Spatial Equilibrium and Transportation Costs

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Abstract

I exploit a spatial discontinuity introduced by a French reform in September 2015 to measure the links between transportation costs, employment and location decisions. I find that the reform led to a 2% decrease in the number of unemployed workers registered in the unemployment agency for the municipalities benefiting from the reform. The employment effect is concentrated on long-term unemployed workers. I build a simple spatial search-and-matching to underline the mechanisms at play.

1 Introduction

Several multi-billion infrastructure projects are currently under way throughout the world. To name a few, the California High-Speed Rail in the US, Crossrail 2 in the UK, the Barcelona metro line 9 and the Grand Paris Express are expected to cost 150 billions USD in total. These projects are expected to reduce transport costs and encourage people to commute using public transports rather than private vehicles, in an effort to limit traffic congestion and curb CO2 emissions. What will be the consequences of such projects in terms of local employment, business creation, location decision and house prices? This paper aims at providing new insights on the links between commuting costs and urban dynamics, using a spatial discontinuity created by a French in September 2015 in the Parisian area. Prior to the reform, owners of a public transport travel pass would pay different fares depending on the zones they crossed during their travel. Parisians and the near suburbs would pay a given price for a travel pass allowing

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them to travel in the zones 1 and 2, including Paris *intra-muros* and the limitrophe municipalities. People living further away from the center (in the zones 3 to 5) and commuting to Paris, where most of the jobs are located, had to pay a premium. In September 2015, the link between the zones crossed and the price of travel passes was removed, with the creation of a unique price scheme ("Forfait Toutes Zones" (FTZ)). This new price scheme consisted in a substantial price discount for former users of the travel passes in zones 3 to 5. This removal of fare areas ("dézonage") created a discontinuity for cities located from different sides of a former price border. I exploit this discontinuity to quantify the link between commuting costs and employment outcome, by carefully selecting a sample of municipalities selected close to the former border.

Can we think of transport infrastructure projects as employment policies? The present paper claims that, to some extent, they are. The present paper is related to the unemployment/inactivity trap literature, which shades lights on the structural hindrances that unemployed workers face when searching for a job, or the disincentives created by the system. In the French context, Anne and L'Horty (2009) show that the complex system of national and local social transfers creates a situation in which minimum wage workers having children are just better off not working. The present paper focuses on a type of disincentives that is spatially located. Conditionally on looking for a job located within Paris intra-muros, where most of the jobs are located, an unemployed worker living in the outskirts of Paris used to face *more disincentives to work* than an unemployed worker living the zones 1 or 2. The FTZ reform reduced the disincentives to work in zones 3, 4 and 5, without altering zones 1 and 2. Individuals who would have previously rejected offers located far away from where they reside are now more keen to accept them. In short, the FTZ reform can be seen as an spatial employment bonus. The impact of this employment bonus is likely to be strong for workers at or close to the minimum wage, for whom the savings generated are more substantial relative to their monthly wage.

Related work include Mayer and Trevien (2017) who using an instrumental variable strategy document that the arrival of the Regional Express Rail (RER) in the Paris area caused a 8.8% increase in employment for the municipalities connected to the network in between 1975 and 1990. Using a similar methodology, Garcia-López et al. (2017) show that improvements in the Parisian transit system led to the emergence of employment subcenters in suburbans municipalities that had a rail station. Duranton and Turner (2012) also relying on an IV strategy, show that a 10% increase in a provision of buses causes the *population* to increase by 0.8% in the US. Instead of using an IV, the current relies on the *spatial regression discontinuity* literature (see Neumark and Simpson (2015) for a review). This literature has emphasised a trade-off between necessity to compare geographical areas close to each others to control for unobservable characteristics and the threat to identification posed by spillovers between neighboring areas. The methodology used in this paper is very close to the one used by Chapelle et al. (2018) who analyse the impact of a housing tax credit on local housing market outcomes using fine-resolution data and address the trade-off above-mentioned. Other related empirical strategies can be found in Einiö and Overman (2016), Kline and Moretti (2013) and Hilber et al. (2019).

From a theoretical standpoint, the model used to underline the mechanisms at play relies on elements from Brueckner et al. (1999) and Wasmer and Zenou (2002). Workers want to reside close to the center of Paris to enjoy high amenities and the proximity to jobs. On the other hand, living close to the city-center entails paying a higher rent. Taking into consideration these factors, workers make an informed decision when choosing where to live. A decrease in commuting costs for workers living in the outskirts of Paris renders working more attractive relative to the state of unemployment, which translates into a lower reservation wage within the model, which in turn boosts employment for people living in the suburbs.

2 A Brief History of the Reform

Commuting by public transport is widespread in the Parisian area. In Paris *intra-muros*, approximately 78% of workers opt for this solution. Many workers choose to buy one of the several public transport passes available, giving full access to the region Ile-de-France public transport network, which includes metros, buses, tramways, RER[1] and some trains.[2]. The most popular option is to buy a Navigo card, valid for a week, a month or a year. Students have access to the yearly equivalent of the Navigo card, called the ImaginR pass, which comes with a substantial student discount. Until September 2015, the price of the Navigo and ImaginR passes depended on the fare areas ("zones") crossed during the travel. Typically, users living in Paris or in cities sharing a border with Paris (fare areas 1 or 2) and working in Paris would opt for the Navigo pass zones 1-2. Users living in the close suburbs (fare area 3) and working in Paris would choose the Navigo pass zones 1-3, paying a premium for the extra distance traveled (see Figure 12 for the different fare areas in the region Ile-de-France).

In September 2015, the "dézonage" reform removed the link between the areas crossed and the travel pass price the for the most popular travel passes .[4] For instance, users of the yearly Navigo pass zones 1-3 experienced a 14.3€ monthly decrease in their commuting costs, while users of the yearly Navigo pass zones 1-2 experienced a 3.5€ monthly increase. Hence, the reform generated a discontinuity in commuting costs for people living from each side of the border separating the fare areas 2 and 3. Taking into account the number of users of each travel pass, I find that people commuting to the city center and living in the fare area 3 experienced on average a 15.3€ decrease in their monthly commuting costs[5] relative their neighbors living in the fare area 2 as a consequence of the reform (see Figure 3). This

[1] RER (Réseau Express Régional) are express train lines connecting Paris city centre to surrounding suburbs.

[2] On a typical month in 2016, there were more than 4 million people residing in the region Ile-de-France using one of the different public transport travel passes available and approximately 3 million people using single-ride tickets,[3] for a region with approximately 12 million inhabitants

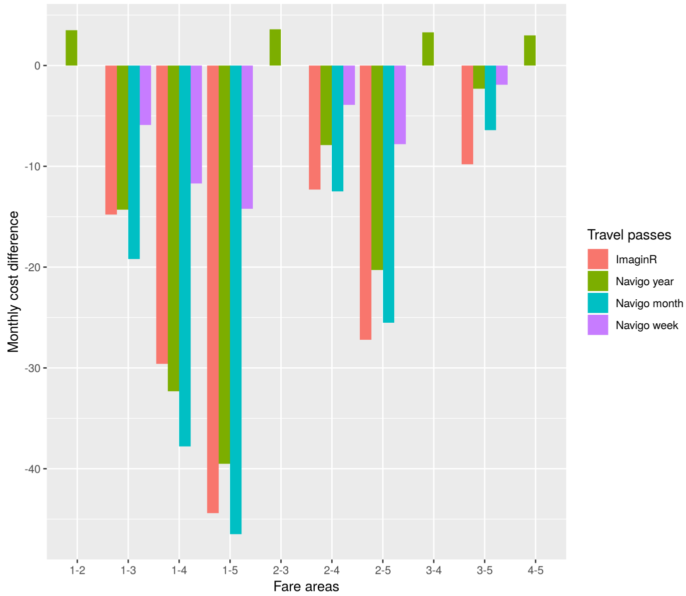
[4] The price of single-ride tickets is still dependent on the fare areas crossed during the travel.

[5] To give a point of comparison, a minimum wage worker earned a net monthly salary of 1136€.

number is likely to be a lower bound, as it was reported that the reform encouraged users to buy weekly or monthly Navigo passes instead of pricier single-ride tickets, hence generating an additional cost-saving channel for people residing in the fare area 3.

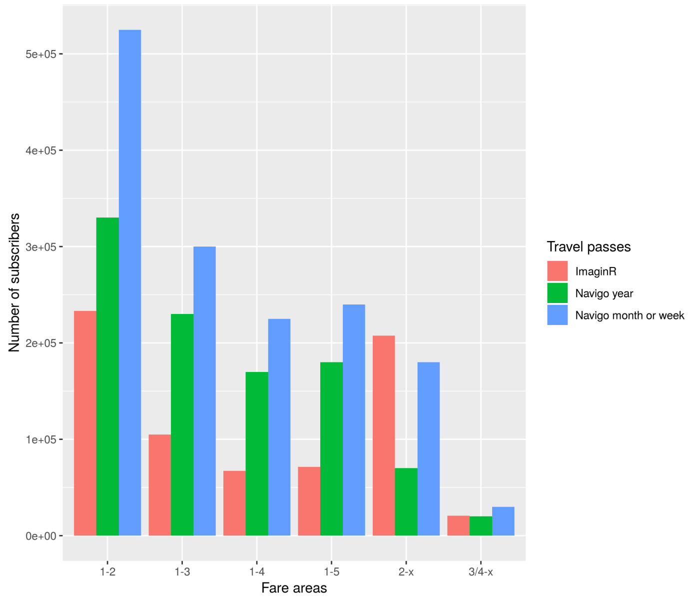
My empirical strategy relies on the fact that for cities close to the border separating the fare areas 2 and 3, the fact of falling on one side of the border can be considered as a random experiment. Hence, the "dézonage" reform generates a quasi-random variation in commuting costs for "treated" (cities in the fare area 3 close to the fare area 2) relative to the "non-treated" (cities in the fare area 2, close to the fare area 3).

Figure 1: Impact of the reform on travel pass cots



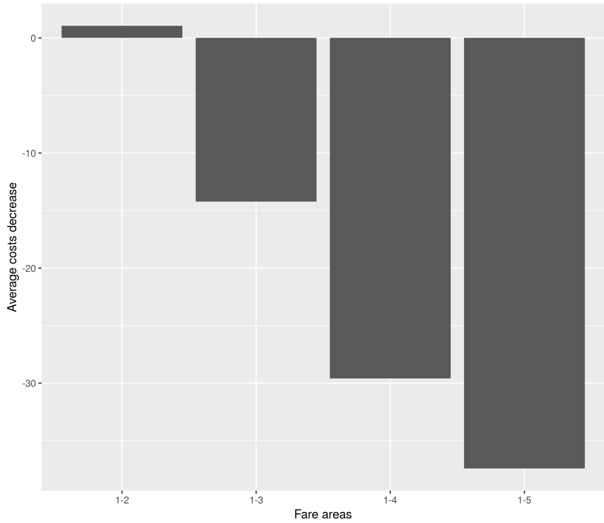
Notes: This figure shows the impact of the "dézonage" reform on the monthly cost of using a travel pass by fare area. Users of the yearly Navigo pass for fare areas 1 and 2 experienced a 3.5 € monthly increase, while users of the yearly Navigo pass for fare areas 1 and 3 saw their costs decrease by approximately 15 €. The absence of a bar indicates that the monthly cost was not impacted by the reform.

Figure 2: Number of subscribers by travel pass and fare area in 2015



Notes: This figure shows the number of subscribers by travel pass and fare areas. $2-x$ and $3/4-x$ are suburbs-to-suburbs passes: $2-x$ is used to indicates passes valid for the fare areas $2-3$, $2-4$ and $2-5$; $3/4-x$ indicates passes valid for the fare areas $3-4$, $3-5$ and $4-5$.

Figure 3: Average change in commuting costs for travel pass users



Notes: This figure shows the average cost impact (in euros) of the "dézonage" reform by fare area, for suburbs-to-center travel passes. This is weighted average taking into account the number of users reported in figure 2.

3 Data and Empirical Facts

For my empirical analysis, I use a combination of administrative data and data I gathered directly from specific websites

Municipalities characteristics and employment data

To measure the pre-reform characteristics of cities in region Ile-de-France, I use the database "Activité des résidents en 2015"[6] from the INSEE (the national statistics bureau of France). This database, relying on observations from the French national census, includes characteristics on the population as of January 2015 at the IRIS level, which is a sub-city level containing approximately 2000 inhabitants. Typically, a city is composed of several IRIS. The "Activité des résidents" database contains detailed information on the population structure by age group, gender and employment status. For employed workers, the database offers insights on their sector of activity and their commuting habits. When needed, I aggregate this dataset to produce data at the city ("communes") level. To measure both pre-reform and post reform employment dynamics, I use data from Pole Emploi, the French employment center. The dataset contains monthly observations on the number of unemployed workers registered to Pole Emploi at the city level for the period January 2014 - February 2019, for cities with more than 5000 inhabitants.[7] It is important to keep in mind that the number of unemployed workers registered to Pole Emploi is not a perfect measurement of unemployment, as a worker can be registered to Pole Emploi without actively looking for a job, and unemployed workers may not register to Pole Emploi if they are not eligible. Senior workers are more likely to be enrolled to Pole Emploi while not actively looking for a job, while young workers are more likely to be unemployed, while not being registered to Pole Emploi.[8] An alternative would be to build a repeated cross-section dataset at the IRIS using several iterations of the database "Activité des résidents", which uses the ILO definition of unemployment. However, the latest year available is (January) 2015.

Commuting time and fare ares

It is not straightforward to classify cities as belonging to the fare area 2 or 3, as cities may overlap the theoretical border separating them. To generate such a classification, I gather data on the optimal route to the city center (Châtelet-les-Halles) at the IRIS level using the website Vianavigo[9]. For each IRIS, I draw an address at random, which gives me a starting point for the itinerary. I let Vianavigo find the optimal itinerary (the one with shortest time) on a typical Monday morning to arrive at Châtelet-les-Halles at 9:00 a.m. The optimal itinerary may combine several public transports (bus, metro, train) and

[6] https://www.insee.fr/fr/statistiques/3627009#documentation
[7] https://statistiques.pole-emploi.org/stmt/defm?fh=1&lk=0&pp=las&ss=
[8] https://www.insee.fr/fr/statistiques/fichier/2022025/insee-en-bref-chomage.pdf
[9] https://www.vianavigo.com/accueil

walking. A price is associated to each optimal itinerary: 1.90 € for IRIS in the fare area 1 or 2, 2.80 € for IRIS in the fare area 3.[10] Given that each city in my sample is composed of several IRIS, I calculate the city area as the median value across IRIS, which I round to the nearest integer.

Housing Price Data

To measure house prices at the IRIS level, I use the standardized price index as of the fourth quarter of 2013 provided by the Grand Paris notary agency.[11] This standardized price index measures the value of a square meter, controlling for differences in the houses sold using a hedonic pricing model.

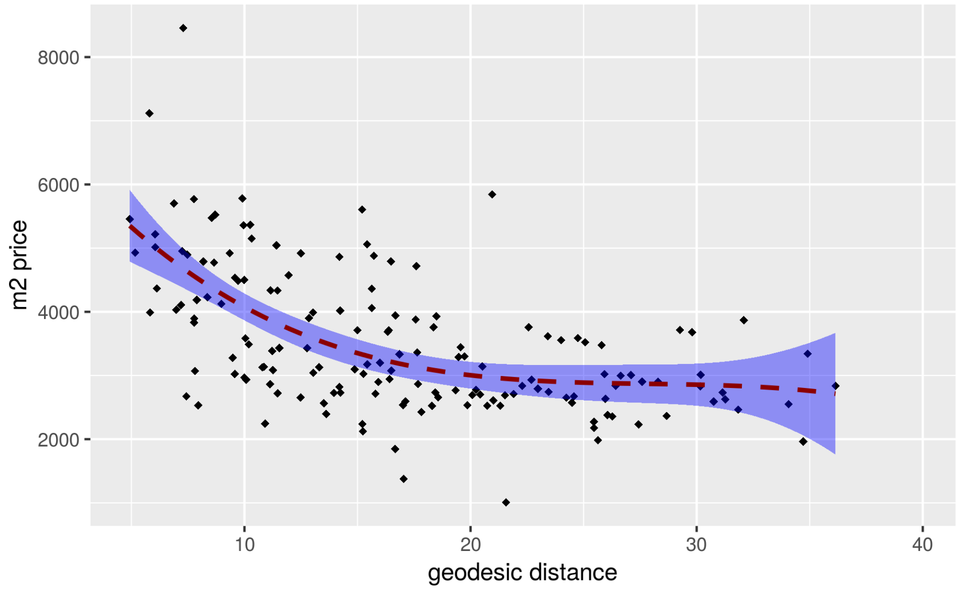
Empirical Facts

The Parisian region features several interesting characteristics. In particular, the region features three interesting gradients: (i) square meter price (ii) population density (iii) unemployment rate. Figure 4 shows that the price of a square meter decreases as the distance to the city center increases. Population density follows a similar patterns, with a density of approximately 20,000 inhabitants per km^2 in Paris (see Figure 5) decreasing to less than 10,000 when distance to the center reaches 10 km. Job density closely follows population density: Chapelle et al. (2017) documents that 50% and 90% of jobs are situated less than 10 and 30 km away from Paris center respectively. Overall, the *monocentric assumption*, according to which jobs are located in a single area, seems to be appropriate for the Paris area. Interestingly, the unemployment rate first increases before reaching plateau at around 10 km from the city center, before starting to decrease again (see Figure 6). Some wealthy workers choose to live in the city center to enjoy Paris amenities and the proximity to their jobs, at the expense of a higher rent. Unemployed workers will tend to settle in the *banlieues* (suburbs), where rent is more affordable and the city center is still quite accessible by public transport. As the distance to the city center increases again, the unemployment rate decreases and workers are more likely to use their own means of transport rather than the public transport network (see Figure 6).

[10] Ticket prices as of April 2019.

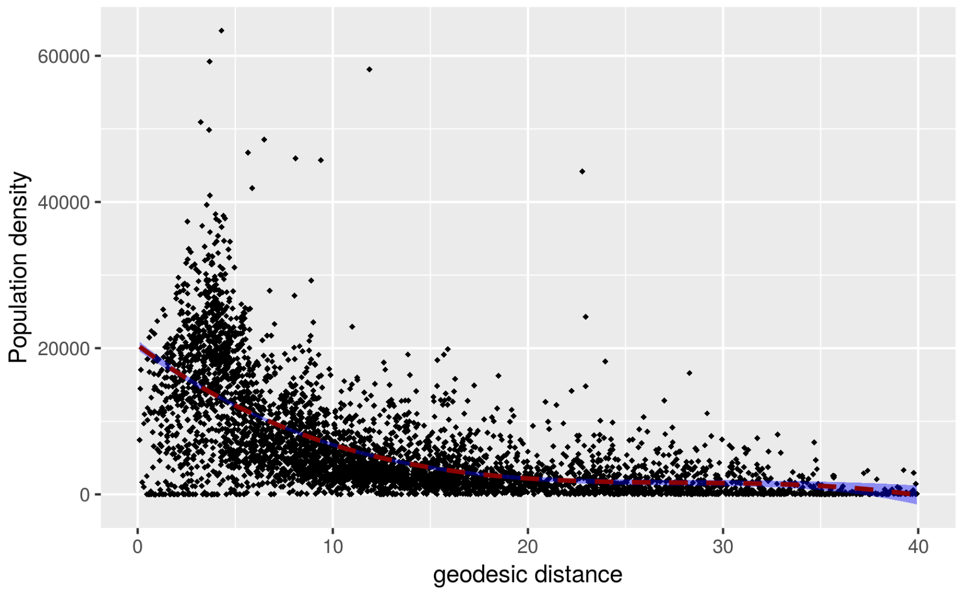
[11] http://paris.notaires.fr/fr/carte-des-prix#paris

Figure 4: Standardized square meter price index and distance to the city center, 2013 - Q4



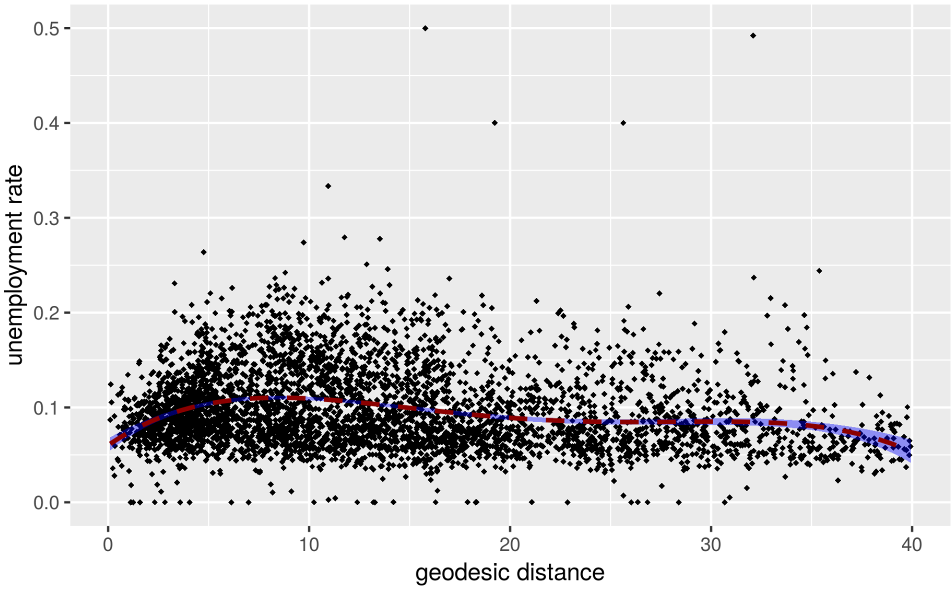
Notes: This figure shows the standardized square meter price index as a function of the geodesic distance to the center of Paris (Châtelet) as of 2013 - Q4. The dotted line is a fitted third-order polynomial and the shaded area represents a 95% confidence interval.
Source: author's calculations based on data from the Grand Paris notary agency

Figure 5: Population density and distance to the city center 2015



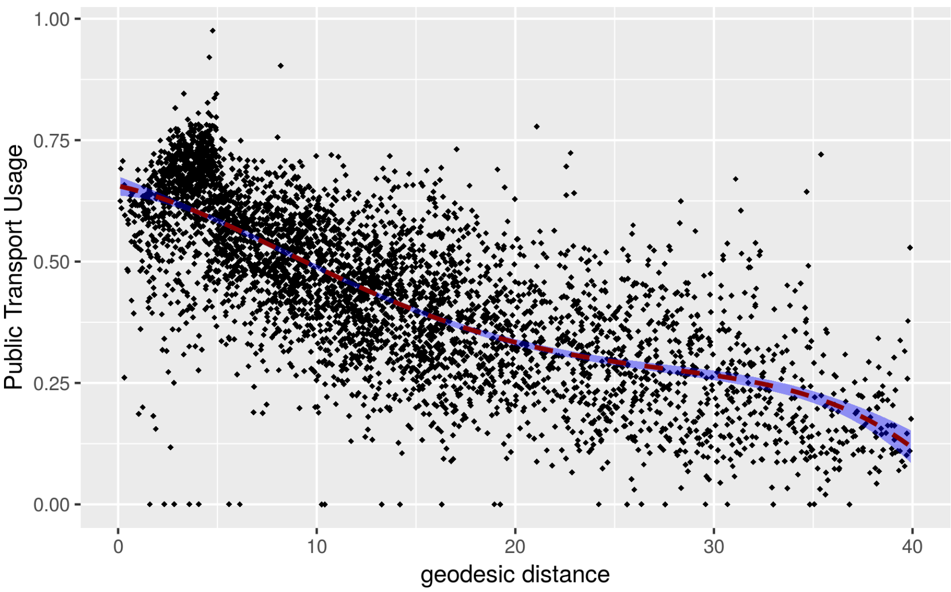
Notes: This figure shows the number of inhabitant per km^2 a function of the geodesic distance to the center of Paris (Châtelet), as of 2015. The dotted line is a fitted fourth-order polynomial and the shaded area represents a 95% confidence interval.
Source: author's calculations based on data from the INSEE, Activité des résidents

Figure 6: Public transport usage among workers and distance to the city center 2015



Notes: This figure shows the unemployment rate (at the IRIS level) as a function of the geodesic distance to the center of Paris (Châtelet) as of 2015. The dotted line is a fitted fourth-order polynomial and the shaded area represents a 95% confidence interval.
Source: author's calculations based on data from the INSEE, Activité des résidents

Figure 7: Public transport usage and distance to the city center 2015



Notes: This figure shows the percentage of workers (at the IRIS level) using public transports to go to work as a function of the geodesic distance to the center of Paris (Châtelet), as of 2015. The dotted line is a fitted fourth-order polynomial and the shaded area represents a 95% confidence interval.
Source: author's calculations based on data from the INSEE, Activité des résidents

4 Sample Selection

I build my sample with the double objective of maximizing (i) the proximity to the border separating the fare areas 2 and 3 (ii) the similarity between the treated and non-treated groups in terms of observable variables *before* the advent of the reform. The rationale for (i) is that the proximity to the border ensures that cities from both groups are experiencing similar trends in terms local market conditions (rent, population dynamics, etc.), and more importantly that the political motives for the reforms are nullified by considering cities "at the border". The reason for (ii) is that I do not have access to a wide set of observable variables post-reform. By maximizing similarity in terms of observable characteristics, I maximize the chances that the *common trend assumption* holds. That is, both groups were following a similar trend before the reform and the average deviation from the pre-treatment period is to be attributed to the "dézonage" reform only. It is also important to note that the main goal of this data selection step is not to build two groups that are perfectly identical, as permanent differences between cities will be taken into account using *entity fixed effects*. In practice, I include only cities in zones 2 and 3 meeting the following criterion:

$$\begin{cases} d_i \leq \bar{d}_{2,3} + \mu_{2,3} \times \sigma_{2,3} \\ d_i \geq \bar{d}_{2,3} + \mu_{2,3} \times \sigma_{2,3} \end{cases} \tag{1}$$

where d_i measures the geodesic distance to the city center; $\bar{d}_{2,3}$ the mean distance to the city center for cities in zones 2 and 3; $\sigma_{2,3} \equiv \frac{1}{2}(\sigma_2 + \sigma_3)$ with σ_2 and σ_3 the standard deviation of the geodesic to the city center for the zones 2 and 3 respectively; $\mu_{2,3}$ a coefficient to be determined empirically. The condition (1) defines a ring with origin the city center. The bigger $\mu_{2,3}$, the wider the ring and the more likely it is for one city to be retained in the sample. When $\mu_{2,3}$ gets sufficiently large, all the cities in the fare areas 2 and 3 are included in the sample.

Mathematically, I solve the following one-dimensional problem:

$$\mu_{2,3} \equiv \arg\min_{\mu} \sum_{k=1}^{K} \left(\frac{\hat{x}_{2,k}(\mu) - \hat{x}_{3,k}(\mu)}{\hat{x}_{2,k}(\mu) + \hat{x}_{3,k}(\mu)} \right)^2 \tag{2}$$

where $\hat{\boldsymbol{x}}_{\mathbf{2}}(\mu) \equiv (\hat{x}_{2,1}, \hat{x}_{2,2}, ..., \hat{x}_{2,K})$ and $\hat{\boldsymbol{x}}_{\mathbf{3}}(\mu) \equiv (\hat{x}_{3,1}, \hat{x}_{3,2}, ..., \hat{x}_{3,K})$ are vectors of mean characteristics for city in zone 2 and 3 respectively. Both vectors depend on the scalar μ because changing its value alters the composition of the sample, thus the group-specific mean values. As characteristics of interest, I include a wide range of variables as of January 2015, informative on the structure of the active and non-active population by gender, age, occupation and commuting habits (going to work using public transports or by car). The results of the minimization is shown in Figure 14. The corresponding value for $\mu_{2,3}$ defines a ring that includes cities in the "petite couronne", an area that forms a ring around Paris (see Figure 15). Descriptive statistics for the treated and non-treated groups are reported in table 1. While cities located in the fare area 2 are slightly more populous than cities in the fare area 3 and are located closer to the city center, they are rather similar in terms of population characteristics, measured by age, gender, the percentage of the population having or looking for a job and the type of job (permanent or temporary position). In terms of commuting habits, workers in the fare area 2 are more likely to go to work using public transports rather than using a car compared to workers in the fare area 3.

Table 1: Selected city characteristics included in the objective function in (2)

	Fare area 2	Fare area 3
Population 15-64	34075	26512
Population 15-24/Population 15-64	17.92%	18.86%
Population 25-54/Population 15-64	66.58%	64.81%
Population 55-64/Population 15-64	15.50%	16.32%
Men 15-64/Population 15-64	48.51%	48.33%
Women 15-64/Population 15-64	51.49%	51.66%
Active Population 15-64/Population 15-64	77.33%	76.57%
Unemployed men 15-64/Active Population 15-64	6.96%	6.78%
Unemployed women 15-64/Active Population 15-64	7.06%	6.80%
Salaried workers 15-64/Active Population 15-64	76.83%	79.01%
Salaried permanent position/Active Population 15-64	66.29%	68.98%
Salaried temporary position/Active Population 15-64	0.84%	0.89%
Salaried subsidized job/Active Population 15-64	2.02%	2.06%
Working from home/Employed Workers	3.67%	3.14%
Walking to work/Employed Workers	9.37%	7.92%
Biking to work/Employed Workers	6.70%	5.77%
Going to work by car/Employed Workers	26.82%	34.93%
Going to work using public transports/Employed Workers	53.42%	48.19%
Latitude	48.865	48.845
Longitude	2.354	2.335
Commuting time to city center (mn)	31.9	38.5
Geodesic distance to city center	6.845	9.029

Notes: This table displays mean values for cities in the fare area 2 (left column) and fare area 3 (right column). The city center is defined as the metro and train station Châtelet-les-Halles. Commuting time to city center is the theoretical time according to Vianavigo, using the optimal combination of public transports (bus, metro, train) to arrive at 9:00 a.m to the city center, on a usual Monday morning.

Source: Vianavigo and INSEE, Activité des résidents en 2015.

5 Empirical Specifications and Results

My baseline specification is the following:

$$y_{it} = \alpha_i + \gamma_t + \beta \times \delta_{i,t} + \boldsymbol{\eta x_{i,t}}' + \varepsilon_{i,t} \tag{3}$$

with $y_{i,t}$ the log of a dependent variable of interest; α_i a city-level fixed effect capturing permanent differences between cities; γ_t a time fixed effect capturing macro changes impacting all the cities in the sample over the period; $\delta_{i,t}$ and indicator variable equal to 1 if the city is in zone 3 and the time index t is such that the observation is after 1 September 2015; $\boldsymbol{x_{i,t}}$ a vector of control variables and $\varepsilon_{i,t}$ a city and time-specific $i.i.d$ error term. To quantify the dynamic impact of the reform, I estimate a year-dependent model, were the dummy $\delta_{i,t}$ is interacted with a year-specific dummy δ_y equal to 1 when the underlying year is equal to y:

$$y_{it} = \alpha_i + \gamma_t + \sum_{y=2015}^{2019} \beta_y \times \delta_{i,t} \times \delta_y + \boldsymbol{\eta x_{i,t}}' + \varepsilon_{i,t} \tag{4}$$

The parameter β_y measures the average treatment effect on year y. To test the robustness of results from regression (3) and (4), I estimate a continuous version of them. In the construction of my sample, I rounded the median fare area to the nearest integer (using observations at the IRIS level) to generate a clear cut between the treated and non-treated cities. Instead, one may want to use the fact that some cities overlap over the border separating the fare areas 2 and 3. One should expect the impact of the reform to be a function of the intensity of the "treatment" received. That is, the impact of the reform for a city with a median fare close to 3 should be higher than for cities with a median fare area close to 2. To test that hypothesis, I estimate the two following regressions:

$$y_{it} = \alpha_i + \gamma_t + \beta \times z_{i,t} + \boldsymbol{\eta x_{i,t}}' + \varepsilon_{i,t} \tag{5}$$

$$y_{it} = \alpha_i + \gamma_t + \sum_{y=2015}^{2019} \beta_y \times z_{i,t} \times \delta_y + \boldsymbol{\eta x_{i,t}}' + \varepsilon_{i,t} \tag{6}$$

where $z_{i,t}$ is an *intensity of treatment variable*, equal to the median fare area (minus 2) if t is such that the observation is after 1 September 2015; 0 otherwise. In the post treatment period, $z_{i,t}$ is equal to (i) 1 for cities that are unambiguously located in the fare area 3, (ii) for cities that are unambiguously located in the fare area 2. The variable $z_{i,t}$ is in between 0 and 1 for cities that have neighborhoods from each side of the border.

The main identifying assumption for β to be an unbiased estimate for the treatment effect is that the *common trend assumption* holds: in absence of treatment, both the treated and untreated units would have evolved along the same path. I claim that the common trend assumption (conditional on my control variables) holds in my setting for two reasons. Firstly, my data selection procedure maximizes the similarity between the treated and untreated groups in terms of pre-reform observable characteristic. I also estimate models that are robust to pre-treatment differences in trends by interacting pre-treatment variables (as of January 2015) with a linear time trend and adding monthly dummy variables to capture the cyclical patterns of unemployment. The variables (in log) interacted with a linear time trends are the of the size of the population in between 15 and 64; the number of employed workers in between 15 and 64; the number of them having a permanent contract and the number of them having a temporary contract. The rationale for the inclusion of these control variables is that the pre-treatment structure of the workforce would have caused the treated and the non-treated units to diverge, even in absence of the treatment. Secondly, by selecting municipalities that are close to each others, I control for the impact of potential unobservable characteristics on local employment.

5.1 Impact on employment

I first estimate the impact of the "dézonage" on employment. Results are presented in table 2. Column (1) indicates that the reform *decreased* the number of unemployed workers registered to Pole Emploi by approximately 2% workers for cities in the treatment group. The p-value is not below the usual 0.1 standard, which is in part due to the small size of the coefficient itself. To give an idea of the magnitude of the coefficient, Column (1) implies that on average 72 jobs were created per municipality in the treatment group.[12] Column (2) underlines that the treatment effect starts to materialize in 2016-2017. Given the frictional nature of unemployment, this result is expected: any reform impacting the labor market, having a direct impact on employment flows, takes a certain time to be visible on employment levels. Columns (3) and (4) indicate that using the "intensity of treatment" variable generates similar results in terms of magnitude and patterns.

The visual counterpart of the first column of table 2 is displayed in Figure 16, which shows the average number of people enrolled to their local branch of Pole Emploi for the treated (in blue) and non-treated cities (in red). Figure 16 indicates that the pre-trend assumption is slightly violated, with the treated units experiencing a slightly sharper increase in the number of workers registered to Pole Emploi. This visual inspection is confirmed by a Placebo test (See Table 7). This fact justifies the inclusion of control variables interacted with a linear time trend.

What types of workers benefited from the reform? Depending on their number of hours they worked last month and on their availability, workers registered to French unemployment agency (Pole Emploi) are assigned to 5 categories (see B for an exhaustive description of the categories). Unemployed workers having worked zero hours last month and actively searching for a job are in category A while unemployed workers having worked less than 78 hours last month are in category B. Table 3 show results for

[12] On average, there were approximately 3606 workers registered to Pole Emploi in the treatment group for the period of observation.

the former and Table 4 for the latter. Column (1) of Table 3 suggests that the reform generated a 3.1% decrease in the number of category A workers. Column (2) indicates that the reform started to have employment effects in zone 3 in 2016. Table 4 indicates an overall decrease of category B workers for the treated units over the 2015 - 2019 period, but results are statistically significant. Interestingly, Both columns (2) and (4) indicate the FTZ reform *increased* the number of category B workers in 2015. This results could be explained by the enrollment of new workers (previously not registered to Pole Emploi) and finding a temporary job and working less than 78 hours and/or by workers coming from other Pole Emploi categories. Results for categories C to E are presented in the Appendix (see Tables 10, 11 and 12). While no clear results are visible for categories C to D, Table 12 shows a spike in the number of workers registered in category E of approximately 12 % in 2016. Category E is composed of employed workers searching for an alternative job. One explanation is that the reform boosted the willingness of workers to look for jobs in other employment pools. To summarize, the reform mainly impacted category A workers, the category of workers with zero hours worked last month and mainly composed of long-term unemployed workers.[13]

[13] In 2011, 80% of French long-term unemployed workers were in caterogy A according to the Conseil d'Orientation pour l'Emploi: http://www.coe.gouv.fr/COE_Chomage_de_longue_duree_Rapport-_version_finale-33ddd.pdf?file_url=IMG/pdf/COE_Chomage_de_longue_duree_Rapport-_version_finale-3.pdf

Table 2: Number of workers registered to Pole Emploi

	Dependent variable: Log workers registered to Pole Emploi			
	(1)	(2)	(3)	(4)
β	-0.021		-0.021	
	$p = 0.152$		$p = 0.147$	
β_{2015}		0.006		0.004
		$p = 0.325$		$p = 0.513$
β_{2016}		-0.009		-0.013
		$p = 0.450$		$p = 0.299$
β_{2017}		-0.032^{*}		-0.038^{**}
		$p = 0.065$		$p = 0.033$
β_{2018}		-0.039^{*}		-0.044^{*}
		$p = 0.072$		$p = 0.067$
β_{2019}		-0.035		-0.047
		$p = 0.192$		$p = 0.108$

*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 3008 observations. The panel contains 47 cities and 64 periods. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0, 1)$.

Table 3: Number of workers registered to Pole Emploi in category A

	Dependent variable: Log workers registered to Pole Emploi in category A			
	(1)	(2)	(3)	(4)
β	-0.031^{*}		-0.033^{**}	
	$p = 0.078$		$p = 0.048$	
β_{2015}		-0.0001		-0.004
		$p = 0.991$		$p = 0.609$
β_{2016}		-0.027^{*}		-0.032^{**}
		$p = 0.078$		$p = 0.031$
β_{2017}		-0.041^{*}		-0.047^{**}
		$p = 0.052$		$p = 0.033$
β_{2018}		-0.038		-0.047
		$p = 0.132$		$p = 0.113$
β_{2019}		-0.045		-0.056
		$p = 0.140$		$p = 0.112$
Note:			*p<0.1; **p<0.05; ***p<0.01	

Notes: Each regression is based on 3008 observations. The panel contains 47 cities and 64 periods. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0,1)$.

Table 4: Number of workers registered to Pole Emploi in category B

	Dependent variable: Log workers registered to Pole Emploi in category B			
	(1)	(2)	(3)	(4)
β	-0.017		-0.012	
	$p = 0.454$		$p = 0.541$	
β_{2015}		0.037^{**}		0.033^{**}
		$p = 0.044$		$p = 0.033$
β_{2016}		0.002		0.001
		$p = 0.915$		$p = 0.951$
β_{2017}		-0.027		-0.037
		$p = 0.307$		$p = 0.152$
β_{2018}		-0.060^{*}		-0.055^{*}
		$p = 0.082$		$p = 0.073$
β_{2019}		-0.059		-0.065^{*}
		$p = 0.113$		$p = 0.085$
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 3008 observations. The panel contains 47 cities and 64 periods. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0,1)$.

5.2 Discussion on internal migrations and population size

In my sample, I am unable to track individuals. The results discussed above could be polluted by people migrating from zone 2 to 3, and conversely. In technical terms, the single unit treatment value assumption (SUTVA), according to which there should be no interference or spillovers between treated and untreated units, is likely to be violated. If unemployed workers from the fare area 3 were moving to the fare area 2, this would artificially increase the number of unemployed workers registered at Pole Emploi in zone 2 relative to zone 3, and create an upward bias in the estimates. But this case seems unlikely, as unemployed workers from the fare area 3 have more incentives to stay after the reform than before, as their commuting costs has decreased. The alternative scenario, in which unemployed workers from zone 2 move to zone 3 to enjoy a cheaper rent while keeping their commuting costs constant seems more plausible. Yet, this channel would push the number of unemployed in zone 3 upward and decrease the number of unemployed workers in zone 2. Thus, this would create a downward bias on my estimates (making it less negative). This intuition about the sign of the bias is supported by simulation of a simple structural model in the next section.

5.3 Impact on public transport usage

The "dézonage" reform led to a decrease in commuting costs for users living in the zones 2 - 5. The STIFF documents that this reform led to an increase in the number of people subscribing to annual, monthly and weekly travel passes. But did it lead to an increase in the number of travels via the public transport network? The answer to this question is essential, since a negative answer would cast serious doubt on the causal impact of the reform on employment. To the contrary, if usage of public transport in the treatment group increased relative to the control group, I interpret that as evidence that the cost differential boosted usage of public transport.

To answer this question, I estimate the specification (3) and (4) using a dataset with the yearly number of travellers passing trough each metro and RER stations. I restrict the sample to the stations in the zones 1, 2 and 3. I define the control group as stations in zones (1-2) and the treatment group as stations in zone 3. Results presented in Table 5. Column 1 shows that the reform led to a 5.1% increase in the number of travelers in zone 3 for the period 2016 - 2018. One word of caution is needed. The estimated value for β is likely to be positively biased because single-ride tickets are not taken into account. People in zone 3 previously commuting using single-ride tickets and switching to travel passes will raise the number of users in zone 3. Overall, Table 5 can be read as evidence of an increase in public transport commuting in zone 3 and of a tendency to switch from single-ride tickets to cheaper travel passes.

Table 5: Impact of the reform on public transport usage

	Dependent variable: log traffic	
	(1)	(2)
β	0.051^{***}	
	$p = 0.00000$	
β_{2016}		0.036^{***}
		$p = 0.00001$
β_{2017}		0.053^{***}
		$p = 0.00002$
β_{2018}		0.065^{***}
		$p = 0.00000$
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: Each regression is based on an unbalanced panel with data from 2013 to 2018: $n = 236$, $T = 5-6$, $N = 1415$. Columns (1) and (2) correspond to regressions (3) and (4). For columns (1) and (2), the treatment (control) group includes stations in the fare area 3 (1-2).

6 Model

The empirical analysis indicates the "dézonage" reform boosted employment for cities receiving the treatment, generating a 2% drop in the number of workers registered to Pole Emploi. To rationalize these findings, I develop a simple spatial search-and-matching model in which workers decide where to live, taking into considerations rent prices, commuting costs and the probability of finding a job. This is a partial equilibrium model: I do not explicit the process of job creation from the firm's side and I abstract from the housing market. Developing a full-fledged general equilibrium model is outside the scope of the present paper. The model features two channels through which commuting costs may affect unemployment: smaller commuting costs in some areas (i) decrease workers' reservation wage, hence boosts employment (ii) affect the attractiveness of these areas relative other cities, hence alter migrations patterns.

6.1 Setting and value functions

I model the Parisian region as a network of L nodes (cities/municipalities). Time is discrete and infinite. At each node is attributed a commuting time to the center c_l, a rent price r_l and a probability of finding a job λ_l. There is a mass 1 of ex-ante identical, risk-neutral and infinitely lived workers. Each worker, whether employed unemployed, consumes one unit of housing. When unemployed, they enjoy a flow of utility $b(l)$, which depends on location to capture differences in amenities between cities, in the spirit of Brueckner et al. (1999). When employed, they receive a wage w, which may depend on workers' location, and they produce an output of value py. The variable p is a random variable with cdf F and pdf f. One can think of p as measuring the dispersion of firms productivity in the economy, or as an idiosyncratic match-specific productivity shock (the "quality" of a match between similar workers and firms). The value of p is unknown to workers until meeting with firms, during which its value is fully revealed. I use the monocentric assumption according to which all jobs are located in the city center. Employed workers go to the CBD every weekday to work, while unemployed workers may go to the CBD to participate in interviews. The cost of going to the CBD every weekday while living in city L is denoted by c_l, while the cost of going to occasional interviews for unemployed workers is denoted by μc_l. As in Wasmer and Zenou (2002), I assume that unemployed workers have smaller commuting costs compared to employed workers residing in the same city: $\mu \in (0,1)$. If employed workers go to the CBD 5 times a week and unemployed workers go to city center once a week, μ would be equal to $\frac{1}{5}$.

At the beginning of each period, unemployed workers search for a job. They meet with a firm with probability λ_l. Unemployed workers not meeting with firms have the possibility to stay in the same city, or to move to a new city l', in which case they incur a moving cost denoted by $m_{l,l'}$.[14] The ex-ante value of being unemployed to a worker is location l solves:

[14]The cost of staying put is $m_{l,l}$ is equal to 0.

$$U(l) = b(l) - \mu c_l - r_l + \frac{1}{1+r}\lambda_l E_p\big(\max\{W(l,p), U(l)\}\big) + \frac{1}{1+r}(1-\lambda_l)E_\epsilon \max_{l' \in 1,\dots,L}\Big[\big(U(l') - m_{l,l'} + \epsilon\big)\Big] \quad (7)$$

where ϵ is a worker-specific $i.i.d$ shock capturing unobservable reasons for preferring a given location. I assume ϵ to be drawn from a type I extreme value distribution.[15] $W(l,p)$ denotes the value of being employed in city l with a firm of productivity type p. To simplify the model, let us make the assumption that workers have zero bargaining power, as in Postel-Vinay and Robin (2002). As a result, workers are offered a wage making them indifferent between being employed or unemployed: $U(l) = W(l,p)$. Equation (7) becomes:

$$U(l) = b(l) - \mu c_l - r_l + \frac{1}{1+r}\lambda_l U(l) + \frac{1}{1+r}(1-\lambda_l)E_\epsilon \max_{l' \in 1,\dots,L}\Big[\big(U(l') - m_{l,l'} + \epsilon\big)\Big] \quad (8)$$

At the end of each period, unemployed workers solve the following discrete choice problem:

$$j \equiv \arg\max_{l \in 1,\dots,L}\Big[\big(U(l') - m_{l,l'} + \epsilon\big)\Big] \quad (9)$$

Let us define the ex-ante choice-specific value function $V_l(j)$, denoting the net present value of payoffs conditional on taking action j, while in location l, before the exogenous taste shock is realized:

$$V_l(j) \equiv U(l') - m_{l,l'} \quad (10)$$

The probability for a worker in city l to move to city l', before the individual-specific idiosyncratic shock is ϵ is observed, is given by the multinomial logit formula:

$$P_l(l') = \frac{\exp\big(V_l(l')\big)}{\sum_{k=1}^{L}\exp\big(V_l(k)\big)} \quad (11)$$

Let us assume that unemployed workers cannot search for alternative jobs or move to a new location. A match is destroyed exogeneously at a rate δ, in which case newly unemployed workers receive the value $U(l)$. Employed workers stay employed with probability $1-\delta$, in which case they receive the value $W(l,p)$. The value of being employed in city l solves:

$$W(l,p) = w(l,p) - c_l - r_l + \frac{\delta}{1+r}U(l) + \frac{1-\delta}{1+r}W(l,p) \quad (12)$$

Combining equations (8) and (12) and using the assumption that $U(l) = W(l,p)$ yields the following expression for wages, conditional on the job being feasible:

[15]With cdf $F(a) = \exp(\exp(-a))$.

$$w(l) = b(l) + (1-\mu)c_l + \frac{1-\lambda_l}{1+r} E_\epsilon \max_{l' \in 1,\dots,L} \left[U(l') - U(l) - m_{l,l'} + \epsilon \right] \tag{13}$$

The intuition for equation (13) is simple: workers should be compensated (i) for the flow utility they enjoy while being unemployed $b(l)$ they lose by working (ii) the additional commuting cost to the CBD they incur when working (iii) the option value of changing location they lose when accepting a job. How do wages vary as we move away from the city center? If one neglects expectations effects, equation (13) tells us that wages are decreasing in the distance to the city center, denoted by d, if amenities are decreasing *faster* than the rate at which commuting costs are increasing: $\frac{\partial b(l)}{\partial l}\frac{\partial l}{\partial d} < \mu \frac{\partial c_l}{\partial l}\frac{\partial l}{\partial d}$.

Remark that the maximum wage any firm can offer is the value of output py. If a firm were to offer a wage $w(l)$ greater than py, it would make negative profits. Any meeting for which $w(l) \le py$ results in a new job being created. As a result, the wage offer function in city l for a firm with productivity p is:

$$w(l,p) = \begin{cases} w(l) & \text{if } w(l) \le py \\ \varnothing & \text{if } w(l) > py \end{cases} \tag{14}$$

From equation (13), what is the impact of decreasing commuting costs on employment? A decrease in c_l leads to a lower reservation wage $w(l)$, thus one should expect a decrease in the unemployment rate, especially in the areas far away from the city center, as the set of feasible jobs expands. However, migration patterns are altered. Living further away from the city center is now more interesting from a worker' perspective. As a result some unemployed workers will move away from the city center. The final outcome depends on which of the two forces is more important.

Note that by virtue of the type I extreme value distributional assumption on ϵ, the expectation term in (8) admits the following closed-form solution

$$U(l) = b(l) - \mu c_l - r_l + \frac{\lambda_l}{1+r} U(l) + \frac{1-\lambda_l}{1+r}\left[\gamma + \log\Big(\sum_{l'=1}^{L} \exp\{U(l') - m_{l,l'}\}\Big)\right] \tag{15}$$

where γ is the Euler–Mascheroni constant.

6.2 Flow equations

Using equations (15) and (11), one can solve the model and find the probability that unemployed workers not receiving an offer have to move to each location. For workers meeting with firms, the job feasibility condition $w(l) \le py$ tells us how many meetings are translated into jobs. Let us use $u_t(l)$ to denote the measure of unemployed workers residing in city l at time t. The flow equation for unemployment in city l has to take into account exogenous job destruction, job creation for unemployed workers in city l, unemployed workers from city l migrating to other cities and unemployed workers from other cities moving to city l:

$$u_{t+1}(l) = \delta\big(1-u_t(l)\big) + \lambda_l u_t(l)\big(P(w(l) > py) - P(w(l) \leq py)\big) - \big(1-\lambda_l\big)u_t(l)\Big[\Big(\sum_{k=1;k\neq l}^{L} P_l(k)\Big) - P_l(l)\Big] + \sum_{k=1;k\neq l}^{L} \big(1-\lambda_k\big)P_k(l)u_t(k) \tag{16}$$

To get a simpler expression for (16), let us make the assumption that firms' types p are normally distributed $p \sim \mathcal{N}(\mu_p, \sigma_p^2)$. Under this assumption, the term capturing the measure of unemployed workers finding a job in period t simplifies and the flow equation writes:

$$u_{t+1}(l) = \delta\big(1-u_t(l)\big) + \lambda_l u_t(l)\Big(1-2\Phi\big(\frac{w(l)-\mu_p}{\sigma_p}\big)\Big) - \big(1-\lambda_l\big)u_t(l)\Big[\Big(\sum_{k=1;k\neq l}^{L} P_l(k)\Big) - P_l(l)\Big] + \sum_{k=1;k\neq l}^{L} \big(1-\lambda_k\big)P_k(l)u_t(k) \tag{17}$$

Note that $f(l) = 1 - 2\Phi(\frac{w(l)-\mu_p}{\sigma_p})$ is in between -1 and 1. If the reservation wage $w(l)$ in city l is so high that no match is feasible, $f(l)$ is equal to 1 and the measure of workers meeting with firms goes back to the pool of unemployed workers. On the other hand, if all matches are feasible $f(l)$ is equal to -1 and the measure of workers meeting with firms are joining the pool of employed workers.

6.3 Equilibrium

I define an equilibrium as a pair $(U, \boldsymbol{u})$ such that:

- U is a function satisfying equation (15)
- $\boldsymbol{u} \equiv (u(1),...,u(l))$ is a joint distribution of employment and city location being such that each u_l is a fixed point of (16)

First note there exists a unique solution to (15). Consequently, flows between cities are uniquely determined by equation (11). As a result, equation (16) can be written as a matrix difference equation $\boldsymbol{u_{t+1}} = \mathbb{1}_L\delta + A\boldsymbol{u_t}$, where A is a deterministic matrix uniquely determined by the primitive parameters of the model (see the Appendix). If an equilibrium exists, the steady state $\boldsymbol{u}$ solves $\boldsymbol{u} = (\boldsymbol{I} - A)^{-1}\mathbb{1}_L\delta$. Thus, existence and uniqueness of an equilibrium hinges on the invertibility of the matrix $B \equiv \boldsymbol{I} - A$. There exists at least one trivial equilibrium in which everyone is unemployed, if δ is high enough (see the Appendix). Without imposing further restrictions to the model, it is difficult to characterize conditions on parameters under which an equilibrium is reached. To gain insights on the model, let us focus on a non-degenerate "symmetric" equilibrium in which the outflows and inflows of workers from and to city L cancel out:

$$\big(1-\lambda_l\big)u(l)\sum_{k=1;k\neq l}^{L}P_l(k)=\sum_{k=1;k\neq l}^{L}\big(1-\lambda_k\big)P_k(l)u(k) \tag{18}$$

In this symmetric equilibrium (16) simplifies to:

$$u_{t+1}(l)=\delta\big(1-u_t(l)\big)+\lambda_l u_t(l)\big(1-2\Phi\big(\frac{w(l)-\mu_p}{\sigma_p}\big)\big)+\big(1-\lambda_l\big)u_t(l)P_l(l) \tag{19}$$

and the equilibrium is such that $\forall l, \in \{1,...,L\}$:

$$u_l=\frac{\delta}{1+\delta-\lambda_l\big(1-2\Phi\big(\frac{w(l)-\mu_p}{\sigma_p}\big)\big)-\big(1-\lambda_l\big)P_l(l)} \tag{20}$$

Equation (20) illustrates the two channels through which a change in the commuting costs may impact the joint distribution of employment and location, modeled as a decrease in c_l for some cities. Firstly, there is a direct employment effect: $w(l)$ decreases, causing more jobs to be feasible, leading to a decrease in the unemployment rate for city l. Secondly, there is a reallocation effect: an asymmetric decrease in c_l drives up the value of residing in city l relative to "non-treated" cities, leading to an increase in $P_l(l)$. As a result, more unemployed workers decide to stay in city l rather than moving to an alternative city. Remark that this analysis ignores the reaction of the land market: an increase in the attractiveness of a city should lead to an increase in rent, which may offset the reallocation effect. The discussion above also ignores the differences in timing: in the short run, the employment effect is likely to dominate if the moving costs are high and the proportion of movers is small.

6.4 Algorithm

To find an equilibrium, I first solve for $U(l)$ and $P_l(l')$ $\forall l, l' \in \{1,...,L\}^2$ using equations (8) and (11). Using equation (13), I am able to determine which wages are feasible across space. I Initialize an economy with an initial distribution of unemployed and employed workers across the cities $\{u_0(l)\}_{l=1,...,L}$, $\{e_0(l)\}_{l=1,...,L}$ with the constraint that the total mass integrates to 1: $\int u_0(l)dl+\int e_0(l)dl=1$. I can then iterate forward the joint distribution of unemployment and city location using equation (16). I stop when the distance between two iterations reaches an arbitrary small value $d(u_{t+1}(l)-u_t(l))<\varrho$

6.5 Parametrization

I draw 100 cities at random in a square. I calculate the median distance to the city center, and I use the median to separate cities between two fare areas (zones 2 and 3). For the rent price associated to each city, I use a third order polynomial estimated from empirical data, using IRIS located in a distance between 0 and 20 km away from the city center (see Figure 4). For the value of home production and leisure, I chose a simple linear function that depends on distance, to capture that fact that amenities might be a decreasing function to the city-center in the Paris area

$$b(l) = b_0 + b_1 d(l) \tag{21}$$

For commuting costs, I choose a function that depends on the time travelled before reaching the CBD and on the fare area:

$$c(l) = c_0 + c_1 \times t(l) + c_2 \times f(l) \tag{22}$$

where t is the commuting time to the city center using public transports and f denotes an indicator variable equal to 1 if the city is in the fare area 3 and 0 otherwise. I follow the literature and assume that the job meeting rate is a decreasing function of distance:

$$\lambda(l) = \lambda_0 - \lambda_1 \times d(l) \tag{23}$$

In the age of internet and the widespread use of job-search websites, this assumption may be regarded with scepticism. But being close to the city center, where jobs are located, may have benefits through network effects (Bayer et al. (2008)). I set μ, which would imply that unemployed workers go on average to the CBD once a week, while employed workers go to the CBD 5 times a week, as in Wasmer and Zenou (2002). For the moving costs, I assume that there is a fixed cost associated with moving and an additional cost that is linked to the distance between the previous and the new location:

$$m_{l,l'} = m_0 \mathbb{1}\{l \neq l'\} + m_1 |l - l'| \tag{24}$$

For the yearly discount factor, I use $r = 0.05$. I calibrate the remaining 9 parameters in order to match the pattern of unemployment rate as a function of distance to the city center, as of 2015. I then simulate the "dézonage" reform by setting the parameter $c_2 = 0$.

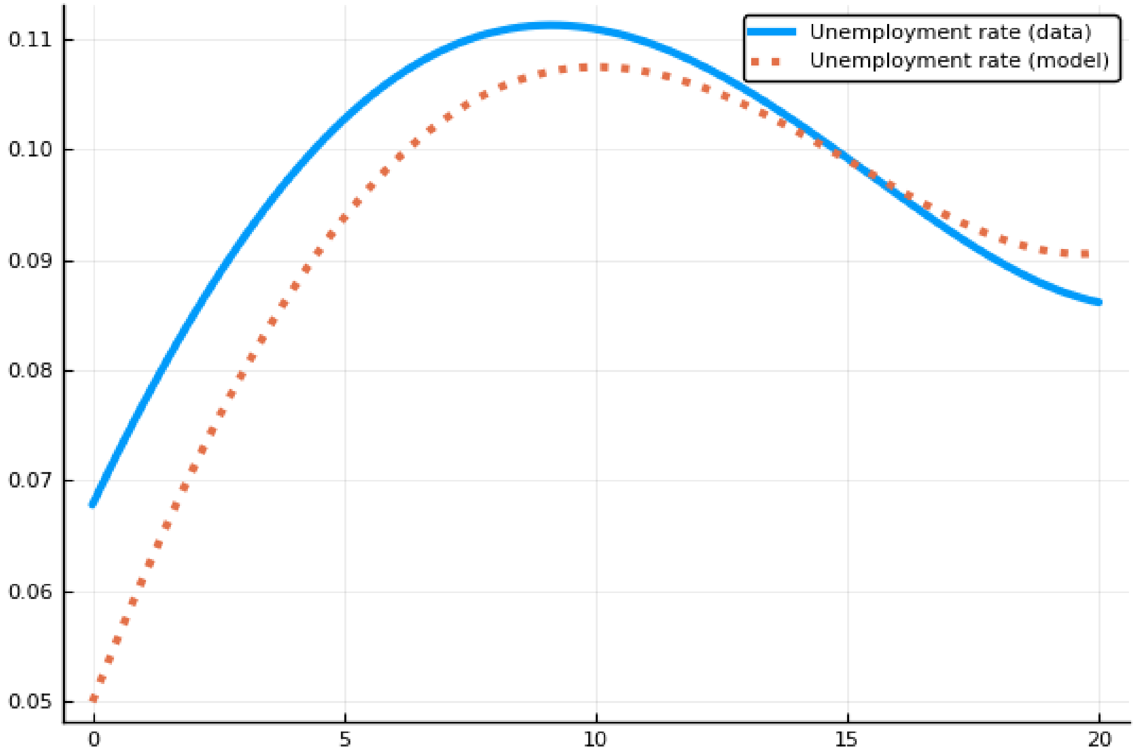
6.6 Calibration

The model is able to reproduces the link between unemployment rate and distance to the city center fairly well (see Figure 8). To generate this pattern, both the job meeting rate and the amenity level have to decrease quite substantially, which is compensated by lower rent prices (see Figure 9)

Table 6: Calibrated parameters

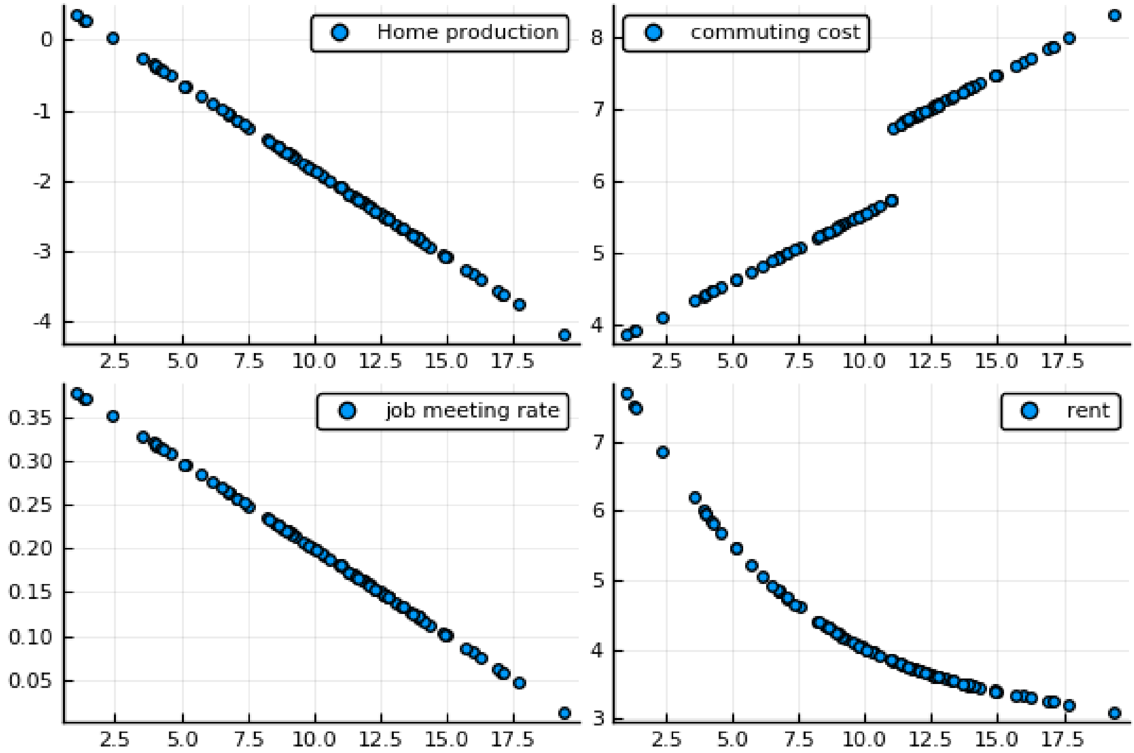
b_0	b_1	c_0	c_1	λ_0	λ_1	m_0	m_1	δ
0.6278	-0.2487	3.6684	0.1883	0.3999	0.0200	3.3616	1.6021	0.0952

Figure 8: Unemployment rate and distance to the CBD



Notes: This figure displays the unemployment rate (at the IRIS level) as a function of goedesic distance to Châtelet. The orange dotted line indicates is the model output, based on a simulation with 100 cities.

Figure 9: Model's primitives and distance to the city center



Notes: This figure displays the some of the model's primitives as a function of distance to the city center.

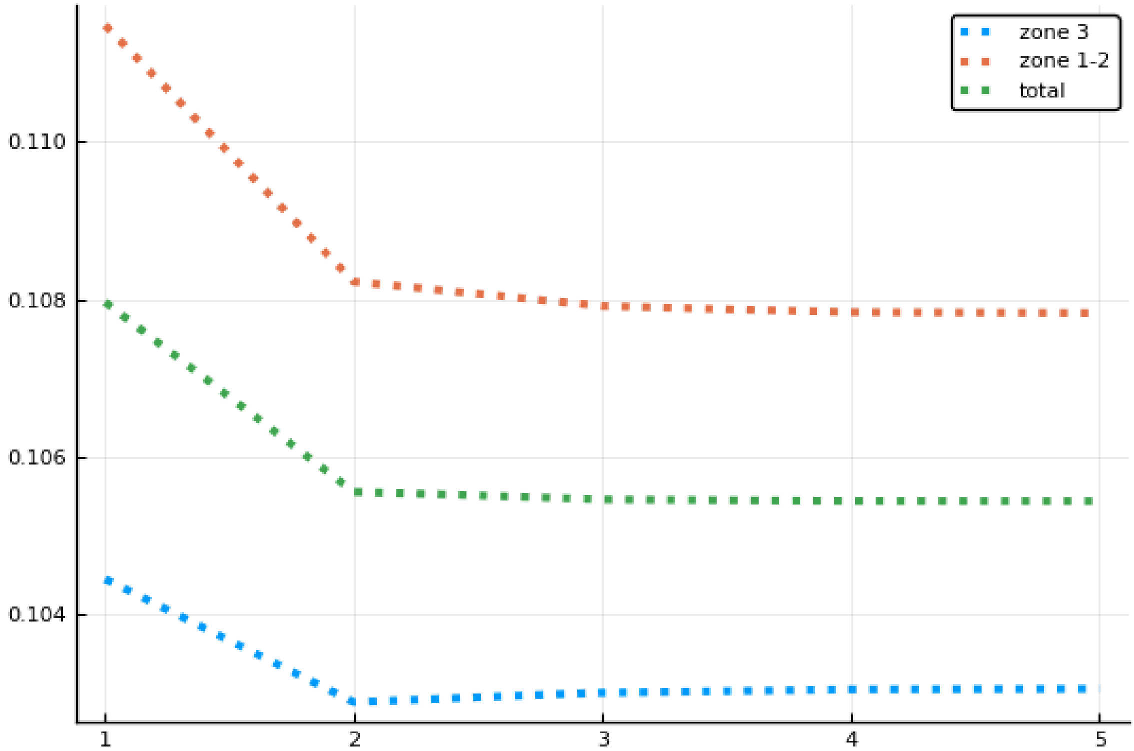
6.7 Counterfactual

To model the reform, I decrease the parameter from $c2 = 1$ to $c2 = 0$. This corresponds to approximately a 13% decrease in commuting costs for workers residing in zone 3.[16] I solve the model with the new set of parameter values and I simulate forward the distribution of unemployment, using as starting value the steady-state distribution of unemployment obtained with $c2 = 1$. Results are presented in Figure 10. The reform generates a drop in the unemployment rate for cities in zones 3 *and* 2. Explaining the impact in zone 3, is straightforward. A decrease in the reservation wage for workers in zone 3 boosts employment. Why cities in zone 2 are impacted? Lower transportation costs makes cities in the zone 3 more attractive for workers in zones 3 *and* 2. When having the opportunity to move to a new location, workers in zone 2 are more likely choose a city in zone 3 (see Figure 11). As a result, the measure of unemployed workers in zone 2 decreases.

Hence, the model underlines that internal migrations decisions are likely to create a downward bias in the empirical estimate of section 5.1. However, the severity of the bias is probably mitigated by the fact that, at the equilibrium, rent prices should react to the inflow of workers in zone 3. This feedback effect is not taken into account in the current model.

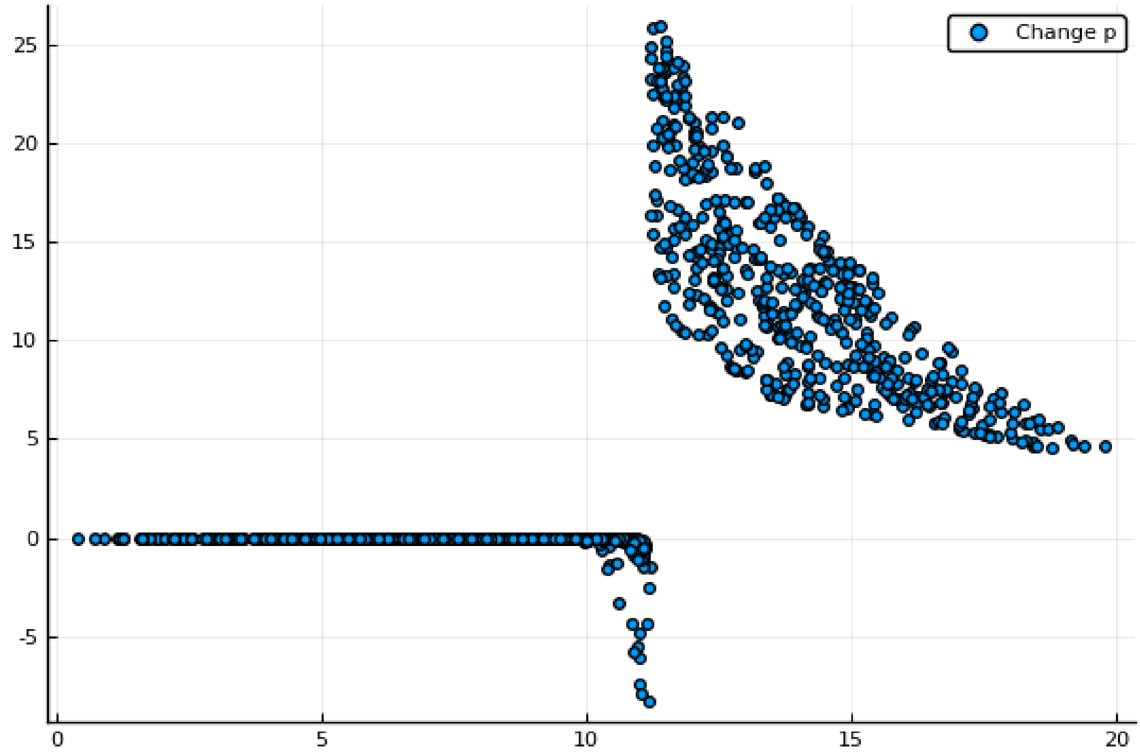
[16]The FTZ reform led to a 15.3/89.20 ≈ 17% decrease in commuting costs for workers previously owning a zone 1-3 annual Navigo pass.

Figure 10: Simulation of the FTZ reform: impact on unemployment



Notes: This figure shows the evolution of the unemployment rate in the treated (zone 3) and non-treated groups (zone 1-2) (simulated data).

Figure 11: Simulation of the FTZ reform: impact on migration decisions



Notes: This figure shows the percentage change in the probability of staying in the same city, when facing the opportunity to change location, as a function of the geodesic distance to the city center (simulated data). The discontinuity at 11 represent the border separating the zones 1-2 and 3 before the FTZ reform. Based on a simulation with 1000 cities.

7 Conclusion

The "dézonage" of the public transport passes in the Paris area in September 2015 provides a rich setup to measure the links between transportation costs, employment and location decisions. My reduced form estimates, relying on the spatial discontinuity introduced by the former fare areas, indicate that the reform led to a 2% *decrease* in the number of unemployed workers registered in the unemployment agency for the municipalities benefiting from the reform. The reform mainly impacted category A workers, more likely to be in a situation of long-term unemployment. A simple spatial search-and-matching highlights that due to migration between the group of treated and non-treated, the reduced form estimates are likely to be downward biased. If the FTZ reform did encourage people to move from Paris *intra-muros* to the suburbs, this should be reflected in the housing market. The links between the FTZ reform and house prices are currently being investigated and the model is being extended to take into consideration the feedback effects that higher rents have on migration towards the suburbs.

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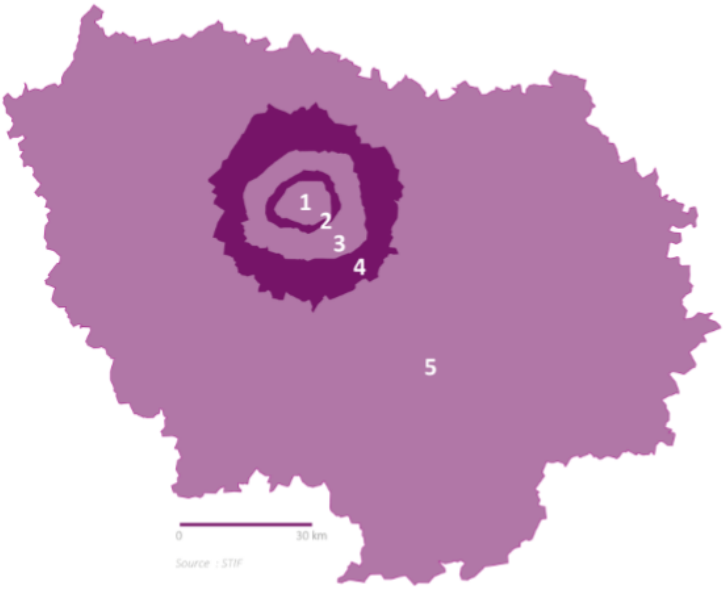
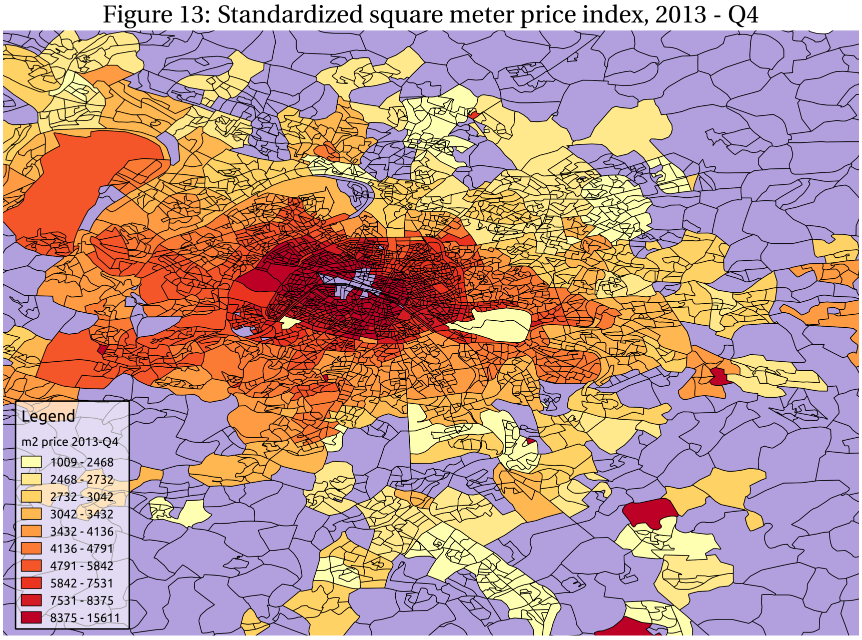
A Data

Figure 12: Public transport networks fare areas in the region Ile-de-France



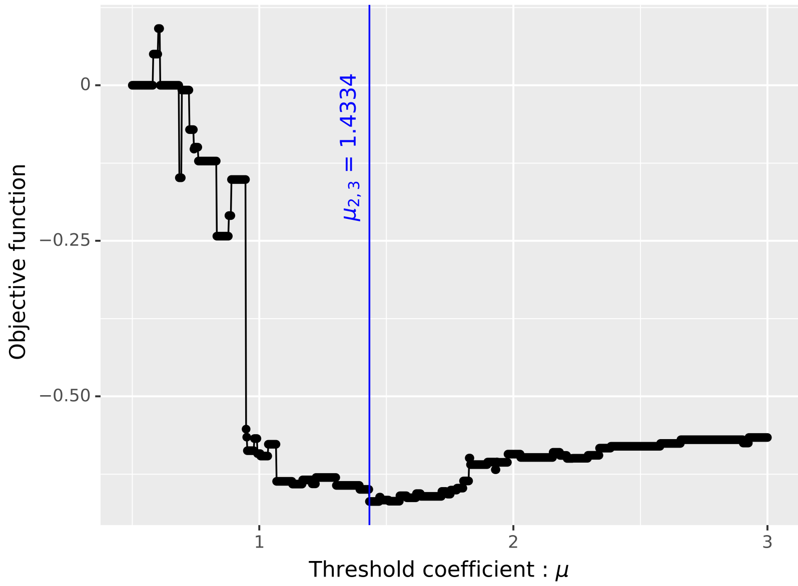
Notes: This figure shows the public transport networks fare areas for the region Ile-de-France.

Figure 13: Standardized square meter price index, 2013 - Q4



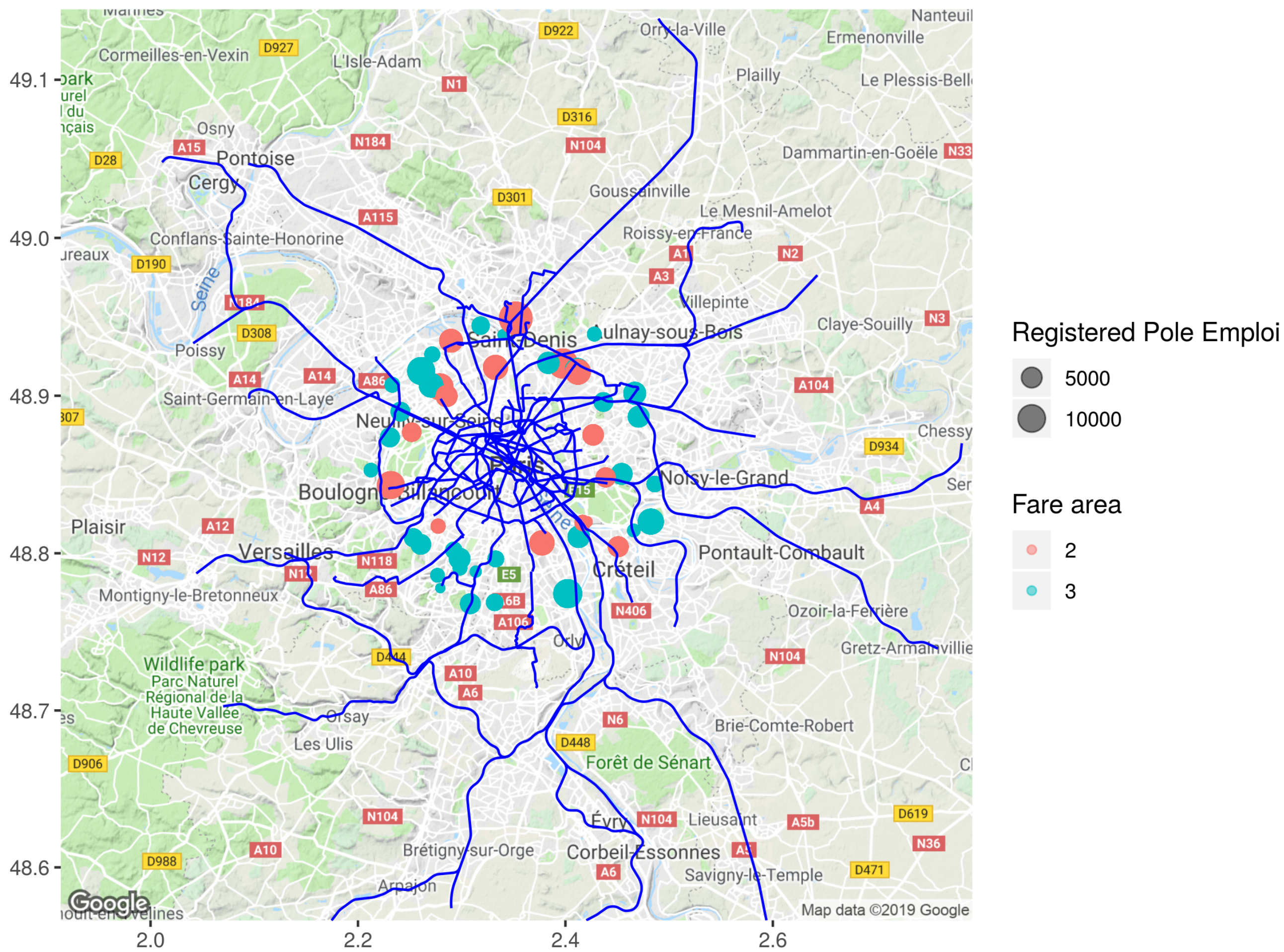
Notes: This figure shows the standardized square meter price index (at the municipality level) in the Parisian region. Missing values (not enough transactions were realized to generate a reliable measurement) are in purple. Source: data from the Grand Paris notary agency

Figure 14: Minimization of the objective function in (2)



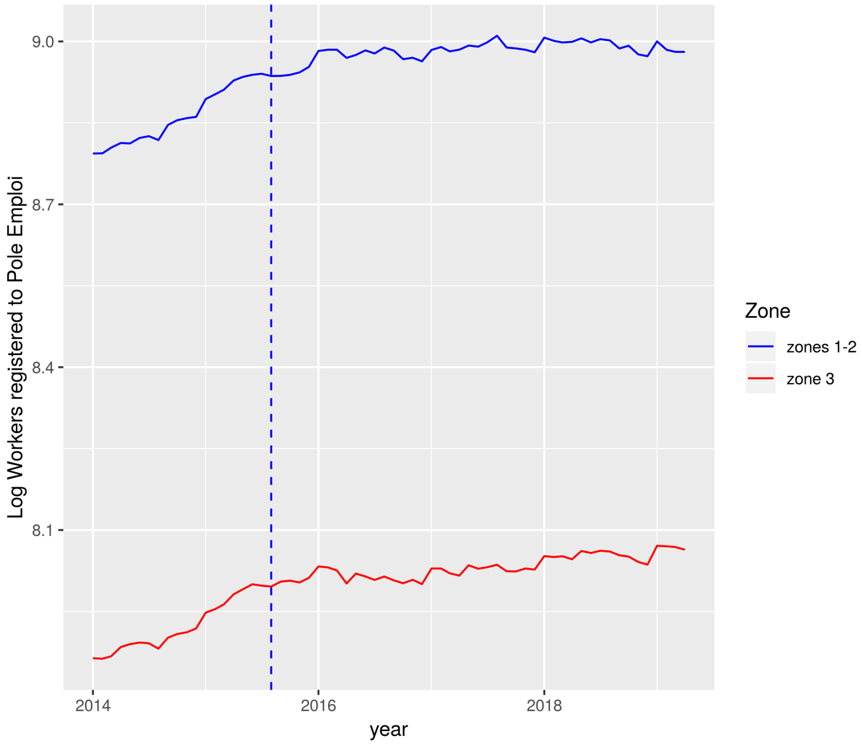
Notes: This figure shows the objective function being minimized in (2). The smaller the objective function, the more similar the treated and non-treated groups are in the pre-treatment period. The vertical blue line is the minimum of the objective function (found by a naive grid search with 1000 grid points evenly spaced on [0.5; 3.0]. The objective function was normalized such that its value is equal to 0 for $\mu = 0$.

Figure 15: Municipalities included in the sample



Notes: This figure display the cities included in the sample. Each circle represents a city. The size of the circle is proportional to the number of workers registered to Pole Emploi (French unemployment center) as of April 2015. Cities in blue are in the fare area 3, while the ones in blue are in the fare area 2. The blue lines represent available rail public transport lines (metro and RER).

Figure 16: Number of workers registered to Pole Emploi by fare area



Notes: This figure displays the average (log) number of workers enrolled to Pole Emploi for cities in the fare areas 2 (red) and 3 (in blue) for my selected sub-sample. The vertical blue line indicates the date at which the "dézonage" reform became effective (September 2015).

B Pole Emploi Categories

Workers registered to Pole Emploi (the French unemployment agency) are assigned to one of the 5 existing categories (A, B, C, and E)[17]:

- A: unemployed worker registered to Pole Emploi and actively searching for a permanent, temporary or seasonal job
- B: unemployed worker registered to Pole Emploi and actively searching for a permanent, temporary or seasonal job, having worked no more than 78 hours in the last month
- C: unemployed worker registered to Pole Emploi and actively searching for a permanent, temporary or seasonal job, having worked more than 78 hours in the last month
- D: unemployed worker registered to Pole Emploi, but not directly available for a vacancy because of an internship, a training program, a sick leave
- E: employed worker registered to Pole Emploi and searching for an alternative position

[17] source:https://www.insee.fr/en/metadonnees/definition/c2010

C Robustness

C.1 Placebo tests

Table 7: Placebo test (all categories)

	Dependent variable: Log number of workers registered to Pole Emploi	
	(1)	(2)
β	0.002	0.007
	$p = 0.765$	$p = 0.255$
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 940 observations (balanced panel: n = 47, T = 20, N = 940). In the Placebo test, I pretend that the reform happened in September 2014. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0,1)$.

Table 8: Placebo test category A

	Dependent variable: Log number of workers registered to Pole Emploi in category A	
	(1)	(2)
β	0.004	0.009
	$p = 0.677$	$p = 0.310$
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 940 observations (balanced panel: n = 47, T = 20, N = 940). In the Placebo test, I pretend that the reform happened in September 2014. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0,1)$.

Table 9: Placebo test category B

	Dependent variable: Log number of workers registered to Pole Emploi in category B	
	(1)	(2)
β	0.009	0.012
	$p = 0.629$	$p = 0.529$
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 940 observations (balanced panel: n = 47, T = 20, N = 940). In the Placebo test, I pretend that the reform happened in September 2014. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0,1)$.

C.2 Main regression and categories C - E

Table 10: Number of workers registered to Pole Emploi in category C

	Dependent variable: Log number of workers registered to Pole Emploi in category C			
	(1)	(2)	(3)	(4)
β	0.004		0.001	
	$p = 0.876$		$p = 0.977$	
β_{2015}		0.001		0.005
		$p = 0.963$		$p = 0.695$
β_{2016}		-0.002		-0.002
		$p = 0.912$		$p = 0.918$
β_{2017}		0.003		-0.004
		$p = 0.912$		$p = 0.871$
β_{2018}		0.014		0.012
		$p = 0.628$		$p = 0.674$
β_{2019}		0.010		0.003
		$p = 0.777$		$p = 0.940$
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 3008 observations. The panel contains 47 cities and 64 periods. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0, 1)$.

Table 11: Number of workers registered to Pole Emploi in category D

	Dependent variable: Log number of workers registered to Pole Emploi in category D			
	(1)	(2)	(3)	(4)
β	0.037		0.008	
	$p = 0.440$		$p = 0.877$	
β_{2015}		0.021		0.012
		$p = 0.711$		$p = 0.804$
β_{2016}		0.087		0.059
		$p = 0.194$		$p = 0.373$
β_{2017}		-0.028		-0.065
		$p = 0.633$		$p = 0.271$
β_{2018}		0.033		-0.011
		$p = 0.559$		$p = 0.879$
β_{2019}		0.116		0.094
		$p = 0.116$		$p = 0.302$
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 3008 observations. The panel contains 47 cities and 64 periods. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0, 1)$.

Table 12: Number of workers registered to Pole Emploi in category E

	Dependent variable: Log number of workers registered to Pole Emploi in category E			
	(1)	(2)	(3)	(4)
β	0.064		0.087	
	$p = 0.253$		$p = 0.172$	
β_{2015}		0.046		0.050
		$p = 0.332$		$p = 0.195$
β_{2016}		0.120^{**}		0.138^{**}
		$p = 0.035$		$p = 0.021$
β_{2017}		0.068		0.074
		$p = 0.298$		$p = 0.339$
β_{2018}		-0.020		0.0002
		$p = 0.802$		$p = 0.998$
β_{2019}		0.055		0.037
		$p = 0.634$		$p = 0.743$
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Each regression is based on 3008 observations. The panel contains 47 cities and 64 periods. Columns (1) and (2) correspond to regressions (3) and (4). Columns (3) and (4) correspond to regressions (5) and (6). For columns (1) and (2), the treatment (control) group includes cities in the fare area 3 (2), where the clear separation between the treated and non-treated is obtained by rounding the median fare area (measured at the IRIS level) to the nearest integer. Columns (3) and (4) measure the treatment effect by allowing for differences in the intensity of treatment. Cities entirely located in the fare area 2 are assigned an intensity of 0; cities entirely in the fare area 3 are assigned an intensity of 1; cities overlapping the border are assigned a value in $(0,1)$.

D Existence and uniqueness of a solution to $U(l)$

Let us show that the operator T satisfies Blackwell's sufficient conditions for a contraction.

D.1 Monotonicity

Let us fix $x \in X$ and consider two function $U, W \in B(X)$ such that $\forall x \in X, U(x) \leq W(x)$. Monotonicity of T follows from the fact that the exponential and the logarithm functions are strictly increasing on their respective domains:

$$
\begin{aligned}
[T(U)](x)-[T(W)](x) &= \frac{\lambda_l}{1+r}\big(U(x)-W(l)\big)+\frac{1-\lambda_l}{1+r}\big[log\big(\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}\big)-log\big(\sum_{l'=1}^{L}\exp\{W(l')-m_{l,l'}\}\big)\big]\\
&\le \frac{1-\lambda_l}{1+r}\big[log\big(\frac{\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}}{\sum_{l'=1}^{L}\exp\{W(l')-m_{l,l'}\}}\big)\big]\\
&\le \frac{1-\lambda_l}{1+r}\big[log\big(\frac{\sum_{l'=1}^{L}\exp\{W(l')-m_{l,l'}\}}{\sum_{l'=1}^{L}\exp\{W(l')-m_{l,l'}\}}\big)\big]\\
&= 0
\end{aligned}
$$

Where the first inequality comes from the assumption $\forall x \in X, U(x) \le W(x)$ and the properties of the logarithm. The second inequality uses the fact that the logarithm and the exponential functions are strictly increasing on their domain. Hence $\forall (U,W) \in B(X)^2$ such that $U \le W$, $(TU)(x) \le (TW)(x)$.

D.2 Discounting

$$
\begin{aligned}
[T(U+a)](x)-[T(U)](x) &= \frac{\lambda_l}{1+r}(U(x)+a-U(x))+\frac{1-\lambda_l}{1+r}\big[log\big(\sum_{l'=1}^{L}\exp\{a+U(l')-m_{l,l'}\}\big)-log\big(\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}\big)\big]\\
&= \frac{\lambda_l}{1+r}a+\frac{1-\lambda_l}{1+r}\big[log\big(\frac{\sum_{l'=1}^{L}\exp\{a+U(l')-m_{l,l'}\}}{\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}}\big)\big]\\
&= \frac{\lambda_l}{1+r}a+\frac{1-\lambda_l}{1+r}\big[log\big(\frac{\sum_{l'=1}^{L}\exp\{a\}\exp\{U(l')-m_{l,l'}\}}{\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}}\big)\big]\\
&= \frac{\lambda_l}{1+r}a+\frac{1-\lambda_l}{1+r}\big[log\big(\frac{\exp\{a\}\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}}{\sum_{l'=1}^{L}\exp\{U(l')-m_{l,l'}\}}\big)\big]\\
&= \frac{\lambda_l}{1+r}a+\frac{1-\lambda_l}{1+r}\big[log(\exp\{a\})\big]\\
&= \frac{1}{1+r}a\\
&\le \beta a
\end{aligned}
$$

where $\beta = \frac{1}{1+r} \in [0,1]$ for $r > 0$.

Hence $\forall U \in B(X)$ and $a > 0$, there exists $\beta \in [0,1]$ such that $[T(U+a)](x)-[T(U)](x) \le \beta a$.

D.3 Existence and uniqueness of the difference equation (16)

Let us define $\boldsymbol{u_t} \equiv (u_t(1),...,u_t(L))$, $f(l) \equiv \big(1-2\Phi\big(\frac{w(l)-\mu_p}{\sigma_p}\big)\big)$ and $\Omega_l \equiv \big(\sum_{k=1;k\neq l}^{L} P_l(k)\big)-P_l(l)$. For a given $l \in \{1,...,L\}$, equation (16) can be written as:

$$
u_{t+1}(l) = \delta+\Delta(l)u_t(l)+((1-\lambda_1)P_1(l),...,(1-\lambda_{l-1})P_{l-1}(l),0,P_{l+1}(l),(1-\lambda_L)P_L(l)).\boldsymbol{u_t} \tag{25}
$$

where the scalar $\Delta(l) \equiv \lambda_l f(l) - \delta - (1-\lambda_l)\Omega_l$ captures the net inflow into unemployment in city l, without taking into account immigration to city l. Stacking up the L equations (25), equation (16) can be compactly written as:

$$\boldsymbol{u_{t+1}} = \mathbb{1}_{\boldsymbol{L}}\delta + A\boldsymbol{u_t} \tag{26}$$

where $\mathbb{1}_{\boldsymbol{L}}$ is a column vector of size L filled with one and the matrix A a $(L \times L)$ matrix defined as:

$$A \equiv \begin{pmatrix} \Delta(1) & (1-\lambda_2)P_2(1) & \dots & (1-\lambda_L)P_L(1) \\ (1-\lambda_1)P_1(2) & \Delta(2) & \dots & 1-\lambda_L)P_L(2) \\ \dots & & & \\ (1-\lambda_1)P_1(L) & (1-\lambda_2)P_L(2) & \dots & \Delta(L) \end{pmatrix} \tag{27}$$

If the $L \times L$ matrix $\boldsymbol{I} - A$ is invertible, the unique fixed point of (26) is given by $\boldsymbol{u_*} = (\boldsymbol{I} - A)^{-1}\mathbb{1}_{\boldsymbol{L}}\delta$. To find the conditions under which $\equiv I - A$ is invertible, let us use the fact that if:

1. (i) the real matrix $L \times L$ matrix B is column diagonally dominant

2. (ii) with strictly positive diagonal entries,

then the real parts of the eigenvalues of B are all strictly positive.[18] As a result, if points (i) and (ii) hold, 0 is not an eigenvalue of B and B is invertible.

Let us first characterize conditions under which (ii) holds. First note that the diagonal entries of B are of the form $1-\Delta(l)$. Second, the condition $1-\Delta(l) > 0$ is equivalent to $\Delta(l) < 1$.

$$\begin{aligned} \Delta(l) &= \lambda_l f(l) - \delta - (1-\lambda_l)\Omega_l \\ &\leq \lambda_l - \delta - (1-\lambda_l)\Omega_l \end{aligned}$$

where the inequality follows from the fact that $f(l) \in [-1,1]$. Hence, a sufficient condition for $\Delta(l) < 1$ is that $\lambda_l - \delta - (1-\lambda_l)\Omega_l < 1$. This condition is met for

$$\frac{\delta - \lambda_l}{(1-\lambda_l)\Omega_l} > 1 \tag{28}$$

Let us first characterize conditions under which (i) holds. Let us consider column l. For the matrix to be column diagonally dominant, the following condition needs to be true:

[18] https://www.e-ce.uth.gr/wp-content/uploads/formidable/inf-001.pdf

$$
\begin{aligned}
1-\Delta(l) &> \sum_{k=1;k\neq l}^{L} (1-\lambda_1) P_l(k) \\
1 &> \sum_{k=1;k\neq l}^{L} (1-\lambda_l) P_l(k) + \Delta(l) \\
1 &> \sum_{k=1;k\neq l}^{L} (1-\lambda_l) P_l(k) + \lambda_l f(l) - \delta - (1-\lambda_l)\Omega_l
\end{aligned}
$$

An upper bound for the right hand side term of the previous inequality, denoted by a_l is

$$
\begin{aligned}
a_l &= (1-\lambda_l) \sum_{k=1;k\neq l}^{L} P_l(k) + \lambda_l - \delta - (1-\lambda_l)\Omega_l \\
&= (1-\lambda_l)(\sum_{k=1;k\neq l}^{L} P_l(k) - \Omega_l) + \lambda_l - \delta \\
&= (1-\lambda_l) P_l(l) + \lambda_l - \delta
\end{aligned}
$$

Hence, condition (i) is automatically met when

$$
\frac{\delta - \lambda_l}{(1-\lambda_l)P_l(l)} > 1 \tag{29}
$$

Given that the denominator is strictly positive, this condition is only met when $\delta > \lambda_l$. Combining (28) and (29), a sufficient condition for B to be invertible and an equilibrium to exists is that $\forall l \in \{1, ..., L\}$

$$
\begin{aligned}
\frac{\delta - \lambda_l}{(1-\lambda_l)\Omega_l} &> 1 \\
\frac{\delta - \lambda_l}{(1-\lambda_l)P_l(l)} &> 1
\end{aligned}
$$