The impact of internet job search on unemployment - an agent-based approach

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Word count: 4988

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07 May 2020

Abstract

In this paper an agent-based model is developed to investigate the effect of internet job search on unemployment. The methodology allows to isolate the impact of internet job search from the overall effect of the internet on the labour market. A genetic algorithm is used to calibrate the model to match Italy's dual labour market structure. The results show that internet job search has an overall positive effect on the labour market, e.g. reducing the unemployment rate between 9% and 25%. The results also show that users of internet job search become overconfident and thus have an extended reemployment duration relative to non-users.

Contents

1 Introduction

The popularity of internet job search has rapidly risen in the last two decades. Traditional job search means, like local newspaper ads have shifted to online platforms to the point that Investopedia.com ranks job boards and career websites as the third best way to look for a job in 2020. However, understanding the aggregate effect of internet job search on unemployment faces a substantial challenge. The spread of the internet has taken almost twenty years, making it impossible to separate the time trend, the policy effects and the regional tendencies from the impact of internet job search (Kroft and Pope, 2014).

In this paper, I develop an agent-based model to simulate the labour market *with* and *without* internet job search. With this methodology, I am able to separate the effect of internet job search on unemployment from all other factors, as the only difference between the simulations is the presence of internet job search. The model combines the frictional search and matching model by Mortensen, Pissarides et al. (1999) and the non-equilibrium search theory outlined in M. Richiardi (2006). The model is built on the micro level, that is the agents' behavioural and interaction rules are defined. The aggregate outcome of the model arises from the collective behaviour of agents, which is reached through simulating the model (Arthur, 2006). Consequently, the model is a dynamic process of the labour market in which the steady state equilibrium forms the solution (M. Richiardi, 2017).

The model is calibrated to capture the dynamics of the labour market in Italy. Italy's dual labour market structure provides an experimental setting, where under the same institutional environment, some concrete features of the labour market determine the difference between the North and the South (Romei, 2016). This allows the model to be tested in two alternative settings and to provide a fuller picture of the impact of internet job search on unemployment. For the calibration, a genetic algorithm was used to determine the parameters.

The results show that internet job search has an overall positive impact on the labour market. The unemployment and long-term unemployment rates, as well as the average unemployment duration decreased in the simulations *with* internet job search. The restricting effect of interventions towards non-participants, observed on multiple occasions in the literature (Dahlberg and Forslund, 2005) is reversed in the model. Even though internet job search reduces the mean unemployment duration, internet users have relatively longer unemployment spells compared to non-users. Internet users become overconfident caused by their increased search intensity, resulting in them having a longer unemployment duration relative to non-users.

2 Literature review

Agent based models (ABMs) in economics are computational models that define behavioural rules and interaction protocols of economies or markets on the micro level. The overall outcome of the model arises from the collective behaviour of agents (Dosi, Fagiolo and Roventini, 2010). ABMs introduce a new perspective in economic analysis by relying on the micro-foundations, which in turn allows the close monitoring of agents (Dawid and Gatti, 2018). They provide a way to get around issues arising from using empirical data, such as unobserved heterogeneity or reliance on self-proclaimed information. However, ABMs are a new and experimental field of economics, which require significant computational tools and programming knowledge from the modeller. ABMs have not been used to study internet job search directly, whereas they have been used in the context of active labour market policies (ALMPs). Job search assistance programs, a type of ALMP are closely related to internet job search from a modelling perspective. I will come back to these in the second section of the literature review.

First, I will focus on the existing literature on internet job search. The popularity of internet job search has been increasing rapidly over the last decade. Numerous websites such as "jobs.co.uk" have been created to facilitate online job search by providing a job board for the unemployed. Online search platforms have revolutionised how people search for job opportunities (Goldfarb and Tucker, 2019). By using the internet, the search costs are reduced and information is more accessible, which allows people to make more informed decisions. The effect of the internet on unemployment and job search has been widely studied.

The effect of digitalisation of the labour market in the 1990s was first analysed by Freeman (2002). The results were inconclusive, as he acknowledged the fact that he was an early contributor to the field and internet usage was not widespread enough to fully understand its effect. The lack of data 20 years ago proved to be insufficient in showing the true potential of internet job search.

Following Freeman, Kuhn and Skuterud (2004) investigated the effect of internet technology on the labour market with a new angle. The paper uses the probability of reemployment as a measure of efficiency and evaluates the hypothesis that internet search quickens the unemployment exit rate. After introducing a control for observables, Kuhn and Skuterud found no difference in the reemployment rate between people who look for jobs online and people who only use traditional methods. Following the same methodology, Kuhn and Mansour (2014) revisited the impact of online search on the functioning of the labour market and found contrasting results. They showed that reemployment is 25% faster for online searchers, which is credited to the increase in overall internet usage and the technological advancement of online platforms in the 2000s. However, the paper accounts some of the reduction in unemployment to network externalities generated by internet search, such as emailing friends for job recommendations.

Kroft and Pope (2014) analysed local labour markets in the US before and after the appearance of Craigslist to investigate changes in matching efficiency. They took advantage of the rapid growth of Craigslist in the mid 2000s, which allowed them to look at changes in cities more and less affected by this platform. Even though they found that there was a reduction in apartment vacancy rate, implying a more efficient rental market, no measurable change in the local labour market unemployment rates were observed. The study accounts the different results to the structural differences in the labour and housing markets and the fact that even though Craigslist is a significant platform for rental housing, it is a minor company in the job search industry.

Papers like Kroft and Pope (2014), Kuhn et al. (2004, 2013) and Freeman (2002) investigate the effect of online search platforms from already existing data. However, as Kroft and Pope highlight, the steady growth of internet and search platforms makes it impossible to separate time trend, policy interventions and the specific effect of online platforms on the labour market. Occasions of rapid growth of platforms in local areas allow researchers to analyse the internet's direct effect. This effect, however, is still biased due to the unobserved heterogeneity and selection bias of internet users (Kuhn and Mansour, 2014). In addition- as this paper argues- these models rely on survey respondent's self-proclaimed data on internet usage, which raises concern regarding whether the data can be trusted.

ABMs are able to generate noiseless data through the simulation process. Besides, every agent can be closely controlled and monitored, which allows a more thorough understanding of the underlying processes (Tesfatsion, 2003). Neugart (2008) designed a model to analyse the effect of ALMPs in OECD countries. He found that government subsidies on training programs increase outflow rates from the labour market and thus reduce aggregate unemployment. Neugart also identified a secondary effect: job seekers not involved in training programs and have lower reemployment probabilities. This crowding out effect is also present in Wozniak's (2016) paper towards the long-term unemployed who do not participate in ALMPs. Wozniak (2016) focused on how unemployment durations are affected by job placement agencies in an agent-based environment and identifies a significant reduction in the unemployment rate and long-term unemployment rate for participants.

This paper draws on the methodology used in Wozniak, who simulated the labour market first without any interventions and then introduced job placement agencies, then compared the two simulations. This paper extends Wozniak's model by replacing the job search agencies framework with internet job search and introducing exogenous labour force joining and leaving mechanism.

3 The model

3.1 Overview

The model developed in this paper is a virtual labour market with multiple levels of heterogeneity among agents, industries and skills. The model is intended to capture a simplified version of a local labour market, which after the calibration procedure can highlight the aggregate effect of internet job search. The model is programmed after Wozniak's (2016) paper, implementing the idea of an agent-based search and matching model with on-the-job search. However, instead of the active labour market policy module in Wozniak's model, I programmed a representation of online job search platforms into the model and also added labour force leaving and joining mechanisms.

There are three types of agents in the model, (i) job seekers, (ii) firms and (iii) vacancies. Agents spawn on a 20x20 patch grid. During the initialisation, firms and job seekers are randomly distributed around the grid with a maximum of one firm on a patch. Firms also create randomly a maximum of 3 vacancies to guarantee an even distribution of agents. Job seekers and vacancies are randomly assigned one of the 5 skill levels and 3 industries, which form the heterogeneity among them.

Job seekers are boundedly rational objects in the model, who are either unemployed or employed. Heterogeneity between them besides their skill level and the industry, is also present in productivity and benefits, both of which are randomised (see table 4). Unemployed individuals are always looking for a job, while the employed ones are always working. The goal for the unemployed is to find the highest paying vacancy matching their skill level and preferences as quick as possible. However, their search is constrained by their available search units, which they receive an endowment of every period. Job seekers are considered to be long-term unemployed if they are unable to find a job within 26 periods of the simulation, which corresponds to half a year. The long-term unemployed job seekers experience random skill depreciations and limited search units, which capture their proven disadvantaged place in the labour force(Hornstein and Lubik, 2015).

Firms and vacancies operate closely together in the demand side of the labour market. Firms are identical to each other and they control and monitor the vacancies. They can close down a vacancy or open a new one depending on the labour supply (the type of job seekers) in their local environment. Thus, for example, if there are a large number of job seekers around a firm with the same industry preference, the firm will close down unfilled vacancies in other industries and open new ones in that industry to attract those job seekers. The firm's goal is to maximise production, which is based on the combined productivity of its vacancies and job seekers.

Vacancies capture the demand side heterogeneity of the labour market with their randomly assigned skill requirement, industry type, technology, and wage offer (see table 4). The vacancies' objective is to hire a worker matching their skill requirement and industry type with the highest available productivity.

To include internet job search, I added a central job search platform to the model. It provides a simplified representation of online job boards e.g. glassdoor.co.uk, indeed.co.uk, brightnetwork.com. These websites provide an extensive, customisable job board freely for consumers and charge firms for advertising their vacancy on the job board (Marchal, Mellet and Rieucau, 2007). In the model, the single job search platform acts as an overall representation of the highly competitive online market in real life (adding multiple platforms would generate unnecessary complexity). The job search platform increases the search intensity in addition to providing an extended, personalised list of vacancies for its users. I further detail the job search platform's properties under the matching section.

The model runs for 208 periods each representing a week, which totals to 4 years of runtime. The performance of the labour market is measured after the first year, because in the model it takes approximately 52 weeks for the labour market to reach a steady state equilibrium (M. Richiardi, 2017). During the first year, the labour market adjusts from the initial 100% unemployment rate. The model is programmed in NetLogo (Wilensky, 2006) and analysed in R using the nlrx package (Salecker et al., 2019).

3.2 Design

3.2.1 Time

One period of the model is equivalent to one simulation cycle. The simulation cycle indicates a sequence of actions, which when ends the model moves to the next period (Goudet, Kant and Ballot, 2017). As the units of time in the model represent weeks, one simulated period captures a week's changes in the labour market. In one simulation cycle the sequence of actions is as follows:

1. Firms: Destroy or create vacancies
2. Job seekers: Decide about searching for a job or staying and taking the unemployment benefits
3. Firms: Evaluate applicants and make wage offers
4. Job seekers: Accept the wage offer and start working or reject the offer and continue searching

The model builds on simulating the labour market for 208 weeks, which is intended to capture the aggregate labour market dynamics.

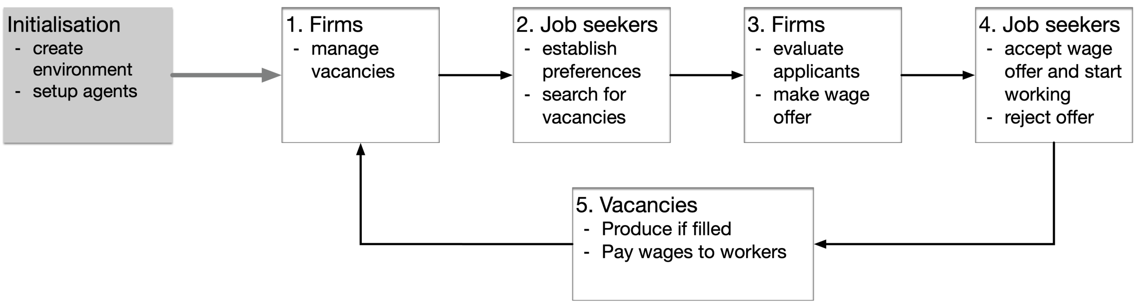

Figure 1: The simulation cycle of the model

3.2.2 Matching

The determination of how agents act is governed by the matching mechanism. The matching between job seekers and vacancies follows a partially random process (M. Richiardi, 2006). Job seekers randomly choose a vacancy satisfying their preferences, which either matches or is below their skill level within their search radius. Then they approach the vacancy's location by moving on the grid. If vacancies receive multiple applications at the same time, only the searcher with the highest productivity will transfer into the evaluation phase and the others will continue searching. Frictions arise from the time it takes for searchers to travel to the vacancy as well as from unsuccessful applications, which keeps job seekers unemployed (Stevens, 2007). The model's job search platform creates a pool of vacancies every period and provides a personalised list to all of its users. Based on the fact that online search has been proven to reduce search costs, users of the job search platform also experience increased search units (Goldfarb and Tucker, 2019). As search units increase the vision of job seekers, the users of the search platform have increased vision, which allows them to consider more vacancies. Thus, job seekers by using the job search platform experience increased search units in addition to having the option to find vacancies through their personalised job board. Users of the platform are randomly selected.

3.2.3 Searching

Searching occurs on the individual level by job seekers and depends on their available search units. The more search units they have, the more vacancies they can visit by travelling to their location. Thus, search units can be thought of as a proxy to the individual search intensity (Petrongolo and Pissarides, 2001). Individual search intensity is a key element of the agent specific labour market tightness, which can be derived from then overall labour market tightness. The overall labour market tightness θ at time t is defined as the number of vacancies divided by the number of unemployed $\theta_t = \frac{V_t}{U_t}$ (Yashiv, 2007). As the count of all vacancies and unemployed is the sum of the industry specific totals $V_t = V_t^{agri} + V_t^{prod} + V_t^{serv}$ and $U_t = U_t^{agri} + U_t^{prod} + U_t^{serv}$, by dividing the industry specific vacancy and unemployment counts, we can break down the overall measure into 3 industry specific tightness ratios, or $\theta_t^j = \frac{V_t^j}{U_t^j}$.

Furthermore, as the decision-making process happens on the micro-level, a job seeker specific tightness ratio can be defined. For a single agent, his/her search intensity imposes a maximum distance constraint that he/she can travel in one period. Therefore, the individual labour market tightness is the ratio of the number vacancies and the number of unemployed within the maximum distance measured from the individuals x and y coordinate, or $\theta_{t,j}^i = \frac{V_{t,j}^i}{U_{t,j}^i}$. This measure is counted for all job seekers to indicate their relative position against the other searchers.

Contrary to Wozniak's (2016) model, there is no overall matching function defined, because at any given time the model depends on both previous iterations and stochastic elements occurring every period. As a result, matches cannot be calculated by a function, only numerically by simulating the model.

3.2.4 Decision making

Agents in the model make decisions based on their idiosyncratic features and their local environment. The expected payoffs of alternative scenarios are compared to make a decision, with expectations formed adaptively (Neugart, M. Richiardi et al., 2012). Adaptive expectations imply, that individuals do not take into account intertemporal trade-offs, but instead form expectations based on the past and present (M. Richiardi, 2006). Adaptive expectations have been praised to be more realistic than rational expectations as agents are not lifetime utility maximisers, but rather focus on the near future (Dawid and Gatti, 2018). In addition, adaptive expectations keep the model simpler and more traceable, which makes the model computationally less expensive.

3.2.5 Behaviour

The behaviour of agents is outlined in Wozniak (2016) and is based on the *asset value* approach from Mortensen, Pissarides et al. (1999) and further derived by Yashiv (2007). Agents compare the expected values of the different outcomes of the situation and choose the one with the highest payoff. The below outlined value functions are the behavioural rules, which determine the agents' actions.

For the job seeker who travels to a vacancy, he/she considers the value of becoming employed at that vacancy now, or of continuing to search in hope of finding a higher paying job opening in the future. If the value of employment exceeds the expected value from searching, then he will accept the job offer. The value of unemployment U for job seeker i at time t is:

$$rU_t^i = b_i + l_i + h_t^i\ [E(w)_t^i - U_{t-1}^i] \tag{1}$$

where unemployment benefits are indicated b_i and the value of leisure is l_i. The sum of these two is considered as the opportunity cost of working. $E(w)_t^i$ is the expected income for continuing to search. As expectations are formed adaptively, it is the mean wage offer by vacancies that match the searchers preferences within the radius outlined by his search units. Thus, the second part of the RHS $h_t^i[E(w)_t^i - U_{t-1}^i]$, is the expected future payoff increase multiplied by the job finding rate h_t^i. The job finding rate h_t^i is

$$h_t^i = \varepsilon * \theta_{t,j}^i.$$

It indicates the individual probability of finding a job, where efficiency ε is a global parameter and θ_t^i is the idiosyncratic labour market tightness, derived in 3.2.3. The value of employment E for worker i is:

$$rE_t^i = \ w_t^i - \ \lambda[w_t^i - U_t^i] + h_t^i[E(w_t^i) - w_t^i] \tag{2}$$

where w_t^i is the current wage or wage offer. The exogenous global shock parameter

λ indicates the job destruction rate. The second term on the RHS indicates the change in value in the event of becoming unemployed, multiplied by that event's probability. For workers, who are overqualified, the value of employment increases by the wage premium of finding a higher skilled job indicated by the third element of the RHS.

Firms evaluate applicants by comparing the payoff from the vacancy getting filled by the current applicant or keeping it vacant and waiting for an applicant with higher productivity. The value of an available vacancy A_t^j on the labour market from its owner firm's perspective is:

$$rA_t^j = -c_j + k_t^j[E(F_t^j) - A_{t-1}^j] \tag{3}$$

where c_j indicates the cost of maintaining the unfilled vacancy. $E(F_t^j)$indicates the expected value of the vacancy being filled in the future, which is equal to the average productivity of the job seekers around the vacancy multiplied by its technology parameter. The expected filled value less the available value is multiplied by the firm specific worker finding rate k_t^j to get the expected payoff increase. The worker finding rate is the product of the global parameter efficiency ε and the inverse of the labour market tightness from the firm's position:

$$k_t^j = \varepsilon * \frac{1}{\theta_t^i}.$$

The value of a filled vacancy consists of the profit it generates for the firm less when the vacancy's production ends due to an exogenous shock, or the abandonment by the worker. A worker, if overqualified, meaning his/her skill level is higher than the vacancy's skill requirement, can abandon his/her job by searching on-the-job. As the firms are aware of this, it is accounted for in the filled value of the vacancy. Therefore, the value function for a filled vacancy F_t^j is:

$$rF_t^j = \Pi_t^j - \lambda[\Pi_t^j - A_t^j\ ] - h_t^i[\Pi_t^j - A_t^j]. \tag{4}$$

As the model only considers the labour market, profit Π from a vacancy is modelled as an explicit function of production and wages:

$$\Pi_t^j = p_t^i x_t^j - w_t^i. \tag{5}$$

Production is assumed to be the product of the worker specific productivity p_t^i and the vacancy specific technology x_t^j less the wages payed to the worker. If the operations of the vacancy ended, the vacancy's value would decrease to its unfilled value A_t^j. As a result, the firm would experience a payoff reduction the size of $\Pi_t^j - A_t^j$. The factor causing this payoff reduction is either the exogenous shock with a likelihood of λ or the successful on-the-job search by the worker with a likelihood of the job finding probability h_t^i. If the worker's and the vacancy's skill levels match, the worker will not search on-the-job, thus making the last element 0 in equation 4.

Now, with the defined behavioural rules, the 2 stage decisions making process of the hiring process is as follows: for a given vacancy and applicant, the firm compares equation 4 to 3, that is the filled value to the vacant value:

$$F_t^i \geq A_t^i$$

if true, then the applicant compares the employment value (equation 2) to the unemployment value (equation 1):

$$E_t^i \geq U_t^i$$

A new employment relationship appears if both conditions are satisfied. Otherwise, the vacancy remains unfilled and the applicant remains unemployed and continues to search. Furthermore, firms create a new vacancy if the expected profit (equation 5) is larger than the expected cost, $c_j * \frac{1}{k_t^j}$, or destroy a vacancy, if it remains unfilled for 20 weeks.

3.2.6 Wage bargaining

Wage bargaining takes place at the start of the employment relationship between the firm and the worker. The mechanism is based on the Mortensen, Pissarides et al. (1999) search model. Bargaining power is assumed to be $\beta = 0.5$ by firms and $(1-\beta)$ by workers, which dictates an equal split of the surplus. The surplus of the employment is always non-negative given that the underlying constraint of wage bargaining is that both parties gain from the relationship. The surplus is equal to the sum of gains from the cooperation for both the worker and the firm. The wage of a worker will be his/her share of the surplus, which outlined in Yashiv (2007) gives us[1]:

$$w_t^i = (1-\beta)\, U_t^i + \beta p_t^i x_t^j \tag{6}$$

A common alternative interpretation of this equation is that the real wage[2] of a worker is equal to the weighted average of the unemployment income and the current match productivity (Yashiv, 2007).

3.3 Calibration

The model is calibrated for two regions, the North (Nord) and the South of Italy (Mezzogiorno). Italy's labour market is considered to be geographically divided with high unemployment rates and slow productivity growth in the south (Jin, Fukahori and Morgavi, 2016). The differences of the two regions is assumed to be because of the unobservable or unmeasurable characteristics of the labour market. As a result, if I determine the observable features from empirical data, the unobservable parameters can form two different labour market environments. As a result, under the same parameter body (table 4), a more advanced and efficient labour market can be compared to a lagged behind counterpart by calibrating the remaining 6 parameters (Ciani, David and De Blasio, 2017).

For the calibration process, the target behaviour of the overall model needs to

[1] see Appendix A.1 for proof

[2] real wage in this case is different from the wage offered by vacancies

be specified. Assuming that the developed ABM is a function of an input vector, the target behaviour is the output of this function (Calvez and Hutzler, 2005). This input vector includes all parameters necessary to set up the model as well as controlling for stochasticity. The model output is then evaluated along the specified conditions according to a pre-defined loss function. I use 3 macroeconomic indicators to assess the overall fitness of the model; the unemployment rate, the long term unemployment rate and the labour market tightness. The target values for the criteria are presented in table 2. The loss function is a simulated minimum distance function (Grazzini, M. G. Richiardi et al., 2013), which takes the sum of squared differences between the target and the mean simulated values (see appendix A.2).

Then, a genetic algorithm is used to minimise the loss function (Stonedahl, 2011). A genetic algorithm optimises the loss function by modifying the initial vector of parameters through mutation and crossover (Calvez and Hutzler, 2005). Due to its computational length, 20 iterations were executed. The output values of the parameters are presented in table 3 and the performance of the algorithm is shown in figure 2.

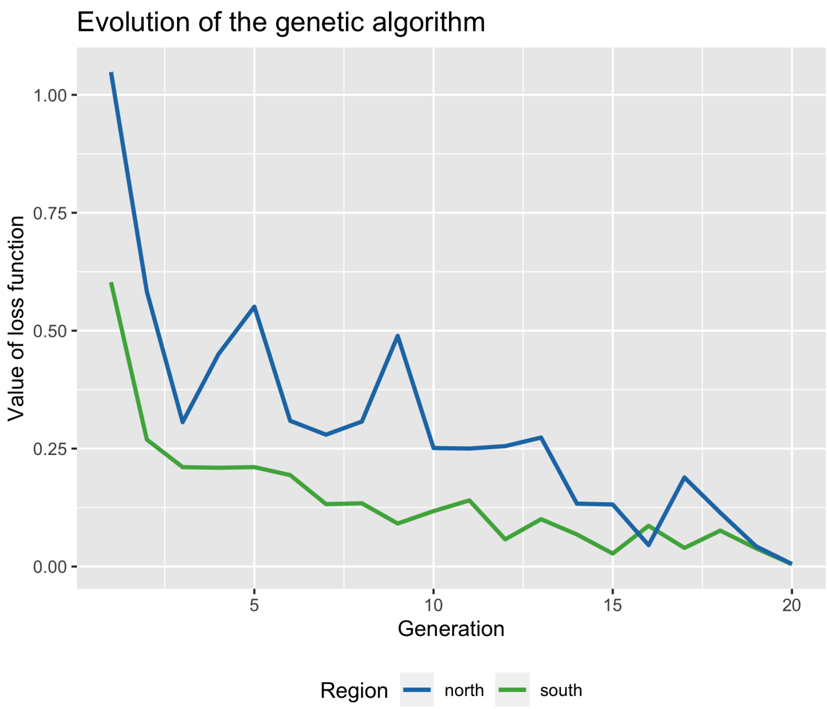

Figure 2: Evolution of the genetic algorithm for the two regions

4 Results

The results of the model are studied once the macro outcomes are in a steady state equilibrium, that is their time series graphs are stationary (Richiardi 2015). As the model is a continuously evolving dynamic process, the results are achieved through simulating the model. Table 1 shows the results of the model for each region and each search platform setting. The search platform can either be *off*, meaning that the labour market is functioning without it, or it can be *on*, meaning that agents can use it in the labour market. The North and South regions indicate the two different parameter vectors in table 3.

Region	North		South	
Platform	Off	On	Off	On
Unemployment rate	0.16	0.099	0.16	0.15
Long-term unemployment rate	0.07	0.053	0.11	0.099
Unemployment duration	52.46	48.69	63.14	62.24
Mismatch	0.43	0.44	0.44	0.46

Table 1: Results of the simulations. Each column is the average of 50 runs.

The presence of job search platform has a positive effect on both regions. The mean unemployment rate for the North is reduced by 18.43% and for the South it is reduced by 3.91%. The long-term unemployment rate decreased for both the North and the South by 24.5% and 9% respectively (see figure 6 and 7). Furthermore, the mean unemployment duration for the North fell by approximately 4 weeks and for the South it decreased by approximately 1 week. The reduction in all 3 of these metrics for both cases imply that job search platforms facilitate quicker matches and improve the exit rate from unemployment. This effect arises from the increased search intensity for a fraction of job seekers, the users of the platform who have increased search units. The difference in the size of the reduction between the regions is explained by the higher shock probability and the lower base search units for the South. Higher shock, which corresponds to the job destruction rate, implies that keeping a job is harder, which leaves job seekers in unemployment more often.

Lower base search units also contribute to a lower exit rate from unemployment, as it limits job seekers' vision more. These two factors as a result limit the effectiveness of the job search platform in the South. To investigate the restricting effect of labour market interventions towards the non-participants observed in the literature (Dahlberg and Forslund, 2005), the density plots in figure 3 depict the distribution of unemployment durations for both regions in the presence of job search platforms. Surprisingly, we find that the crowding out effect towards non-users is reversed. The mean unemployment duration for internet users is higher than for non-users in both regions. This implies that the benefits of internet search raise the mean searching duration for users relative to the non-users. A possible explanation for this is that the increased search units gained from using the job search platform raises the probability of finding a vacancy and thus creating a higher value in being unemployed. Users consequently overvalue their unemployment, which gives the non-users a competitive advantage. Job seekers who are using the job search platform as a result become *overconfident*, making their search process less effective.

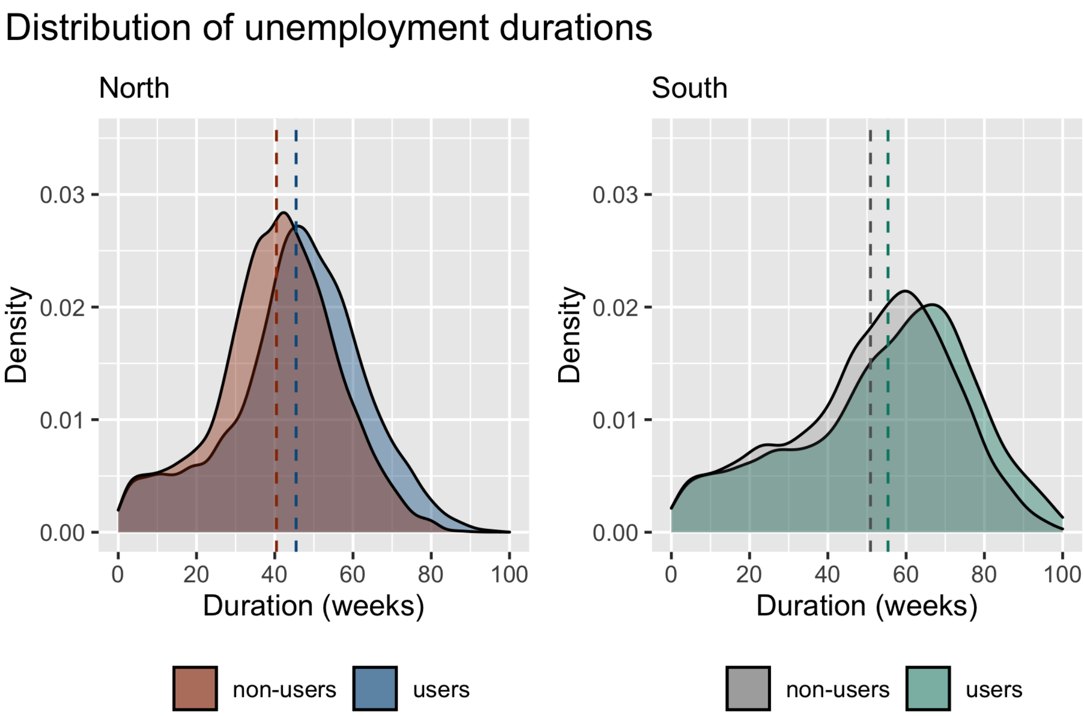

Figure 3: Regional density plots of unemployment duration for internet job search users and non-users. Vertical lines indicate the mean value.

Wages and the mismatch rate (percent of workers overqualified) remain similar with the presence of job search platforms in both regions. The rate of overqualified workers remains fairly high, at around 45% in all simulation runs, which leads me to believe that job seekers make primary decisions about employment based on the wage offer and ignore their skill level. The distribution of wages, shown in figure 4 highlights major differences between the regions[3]. The significant middle-class (weekly wage ≥ 3.5) and the virtually no low-income workers (wage < 3.5) in the North is caused by the high technological advancement (see table 3), which acts as a multiplier in equation 6, the wage bargaining process. The technology parameter in the South however, is rather small, making the distribution of wages less skewed and long tailed. Thus, the South generates high income inequality with a significant portion of workers being payed extremes.

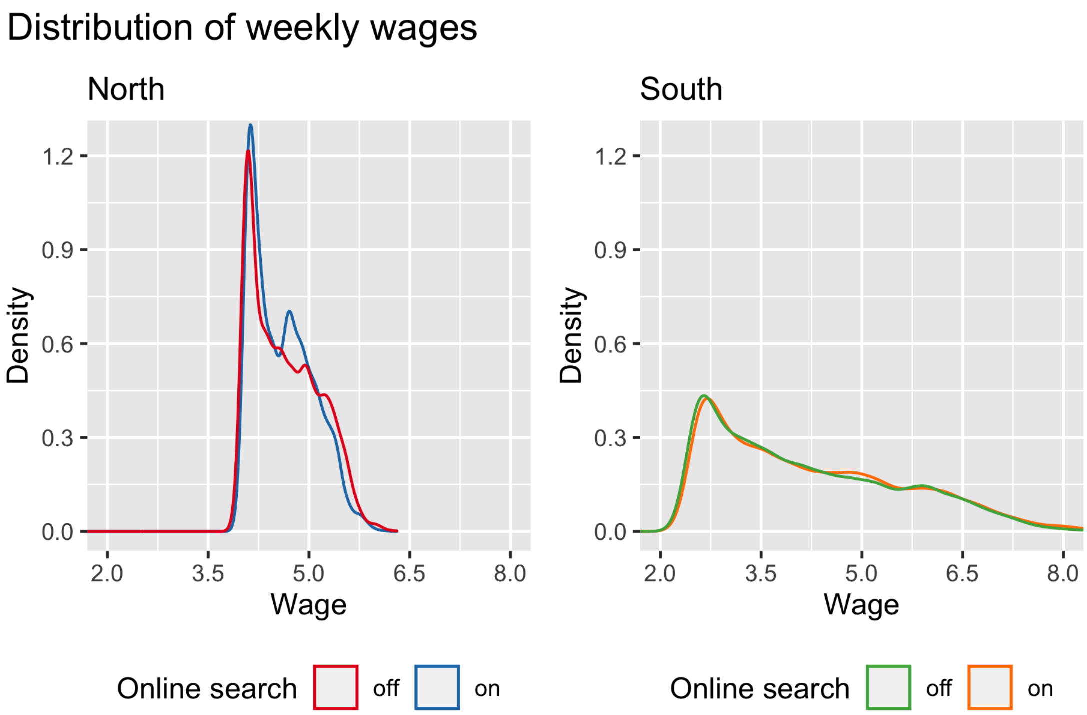

Figure 4: Regional density plot of wages.

The purpose of this model is not to replicate the empirical data of the North or the South of Italy, but to determine the effect online job search in different settings. Consequently, online job search has little effect on weekly wages and mismatch. On-

[3]see section 3.2.6 for how wage is determined

line job search however, has a significant positive effect on the unemployment rate, long-term unemployment rates and the average unemployment duration. Furthermore, users of the job search platform become *overconfident* from the additional search units making them overvalue unemployment. This is an inverse crowding out effect, that is users hinder themselves.

5 Conclusion

In this model I designed an agent-based search and matching model to investigate the effect of internet job search on unemployment. The macro outcome of the labour market arises from the collective behaviour of individuals, which is achieved through computationally simulating the model. The agents' behaviour is defined by a set of value function, which uses the "asset value" approach to compare the payoffs of decisions. The model is intended to function as a simplified version of the labour market to highlight the effect of internet job search on unemployment. Calibrating the model to Italy and taking advantage of its dual labour market allowed the analysis of two alternative labour market settings in the same institutional environment.

The results show that internet job search positively affects the unemployment and long-term unemployment rate in both regions. Internet job search also reduces the overall mean unemployment duration. Surprisingly, however, users of the job search platform experience extended average searching duration compared to non-users. Job seekers using internet job search become overconfident because of their increased search intensity. Consequently, internet job search crowds out its users and increases their average reemployment duration relative to non-users. The results are inconsistent with Kuhn and Mansour (2014) findings, who show that the reemployment duration for internet users is 25% shorter compared to non-users. However, Kuhn and Mansour's findings include significant positive externalities generated by the internet, like emailing friends and networking. Hence, their conclusion is rather about the overall effect of the internet than purely the effect of job search platforms, which is studied here.

Future extensions of the model might include the addition of a consumption goods market to extend the labour market. It would enable a more compound decision making process for job seekers, who could take into account their consumption preferences. However, the model would become significantly more complex and computationally expensive.

A Appendix

A.1 Wage bargaining

Proof of wage bargaining equation: workers in order to get employed sacrifice unemployment income U_t^i to receive wages w_t^i. Similarly, firms resign from the vacancy's vacant value A_t^j to gain the filled value F_t^j (Wozniak, 2016). The Nash bargaining solution as shown in Mortensen, Pissarides et al. (1999) gives:

$$w_t^i = argmax(E_t^i - U_t^i)^\beta (F_t^i - V_t^i)^{(1-\beta)}$$

Substituting back the equation 3 for the vacancy's filled value and equation 2, then solving the first order maximisation problem gives:

$$w_t^i = (1-\beta)\, U_t^i + \beta(p_t^i x_t^j - V_t^j)$$

Then, applying the free entry condition $V_t^j = 0$ leaves us with:

$$w_t^i = (1-\beta)\, U_t^i + \beta p_t^i x_t^j$$

A.2 Loss function

The genetic algorithm minimises the loss function:

$$\begin{aligned} L = (unem.rate - unem.rate.target)^2 + (ltu.rate - ltu.rate.target)^2 + \\ + (tightness - tightness.target)^2 \end{aligned}$$

In every iteration, the value of the loss function is calculated. The algorithm then establishes which parameters contributed to loss function the most, and changes those by mutation or crossover to achieve a new parameter vector. This step is repeated 20 times. The genetic algorithm simulates the model 50 times in each generation to eliminate path dependence and randomness. Ideally, the number generations should be larger, about 200, to guarantee a global minimum, but it comes at tremendous computational cost[4].

A.3 Sensitivity analysis

Sensitivity analysis (SA) helps determine the importance of parameters in the model. SA compares the parameters relative effect on the output, which provides valuable insight into the inner processes of the model (Iooss and Lemaitre, 2015). Unfortunately, however, I lacked computational resources to perform an extensive sensitivity analysis, which requires substantial computational power[5]. The results I present in this section are therefore not robust.

For the SA I use 4 metrics to measure the output: mean unemployment rate, mean long-term unemployment rate, the average duration of unemployment and the percent of overqualified workers. I also limit the parameter space and focus on 3 key parameters of model: efficiency, base search units and technology to limit computational runtime (description of them table 4). The method I use is a Monte Carlo estimation of Sobol' indices due to the fact that the model is highly non-linear and non-monotonic as well as the high computational cost of the sensitivity analysis. (for a full description of the methodology, see Zhang et al. (2015)).

The Sobol method is a global sensitivity analysis that determines the contribution of each input parameter on the variance of the output. It returns a first order and a total effect index for each parameter on each output metric. The first order index measures the impact of the parameter on the variance without interaction with other parameters. The total effect measures the effect of the parameter including all interactions on the response variance (Borgonovo and Plischke, 2016).

[4]My model runs for about 1.5 minutes, making the algorithms execution time 25 hours for 20 generations.

[5]It would have taken 6-7 days to run on my laptop.

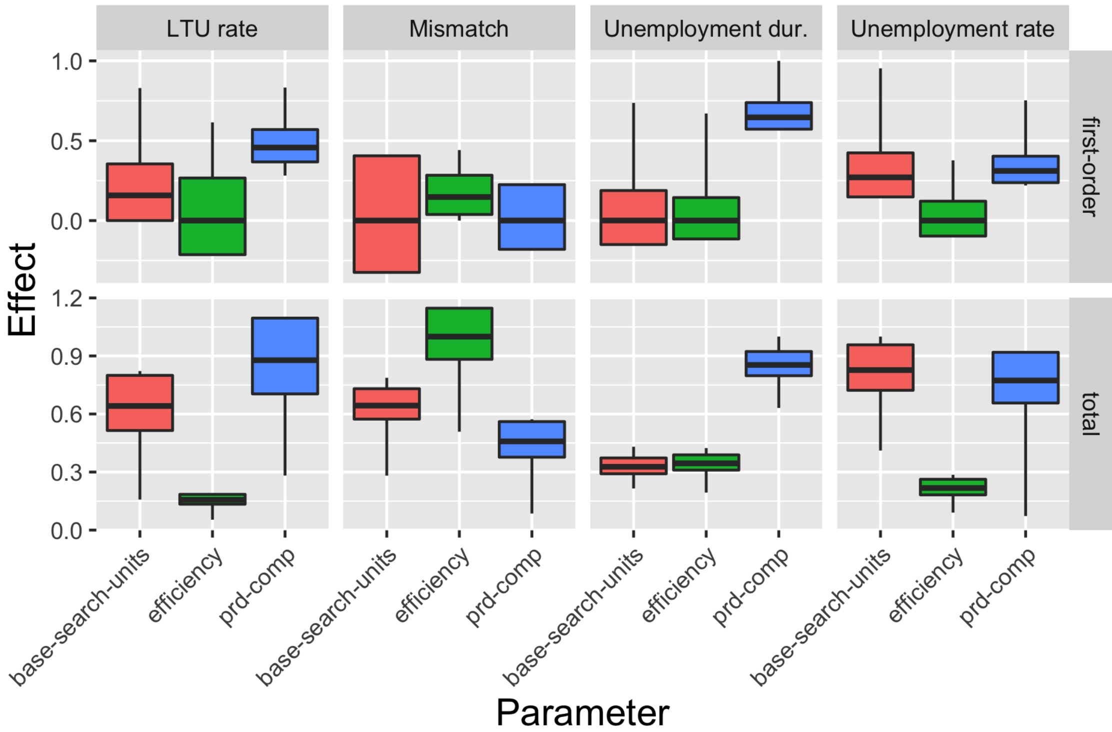

Figure 5: Sensitivity analysis of the model

B Tables

Criteria	Target		Source
	North	South	
Unemployment rate target	0.08	0.15	http://dati.istat.it/?lang=en
Long-term unemployment rate target	0.05	0.12	http://dati.istat.it/?lang=en
Labour market tightness target	0.115	0.11	Kangur (2018)

Table 2: Target values for calibration

Parameter	Description	North	South
prd-growth-rate	Upper limit of productivity increase per period for job seekers	0.0246	0.0778
efficiency ε	Multiplier on labour market tightness	0.321	0.466
benefits b	Lower limit on unemployment benefits	0.613	0.314
shock λ	Exogenous probability of job destruction rate	0.00175	0.0034
base-search-units	Endowment of search units every period	4	3
technology x	Determinant of vacancy production rate	1.59	0.291

Table 3: Estimated parameter values by region

Name	Description	Value
Global parameters		
Number of initial job seekers	The number of job seekers, who spawn in period 0	600
Number of initial vacancies	The number of vacancies, which spawn in period 0	$[550, 500]$
Number of initial firms	The number of firms, which spawn in period 0	225
Minimum wage	Base minimum wage for industry *agri*. Multiplier of 1.23x to industry *prod* and 1.68x to industry *serv*	1
Leaving rate	Probability of unemployed job seekers retiring	0.01
Joining rate	Probility of new unemployed job seekers appearing	0.01
Job seeker specific parameters		
Search-bonus	Additional search units for using the job search platform	4
Ltu search minus	Reduction in search units for the long-term unemployed	4
Leisure l	Randomised value of leisure for each job seeker	$U(0, 0.5)$
Skill-level	Randomised skill level	$U[1, 2, 3, 4, 5]$
Industry	Industry preference of job seeker	$[agri, prod, serv]$
Productivity	Randomised productivity	$N(2, 0.5)$
Vacancy specific parameters		
Rc-cost	Randomised recruitment cost of a worker payed by the firm	$N(1, 0.2)$
Industry	Randomised industry type of vacancy	$[agri, prod, serv]$
Technology	Randomised production capability, base value x calibrated	$N(x, 0.5)$
Skill requirement	Minimum skill level requirement of its worker.	$U[1, 2, 3, 4, 5$
Wage offer	Randomised offered wage to workers. Different from wage under wage bargaining	$min.wage + U[0, 1]$

Table 4: Main parameters of the model

C Figures

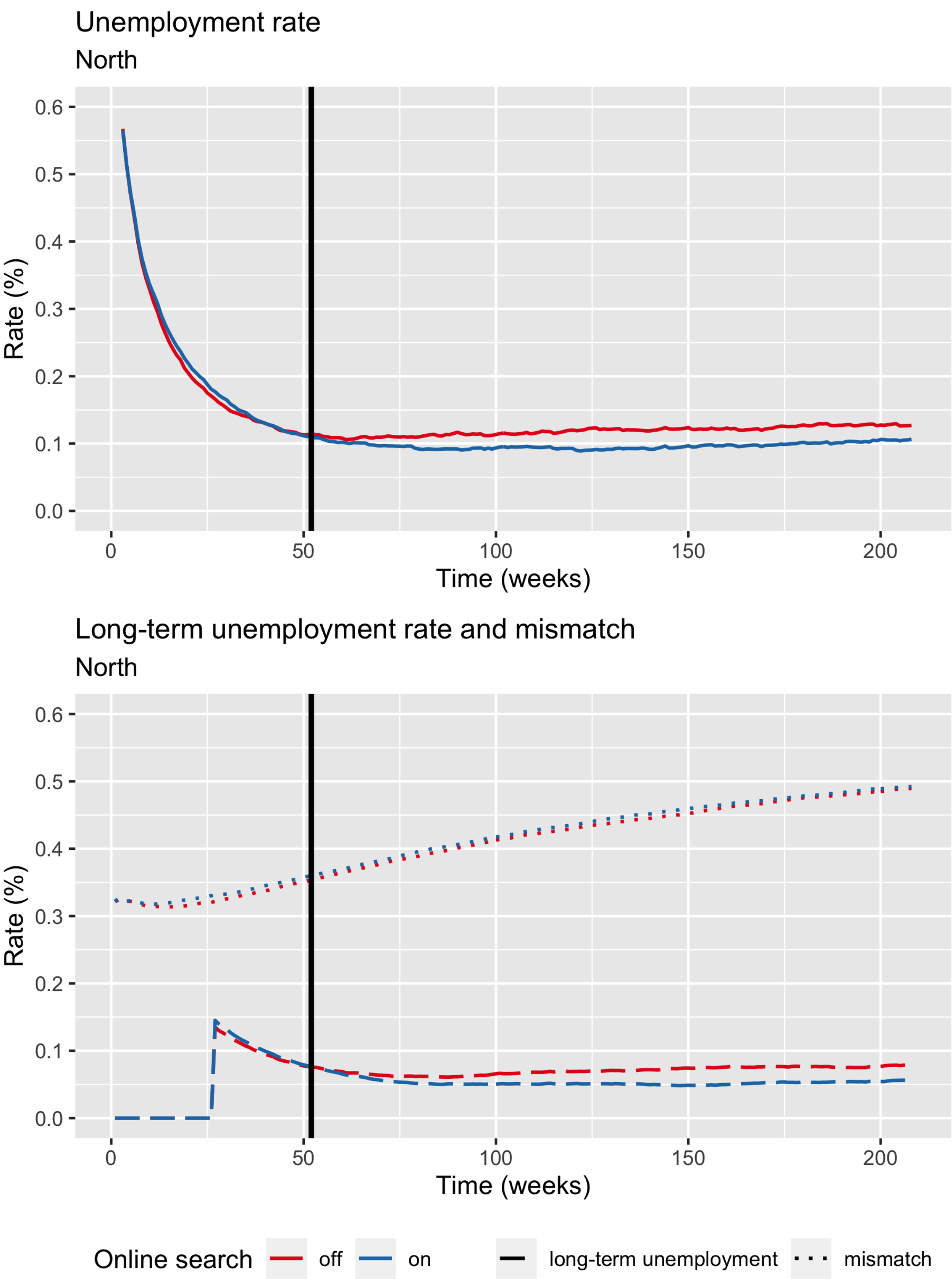

Figure 6: Time series graph of main macroeconomic indicators for the North parameter setting. The lines represent the weekly average value of 50 simulations.

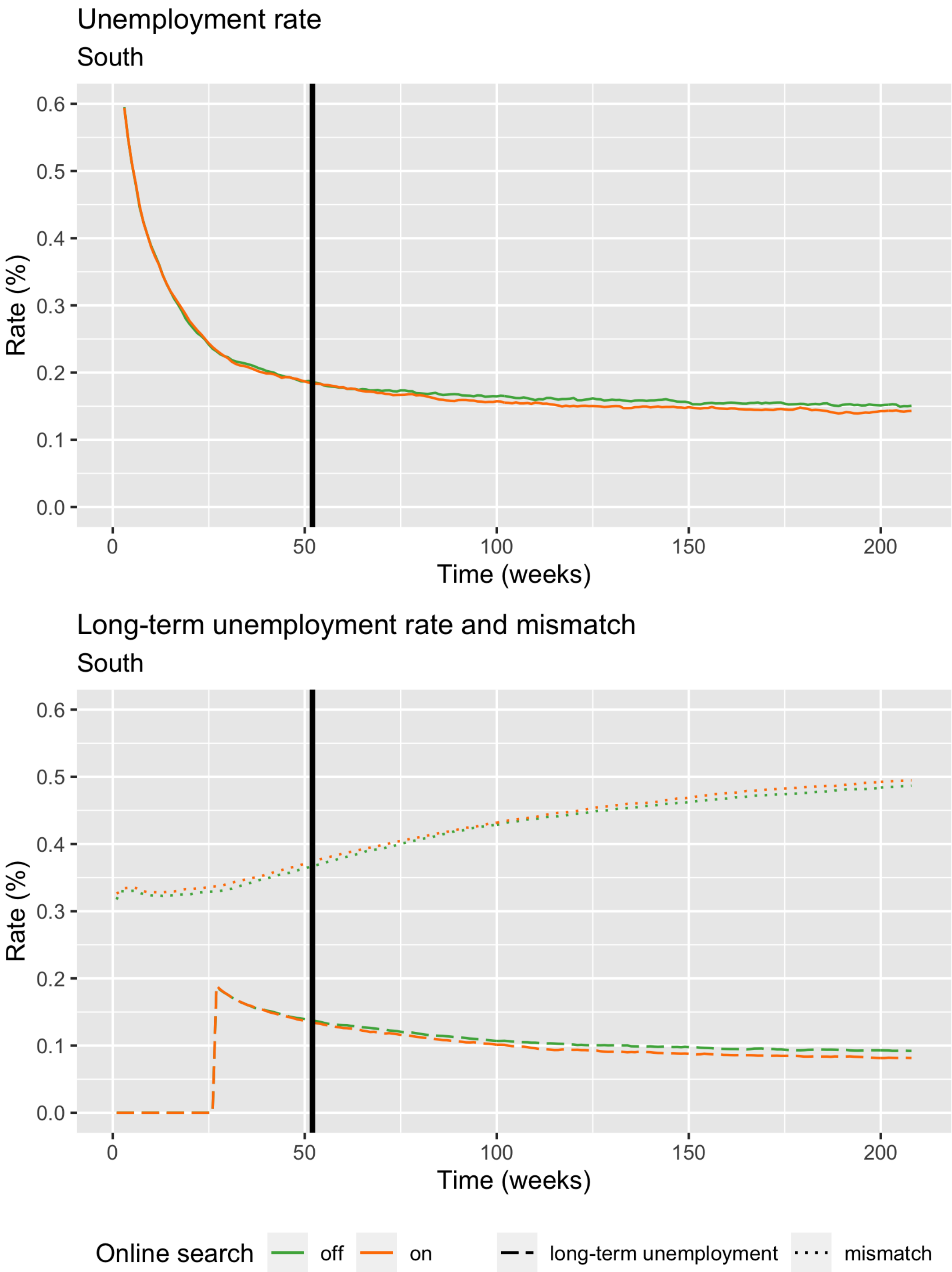

Figure 7: Time series graph of main macroeconomic indicators for the South parameter setting. The lines represent the weekly average value of 50 simulations.

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