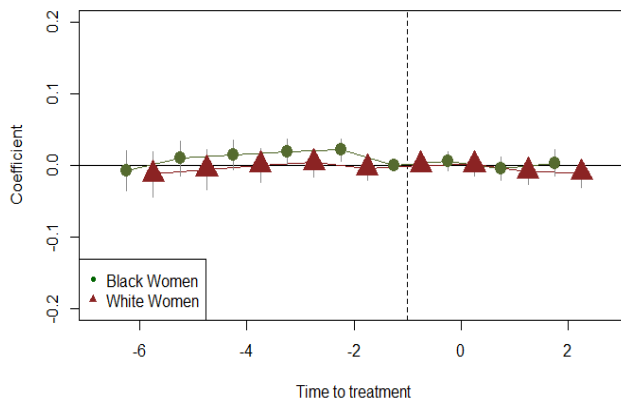
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed by employee's initiative})$ (b) $\ln(1 + \text{total black/white unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total black/white unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 14: Effects on Terminations by Race

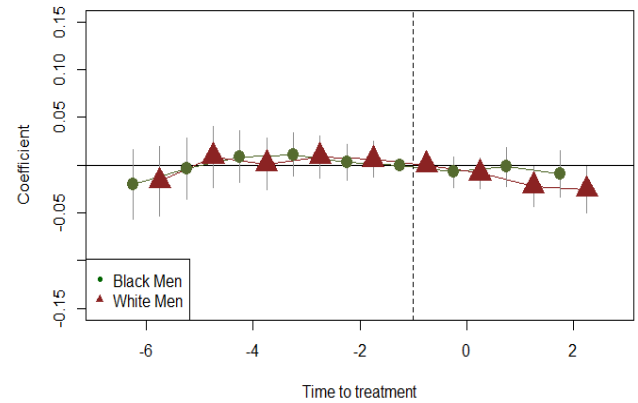
(a) Geral



(b) Black/White Women

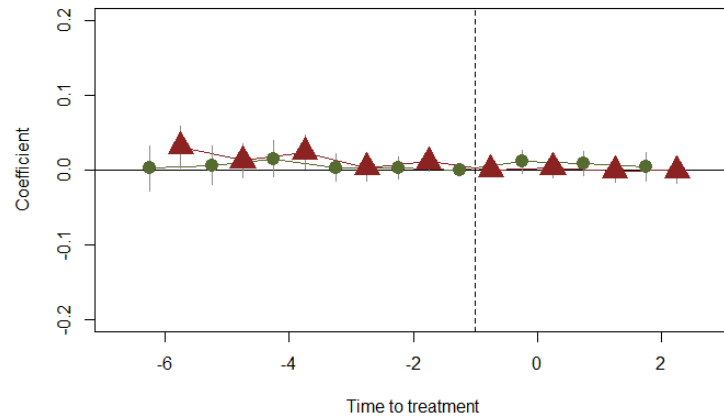


(c) Black/White Men



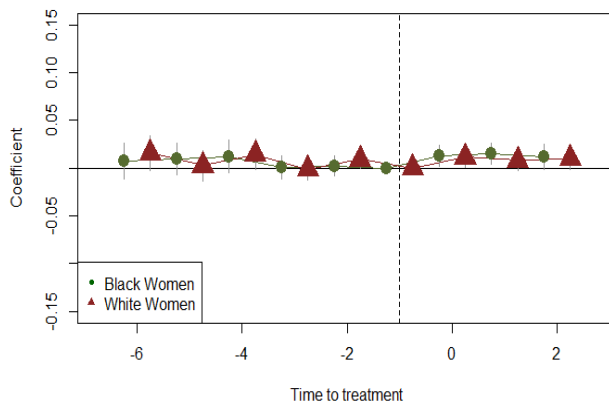
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed by employer's initiative})$ (b) $\ln(1 + \text{total black/white unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total black/white unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 15: Effects on Unemployment by Mutual Agreement by Race

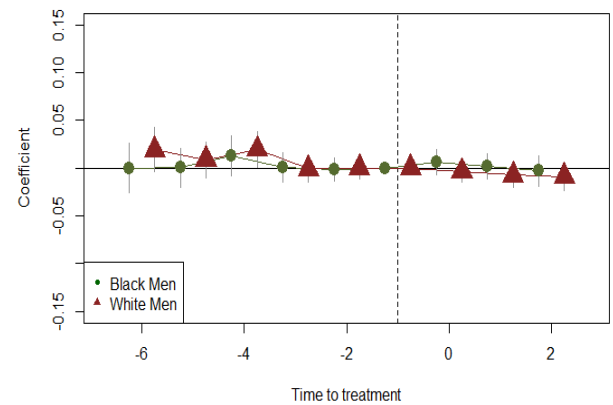


(a) Geral

(b) Black/White Women



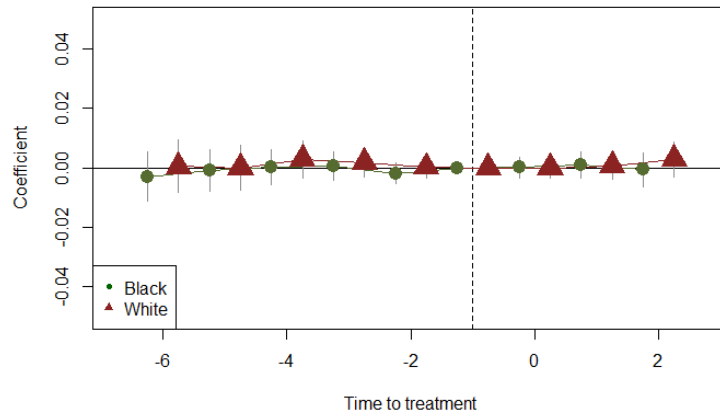
(c) Black/White Men



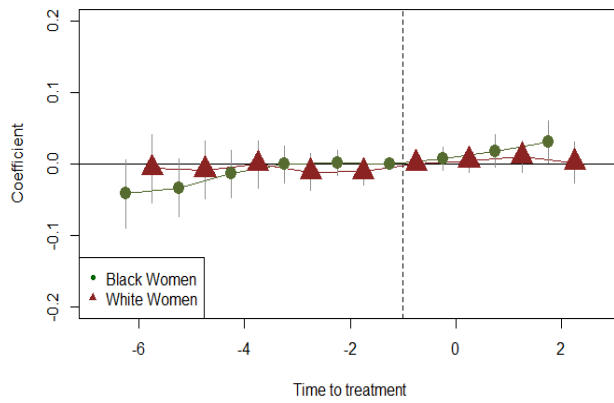
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed by mutual agreement})$ (b) $\ln(1 + \text{total black/white unemployed women by mutual agreement})$ (c) $\ln(1 + \text{total black/white unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 16: Effects on Weekly Hours Worked by Race

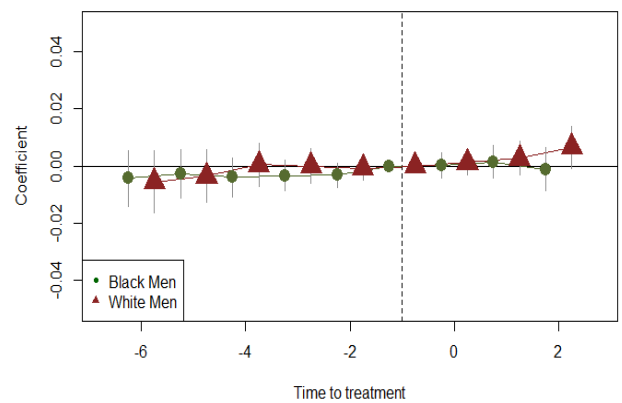
(a) Geral



(b) Black/White Women



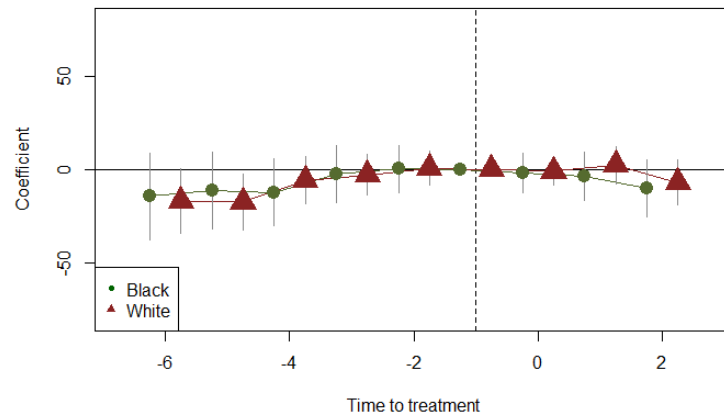
(c) Black/White Men



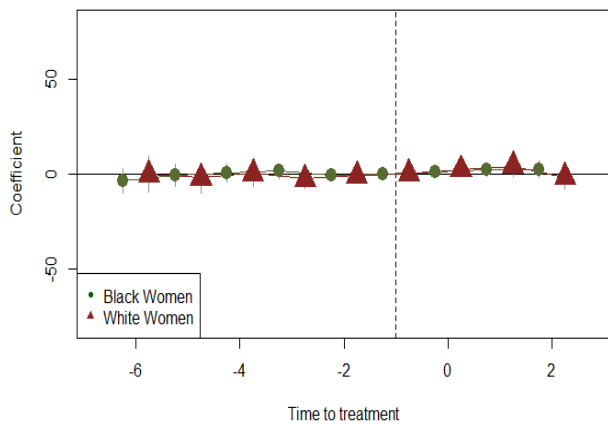
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{black/white weekly hours worked})$ (b) $\ln(1 + \text{women black/white weekly hours worked})$ (c) $\ln(1 + \text{men black/white weekly hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 17: Effects on Weekly Wage by Race

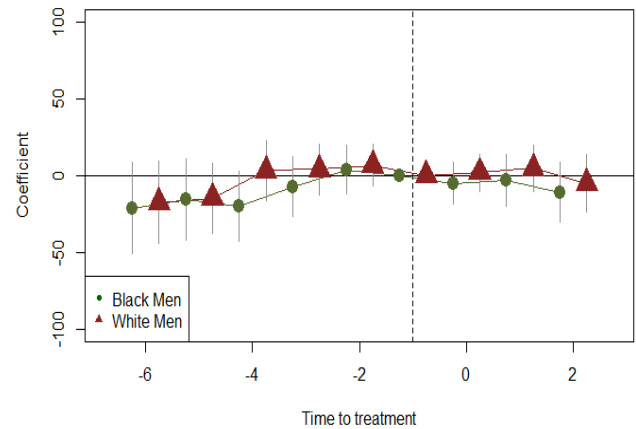
(a) Geral



(b) Black/White Women



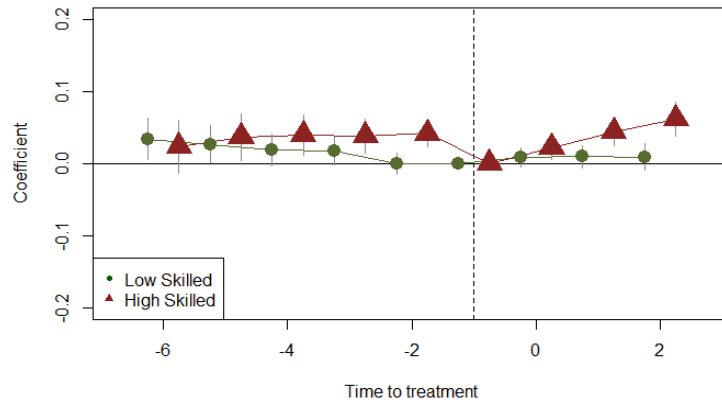
(c) Black/White Men



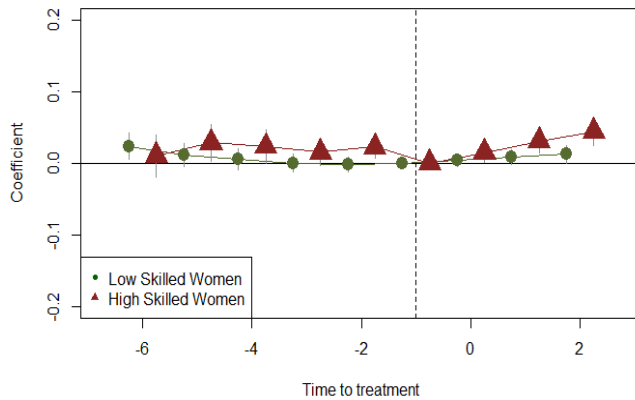
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) black/white weekly wage (in R\$) (b) black/white weekly female wage (in R\$) (c) black/white weekly male wage (in R\$). Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 18: Effects on Resignations by Education Level

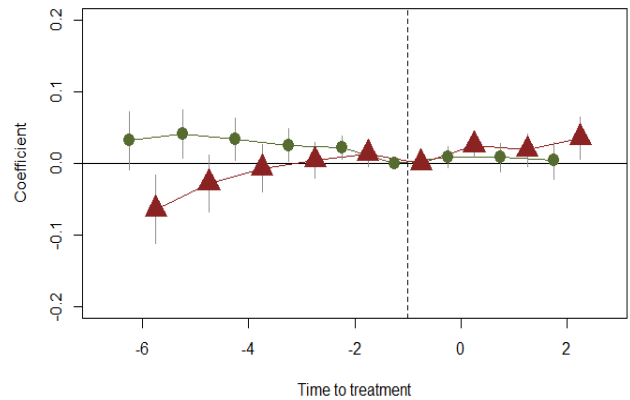
(a) Geral



(b) Low/High Skilled Women



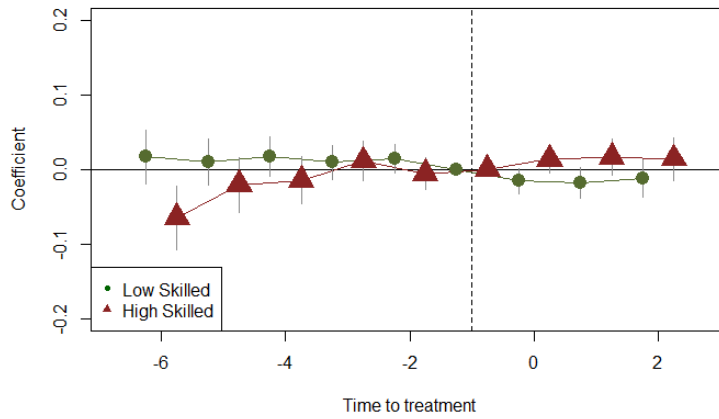
(c) Low/High Skilled Men



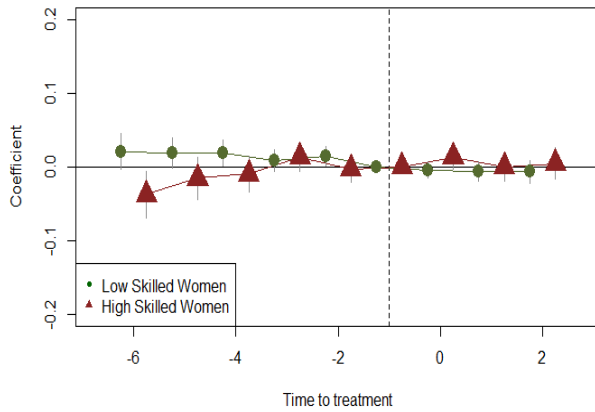
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed by employee's initiative})$ (b) $\ln(1 + \text{total low/high skilled unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total low/high skilled unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 19: Effects on Terminations by Education Level

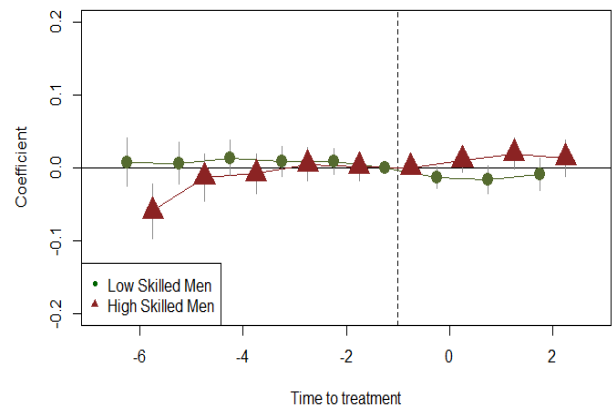
(a) Geral



(b) Low/High Skilled Women



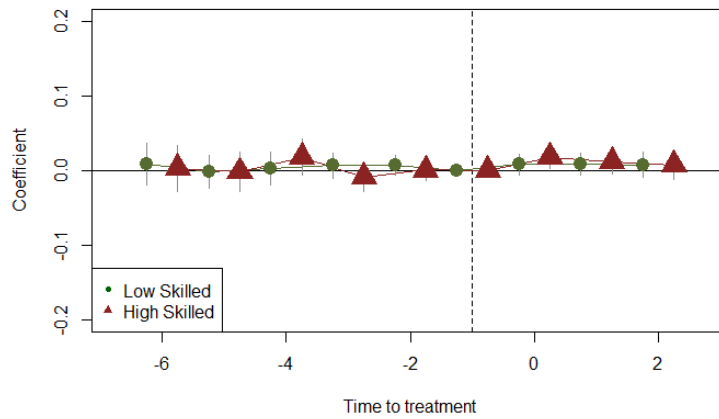
(c) Low/High Skilled Men



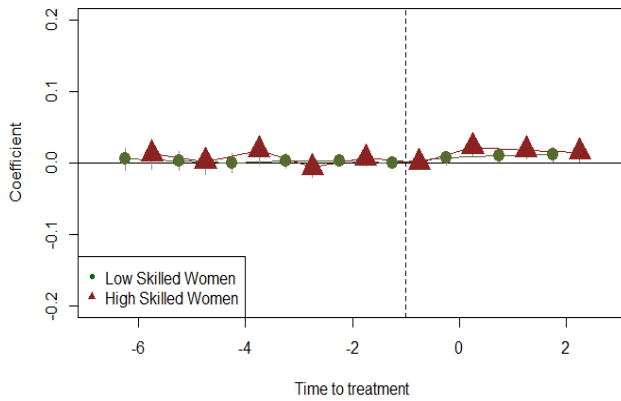
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed by employer's initiative})$ (b) $\ln(1 + \text{total low/high skilled unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total low/high skilled unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment

Figure 20: Effects on Unemployment by Mutual Agreement by Education Level

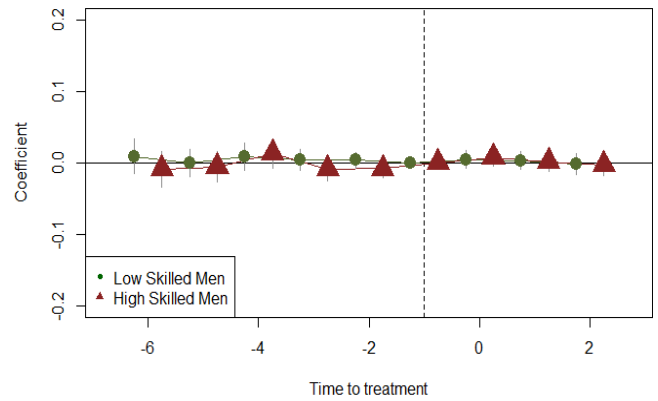
(a) Geral



(b) Low/High Skilled Women



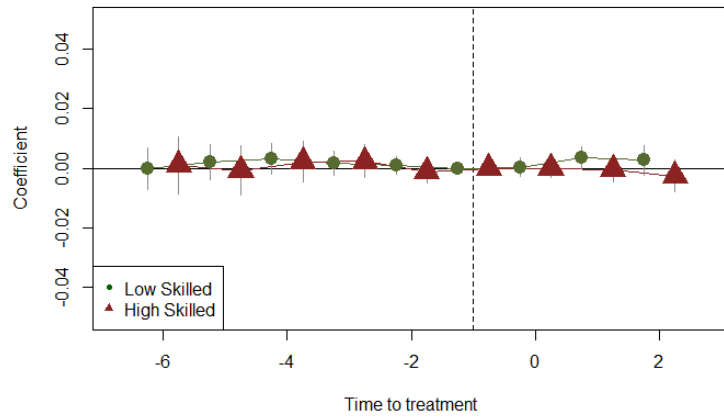
(c) Low/High Skilled Men



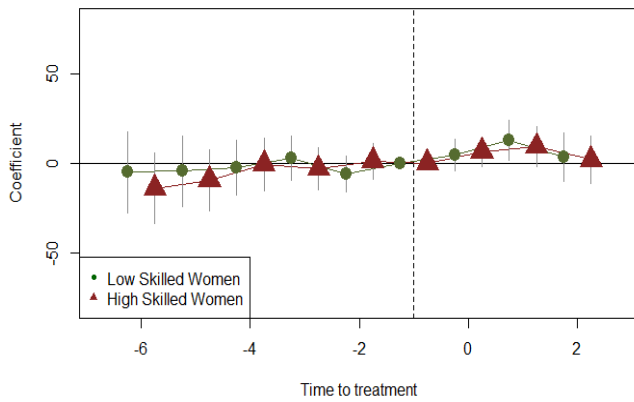
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total black/white unemployed by mutual agreement})$ (b) $\ln(1 + \text{total low/high skilled unemployed women by mutual agreement})$, (c) $\ln(1 + \text{total low/high skilled unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment

Figure 21: Effects on Weekly Hours Worked by Education Level

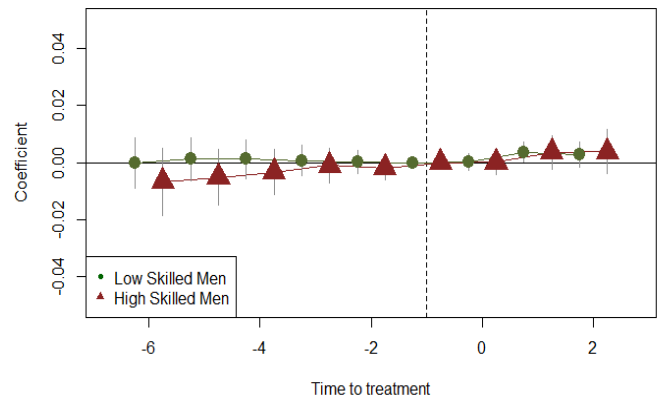
(a) Geral



(b) Low/High Skilled Women



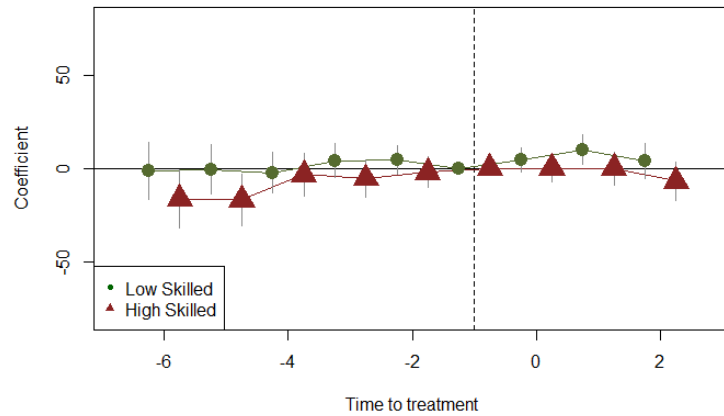
(b) Low/High Skilled Men



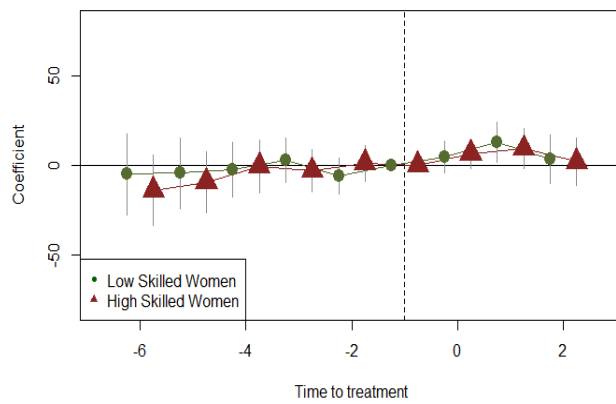
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{low/high skilled weekly hours worked})$ (b) $\ln(1 + \text{women low/high skilled weekly hours worked})$ (c) $\ln(1 + \text{men low/high skilled weekly hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 22: Effects on Weekly Wage by Education Level

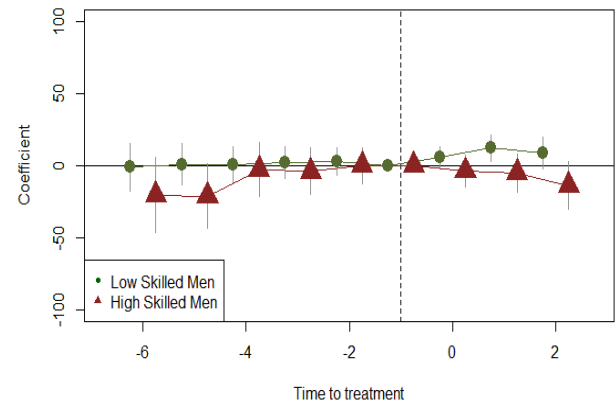
(a) Geral



(b) Low/High Skilled Women



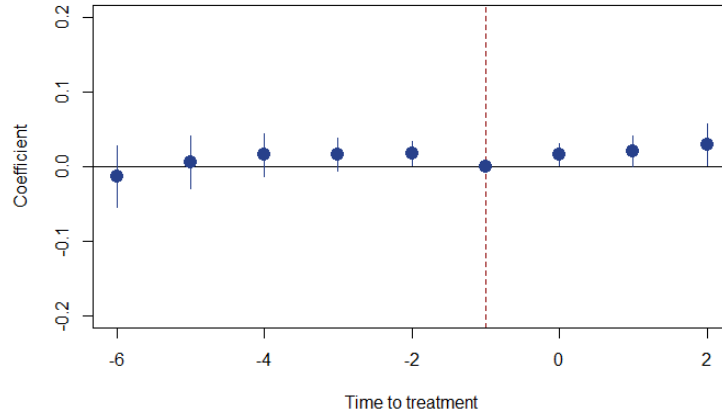
(c) Low/High Skilled Men



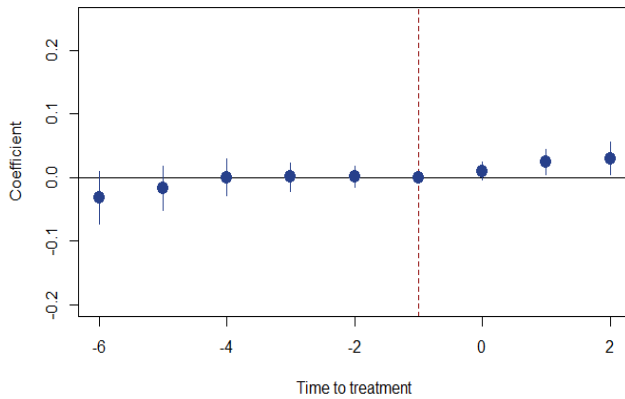
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{low/high skilled weekly hours worked})$ (b) $\ln(1 + \text{women low/high skilled weekly hours worked})$ (c) $\ln(1 + \text{men low/high skilled weekly hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment

Figure 23: Effects on Employment – Alternative Fixed Effects

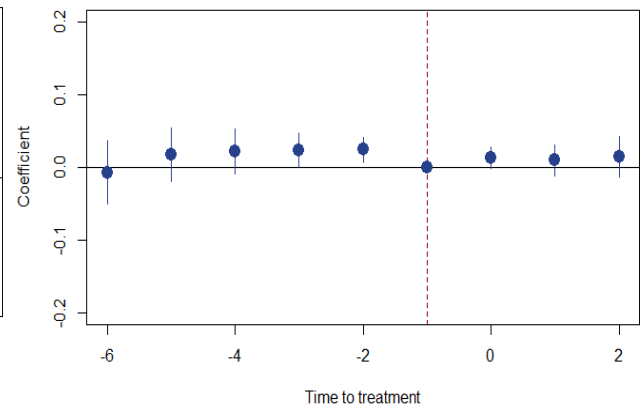
(a) Geral



(b) Women



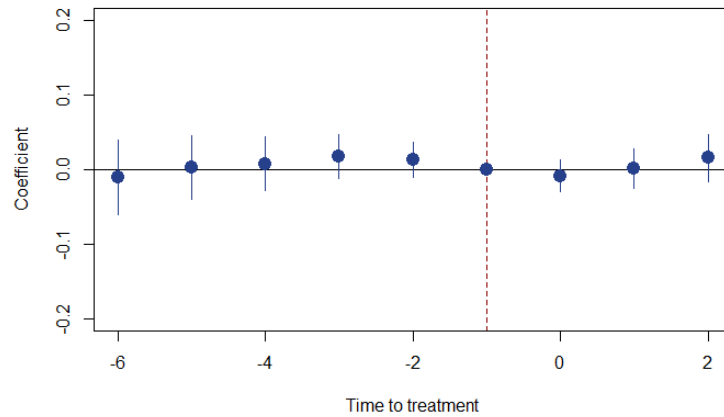
(c) Men



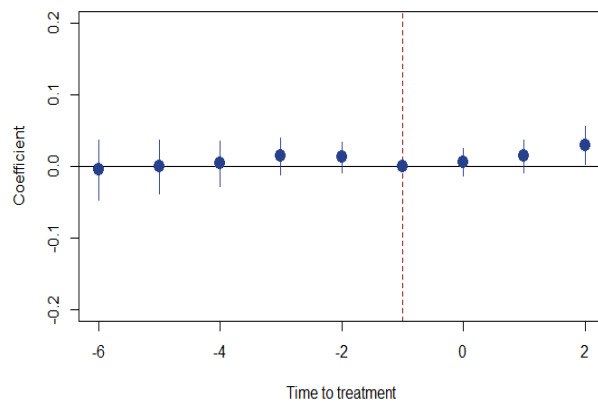
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln(\text{total of employees})$ (b) $1 + \ln(\text{total of female employees})$, (c) $1 + \ln(\text{total of male employees})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 24: Effects on Terminations – Alternative Fixed Effects

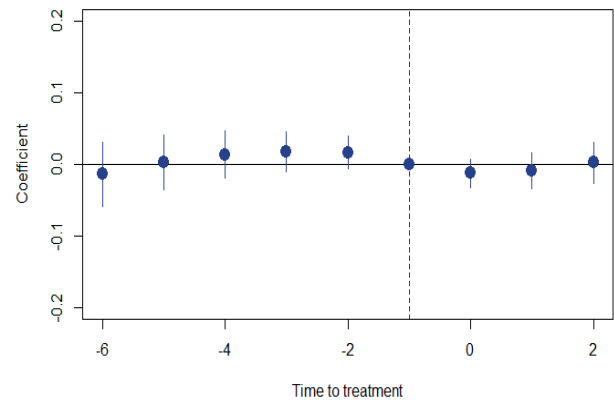
(a) Geral



(b) Women

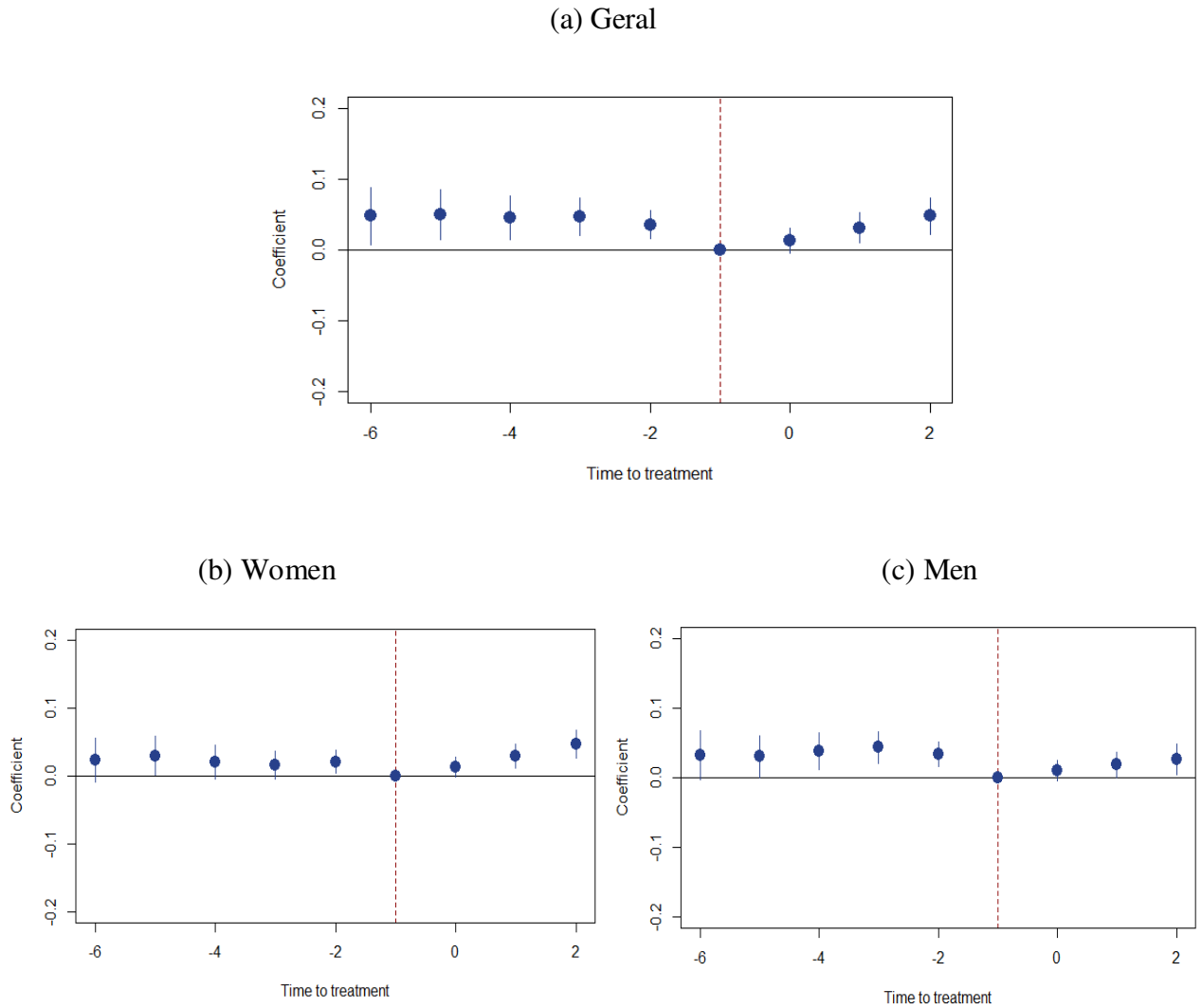


(c) Men



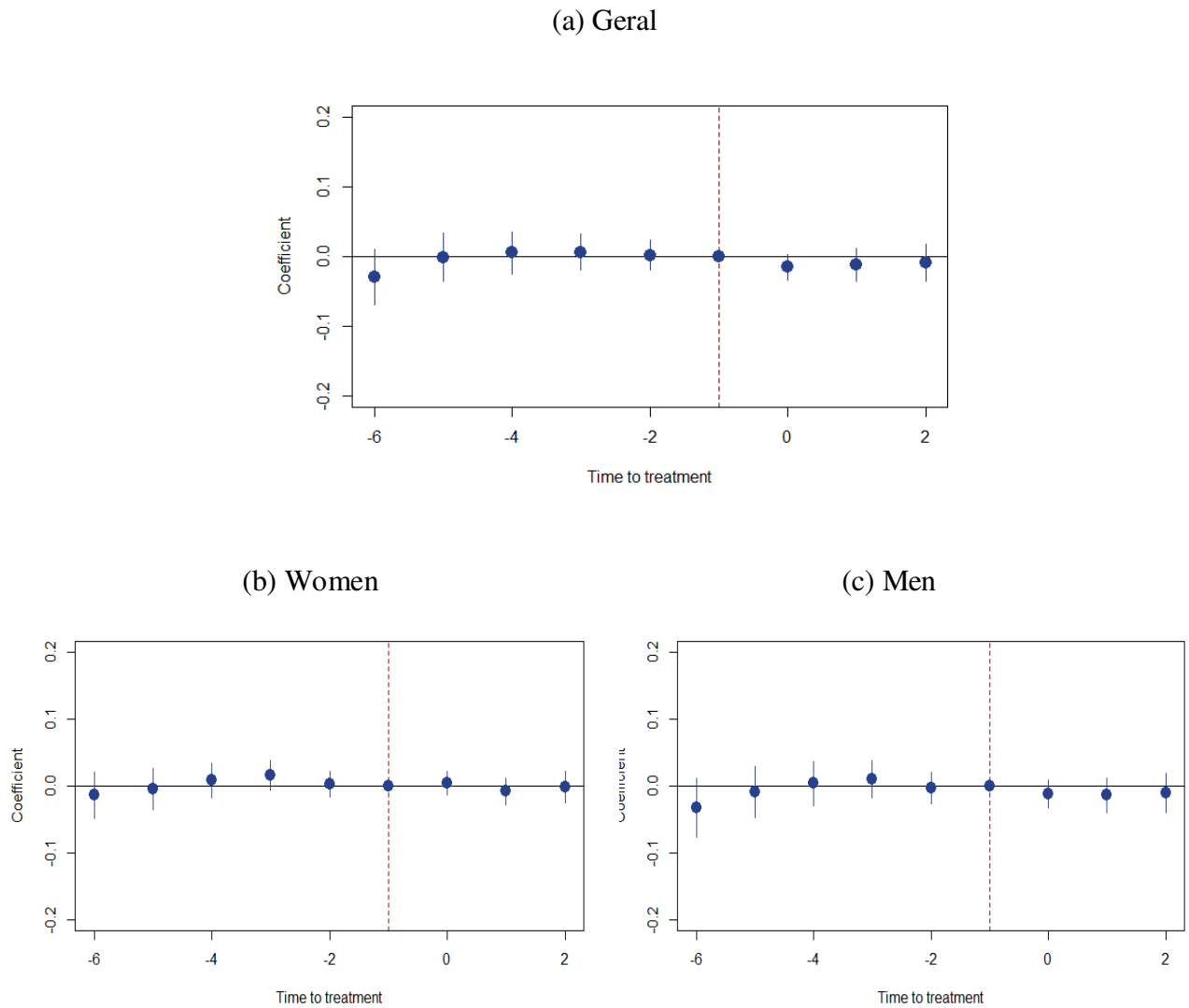
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employer's initiative})$ (b) $\ln(1 + \text{total unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 25: Effects on Resignations – Alternative Fixed Effects



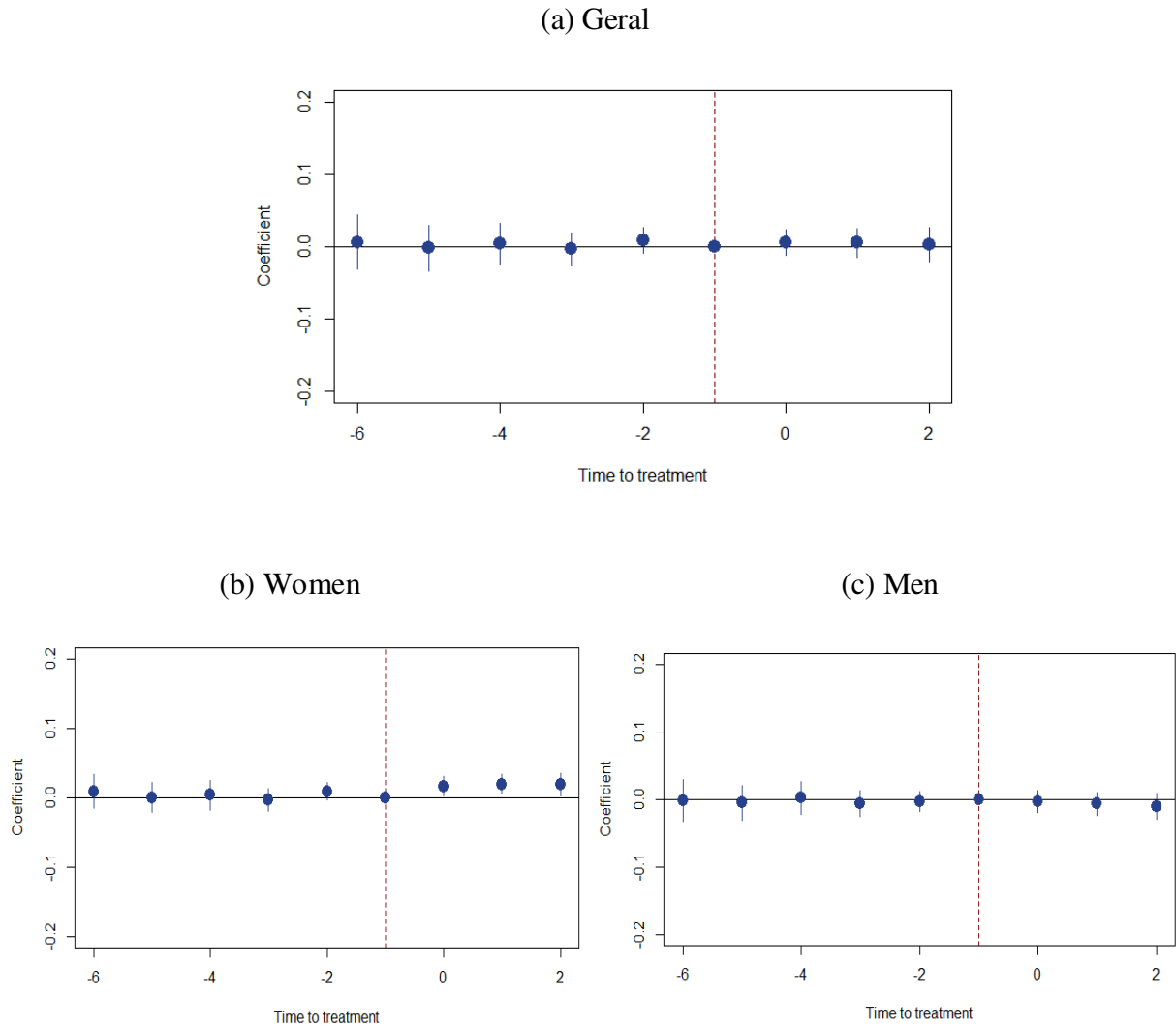
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employee's initiative})$ (b) $\ln(1 + \text{total unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 26: Effects on Terminations – Alternative Fixed Effects



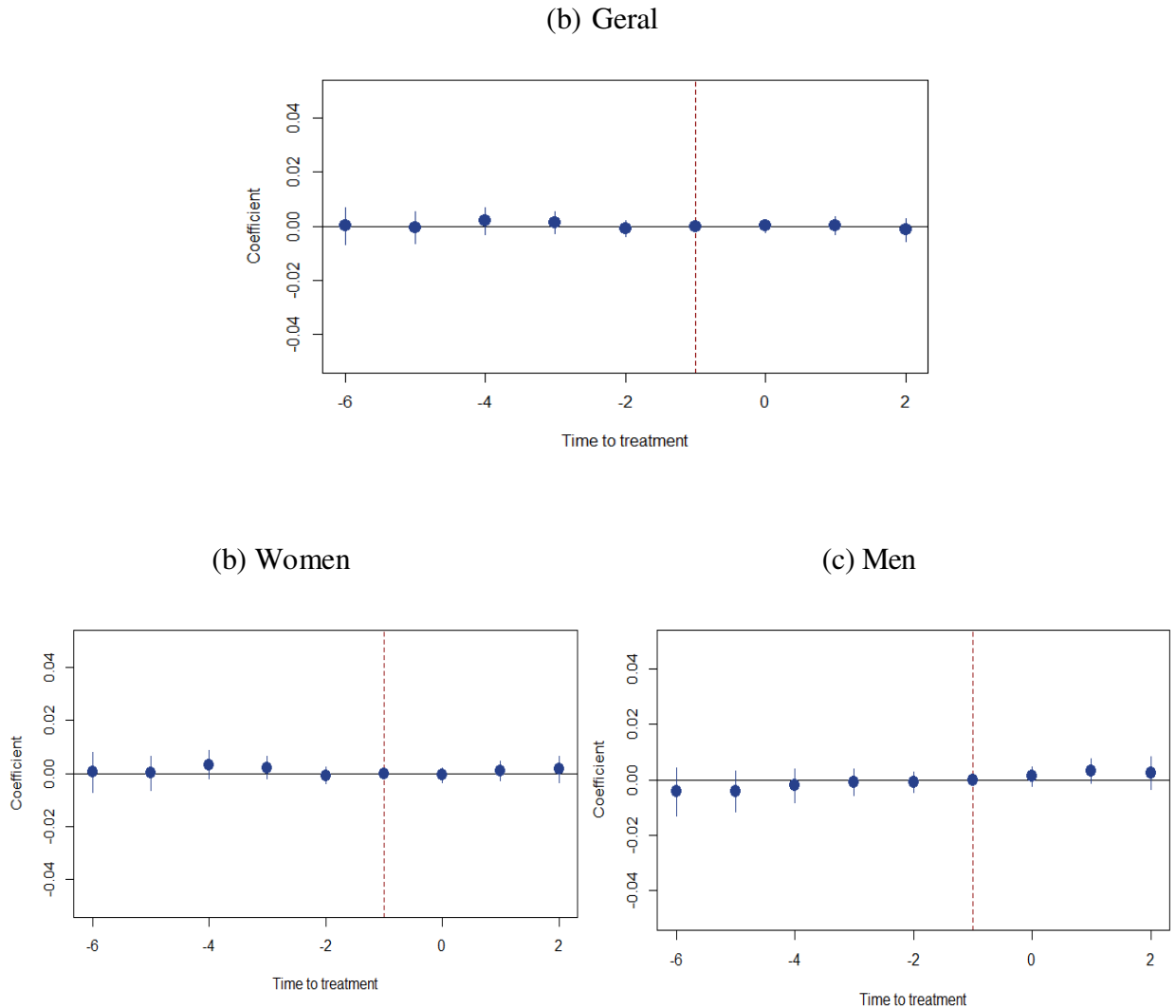
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employer's initiative})$ (b) $\ln(1 + \text{total unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 27: Effects on Unemployment by Mutual Agreement – Alternative Fixed Effects



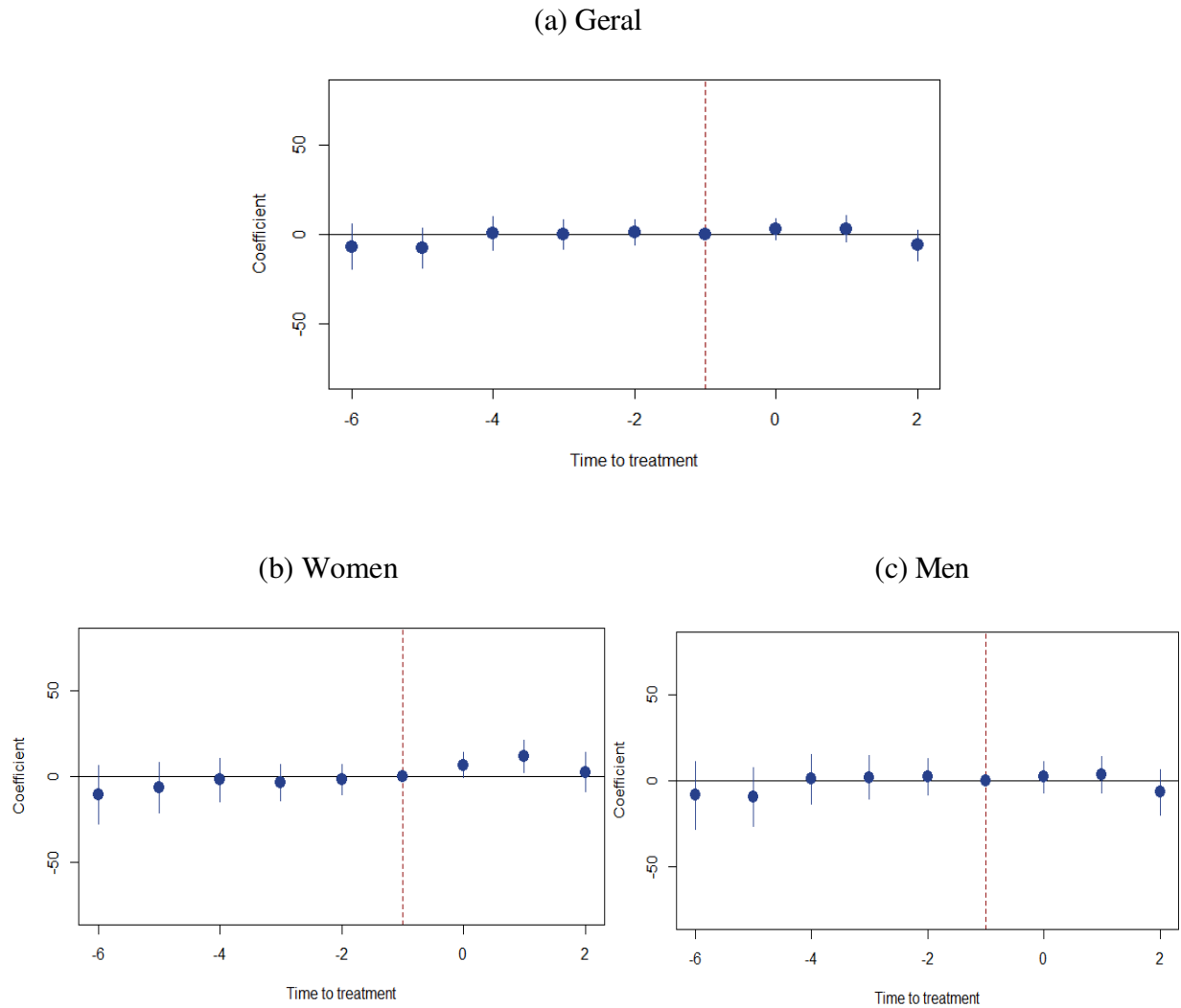
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by mutual agreement})$ (b) $\ln(1 + \text{total unemployed women by mutual agreement})$, (c) $\ln(1 + \text{total unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 28: Effects on Weekly Hours Worked – Alternative Fixed Effects



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{weekly hours worked})$ (b) $\ln(1 + \text{weekly female hours worked})$, (c) $\ln(1 + \text{weekly male hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 29: Effects on Weekly Wage - Alternative Fixed Effects



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 2km from a transportation station. The dependent variable in each panel are: (a) weekly wage (in R\$) (b) weekly female wage (in R\$) (c) weekly male wage (in R\$). Data is from 2010 to 2018. Red vertical line represents time of treatment.

Table 10: Effects on Firm Outcomes - Alternative Fixed Effects - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Post_Transportation	0.0168 (0.0094)	0.0069 (0.0107)	0.0481*** (0.0107)	-0.0055 (0.0096)	0.0062 (0.0073)	0.0019 (0.0013)	-0.7127 (2.842)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

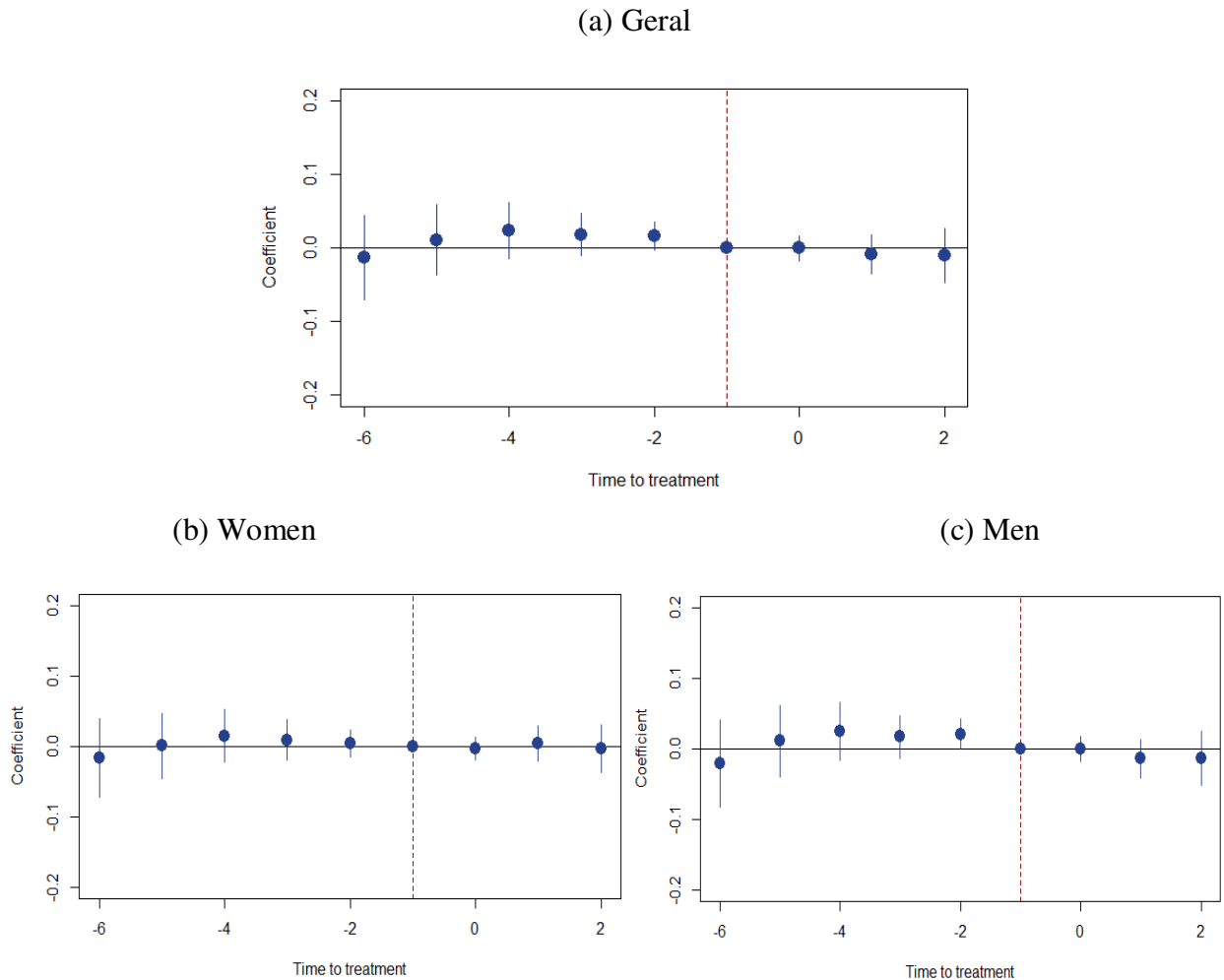
Note: Table 10 presents the results of differences-in-differences estimation for selected labor market variable in alternative fixed effects. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 11: Effects on Firms Outcomes – Alternative Fixed Effects – Women and Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel B: Women							
Post_Transportation	0.0214** (0.0094)	0.0162 (0.0101)	0.0296*** (0.0079)	-0.0019 (0.0087)	0.0183** (0.0065)	0.0007 (0.0018)	6.868 (4.086)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Panel C: Men							
Post_Transportation	0.0120 (0.0101)	-0.0181 (0.0083)	0.0181* (0.0083)	-0.0123 (0.0100)	-0.0069 (0.0017)	0.0023 (0.0021)	-0.4078 (4.643)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓
Sector x date FE	✓	✓	✓	✓	✓	✓	✓
Size x date FE	✓	✓	✓	✓	✓	✓	✓

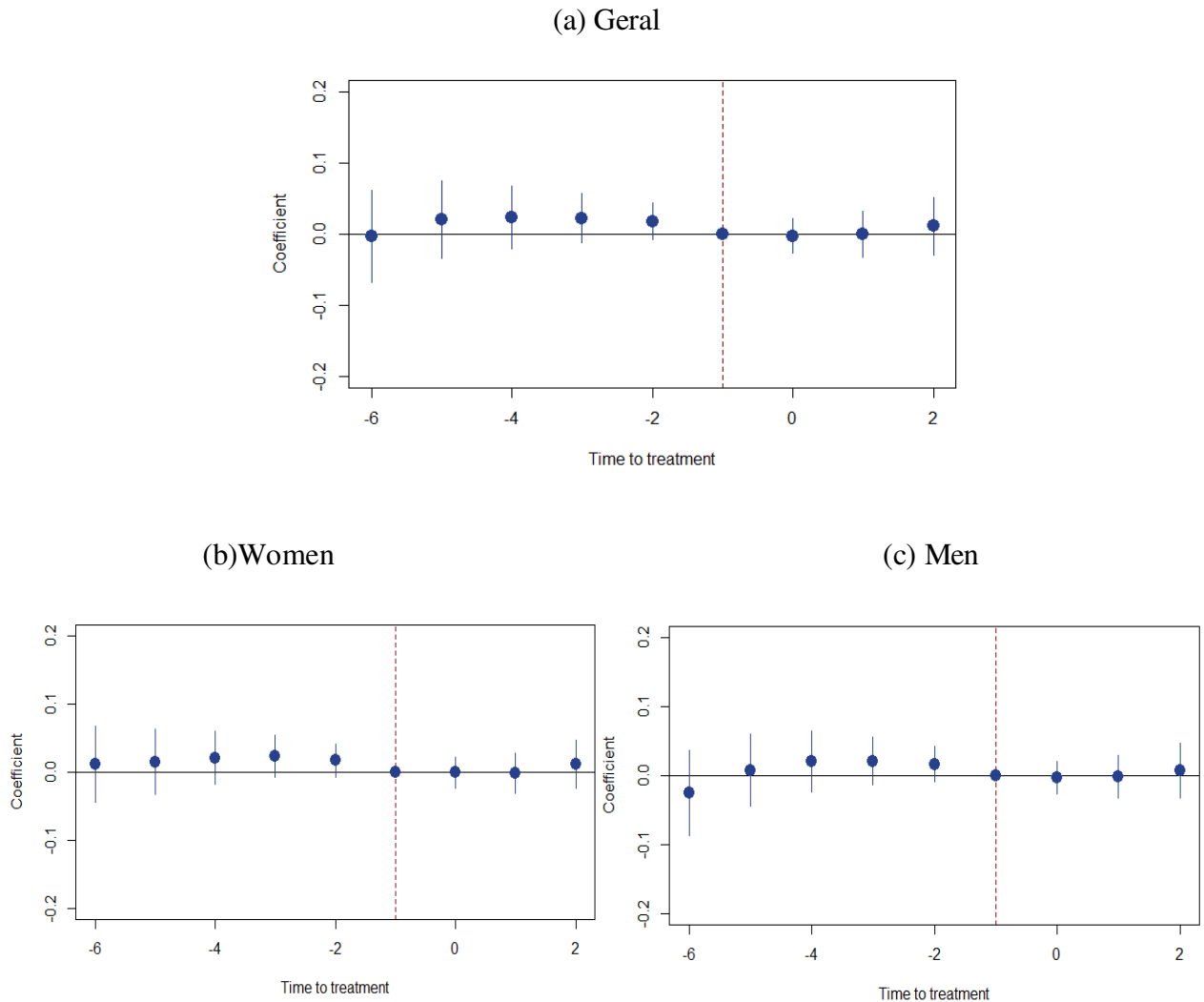
Note: Table 11 presents the results of differences-in-differences estimation for selected labor market variable in alternative fixed effects. In Panel (B), estimations are for female workers, (C) for male workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Figure 30: Effects on Employment – 1km



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln(\text{total of employees})$ (b) $1 + \ln(\text{total of female employees})$, (c) $1 + \ln(\text{total of male employees})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

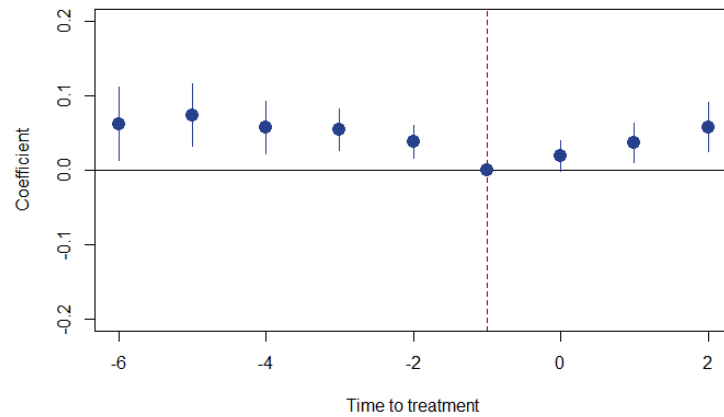
Figure 31: Effects on Unemployment – 1km



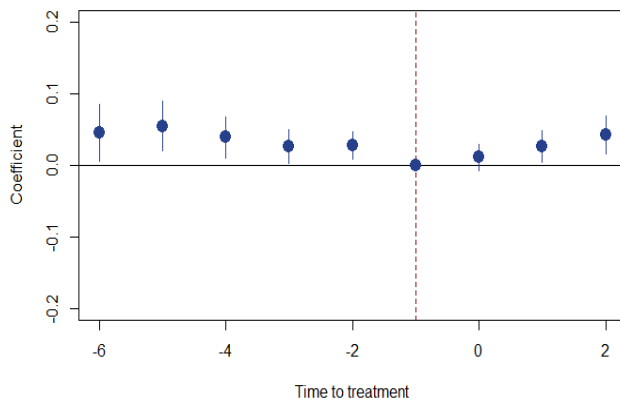
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployment})$ (b) $\ln(1 + \text{total of unemployed women})$, (c) $\ln(1 + \text{total of unemployed men})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 32: Effects on Resignations – 1km

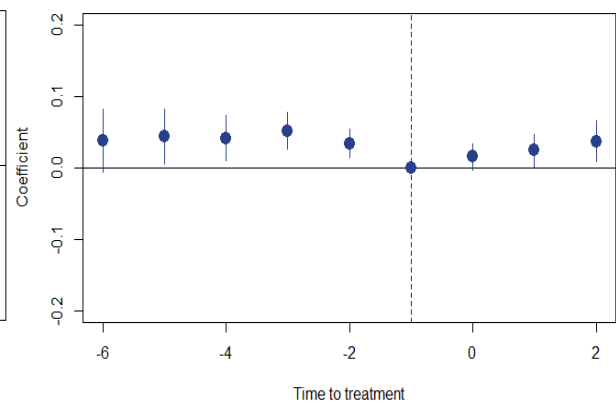
(a) Geral



(b) Women

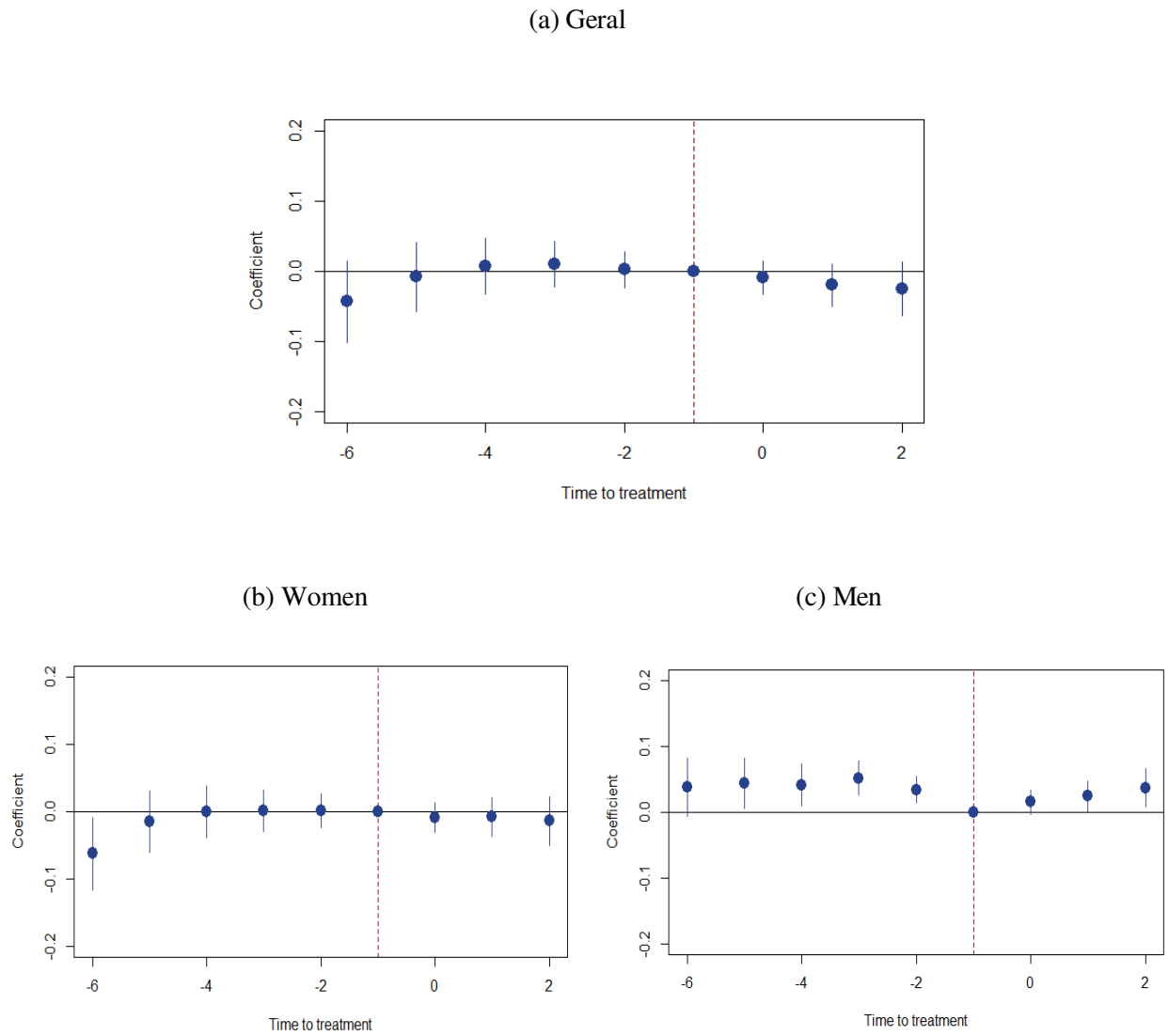


(c) Men



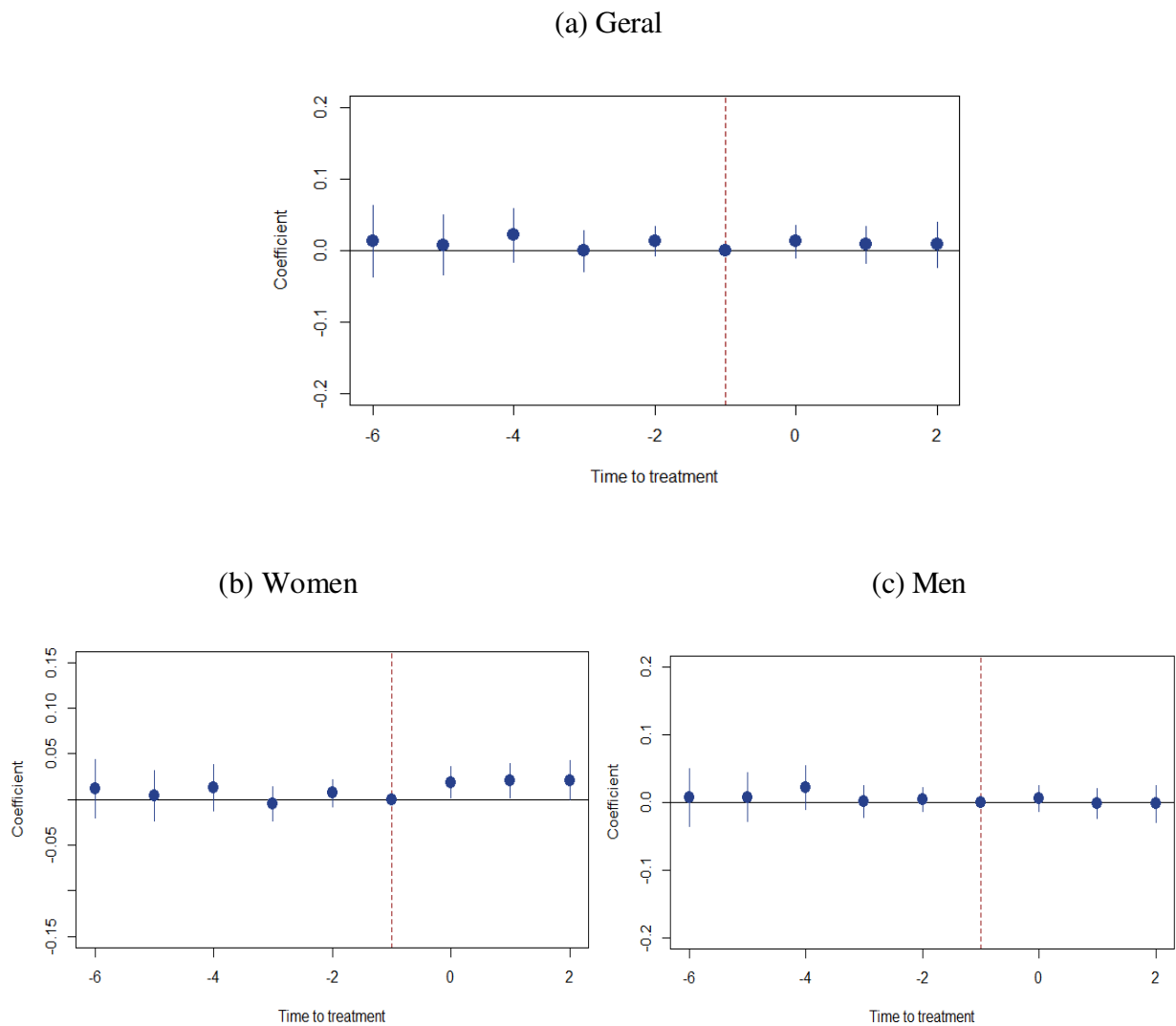
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employee's initiative})$ (b) $\ln(1 + \text{total unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 33: Effects on Terminations - 1km



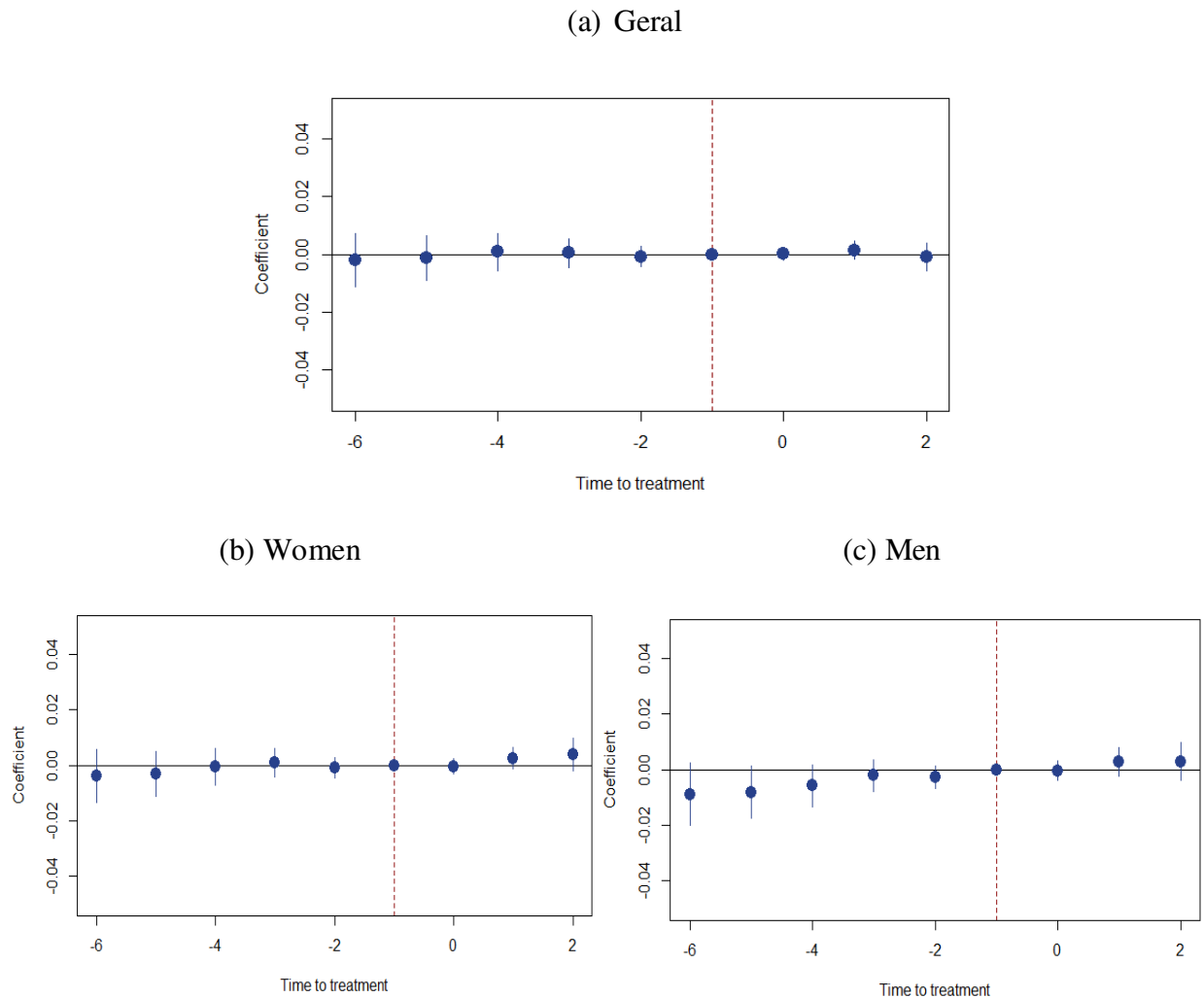
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employer's initiative})$ (b) $\ln(1 + \text{total unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 34: Effects on Mutual Agreement Unemployment – 1km



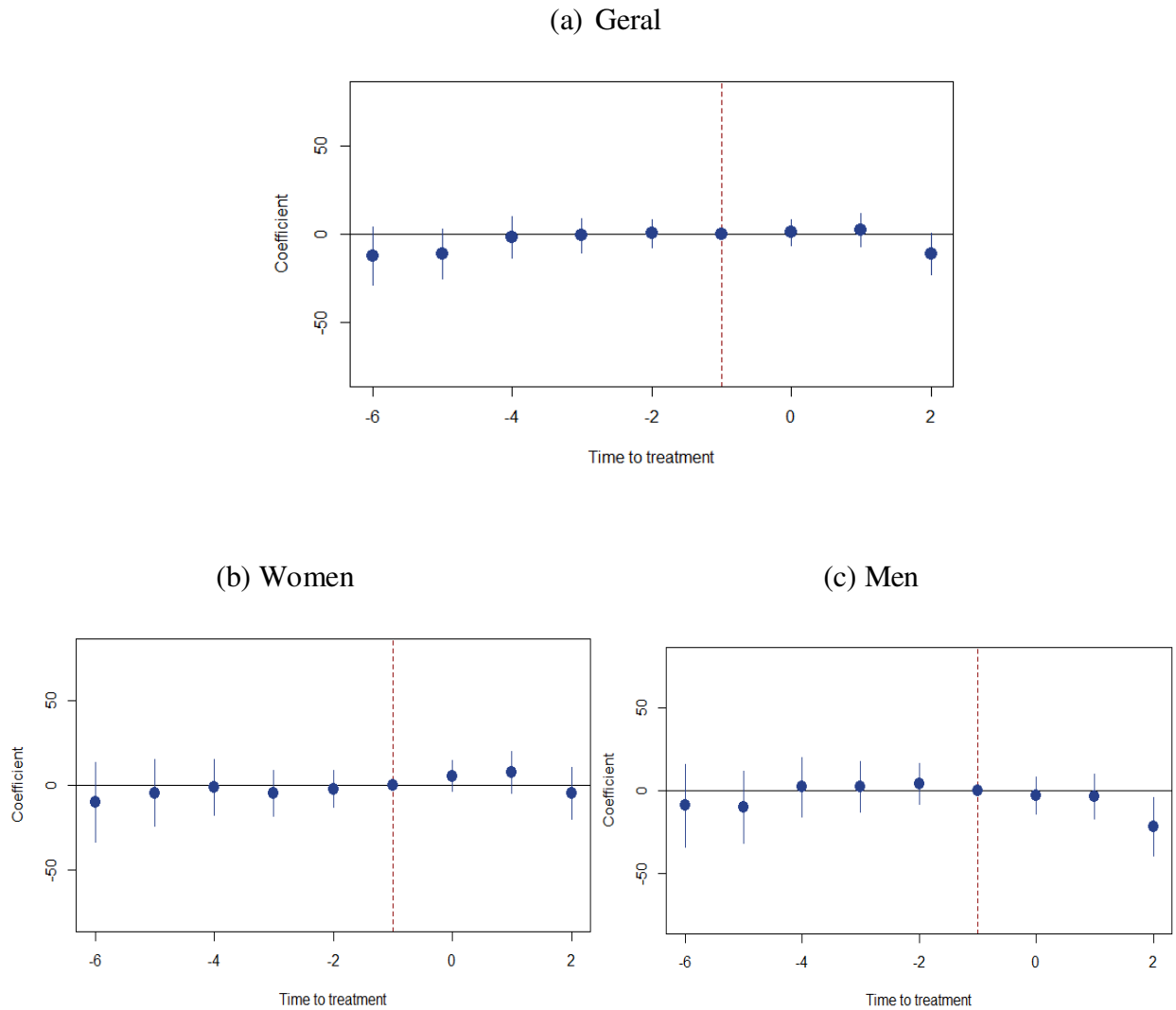
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by mutual agreement})$ (b) $\ln(1 + \text{total unemployed women by mutual agreement})$, (c) $\ln(1 + \text{total unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 35: Effects on Weekly Hours Worked – 1km



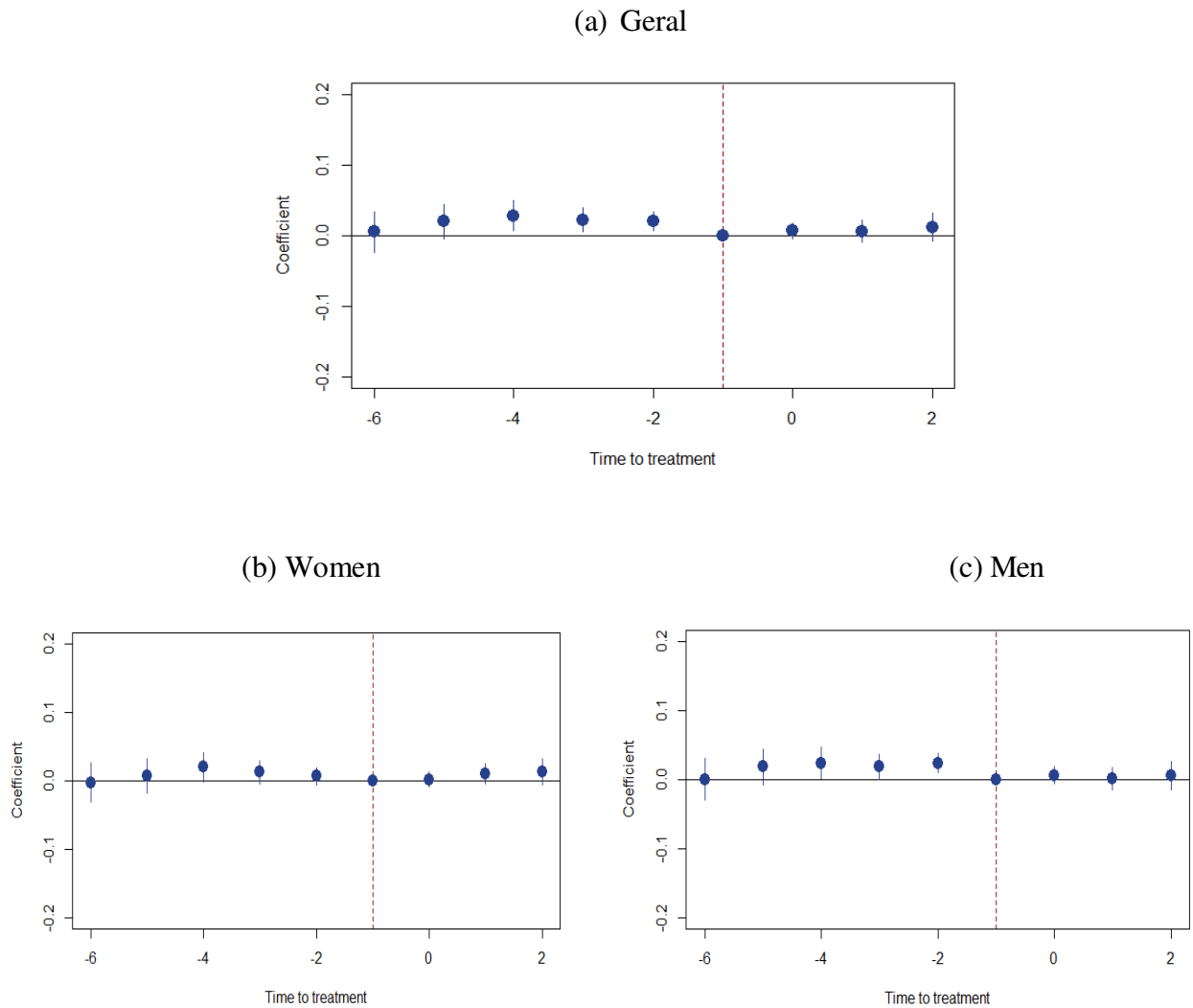
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{weekly hours worked})$ (b) $\ln(1 + \text{weekly female hours worked})$, (c) $\ln(1 + \text{weekly male hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 36: Effects on Weekly Wage – 1km



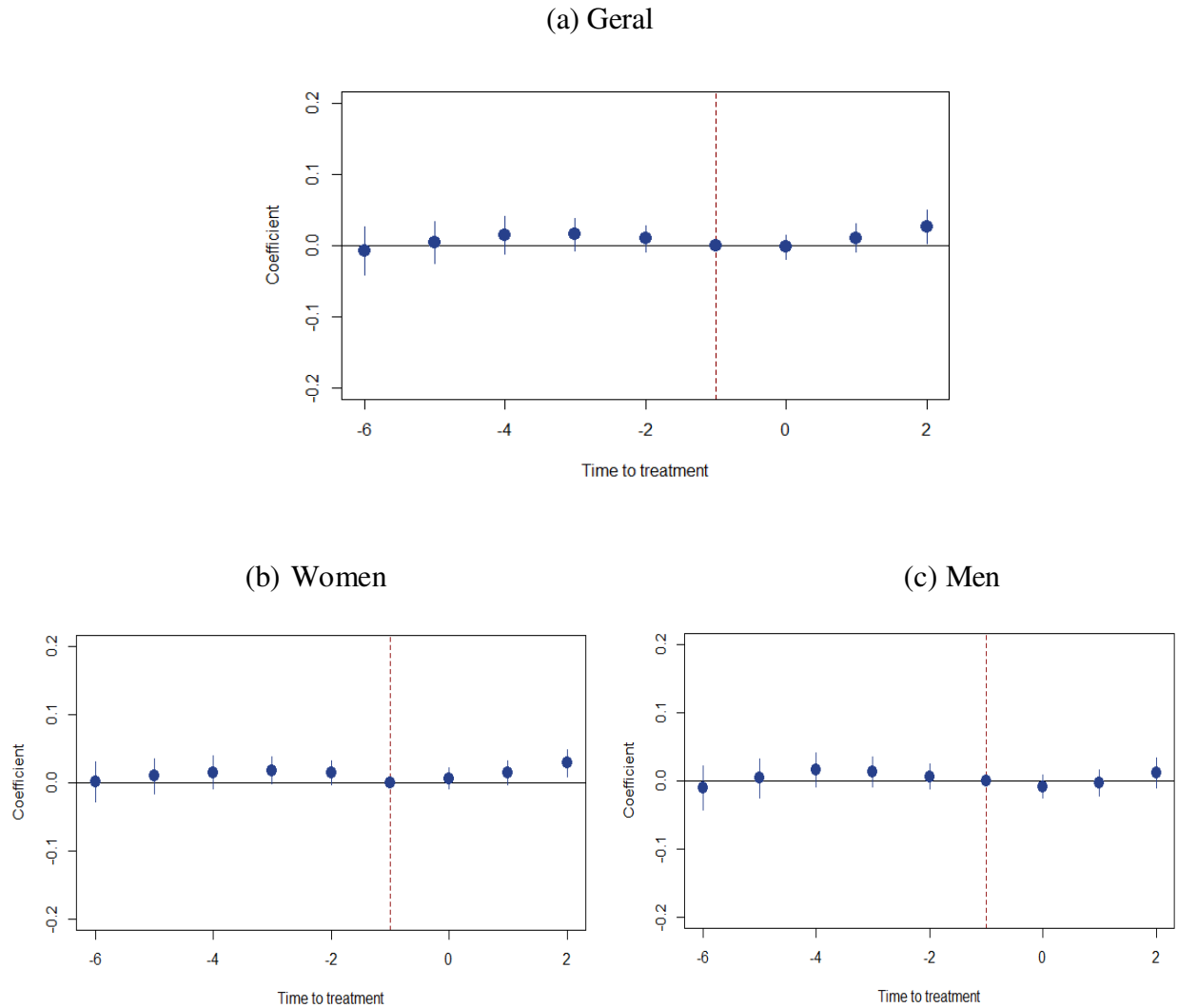
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) weekly wage (in R\$) (b) weekly female wage (in R\$) (c) weekly male wage (in R\$). Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 37: Effects on Employment – 3km



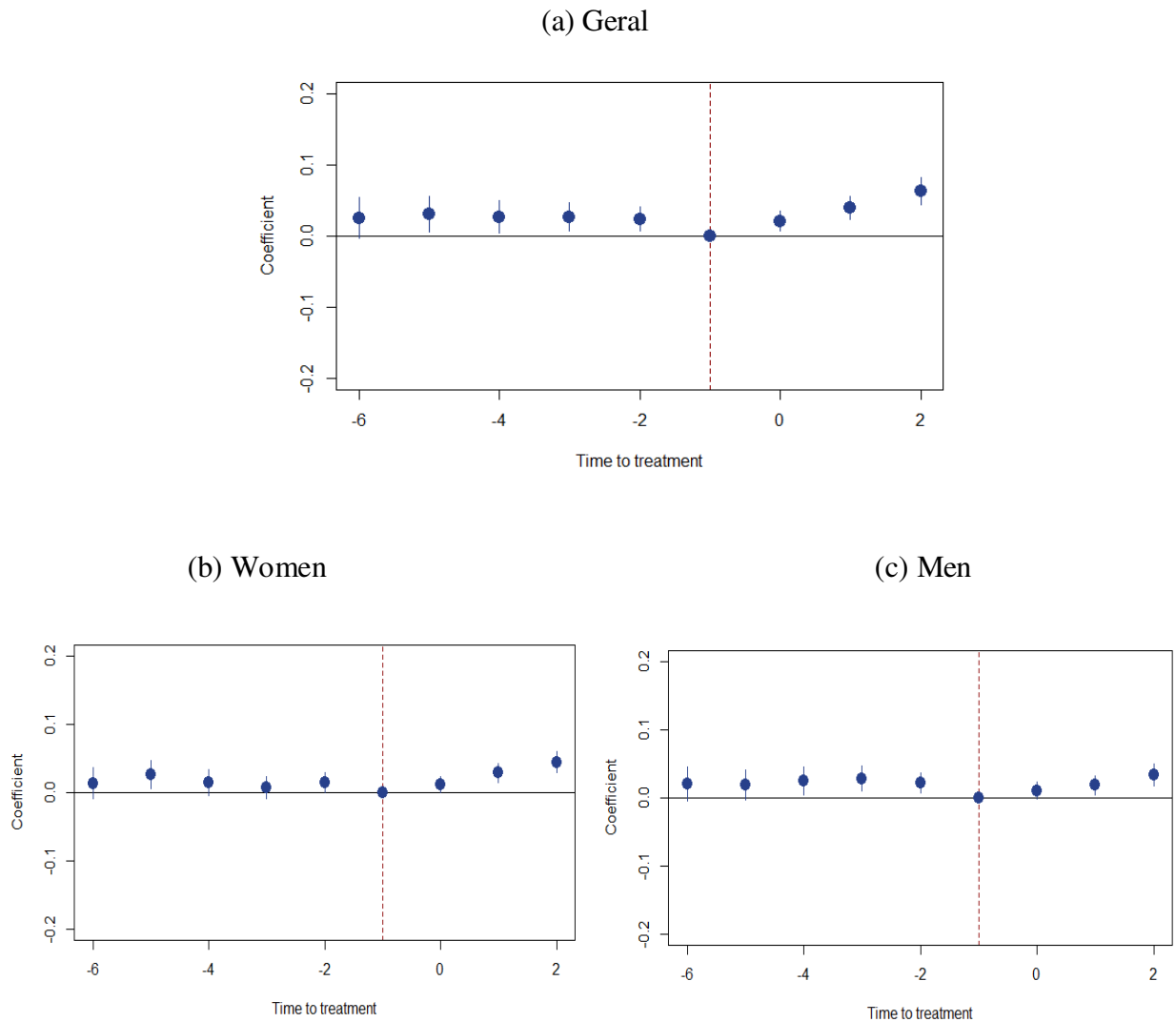
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 3km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln(\text{total of employees})$ (b) $1 + \ln(\text{total of female employees})$, (c) $1 + \ln(\text{total of male employees})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 38: Effects on Unemployment – 3km



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployment})$ (b) $\ln(1 + \text{total of unemployed women})$, (c) $\ln(1 + \text{total of unemployed men})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

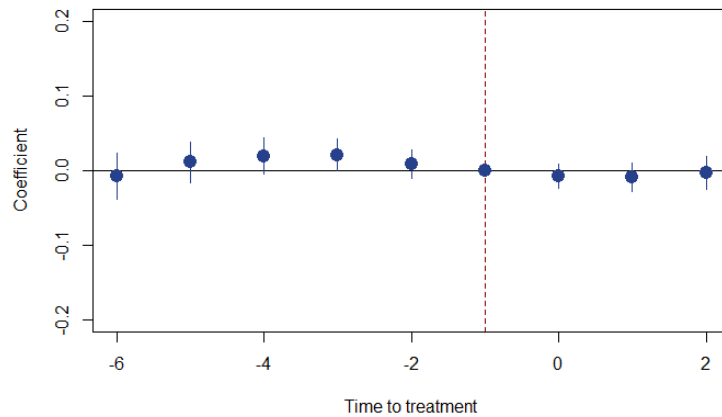
Figure 39: Effects on Resignations – 3km



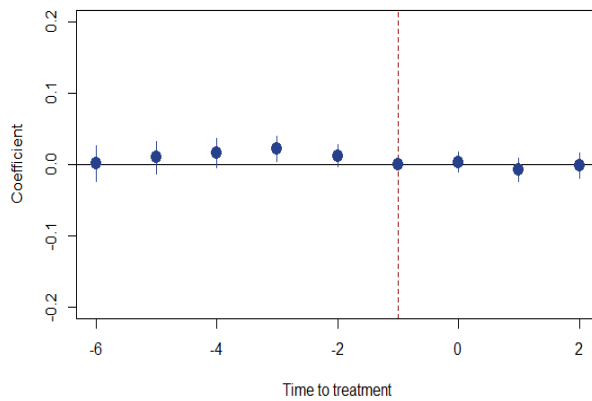
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 3km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employee's initiative})$ (b) $\ln(1 + \text{total unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 40: Effects on Terminations – 3km

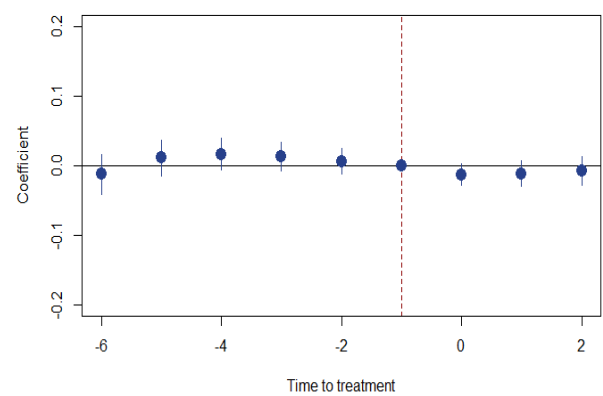
(a) Geral



(b) Women

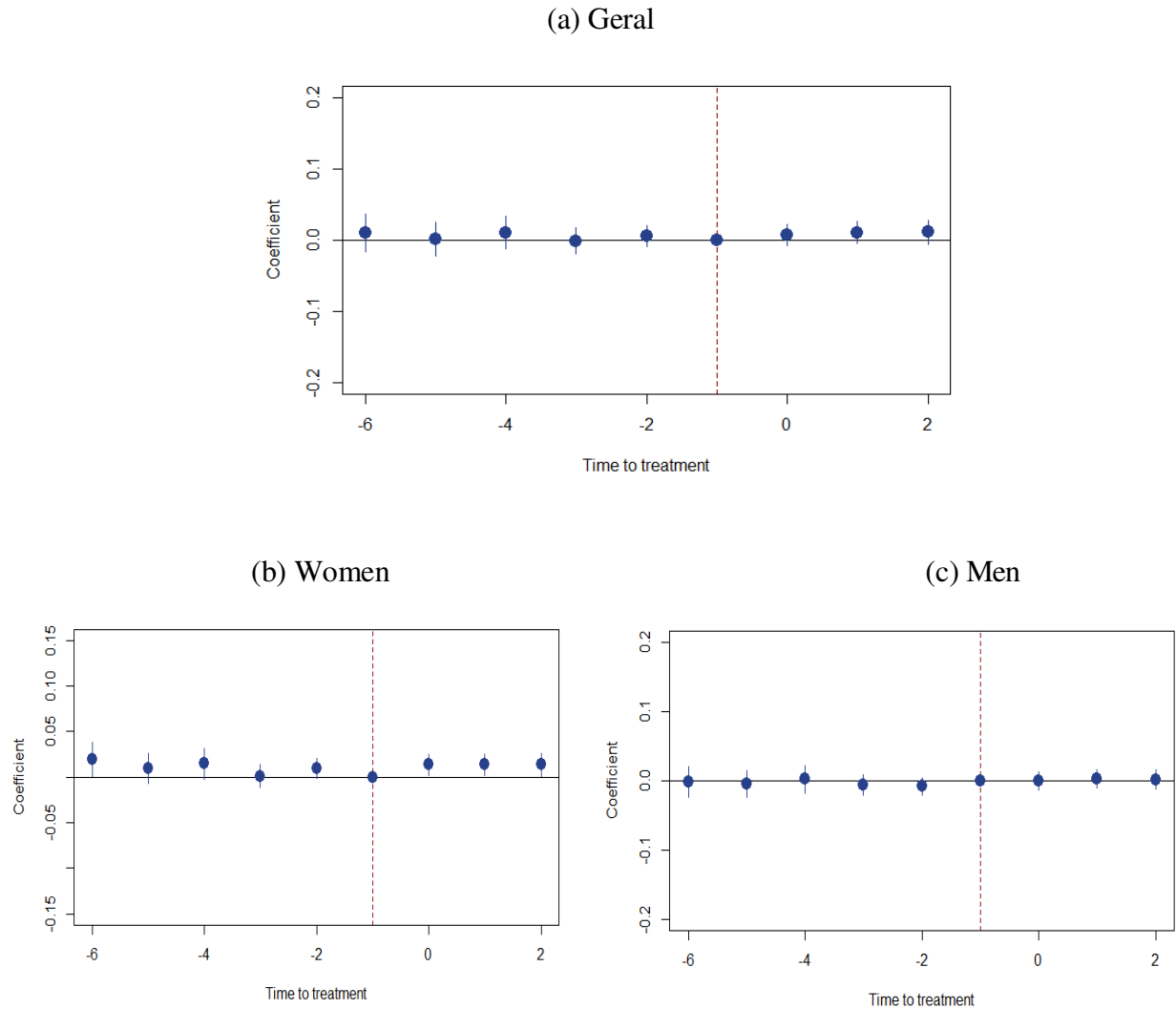


(c) Men



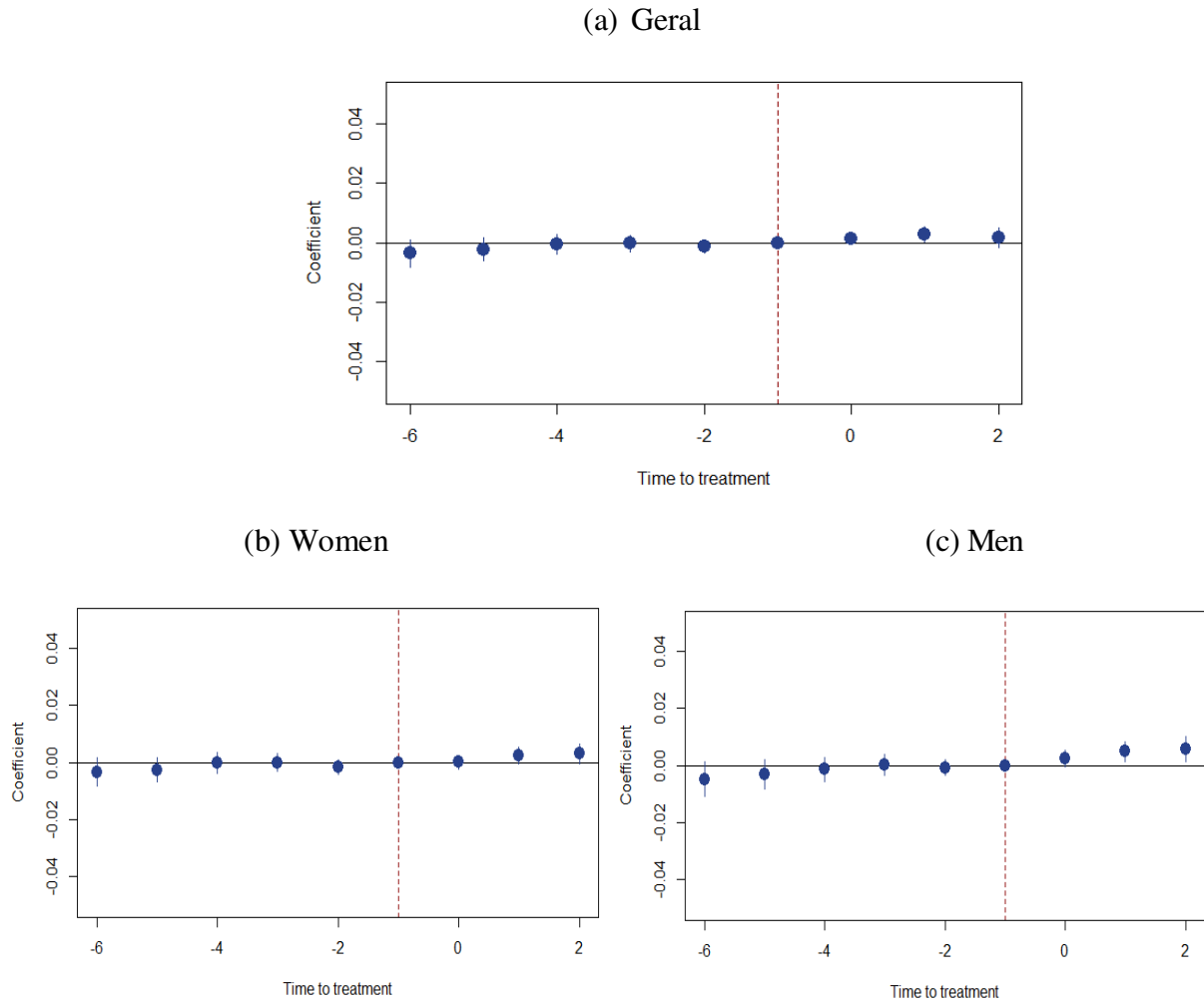
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 3km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employer's initiative})$ (b) $\ln(1 + \text{total unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 41: Effects on Mutual Agreement Unemployment – 3km



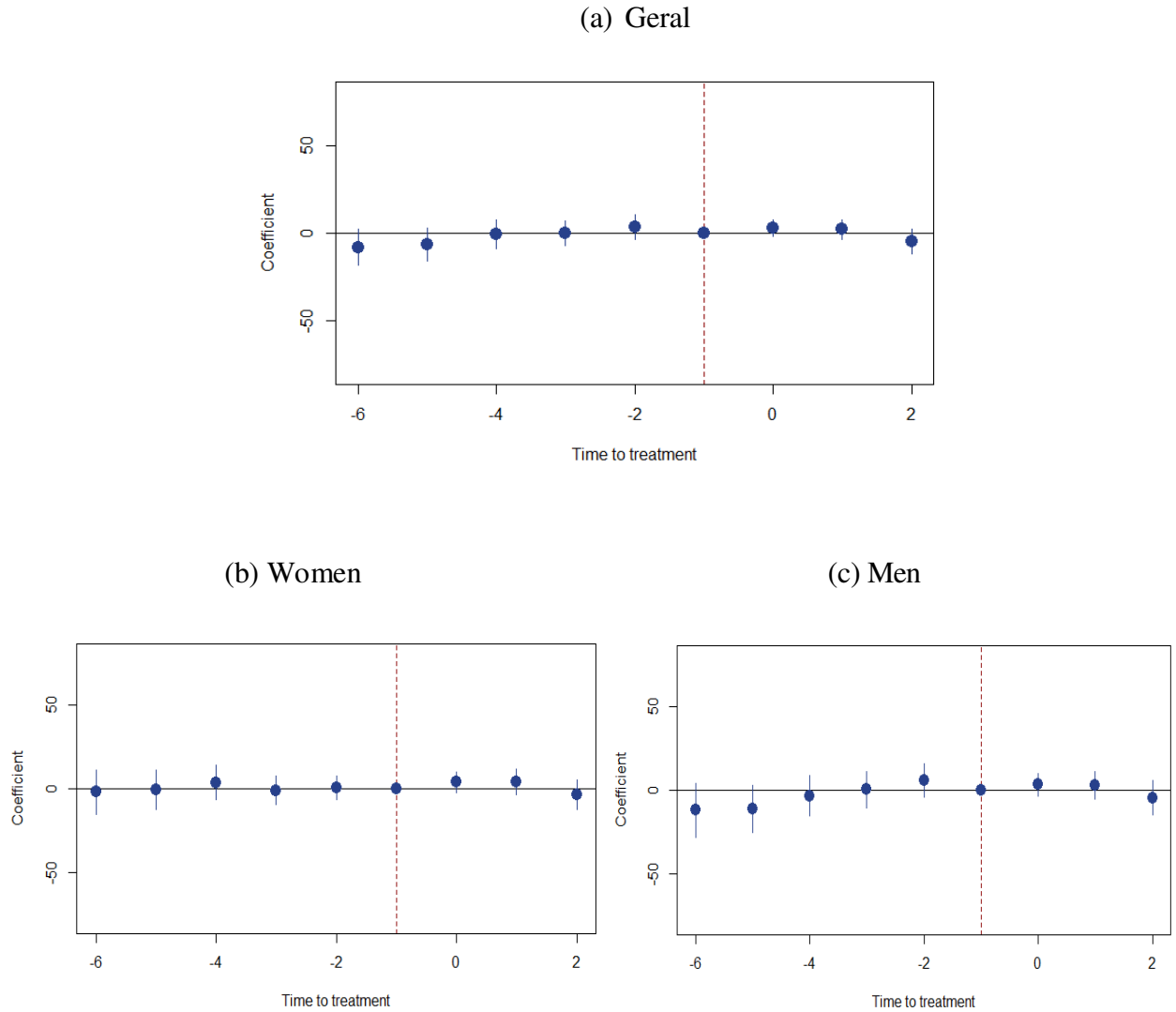
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 3km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by mutual agreement})$ (b) $\ln(1 + \text{total unemployed women by mutual agreement})$, (c) $\ln(1 + \text{total unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 42: Effects on Weekly Hours Worked – 3km



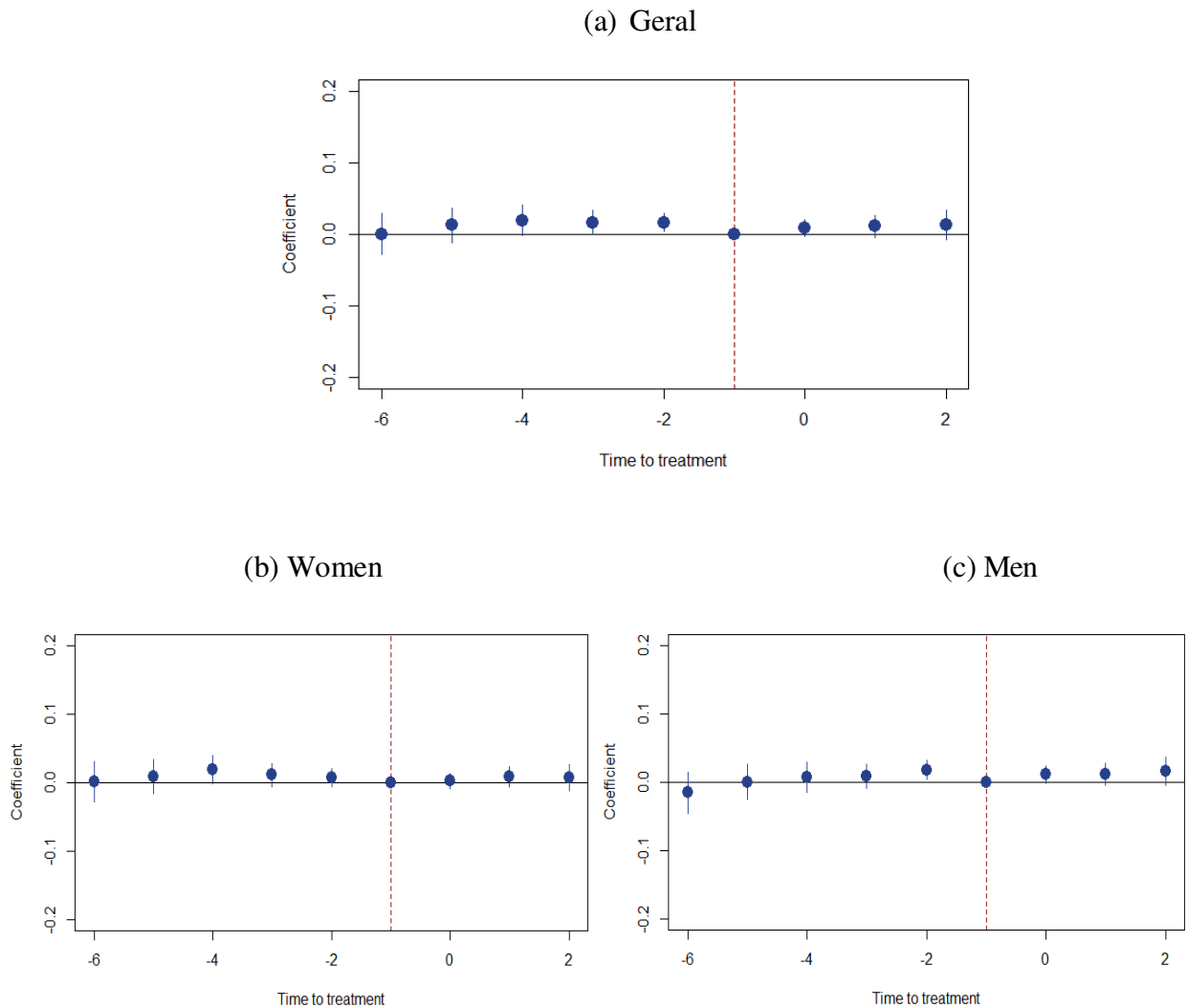
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 3km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{weekly hours worked})$ (b) $\ln(1 + \text{weekly female hours worked})$, (c) $\ln(1 + \text{weekly male hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 43: Effects on Weekly Wage – 3km



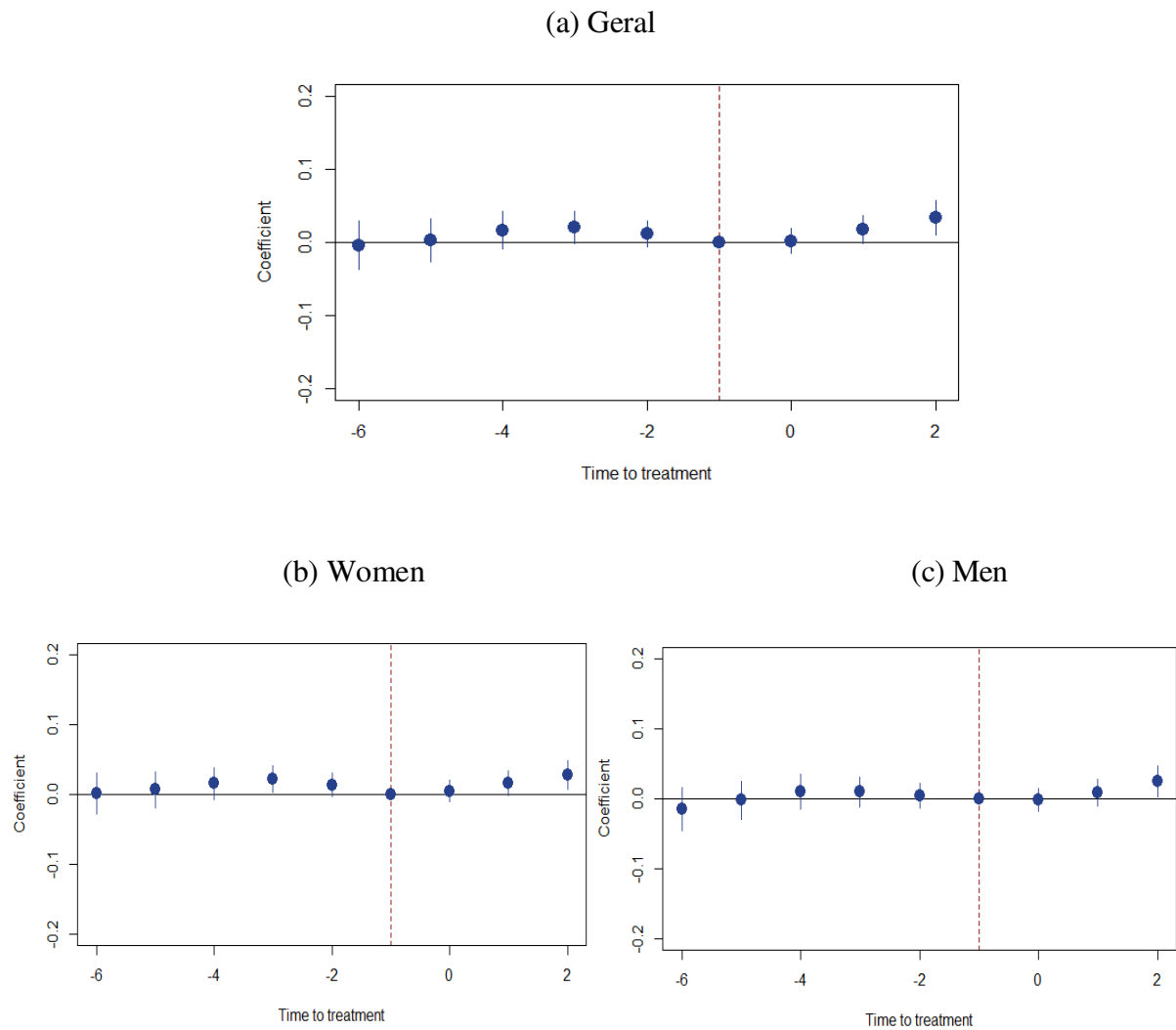
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 1km from a transportation station. The dependent variable in each panel are: (a) weekly wage (in R\$) (b) weekly female wage (in R\$) (c) weekly male wage (in R\$). Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 44: Effects on Employment – 4km



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) $1 + \ln(\text{total of employees})$ (b) $1 + \ln(\text{total of female employees})$, (c) $1 + \ln(\text{total of male employees})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

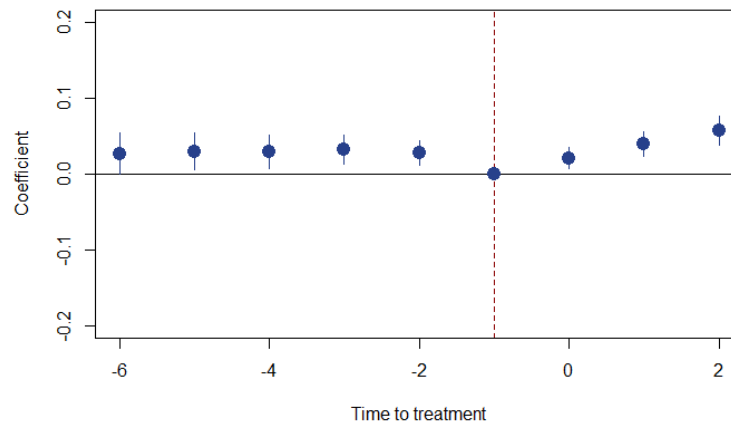
Figure 45: Effects on Unemployment – 4km



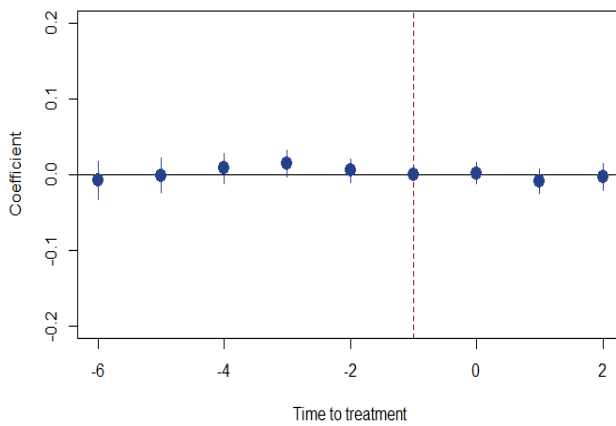
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployment})$ (b) $\ln(1 + \text{total of unemployed women})$, (c) $\ln(1 + \text{total of unemployed men})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 46: Effects on Resignations – 4km

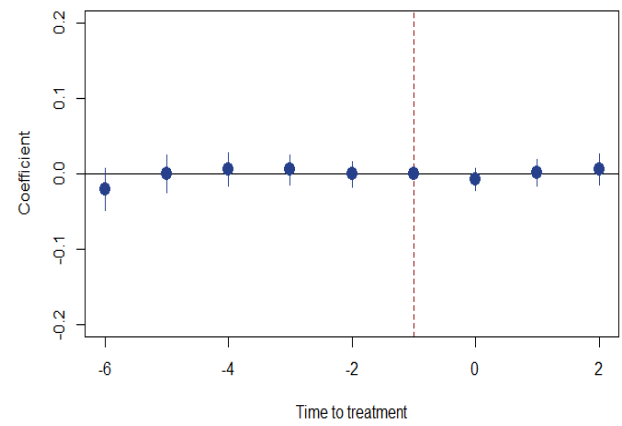
(a) Geral



(b) Women



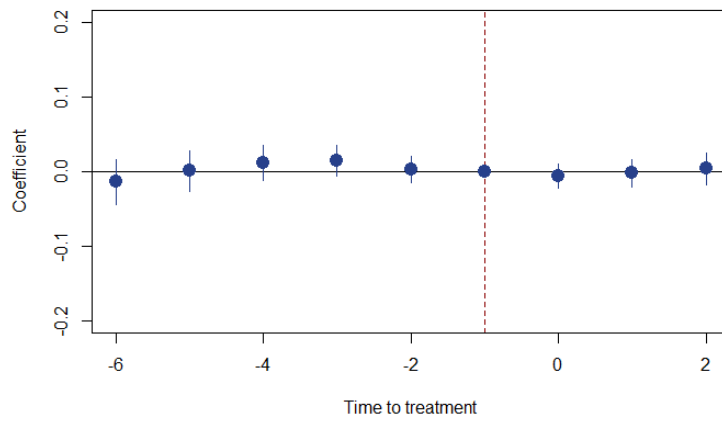
(c) Men



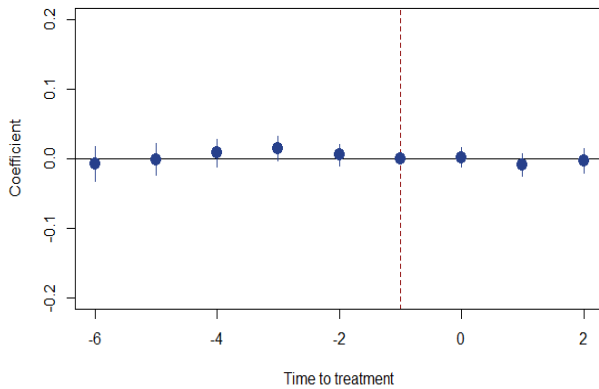
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employee's initiative})$ (b) $\ln(1 + \text{total unemployed women by employee's initiative})$, (c) $\ln(1 + \text{total unemployed men by employee's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 47: Effects on Terminations – 4km

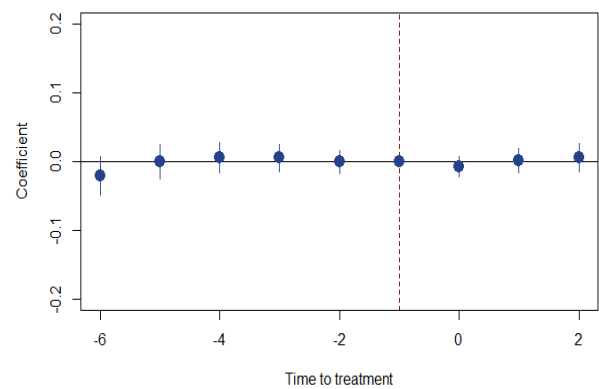
(a) Geral



(b) Women

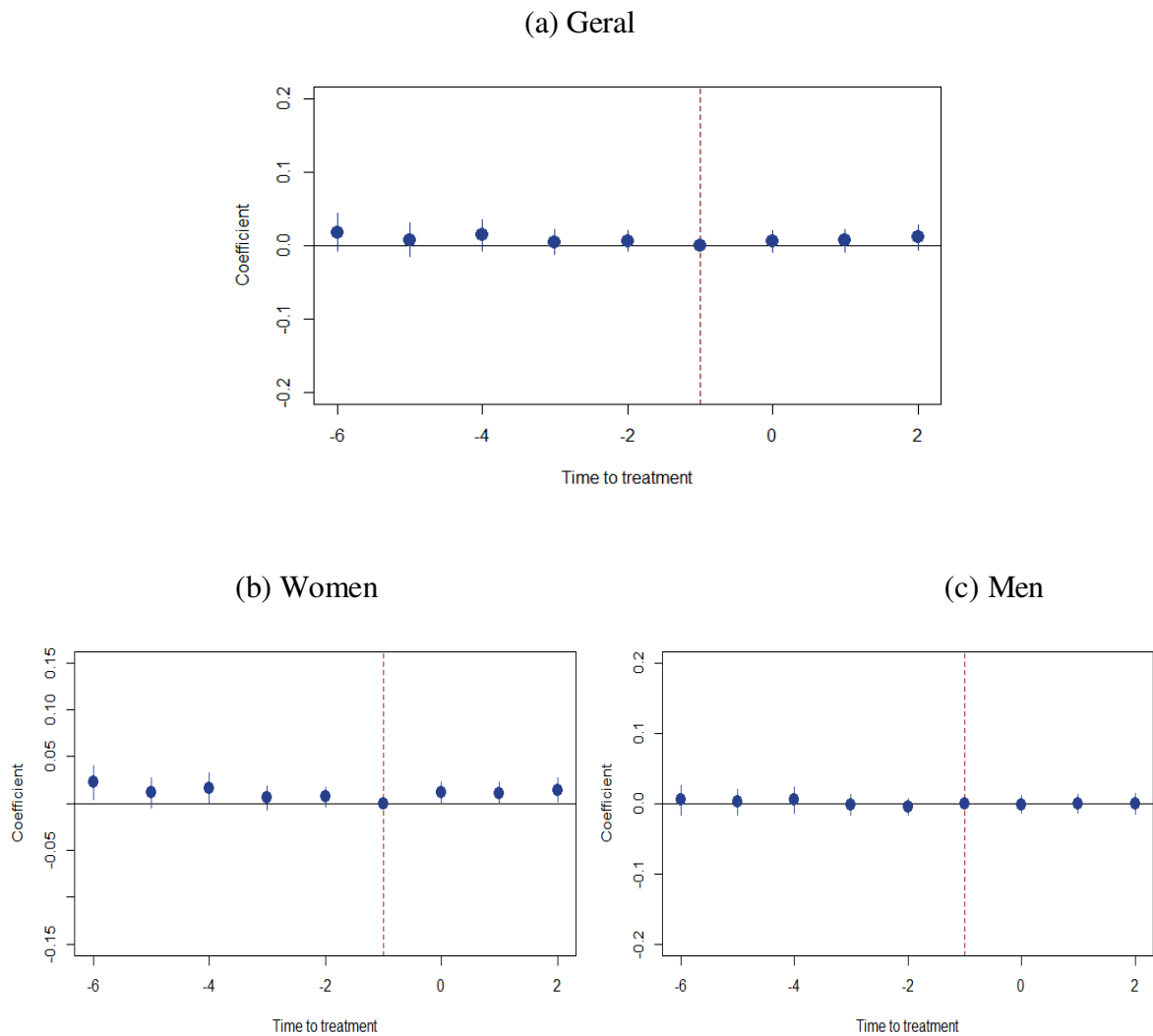


(c) Men



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by employer's initiative})$ (b) $\ln(1 + \text{total unemployed women by employer's initiative})$, (c) $\ln(1 + \text{total unemployed men by employer's initiative})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

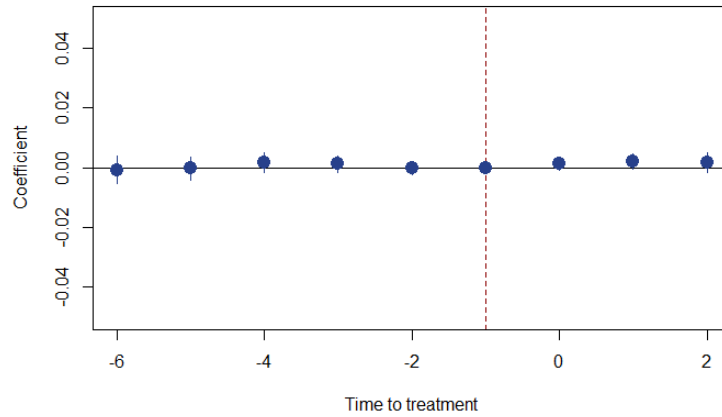
Figure 48: Effects on Mutual Agreement Unemployment – 4km



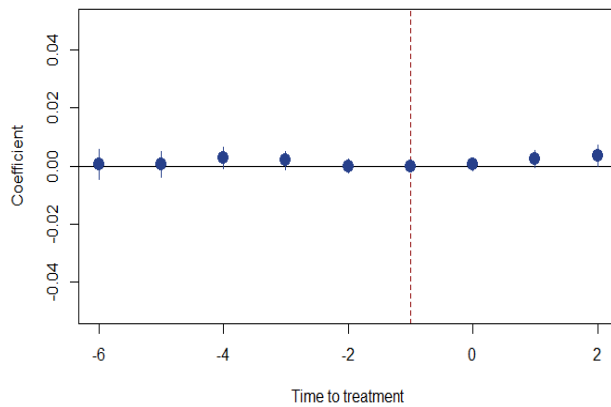
Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{total unemployed by mutual agreement})$ (b) $\ln(1 + \text{total unemployed women by mutual agreement})$, (c) $\ln(1 + \text{total unemployed men by mutual agreement})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 49: Effects on Weekly Hours Worked – 4km

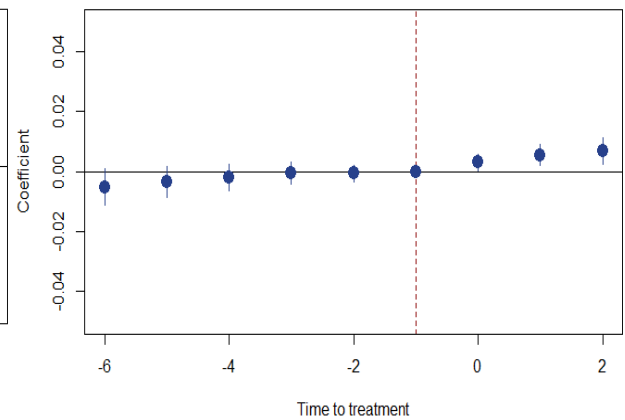
(a) Geral



(b) Women

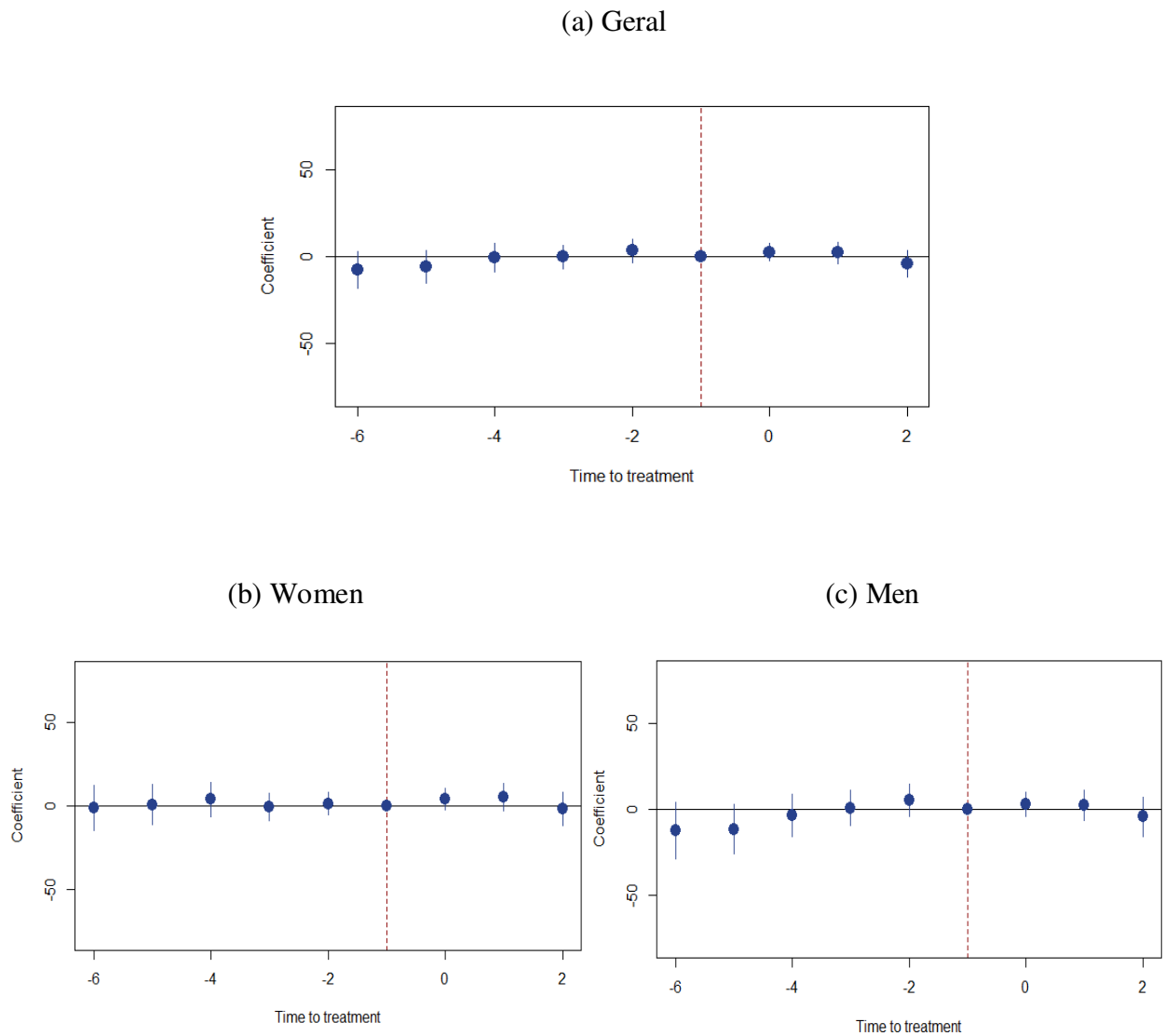


(c) Men



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) $\ln(1 + \text{weekly hours worked})$ (b) $\ln(1 + \text{weekly female hours worked})$, (c) $\ln(1 + \text{weekly male hours worked})$. Data is from 2010 to 2018. Red vertical line represents time of treatment.

Figure 50: Effects on Weekly Wage – 4km



Note: Graph shows DD coefficients and 95% confidence intervals from estimation of Equation (4.1) on employment coefficient. Treatment (Control) defined as employees working in a firm within 4km from a transportation station. The dependent variable in each panel are: (a) weekly wage (in R\$) (b) weekly female wage (in R\$) (c) weekly male wage (in R\$). Data is from 2010 to 2018. Red vertical line represents time of treatment

Table 12: Effects on Firms Outcomes - Alternative Treatment and Control (1km) - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Post_Transportation	-0.0068 (0.0128)	0.0023 (0.0149)	0.0377** (0.0104)	-0.0182 (0.0140)	0.0092 (0.0124)	0.0003 (0.0016)	-2.726 (4.271)
Observations	16.084	16.084	16.084	16.084	16.084	16.084	16.084
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 12, Panel (A), presents the results of differences-in-differences estimation for selected labor market variables in alternative treatment and control ranges (1km). All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 13: Effects on Firms Outcomes - Alternative Treatment and Control (1km) – Women and Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel B: Women							
Post_Transportation	-0.0010	0.0030	0.0263*	-0.0266	0.0201		
	(0.0108)	(0.0119)	(0.0124)	(0.0025)	(0.0087)	(0.0016)	(4.694)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Panel C: Men							
Post_Transportation	-0.0095	0.0006	0.0255*	-0.0107	0.0004	0.0018	-9.536
	(0.0133)	(0.0143)	(0.0100)	(0.0150)	(0.0106)	(0.0004)	(5.332)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 13 presents the results of differences-in-differences estimation for selected labor market variable in alternative treatment and control ranges (1km). In Panel (B), estimations are for female workers, (C) for male workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 14: Effects on Firms Outcomes - Alternative Treatment and Control (3km) - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Post_Transportation	0.0081 (0.0073)	0.0114 (0.0087)	0.0412*** (0.0074)	0.0070 (0.0087)	0.0094 (0.0071)	0.0020 (0.0012)	0.1044 (2.509)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 14 Panel (A), presents the results of differences-in-differences estimation for selected labor market variables in alternative treatment and control ranges (3km). All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 15: Effects on Firms Outcomes - Alternative Treatment and Control (3km) – Women and Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel B: Women							
Post_Transportation	0.0083	0.0162*	0.0278***	0.0021	0.0138**	0.0019	1.446
	(0.0069)	(0.0077)	(0.0060)	(0.0067)	(0.0018)	(0.0012)	(3.280)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Panel C: Men							
Post_Transportation	0.0044	-0.0003	0.0206	-0.0109	0.0011	0.0043	0.472
	(0.0076)	(0.0084)	(0.0128)	(0.0017)	(0.0059)	(0.0016)	(3.532)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 15 presents the results of differences-in-differences estimation for selected labor market variable in alternative treatment and control ranges (3km). In Panel (B),

estimations are for female workers, (C) for male workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 16: Effects on Firms Outcomes - Alternative Treatment and Control (4km) - Geral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel A: Geral							
Post_Transportation	0.0107 (0.0094)	0.0174 (0.0087)	0.0388*** (0.0075)	-0.0017 (0.0080)	0.0076 (0.0070)	0.0017 (0.0012)	0.779 (2.826)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 16, Panel (A), presents the results of differences-in-differences estimation for selected labor market variables in alternative treatment and control ranges (4km). All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

Table 17: Effects on Firms Outcomes - Alternative Treatment and Control (4km) – Women and Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment	Unemployment	Resignations	Terminations	Unemployment by agreement	Weekly Hours Worked	Weekly Wage
Panel B: Women							
Post_Transportation	0.0057 (0.0071)	0.0158 (0.0077)	0.0255*** (0.0074)	-0.0036 (0.0067)	0.0122* (0.0057)	0.0022 (0.0014)	2.399 (3.673)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Panel C: Men							
Post_Transportation	0.0127 (0.0075)	0.0105 (0.0084)	0.0233** * (0.0064)	-0.0005 (0.0076)	-0.0006 (0.0059)	0.0052** (0.0016)	0.2844 (4.029)
Observations	23.433	23.433	23.433	23.433	23.433	23.433	23.433
Controls	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓

Note: Table 17 presents the results of differences-in-differences estimation for selected labor market variable in alternative treatment and control ranges (4km). In Panel (B), estimations are for female workers, (C) for male workers. All estimates include controls and time and firm fixed effects. Robust standard errors in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.