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Abstract: We analyse the existence and underlying mechanisms of neighbourhood effects in welfare-to-work transitions. The analysis is based on Luxembourg social security longitudinal data, which covers the period 2001–2015 and provides precise information at the postcode level, corresponding mostly to streets. Our identification strategy exploits plausible exogenous variations among neighbours provided by the thinness of the housing market once controlling for residential sorting. We first examine interactions among all neighbours using an individual-level analysis, before focusing on interactions among only welfare recipients using a matched-pair analysis. This second step allows us to deal with the mediating effect of welfare recipients' citizenship. The main findings highlight the existence of neighbourhood effects in welfare-to-work transitions, which are also affected by the characteristics of the neighbours, including their citizenship. These characteristics suggest that social norms and/or stigma prevail in welfare-to-work transitions over the support for welfare recipients to find a job, but not over the in-group support for welfare recipients. The matched-pair analysis provides contrasting results across citizenship for individuals from large-sized citizenship groups (interactions within the own group) and individuals from medium-sized groups (interactions between groups).

Keywords: welfare-to-work transitions, neighbourhood effects, diversity, block-level data

JEL classification: H53; I32; J21; J60; R23

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1. Introduction

Empirical literature focusing on participation in social assistance programmes has to deal with a puzzling fact: a non-negligible proportion of individuals eligible for assistance do not claim welfare benefits (Moffitt, 1983; Currie, 2006; Finkelstein and Notowidigdo, 2019). Robust evidence suggests that the decision to apply for welfare is not exclusively linked to individuals' characteristics and to economic incentives. Informational spillovers and norms (through stigma, social approval or peer pressure) have been addressed as important determinants of take-up decisions (Aizer and Currie, 2004; Cohen-Cole and Zanella, 2008a, 2008b). Recent empirical evidence also suggests that the extent and quality of social relations among peers and neighbours play a key role in the likelihood to *receive* social assistance (Figlio *et al*., 2015; Grossman and Khalil, 2020) and are likely to subsequently affect the long-term equilibrium in the take-up rate (Dahl *et al.*, 2014).

Welfare recipients' living environment may also affect *transitions out of social assistance* – a topic that has not been extensively studied and which is the focus of the current paper. Several mechanisms may explain the varying patterns of welfare-to-work transition observed for otherwise identical individuals. First, welfare recipients may imitate the behaviour of successful neighbours who have found work (their peers), leading to a correlation between the place of residence and the place of work (Bayer *et al.*, 2008). Second, neighbours may transmit information about vacancies through the so-called informal job-search approach (Ioannides and Loury, 2004) or may directly refer candidates to employers (Montgomery, 1991). Lastly, other mechanisms may be at play, driven by social norms (Kandori, 1992), stigma (Moffitt, 1983) or the perceived ethnic distribution of local welfare recipients (Alesina *et al.*, 1999; Luttmer, 2001; Alesina *et al.*, 2019).

The challenges related to the identification of neighbourhood effects are well known. For example, the reflection problem makes it difficult to distinguish between social effects and correlated effects (see e.g. Manski, 1993, 2000). We tackle these challenges by exploiting the longitudinal nature of our data, as well as its very fine geographical granularity. The latter allows us to assume (and test on observable characteristics) that variations among neighbours within very small areas are almost randomly distributed because of the thinness of the housing market, once we control for

endogenous residential sorting. To our knowledge, the current paper is one of the first to use this identification strategy—inspired by Bayer, Ross and Topa (2008)—which allows us to provide plausible causal estimates of neighbourhood effects on welfare-to-work transitions.

Based on this identification strategy, our analysis of neighbourhood effects follows two approaches. In the first, we focus on the effects of the *average behaviour* and *average characteristics* of *all* close neighbours on individual welfare-to-work transitions. The analysis of the average behaviour of the neighbours in terms of welfare-to-work transitions provides a first insight into peer effects. Further, the focus on specifically chosen average characteristics allows us to make a distinction between two mechanisms likely to sustain welfare-to-work transition: stigmatization/social norms and informal job search/referral. In addition, it allows us to deal with the potential impact of diversity and so-called racial group loyalty, which suggests that support for welfare increases when members of the own group are locally overrepresented among welfare recipients (Luttmer, 2001).[1] This effect is likely to drive in-group welfare support and shape social norms in a way that would negatively affect welfare-to-work transitions. Deepening our knowledge about the underlying mechanisms of neighbourhood effects among all neighbours in welfare-to-work transitions is the first main contribution of this paper.

In a second approach, we focus solely on pairs of individuals moving out of welfare and into the labour market. This offers a further opportunity to deal with peer effects and to tease out the potential mediating effect of the pairs' citizenship. We address the following questions: (1) How likely is a social assistance beneficiary to move into the labour market if another beneficiary living among the ten closest postcodes has previously made such a transition? (2) Does this likelihood vary according to the citizenship shared or not by the matched beneficiaries? The peculiar composition of Luxembourg resident population—the large proportion of immigrants (since 2012, the median neighbour is foreign born) and the overrepresentation of large-sized groups of migrants among welfare recipients—combined with the small size of the country makes it possible to refine the analysis of neighbourhood effects. This analysis of the mediating

[1] We adopt an alternative strategy to Luttmer (2001) to analyse racial group loyalty in a small-country-size context (see section 5).

effect of the citizenship of individuals moving from welfare into the labour market will constitute our second contribution.

We address the estimation of neighbourhood effects on welfare-to-work transitions by focusing on Luxembourg and its main social assistance scheme from 1986 to 2018: the *Revenu Minimum Garanti* (RMG). The RMG is characterised by a high level of benefits, which reduce the financial gain to work (see OECD, 2012). To counteract this potential work disincentive effect the scheme also contains an activation component to support integration in the labour market. However, only around 10% of the beneficiaries are directed toward the activation scheme (see STATEC, 2012). We use Luxembourg social security longitudinal data, which includes annual information about the resident Luxembourg population from 2001 to 2015. This dataset makes it possible to work at the postcode level, which in the case of Luxembourg corresponds mostly to streets. On average, postcodes comprise 60 households. Our first main finding highlights the existence of neighbourhood effects in welfare-to-work transitions, in both the individual-level and the matched-pair analyses. The second main finding is related to the competing mechanisms underlying welfare-to-work transitions: the analysis of the neighbours' characteristics, including their citizenship, suggests the prevalence of social norms and/or stigma about informal job information sharing, and the remaining impact of diversity and in-group support for welfare recipients when dealing with other parameters of interest. In addition, the third main finding, stemming from the matched pairs of welfare recipients, lies in the contrasting results obtained by citizenship: pairs belonging to large-sized citizenship groups (Luxembourg natives and Portuguese) exhibit some form of homophily,[2] while we find some complementarity between citizens for pairs from medium-sized citizenship groups. For example, the welfare-to-work transition of an individual from another EU-15 country increases the probability of a similar transition for a non-native Luxembourg citizen.

The paper is organised as follows. Section 2 provides a brief literature review of neighbourhood effects on welfare-to-work transitions, while Section 3 describes the RMG scheme and related research. In Section 4, we present the data and descriptive

[2] The homophily concept predicts that people are more likely to interact with individuals sharing similar demographic characteristics, including their citizenship (see McPherson *et al.*, 2001).

statistics and in Section 5 the methods. Section 6 provides the results and Section 7 concludes.

2. Neighbourhood effects on moving out of social assistance: a review

Our paper touches on several strands of literature that we review here. We start by summarizing previous knowledge regarding neighbourhood effects in welfare-to-work transitions. We then give an overview of the general literature on the identification of neighbourhood and network effects. Lastly, we review the literature on the distinct characteristics and use of networks by low-skilled workers and foreigners to access the labour market.

Neighbourhood effects on the transition from social assistance towards the labour market

Literature on social assistance dynamics to date has focused mainly on individual and household socio-economic determinants of welfare transitions (e.g. Cappellari and Jenkins, 2014), on the effect of local labour market variables (Hoynes, 2000) that may support interactions among close or less-close neighbours, or on the evaluation of welfare-to-work programmes on reducing welfare dependence (Huber *et al.*, 2010). Neighbourhood effects on welfare-to-work transitions have been less studied, with the notable exceptions of van der Klaauw and van Ours (2003), and Mood (2010). Using Rotterdam administrative data, van der Klaauw and van Ours (2003) find a negative relationship between the local unemployment rate and welfare-to-work transitions. However, this effect was only found for young and for Dutch welfare recipients. In other words, the composition of the neighbourhood in terms of employment characteristics, as well as demographic variables such as age and citizenship, is an important determinant of welfare-to-work transitions. In addition, van der Klaauw and van Ours (2003) find that their results were not driven by selection effects captured in their settings by housing price. In another study, Mood (2010), using Stockholm data for the 1990s, find that the lagged proportion of beneficiaries in the local area affect the inflow and outflow of welfare recipients.

To our knowledge, no paper to date has attempted to uncover different sets of mechanisms underlying welfare-to-work transitions. Furthermore, the potential impact of the characteristics of neighbours as a mediator of peer effects in welfare-to-work transitions remains unknown. The large proportion of migrants in our case study offers

a specific opportunity to examine this. Furthermore, by focusing on a full country rather than a capital city, we can reduce potential issues related to sample selection, accordingly increasing the external validity of our results.

Identification of neighbourhood and network effects

The identification of the impact of neighbourhood effects is complicated by various elements such as omitted variables, the so-called reflection problem and the non-random sorting of individuals into neighbourhoods (Durlauf, 2004; Ioannides and Topa, 2010). The reflection problem refers to the difficulty of distinguishing between social effects (an individual's decision depends on other individuals' decisions) and correlated effects (neighbours may act in the same way because they share similar characteristics, including the same environment) (see Manski, 1993, 2000).

Two main strategies have previously been used to assess neighbourhood effects. The first is based on (quasi-)random experiments that require the existence of a social experiment where individuals are randomly assigned to an area (see Ludwig *et al.*, 2013 or Kling *et al.*, 2007 about the Moving to Opportunity experiment, and Åslund and Fredriksson, 2009 or Casciano and Massey, 2012 about welfare use and dependence). The limits of this approach are related to the difficulty of finding a fully exogenous setting and to generalizing the results; the external validity being questionable, as experiments are usually carried out in highly deprived areas. In addition, Chetty *et al.* (2016) recently highlighted that existing ties among neighbours are negatively affected by these reallocations, and that an extended time of exposure to new neighbours mediated by the movers' age is needed to counterbalance these losses. The second strategy, based on methodological and empirical modelling of neighbourhood interactions, has documented the existence of neighbourhood effects on welfare use (e.g. Aizer and Currie, 2004; Dahl *et al.*, 2014). The seminal paper by Bertrand *et al.* (2000) uses both residential area and language variation to assess the existence of network effects[3] on welfare use. These authors' results provide an important contribution by supporting the suggestion of varying network effects on welfare use by (language) group.

[3] In their case, network effects are social links between individuals within a neighbourhood. Those effects summarize quantity of contact (through density of language group) and quality of contact (through welfare use of a language group). Neighbourhood and networks effects are closely intertwined (Topa and Zenou, 2015).

An innovative way to identify neighbourhood effects is proposed by Bayer, Ross and Topa (2008). They take advantage of an assumed exogenous source of variation in neighbourhoods at very narrow level (blocks or groups of blocks), induced by the housing market, in order to analyse the effect of social interactions with neighbours. There are at least two factors supporting this exogeneity hypothesis: first, it would be difficult (for buyers or renters) to identify differences in neighbourhood characteristics area by area in a relatively short period of time; second, the housing opportunities within areas, if any, are likely to be restricted. This block-level source of exogenous variation, which requires the availability of finely granulated data, offers an alternative way to solve the non-random sorting of individuals. Grossmann and Khalil (2020) use this identification strategy to analyse the participation of women in Medicaid during pregnancy. They find that information plays a key role in reducing the gap between eligibility and participation in welfare programmes, especially in lower knowledge neighbourhoods. Accordingly, the researchers add to the previous findings of Bayer, Ross and Topa (2008), highlighting that people have a higher probability to work with other individuals living in the same block or group of blocks due to some information spillovers between them.

To the best of our knowledge, this identification strategy, that we will apply to our postcode level data, has not yet been used to study neighbourhood effects on exiting from social assistance, and this requires accounting for three additional elements. First, using and leaving social assistance may depend on the individual's environment, including the specific other individuals available to interact with.[4] One way to further deal with this aspect is to focus both on the whole set of neighbours and on pairs of people moving out of welfare. Second, the possible spatial self-segregation of long-term social assistance claimants, due for example to housing market conditions, need to be accounted for. The focus on transitions provides the opportunity to circumvent this issue, as long-term social assistance beneficiaries are under-represented in these transitions. Third, the transitions to the labour market that we will deal with may be subject to reverse causality for individuals moving to another area. We control for this issue by excluding observations related to recent moves likely to induce reverse causality.

[4] This idea is related to the concept of homophily, which refers to the homogeneity of personal networks (McPherson *et al.*, 2001). It is assumed to limit people's social worlds according to the information they receive (impacting on the cost of acquisition) and the attitudes they form (impacting on stigma).

Skills, citizenship, social ties and access to the labour market

Social ties are assumed to have an important impact on transitions within and into the labour market. A large proportion of jobs (from 30% to 60% in the US) are found through different types of ties (Ioannides and Loury, 2004), including those providing referrals to potential employers (Montgomery, 1991).[5] The effects of social ties on job matching are assumed to depend crucially on skill levels and on the degree of similarity in demographic characteristics between network members (Cappellari and Tatsiramos, 2015). With regard to the former, referral through social ties appears focused on the lower end of the skills distribution scale (Stupnytska *et al.*, 2015). Patacchini and Zenou (2012) provide further evidence that to find a job, migrants rely highly on the origin-community network in the destination country when this network is spatially clustered, while Munshi (2003) shows that the size of the origin-community network in the destination country improves the labour outcomes of migrants.

Focusing more precisely on the neighbouring areas, Patacchini and Zenou (2012) note that the probability of finding a job through social contacts is positively correlated with the percentage of a given ethnic group living nearby. This result appears related to the assumed lower cost of linking with individuals from the same community, while the cost of forming a relationship with individuals from other communities is expected to decrease in line with increased exposure to these communities. Using a theoretical network-formation model, de Marti and Zenou (2017) show however that inter-community networks can prevail over strong segregation patterns for different equilibrium configurations, including when the intra-community costs are low and the inter-community costs high.[6]

3. Luxembourg Social Assistance Scheme

The Luxembourg minimum guaranteed income (*Revenu Minimum Garanti* or RMG) is the main social assistance programme in Luxembourg (see Amétépé, 2012; Fusco *et al.*, 2014; Loutsch and Berger, 2019). It was introduced in 1986 and reformatted in 1999,

[5] In the Montgomery model (1991), it appears optimal for employers to hire workers through referrals from their most productive existing employees, as the latter are more likely to know others with high (unobserved) productivity.
[6] In their model, direct access to parts of the network may be conditioned by costly inter-community links.

with substantial changes to the eligibility criteria of age, residence and resources. Within the RMG scheme, applicants can be entitled to a monetary allowance (the complementary allowance), but may also benefit from an activation measure (paid at the minimum wage) to support their integration in the labour market (see Girardi *et al.*, 2019). The complementary allowance can also be paid as a top-up in the event the integration allowance from the activation measure is insufficient for a household to reach the minimum guaranteed income threshold. The focus of the current paper is on the complementary allowance, although the potential influence of the activation measure on the transition from receiving the complementary allowance into the labour market is taken into account in a robustness check.

The complementary allowance is administered by the *Fonds National de Solidarité* (FNS) within the Ministry of Family and Integration, and can be paid without a time limit as long as the criteria of eligibility are met. In particular, applicants are supposed to have exhausted all other forms of support foreseen by the regulations, must not have resigned or have been fired due to serious misconduct in their previous work activity, and must meet the eligibility requirements in terms of age, residence and resources. It is useful to keep in mind that these eligibility criteria have been stable since 2001 and thus throughout the period covered by our data (2001–2015).[7] Finally, the design of the scheme imposes a marginal tax rate of 100% on the poorer – each Euro earned is deduced from the RMG – are likely to reduce work incentives despite the presence of the activation component (OECD, 2012; Fusco *et al*, 2021).[8] This may affect how people interact with their neighbours and peers when they are likely to transit out of social assistance.

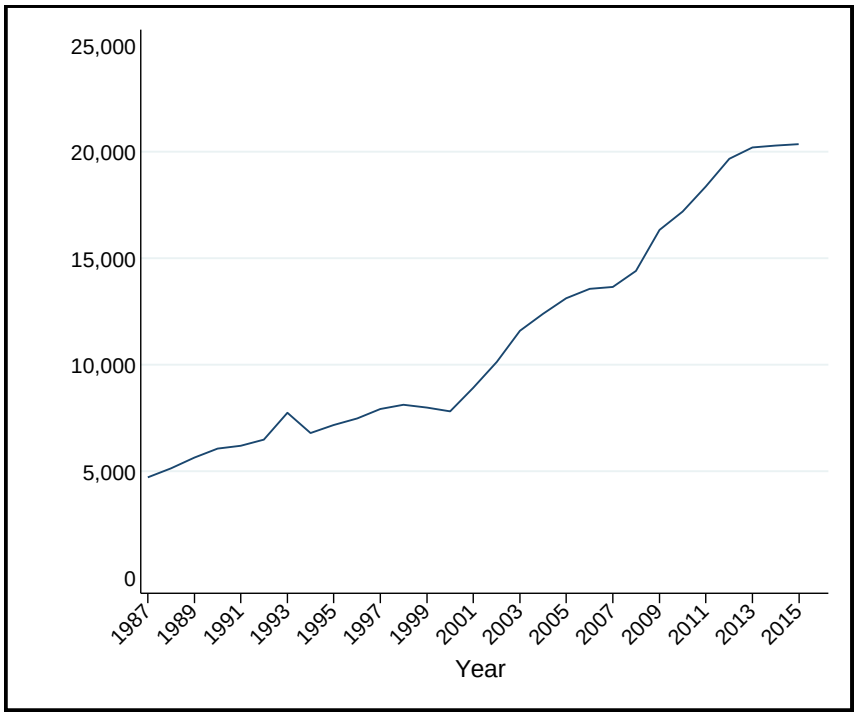
Figure 1 illustrates the number of RMG beneficiaries (individuals and households) since 1987. The changes in eligibility rules before 2001 led to an increase in the eligible population that, coupled with the difficult macroeconomic environment of the 2000s, can explain the rise in the number of beneficiaries up to 2005. A second increase occurred between 2008 and 2011, followed by a stabilization. The proportion of RMG

[7] Individuals must be at least 25 to be eligible to the RMG. Since 2001, nationals from Luxembourg, the European Union and the European Economic Area, as well as refugees and stateless people, are no longer subject to a residence length condition, while other residents must have resided in the country for at least 5 years.

[8] The RMG was replaced in 2019 by the REVIS (*Revenu d'Inclusion Sociale)*. One of the aim of the REVIS was specifically to correct this feature and reduce the effective marginal tax rate.

beneficiaries in the total population increased regularly from 2.3% to around 4% during the period 2001–2011 and then remained at this level until 2015.

Figure 1: Number of RMG beneficiaries (1987–2015)



Source: Authors' Figure based on IGSS official data: https://igss.gouvernement.lu/fr/statistiques/inclusion-sociale/serie-statistique.html

On the basis of the FNS monthly records, Königs (2012, 2018) and Immervoll *et al.* (2015) analyse the dynamics of the RMG receipts for the years 2001–2009. Königs (2012) finds a high level of persistence in RMG (38% of welfare recipiency lasts for more than 2 years) while recurrence is low (85% of individuals have no more than two spells of claiming benefit during the period). These results are similar to those from the Netherlands, but contrast with those for Norway and Sweden, where long term benefit receipt is an exception but recidivism is frequent.

The social security administration and the National Statistical Office provide some portraits of the population of beneficiaries through official statistics. According to STATEC (2012), more than half of the RMG households comprised a single adult (56%) in 2001, while the other most-represented household types were single parents (18%) and couples with or without children (16%) (see also Loutsch and Berger, 2019). The distribution of beneficiaries by nationality has evolved over time. According to Loutsch and Berger (2019), as a result of the changes in the residence eligibility criterion, the proportion of non-Luxembourgers among RMG beneficiaries increased from 21% in 1990 to 38% in 2000, 59% in 2010 and 66% in 2017 (See STATEC, 2012, for a similar

trend for the entire adult population). The latter trend makes the Luxembourg case relevant for studying the potential role played by citizenship in welfare-to-work transitions.

4. Data and definitions

We use a set of register micro-data for Luxembourg, called SPAFIL (Social Policy Analysis File on Income in Luxembourg) maintained by the General Inspectorate for Social Security (IGSS, *Inspection Générale de la Sécurité Sociale*). The dataset is created from administrative social security records and since 2001 has annually covered the whole population linked, at a given time of the calendar year, to the national system of social protection.

The dataset thus pertains to the resident population in Luxembourg during the period 2001–2015. Individuals can be linked together by a household identifier, but the household unit refers to the fiscal household and not the standard 'resident household' that takes into account members of a household living together.[9] The dataset contains information on all the income sources available to individuals registered to social security (capital income, rental income and private transfers between households are excluded). Socio-demographic or labour market characteristics are also included in the data. Time-varying characteristics are measured on 31 December of each year. The individual variables we use include age, gender, marital status, nationality (current and at birth), occupational status and professional experience. The household variables include the number of children and the total household income. Our raw data contains information for 697,201 individuals, which amounts to 7,295,504 observations (see Table A1 in the appendix).

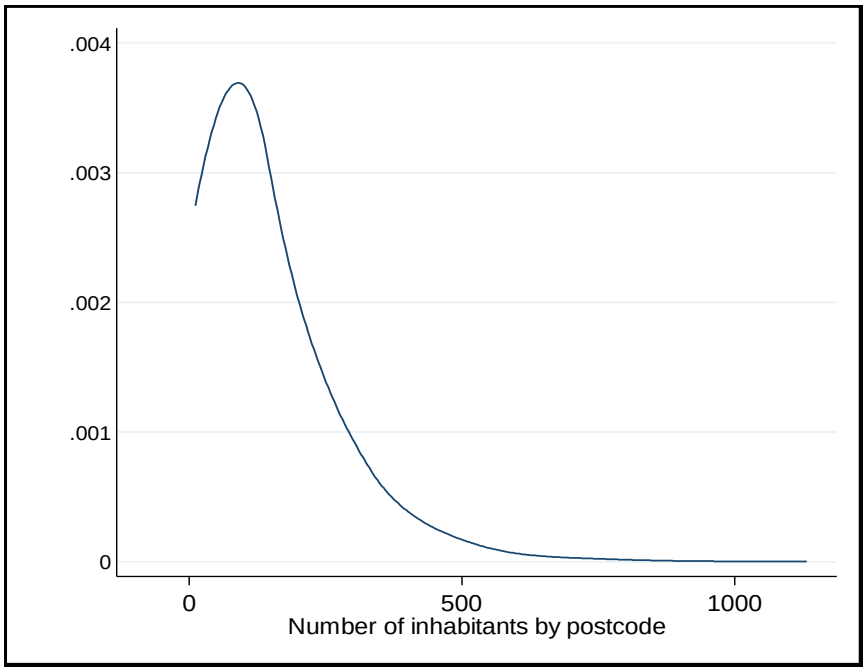
The first key variable extracted from the FNS database indicates whether an individual belongs to a household that received the RMG during the year. If so, this leads us to attribute the RMG status to all the members of a household and accordingly provides a way to control for potential spillover effects among households. In order to not violate the Stable Unit Treatment Value Assumption (SUTVA) hypothesis (Rubin,

[9] Fiscal units comprise individuals who are married or in a formal partnership, and children for whom the adults receive family allowances. Two individuals forming a couple without a formal relationship constitute two households. This is a drawback of the dataset; however, to our knowledge it provides the best available data to analyse transitions in and out of social assistance in Luxembourg. We carry out a robustness check for married individuals only, to rule out those concerns.

1980), which would harm causal inference,[10] we apply the same rule when building our main variable of interest (the welfare-to-work transitions variable): when a member of the household exits social assistance and moves into the labour market, every member of the household within the age range to do so is recorded as following this path.

The key feature of our data is that it provides precise information at a small-sized geographical unit: the postcode. There are approximately 4000 postcodes in Luxembourg, which vary in size and in the number of observations. To give a sense of our data, Figure 2 shows the distribution of the number of observations (and therefore neighbours) per postcode, as well as the number of households in 2001–2015. The number of individuals per postcode ranges from 1 to 1133, with an average of 120 and a median of 82, while at household level the average is 61 and the median is 41. It also appears that only 10% of the postcodes are populated by more than 279 inhabitants (145 households). The number of beneficiaries is naturally lower, owing to the small proportion of social assistance recipients (see previous section), with values ranging from 0 to 205, and with an average of five beneficiaries per postcode over the period. These numbers show that there are opportunities in most of the postcodes to interact with RMG beneficiaries.

Figure 2: Distribution of individuals by postcode (2001–2015)



Source: SPAFIL data, authors' computation.

[10] The SUTVA assumption assumes among other things that the treatment applied to one unit (one member of the household in our case) does not affect the outcome for another unit (other members of the household).

From the database, we can also derive information about the commune of residence in Luxembourg (106 communes) and the local labour market. The local labour market is considered as the spatial area in which residents are expected to find a jobs within a reasonable commuting distance or to switch jobs without having to change their place of residence (five local labour markets may be distinguished: for more details, see Walther and Dautel, 2010; Dautel and Walther, 2014).

Our first variable of interest is the average *behaviour* of the neighbours in the form of the proportion of welfare-to-work transitions. To deal further with the specificity of the direct environment that the individuals face, we focus on the *average characteristics* of the neighbours, their contact availability and their citizenship. We define these three sets of variables based on an individual's neighbours, excluding the individual and all the other household members.

To deal with the *characteristics* of the neighbours, we use four variables to make the distinction between two sets of mechanisms likely to sustain the welfare-to-work transition: (i) stigmatization/social norms and (ii) information spillovers regarding job vacancies:

1. Average household wages among the working-age population (25–55 years old).
2. Proportion of individuals with an employment contract among the working-age population (25–55 years old).
3. Proportion of elderly and disabled individuals among the full population.
4. Proportion of unemployed among the working-age population (25–55 years old).

We selected these indicators for the following reasons. Average household wages (variable 1) is a proxy for the documented importance of self-interest in support for redistribution (Meltzer and Richard, 1981) and then may support both mechanisms: on one hand, higher wage-earners may support welfare-to-work transitions via social norms/stigma effects; on the other hand, assuming that they have better access to employment, they can help welfare recipients to find a job, restricting as such welfare participation.

The proportion of individuals with a working contract (variable 2) and of elderly and disabled (variable 3) allow to distinguish among the two mechanisms. Related to the social norm and stigmatisation mechanism, the two variables focus on subpopulations highly likely (those with a working contract) or unlikely (elderly and disabled individuals) to access information on vacancies and then share it with other welfare recipients. Indeed, Topa (2001) shows that employed individuals are more likely than unemployed ones to transmit useful jobs information to their neighbours. However, a positive impact of the share of individuals with a working contract may also relate to a norm effect, if we assume following Jahn and Neugart (2020) that being employed is regarded as the social norm. In that case, unemployed individuals, including the RMG holders, might increase their employment search in areas with higher share of individuals employed to cope with the local norm.

Related to the information spillover mechanism, the share of elderly and disabled persons (variable 3) proxies as well the fact that older workers discriminate more (Falk and Zehnder, 2007) and then are more likely to follow stereotypes and social norms likely to affect the behaviour of RMG holders and then their transition out of welfare. The proportion of unemployed (fourth variable) is dedicated to follow van der Klaauw and van Ours (2003) in their analysis of welfare-to-work transitions.

Previous literature has shown that contact availability, that is potential contacts with other members of the group, may influence welfare use (Bertrand *et al.*, 2000), preferences regarding redistribution (Luttmer, 2001), the probability to find a job (Patacchini and Zenou 2012), and welfare-to-work transitions (Mood, 2010). Neighbours may either share the economic status of being on welfare or have the same citizenship, which will increase their likelihood to interact. We accordingly build the three following (sets of) control variables:

1. Proportion of RMG beneficiaries in the previous year among the postcode neighbours.
2. Proportion of citizens from the own group among the postcode neighbours.
3. Size of the neighbourhood based on the number of individuals in the postcode.

To deal more specifically with the citizenship of the neighbours, we compute the average number of RMG beneficiaries by citizenship and grouping of postcodes (Table

1), before building a diversity index. The latter is a decreasing transformation of the Herfindahl index, depicting the degree of similarity among individuals regarding their citizenship.[11] Focusing on the largest grouping of postcodes, the distribution of RMG beneficiaries by citizenship highlights the presence of large-sized groups (Luxembourg natives, Portuguese and non-Europeans), medium-sized groups (Luxembourg non-natives, French and other EU-15) and small-sized groups (Belgian, German and other EU-25). Finally, as the size of the neighbourhoods is unevenly distributed, we need to account for interaction opportunities. We therefore control for the number of individuals by postcode by introducing dummy variables for each quartiles of the distribution of neighbours by postcodes, the latter to capturing potential non linearities.

Table 1: Average number of RMG beneficiaries by citizenship and grouping of postcodes

Citizenship	Postcode level	Five closest postcodes	Ten closest postcodes
Lu native	9.3	21.9	36.2
Lu non-native	1.4	3.2	5.4
Portuguese	7.4	17.7	29.5
French	1.3	3.2	5.2
Belgian	0.5	1.1	1.9
German	0.4	1.0	1.7
Other EU-15	1.3	3.2	5.5
Other EU-25	0.2	0.3	0.6
Extra-EU	4.2	9.7	16.0

Source: SPAFIL data, authors' computation.

Two important comments should be made: first, two of the large-sized groups (Portuguese and non-European residents) are overrepresented among welfare recipients; second, interactions with RMG beneficiaries from other groups may be relevant for the RMG beneficiaries from medium-sizes groups, as this increases the restricted number of RMG beneficiaries to interact with. We will return to this point later on.

[11] The value of the Herfindahl index H is the sum of the squares of the c citizenship proportions s within postcode j ($H_{cj} = \sum_c s_{cj}^2$). This gives the probability of two randomly-drawn individuals belonging to the same group. The diversity index of area j is equal to $DIV_j = 1 - H_{cj}$. It takes value 0 if the population is totally homogenous, and increases towards 1 as heterogeneity increases.

5. Methods

Our main strategy for identification takes advantage of the very fine granularity of the data combined with the thinness of the housing market in order to derive an assumed exogenous source of variation with respect to the neighbours (see Bayer *et al*., 2008). In our data, the geographical units of reference are the local postcodes. Furthermore, to focus only on this source of variation (i.e. the neighbours) we exclude from our reference group individuals from the same household when building these variables.

The key to this identification strategy is the exploitation of the thinness of the housing market at a very local level. The distribution of the number of inhabitants at the postcode level is in line with this thinness (see previous section). More precisely, in accordance with Bayer *et al*. (2008), we assume that individuals are unable to follow an endogenous sorting strategy at this level. This would consist of first identifying the advantageous characteristics of the neighbours, and second being able to easily rent or buy in this location. Consequently, in line with this assumption, any correlation between the characteristics of the neighbours should disappear when conditioning on postcode fixed effects and time fixed effects. Table 2 provides evidence of this, by displaying the low correlation between the dependent variable and different observable characteristics of the individuals (e.g. nationality and age), while controlling for postcode and time fixed effects. To estimate these conditional correlations, we follow Hémet and Malgouyres (2018) by regressing the individual characteristics and then the average characteristics of their neighbours onto the year and spatial fixed effects and compute the residuals of both regressions. We then regress the first residual onto the second one, while still controlling for years and spatial fixed effects (i.e. city, postcode or group of post-code fixed effects), and report the resulting within R^2. The results provide evidence, among the observable variables taken into account, of the low remaining sorting at the highest level of analysis retained in this article to deal with interactions among neighbours, i.e. the ten closest postcodes. As suggested by Altonji et al (2005), given that the main potential sorting variables are taken into account and that the selection on unobservable variables is related to the one of observable variables, we assume as plausible, the assumption of low sorting among neighbours, once controlling for narrow fixed effects. Some empirical evidence regarding the Luxembourg housing market strongly supports this assumption. Indeed, according to the 2011 census, 49% of the individuals were living in the same housing unit 9 years earlier (Heinz *et al*., 2013), while the housing

market have shown a fast price rose over the 2010-2017 period (40%) (Observatoire de l'Habitat, 2019). Both suggests then the low availability of affordable housing units that could correspond to the specific needs of any potential buyer or renter.

Table 2: Test of endogenous sorting

Characteristics of the individual	Unconditional	City F.E.	Postcode F.E.	Ten closest Postcodes F.E.
Citizenship				
Lu native	0.553	0.007	0.028	0.055
Lu non-native	0.062	0.002	0.001	0.003
French	0.090	0.003	0.002	0.007
Belgian	0.069	0.010	0.007	0.010
German	0.028	0.009	0.000	0.001
Portuguese	0.310	0.002	0.026	0.059
Other EU-15	0.089	0.008	0.002	0.005
Other EU-25	0.019	0.001	0.002	0.003
Extra-EU	0.120	0.002	0.014	0.022
Age				
0–15	0.180	0.002	0.002	0.004
15–24	0.127	0.001	0.001	0.002
25–34	0.174	0.000	0.004	0.007
35–44	0.169	0.001	0.001	0.002
45–54	0.147	0.001	0.001	0.001
55--	0.105	0.003	0.001	0.001
65+	0.176	0.004	0.021	0.033
Other characteristics				
Single	0.445	0.003	0.002	0.004
No. of children	0.461	0.013	0.007	0.015
Gender	0.503	0.003	0.001	0.002
Wage earner	0.407	0.001	0.004	0.007
Unemployed	0.023	0.000	0.000	0.001
Elderly/disabled person	0.140	0.006	0.004	0.007
RMG beneficiary	0.107	0.003	0.009	0.020

Source: SPAFIL data, authors' computation.
Note: To test for endogenous sorting according to observed characteristics, we regress one by one the individual characteristics over the characteristics of the neighbour, controlling for time and local fixed effects. Beta coefficients of these conditional regressions are reported.

Moreover, the thinness of the data provides the opportunity to deal with standard issues in the identification of neighbouring effects as aggregated shock to a person's own group, or correlated effects due to common unobservables affecting the group as a whole, as these groups are assumed to spread out over larger areas. Economic shocks that may affect labour market opportunities of RMG holders are also ruled out by our setting. We carry out two falsification tests to show that common unobservables are not driving a peer effect among the RMG beneficiaries, those being more likely among neighbours to face this issue, as they share more-similar traits.

Two elements remain to be handled with the application of this identification strategy: the reflection problem and the potential reverse causality. One way to address the reflection problem, corresponding to a simultaneity issue given that everyone affect the others, is to split people likely to interact into two groups according to two different periods, for example $t\text{-}1$ or $t\text{-}2$, and t. This offers the opportunity to distinguish among the potential peers moving during a given period ($t\text{-}1$ or $t\text{-}2$) and potential followers likely to do so thereafter (t). Reverse causality may also apply to moving out of RMG, as individuals making a welfare-to-work transition may, during the same period or the previous one, have moved to another area fostering network effects and employment opportunities, and therefore triggering the welfare-to-work transition. Not controlling for these changes of residence could result in overestimating the network effects in our case. We deal with this issue by taking advantage of the longitudinal dimension of our dataset, which includes the location of the individuals' residence. We exclude from the analysis observations for individuals whose postcode in t is different to their postcode in $t\text{-}1$. This amounts to 7.7% of individuals.

Based on this setup, we develop two main analyses to deal with neighbourhood effects: an individual-level analysis and a matched-pair analysis. While the former provides a way to check for potential interactions with the whole set of direct neighbours, the latter offers the opportunity to focus on interactions taking place among more-specific groups, such as RMG beneficiaries. In both cases, we focus on people moving from receiving the RMG into employment. Thus, the individual analysis models the probability for an individual $i = 1..I$ living in postcode $g = 1..G$ of being in work in the period t conditional on receiving the RMG in the period $t\text{-}1$. To simplify the writing, we present this transition as occurring in t.

Consider the following baseline model for the individual-level analysis of individual *i* and his or her *j* neighbours (excluding all other household members *h*) sharing a postcode *g* in *t*:

$$Y_{igt} = \alpha_i + \eta_1 \bar{Y}_{(-h)gt-1} + \eta_2 \bar{X}_{(-h)gt} + \eta_3 \bar{Z}_{(-h)gt} + \lambda_g + \lambda_t + \varepsilon_{igt} \qquad (1.a)$$

With λ_t as a time fixed effect λ_g as a postcode fixed effect

α_i as the individual fixed effect

$\bar{Y}_{(-h)gt-1}$ as the average proportion of exit from RMG into the labour market among the neighbours (excluding *h*) in *t-1*. The use of a lagged variable is aimed at avoiding the reflection problem.

$\bar{X}_{(-h)gt}$ corresponding to the four variables describing the average characteristics of the neighbours (excluding *h*)

$\bar{Z}_{(-h)gt}$ as the two variables proxying contact availability (excluding *h*)

$Y_{igt} = \Pr\left(Work_{ijt} \middle| RMG_{ijt-1} = 1\right)$ refers to an individual welfare-to-work transition. This variable takes the value of 1 if an individual *i*=1..*I*, living in area *g*=1..*G* at time *t* = 1 ..*T* transits from welfare to work and 0 otherwise.

For the matched-pair analysis of individual *i* and *j* living at time *t* in the same group of postcodes *g* but belonging to different households (*h(i)≠h(j)*), consider the following baseline model:

$$P_{ijgt=} \gamma^M R_{ijgt} + \lambda_g + \lambda_t + \epsilon_{ijgt} \qquad (2.a)$$

With R_{ijgt} as a binary variable equal to 1 if both individuals *i* and *j* reside in the same postcode, and 0 otherwise.

λ_g as a fixed effect at postcode group level

λ_t as a time fixed effect

P_{ijgt} as a binary variable equal to 1 (0 otherwise) if *i* and *j*, belonging to a given pair of RMG beneficiaries, transit into the labour market in respectively *t-1* and *t*

These two models focus on different parameters of interest. In model (1.a), the focus is on the potential impact of the exit of other RMG beneficiaries among the

neighbours into the labour market (η_1) and the characteristics of these individuals (η_2), while in model (2.a), these are the potential interactions among neighbours (γ^M), while not distinguishing the source of any such interaction.

In the next step, we extend these two baseline models to focus on additional parameters of interest. In the individual-level analysis, we include a diversity index (see model 1.b)—or the components of this index—with the proportion of individuals by citizenship that reflect (in our small country size setting) the racial group loyalty introduced by Luttmer (2001).[12] In the matched-pair analysis, we first extend the analysis at varying aggregate levels where interactions may take place (see model 2.b) and then introduce an interaction between these aggregate levels and a specific characteristic shared (or not) by the pair of individuals, such as their nationality (see model 2.c). Through this characteristic, the second extension allows us to distinguish between the source and destination of the interaction.

$$Y_{igt} = \alpha_i + \delta_1 DIV_{(-h)gt} + \eta_1 \bar{Y}_{(-h)gt-1} + \eta_2 \bar{X}_{(-h)gt} + \eta_3 \bar{Z}_{(-h)gt} + \lambda_g + \lambda_t + \varepsilon_{igt} \quad (1.b)$$

With $DIV_{(-h)gt}$ as the diversity index with respect to the citizenship of the neighbours (excluding h), computed as the decreasing transformation of the Herfindahl index. To compute this index, the following citizenships are considered: Luxembourg native, Luxembourg non-native, Portuguese, French, Belgian, German, citizens from other EU-15 countries,13 citizens from other EU-2514 countries and citizens from other countries. The other variables are as defined before.

$$P_{ijgt=} \gamma^M R_{ijgt} + \lambda_g + \lambda_t + \epsilon_{ijgt} \quad (2.b)$$

With g=5 or 10, the number of postcodes grouped together. The other variables are as defined before.

[12] We hypothesize that the ranking of the proportion of welfare recipients by citizenship does not vary much by location due to the small size of the country. To check this assumption, different analyses were carried out (results available on request). This statement offers the opportunity to deal with racial group loyalties by focusing on the potential impact of the proportion of a given citizenship among neighbours for some citizenships overrepresented among welfare recipients at the country level.

[13] This group includes other EU-15 citizens not already covered by other groups (i.e. Lu, Pt, Fr, Be, De).

[14] This group includes other EU-25 citizens not already covered by other groups (i.e. Lu, Pt, Fr, Be, De, Other EU-15).

$$P_{ijgt=}\ \gamma_0^M\ R_{ijgt} + \gamma_1^M\ R_{ijgt} * X_{ijgt} + \alpha X_{ijgt}\ +\ \lambda_g +\ \lambda_t + \epsilon_{ijgt} \qquad (2.c)$$

With X a specific characteristic of the individuals, for example their citizenship. The other variables are as defined before.

It should be noted that the proportion of RMG beneficiaries is relatively low in our dataset (around 4%), so that many postcodes do not include any welfare recipients in t (1112 out of 3752). We therefore restrict our estimation sample of models 1[15] and 2[16] to specific postcodes in which RMG beneficiaries can be observed. Furthermore, due to the complex setup of both models, they are estimated using linear probability models.[17] Lastly, to control for correlation among unobserved components at the cluster level, we follow the recommendations of Abadie et al. (2017) and cluster the standard errors at the postcode level for the first model and at the postcodes group level for the second one; the spatial levels at which the treatment (peer effect among welfare recipients) takes place in each of these cases.

6. Empirical results

To present our main findings, we first focus on the potential interactions at the postcode level on welfare-to-work transitions using the individual-level analysis that takes into account all the neighbours, described in model 1 (Table 3a and Table 3b). We then restrict the analysis to RMG beneficiaries and proceed to the matched-pair analysis described in model 2 (see Table 4 to Table 7), to take into account the mediating effect of individuals' characteristics.

[15] We restrict model 1 to postcodes with at least one RMG recipient among the neighbours in *t*. The number of observations goes from 6,697,076 to 2,314,073.

[16] We restrict model 2 to postcodes with at least one RMG recipient among the neighbours in the peer group in *t-1* and *t*. The number of observations goes from 10,188,715 to 4,150,982 for the grouping by the five closest postcodes, and from 17,264,147 to 6,529,402 for the grouping by the ten closest postcodes. The unit of observation in model 2 is a single pair of RMG beneficiaries (*i*, *j*) belonging to the same grouping of postcodes in *t*. The number of observations corresponds to all the pairs that can be formed. We further restrict model 2.c to at least one RMG recipient from citizenship C among the neighbours in the peer group in *t-1* or *t*, and at least one RMG recipient from citizenship C among the neighbours in the non-peer group in *t-1* or *t*.

[17] As robustness checks, simplified versions of both models (not controlling for endogenous sorting) were estimated using logit. The results are similar using both types of specification (sign of the estimate, significance level and size of the marginal effect).

6.1. Individual-level analysis

The effect of neighbours' behaviour and characteristics

We begin the individual analysis (model 1.a) by investigating whether social interactions lead individuals to follow the behaviour of their neighbours with respect to exit from the RMG (Table 3a). Estimations 1 and 2 focus on peers' transition behaviour in t_{-1} and t_{-2} (in column 1 and 2). They provide naive estimates by only controlling for potential aggregated shocks that may affect employment opportunities with local labour market fixed effects. As such they allow for the endogenous sorting of the individuals while not controlling for individual fixed effects. These two elements are controlled for in estimation 3 and 4 by conditioning on postcode fixed effects and individual fixed effects. The results highlight a similar positive and significant effect for both lagged and double lagged peers' transitions, when controlling or not for sorting and fixed effects. An increase of 1 percentage point (pp) in the transition to the labour market among the neighbours leads to an increase in individuals' transition of between 0.051 and 0.137 pp (column 1 to 4), therefore suggesting a peer effect among welfare recipients within the same postcode. Moreover, the lagged and double lagged peers' transitions lead to very similar effect when applying the two controls (0.135 and 0.137), while downward biased estimate could have been assumed in these cases. From here on, all the results related to this model apply these two controls. Furthermore, all the results presented in this section deal with reverse causality, as highlighted in the previous section.

In the second step, we examine the impact of the neighbours' characteristics on the transition of welfare recipients into the labour market. The almost random remaining variations, once controlling for postcode fixed effects, appear to significantly affect the extent of the transitions (see column 5). While the proportion of people with an employment contract among the working-age population in the neighbourhood negatively influences the transitions[18], the average household wages among the working-age population and the proportion of elderly and disabled workers among the full population increase the likelihood of transitions. The direction of these effects suggests that the social norms and/or the stigma effects prevail over the support of welfare

[18] The negative sign does not imply that social ties with people employed do not generate employment opportunities. The dependent variable is here more specific, i.e. welfare-to-work transitions and the Luxembourg social assistance scheme generates low monetary incentives to transit to the labour market for low skilled workers.

recipients to find a job.[19] The statistically significant and positive sign of the first variable related to cumulated wages at the household level, suggesting that higher income among the neighbours affect the transition out of welfare is in accordance with previous literature assuming the importance of self-interest in support for redistribution. However, as mentioned earlier, it does not provide clear insights regarding the mechanism involved i.e. social norms and/or the stigma effects vs support of welfare recipients to find a job.

The effect of the two other variables are clearer in that respect. Indeed, whereas a positive sign could be expected concerning the proportion of people with an employment contract (as they might transmit useful information regarding job vacancies[20]) a negative effect is actually observed. In addition, despite the fact that elderly and disabled people are unlikely to help welfare recipients find a job, thus suggesting a non-positive effect of this variable, a positive effect is observed. The latter result is however in line with previous literature assuming that older people discriminate more (e.g. Falk and Zehnder, 2007) suggesting that they are more likely to follow stereotypes and then social norms. For the remaining variable related to unemployment among the neighbours, the negative result is in line with the findings of van der Klaauw and van Ours (2003). However, the point estimate is non-significant in our case once we control for individual fixed effects, as we do in our baseline estimation. To strengthen these results, we control for both the average behaviour of the neighbours in *t-1* and the proportion of RMG beneficiaries among neighbours, also in *t-1*, which has been reported to impact negatively on welfare-to-work transitions (see Mood, 2010). The results remain relatively stable in comparison with previous estimates (see Column 6), while the latter variable appears as significant.

[19] Social norms and stigma are difficult to distinguish in our case. In line with Durlauf and Blum (2018), stigmatized individuals may be defined as individuals holding characteristics that devalue them in the eyes of others; for example being a welfare recipient induces status loss or discrimination. To avoid suffering from these issues, people may then act so as not to be perceived as a welfare recipient, or to move out of welfare, or to never move into it. In the same way, the global/local social norm may also impact on the behaviour of an individual wishing to conform to the dominant practice, which could stem from fairness and in-group reciprocity.

[20] Such a hypothesis is in line with Topa's (2001) empirical evidence, showing that neighbours are more likely to provide useful information regarding job opportunities if they are themselves employed.

Table 3a: Interaction among neighbours sharing a postcode

	Dependent variable: welfare-to-work transitions					
	(1)	(2)	(3)	(4)	(5)	(6)
$\bar{y}_{t-1}$	0.051**		0.135***			0.161***
	(0.020)		(0.026)			(0.029)
$\bar{y}_{t-2}$		0.080***		0.137***		
		(0.021)		(0.025)		
Contact availability among Neighbours (N.)						
% of citizens from own group						-0.018**
						(0.009)
% of RMG beneficiaries among N. in *t-1*	-0.006***	-0.006***	0.004	0.004	0.004	0.003
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Size of the neighborhood	inc.	inc.	inc.	inc.	inc.	inc.
Other average characteristics among N.						
$\bar{x}_{1,t}$ among N.					0.007***	0.007***
					(0.001)	(0.002)
$\bar{x}_{2,t}$ among N.					-0.042***	-0.045***
					(0.010)	(0.012)
$\bar{x}_{3,t}$ among N.					0.034***	0.034***
					(0.011)	(0.013)
$\bar{x}_{4,t}$ among N.					0.007	0.000
					(0.024)	(0.026)
Postcodes F.E.			inc.	inc.	inc.	inc.
Char. of individual i	inc.	inc.				
Local labour market F.E.	inc.	inc.				
Year F.E.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	0.024***	0.026***	0.006***	0.006***	0.095***	0.058***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.026)	(0.022)
Observations	1,581,072	1,446,867	1,557,247	1,423,420	1,621,658	1,466,249
R^2	0.013	0.013	0.287	0.295	0.278	0.288

Source: SPAFIL data, authors' computation.

$\bar{x}_{1,t}$: average accumulated wages of the household among the working-age population (25–55 years old),

$\bar{x}_{2,t}$: proportion of individuals with an employment contract among the working-age population (25-–55 years old)

$\bar{x}_{3,t}$: proportion of elderly and disabled individuals among the full population,

$\bar{x}_{4,t}$: proportion of jobless individuals among the working-age population (25–55 years old)

Characteristics of individual i include age, gender, number of children, income and years of experience on the national labour market. Size of the neighbourhood corresponds to dummies variables related to the quartiles of the distribution of the number of neighbours by postcodes.

*Standard errors in brackets are clustered at the postcode level. ***, **, * indicate significance at the 1, 5 or 10% level.*

The negative impact of the share of RMG beneficiaries in *t-1* may be related to the assumption that an higher share of (local) people receiving welfare benefits decrease the (local) social norm to live off one's work as suggested by Lindbeck *et al.* (1999). As such, it strengthens our previous evidence suggesting that welfare-to-work transitions are driven by social norms and/or the stigma effects.

The effect of diversity

To examine further the influence of the neighbours' characteristics (model 1.b), we focus on their citizenship (Table 3b). This has the potential to further deepen our understanding of how norms concerning redistribution are shaped at the neighbourhood level. Indeed, a growing body of literature, reviewed by Stichnoth and Van der Straeten (2013), focuses on the impact of (perceived) ethnic diversity on individuals' support for the welfare state; and therefore on support for transitions in and out of welfare across populations. A recent contribution from Alesina *et al.* (2019) highlights, for the European case, lower support for redistribution from natives in areas where the proportion of migrants is high. This result may be explained by the combination of the generosity of the welfare system, the skills of the foreigners and racial heterogeneity. In the context of the Luxembourg society, it appears more relevant to extend the analysis to the full population, as the median neighbour changed from being Luxembourg to foreign born before the end of the observation period.

We begin by computing a diversity index among the neighbours of each individual, based on all citizenships available and distinguishing between native and non-native Luxembourgers. The computation of this index at the very narrow level considered here provides the opportunity to control for the randomness of local diversity faced by individuals that is likely to mediate their attitudes regarding diversity.[24] The result highlights a negative impact of this diversity index (column 1) that holds if we compute the index by grouping the five closest postcodes (column 1b), but not by grouping the ten closest postcodes (column 1c).[25] In other words, the more diverse the direct social environment is, the less individuals are likely to exit from social assistance. Assuming that this result is driven by higher support for redistribution in more diverse areas, it contrasts with the well-known findings of Alesina *et al.* (1999). Alesina *et al.* (1999) take into account local-level population mitigating bias from omitted variables, and find a negative link between ethnic fractionalization and public expenditure. However, some recent contributions highlight that these findings are not robust to the use of a panel approach (e.g. Boustan, 2013) or the introduction of additional controls

[24] Previous literature highlights that migrants are attracted to specific countries/regions by, among other things, the generosity of the welfare system (see e.g. Boeri (2010) for the European case).

[25] We obtain a negative result for the diversity effect when focusing on the subgroup of postcodes with at least four RMG beneficiaries experiencing a transition. In this case, 3453 postcodes are covered against 3726 in the baseline model.

(Gisselquist, 2014).[26] The negative result in our case may be related to the unusual composition of the resident population, with the median neighbour being foreign born after 2011.

To go further, we then focus on the components of the index, by first comparing the impact of different groups of foreigners among neighbours using Luxembourgers as the baseline; and then by comparing the impact of native versus non-native Luxembourgers among neighbours, using the foreigners as the baseline. Among the foreigners, the proportions of two large-sized groups—the Portuguese and the non-Europeans, who are both overrepresented among welfare recipients (see Table 2, Appendix)—appear to impact negatively on moving out of RMG. The proportion of a relatively medium-sized group (the other EU-15) also negatively affects exiting from RMG. All of this suggests that the size of the different groups of foreigners plays a role in welfare-to-work transitions. On the one hand, the size of these groups combined with the hypothesis of racial group loyalty (Luttmer, 2001)—that is, that individuals increase their support for redistribution as the proportion of recipients from their own group rises—may support these results. On the other hand, the increasing opportunity to actively interact with peers from the own group by passing on information about vacancies (assumed to foster labour opportunities) in areas with large groups of foreigners may not explain these findings, as positive estimates would have been expected. However, we show above that interactions among neighbours may be driven more by social norms and stigma than by employment referral or information about job vacancies. Interactions with peers within these large groups (which are quite specific to our case study) will be examined hereafter through model 2. Focusing on the nationals (column 2)—only the native ones, corresponding to a substantially larger group than the non-natives—appears to positively affect exit from RMG in comparison with the foreigners. The latter results may suggest, in line with Hémet and Malgouyres (2018), that the culture of individuals possibly transmitted by the parents may overcome the citizenship effect.

[26] While a panel approach is applied in our baseline results, additional controls are introduced in a robustness check showing that they also matter in our case. These additional controls are four average characteristics of the neighbours, reflecting the prevalence of the social norms/stigma among them.

Robustness checks

Bearing in mind the potential bias induced by omitted variables, as a first robustness check we introduce both types of variables related to the characteristics of the neighbours: the one focusing on the four selected characteristics of the neighbours and highlighting the prevalence of social norms/stigma, and the one focusing on their citizenship, suggesting welfare support among large ethnic groups. It may be the case that the diversity variable regarding the neighbours captures some effect correlated with the ones emanating from our four selected variables and therefore has no effect itself. If so, the significance of the four selected characteristics of the neighbours remains (see column 4, Table 3b), but the significance of the diversity variable vanishes. However, restricting the estimation to postcodes with at least three RMG beneficiaries experiencing a transition (1575 postcodes instead of the 2367 in the baseline model) leads to reintroducing the diversity effect (see column 4b, Table 3b). The results therefore suggest some interactions between both sets of variables, despite the fact that the social norms/stigma do not fully prevail over the in-group incentives. To further deal with a potential measurement issue related to individuals not formally declared as belonging to the same household—which is likely to positively bias the interaction among neighbours[27]—we focus on individuals belonging to households in which the reference person is married. The coefficient remains significant and the point estimate appears even higher in such a case ($\hat{\beta}(\bar{y}_{t-1})$=0.19; $\hat{\sigma}(\bar{y}_{t-1})$=0.037; n=947,483) than for the full population including the unmarried individuals (detailed results can be provided on request).

[27] We assume that individuals are likely to interact with neighbours with whom they have some commonality.

Table 3b: Interaction among neighbours sharing a postcode: focus on their citizenship

	Dependent variable: Welfare-to-work transitions						
	(1)	(1b)	(1c)	(2)	(3)	(4)	(4b)
$\bar{y}_{t-1}$	0.159***	0.018	0.010	0.160***	0.160***	0.161***	0.358***
	(0.029)	(0.020)	(0.021)	(0.029)	(0.029)	(0.029)	(0.052)
Contact availability among Neighbours (N.)							
% of RMG beneficiaries among	-0.020**	0.019***	0.028***	-0.020**	-0.020**	-0.019**	-0.069***
N. in *t-1*	(0.008)	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)	(0.016)
Size of the neighborhood	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Citizenship among N.							
Diversity index	-0.010*	-0.005*	-0.004			-0.007	-0.026*
	(0.006)	(0.003)	(0.003)			(0.006)	(0.013)
% Native Lu among N.				0.014**			
				(0.006)			
% Non-native Lu among N.				0.000			
				(0.012)			
% Pt among N.					-0.015**		
					(0.006)		
% Fr among N.					-0.007		
					(0.013)		
% Be among N.					0.018		
					(0.017)		
% De among N.					-0.011		
					(0.023)		
% Other EU-15 among N.					-0.022*		
					(0.014)		
% Other EU-25 among N.					0.022		
					(0.026)		
% Extra-EU among N.					-0.012		
					(0.008)		
Other $\bar{x}$ among N.							
$\bar{x}_{1,t}$ among N.						0.007***	0.012***
						(0.002)	(0.004)
$\bar{x}_{2,t}$ among N.						-0.045***	-0.067***
						(0.012)	(0.024)
$\bar{x}_{3,t}$ among N.						0.032**	0.076**
						(0.013)	(0.030)
$\bar{x}_{4,t}$ among N.						-0.000	-0.027
						(0.026)	(0.052)
Postcodes F.E.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Individual characteristics FE	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Year FE	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Constant	0.069***	0.007**	0.003	0.056**	0.068***	0.064***	0.088**
	(0.023)	(0.003)	(0.003)	(0.022)	(0.022)	(0.023)	(0.035)
Observations	1,466,249	3,473,913	4,415,570	1,466,249	1,466,249	1,466,249	652,839
R^2	0.288	0.182	0.156	0.288	0.288	0.288	0.363

Source: SPAFIL data, authors' computation.

$\bar{x}_{1,t}$: average accumulated wages of the household among the working-age population (25–55 years old),

$\bar{x}_{2,t}$: proportion of individuals with an employment contract among the working-age population (25-–55 years old)

$\bar{x}_{3,t}$: proportion of elderly and disabled individuals among the full population,

$\bar{x}_{4,t}$: proportion of jobless individuals among the working-age population (25–55 years old)

*Characteristics of individual i include age, gender, number of children, income and years of experience on the national labour market. Size of the neighbourhood corresponds to dummies variables related to the quartiles of the distribution of the number of neighbours by postcodes. Standard errors in brackets are clustered at the postcode level. ***, **, * indicate significance at the 1, 5 or 10% level.*

An additional bias may come from the activation component of the RMG scheme, which may influence welfare-to-work transitions. On the one hand, as the complementary allowance is refundable but the activation measure is not, any transition towards an activation measure combined with leaving the RMG may decrease the RMG amount to be refunded if the recipient becomes wealthier. Higher-skilled individuals are more likely to anticipate such refunds and thus to follow this path. On the other hand, by providing training, any transition into an activation measure may facilitate access to the labour market afterwards. To control for these issues, we add two control variables to our baseline estimation (that is, activation status in *t* and *t-1*). The key parameters remain unchanged (detailed results can be provided on request). As a last robustness check, we drop the individual fixed effect—people frequently changing postcode and being less likely to be covered in our baseline estimation—removing every switch of postcode between *t-1* and *t*. The main results remain unchanged (detailed results can be provided on request).

6.2. Matched-pair analysis

To complete the examination of local interactions, we focus on all pairs of individuals from different households, among groups of postcodes (See Table 4 and model 2.a). This strategy, dealing with the reflection issue by distinguishing between potential peers and followers, provides a way to handle potential interactions among specific neighbours (RMG beneficiaries) and to determine the likelihood of a social assistance beneficiary transiting into the labour market when another beneficiary living in the same postcode has previously made such a transition. In addition, this setup offers the opportunity to examine social interactions in greater detail, by taking into account individuals' characteristics. In practice, we focus on the citizenship of the RMG beneficiaries, who are categorized as follows: Luxembourg native, Luxembourg non-native, Portuguese, French, Belgian, German, citizens from other EU-15 countries, citizens from other EU-25 countries, and citizens from non-EU countries.

By dealing with all pairs of RMG beneficiaries among postcode groups, the key parameter becomes sharing (or not) the same postcode. The basic hypothesis of this setup is that individuals with the same postcode are more likely to interact in private life, for example by sharing information, accordingly mediating the likelihood that the individuals observed in *t* follow the behaviour of the individuals observed in *t-1*; that is,

moving from RMG into the labour market. In practice, we deal with relatively restricted local areas by grouping pairs of RMG beneficiaries by the five and ten closest postcodes.

We present our results following successive steps. We first deal with a basic specification, before restricting this to frequent exits from RMG in the peer group to check whether peer interactions are more frequent in places where peers are more numerous. We then further assess the specification in two ways, first with two falsification tests in order to check for remaining variation at the postcode level grouping, and second by individual and dyads fixed effects.[28] To conclude, we focus on the interaction of pairs of RMG beneficiaries according to their citizenship (model 2.c).

Social interactions with former beneficiaries having found a job

Table 4 shows that when controlling for years and local labour market fixed effects, a peer effect stands out. Indeed, an RMG recipient is 0.18 pp more likely to move into the labour market in *t* if a neighbour RMG beneficiary from the five closest postcodes did so in *t-1* (column 1a); and 0.13 pp more likely when extending the neighbouring area to the ten closest postcodes (column 1b). Controlling in addition for postcode groups fixed effects (columns 2a, 2b) and individual characteristics (columns 3a, 3b) does not substantially change these findings for either grouping.

However, contrary to our expectations, having the same postcode seems to involve a lower incidence of the peer effect within the largest grouping of postcodes, which includes more-distant peers. One driving factor of this potential bias could be related to the fact that postcodes with more transitions towards the labour market may be more diluted among the largest grouping of postcodes.

[28] To construct the dyads fixed effects, we select two individuals randomly within each grouping of postcodes, one in *t* another one in *t-1*, we then match each of them with the individuals from the pairs, before mean-differencing all the new pairs.

Table 4: Baseline results of the dyads specification

	Dependent variable: Welfare-to-work transitions					
	five closest postcodes			**ten closest postcodes**		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
Same postcode	0.0018***	0.0026***	0.0027***	0.0013**	0.0015***	0.0016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Char. of individual i, j	-	-	inc.	-	-	inc.
Local labour market F.E.	inc.	-	-	inc.	-	
Years F.E.	inc.	inc.	inc.	inc.	inc.	inc.
Postcodes Group F.E.	-	inc.	inc.	-	inc.	inc.
Constant	0.0116***	0.0171**	0.0278***	0.0081***	0.0158***	0.0282***
	(0.003)	(0.008)	(0.009)	(0.002)	(0.005)	(0.007)
Observations	3,713,685	3,713,685	3,459,354	5,290,907	5,290,907	4,917,042
R^2	0.001	0.014	0.016	0.001	0.007	0.010

Source: SPAFIL data, authors' computation.
The unit of observation is a matched-pair of an I individual transiting from RMG into the labour market in t-1 and j individual doing the same in t.
Characteristics of individual i and j include age, gender, number of children and years of experience in the national labour market.
Standard errors in brackets are clustered at the postcodes group level.
****, **, * indicate significance at the 1, 5 or 10% level.*

To deal with this dilution and to examine whether the peer effects are strengthened in areas where more transitions occur, we restrict our estimation sample to areas with at least three or five transitions among the peer group (Table 5). By doing so, the results from both groupings of postcodes become very similar, especially when dealing with the largest number of switches that may further restrict the dilution effect (column 3a, 3b). In addition, it appears that for both types of groupings, having the same postcode induces a substantially higher peer effect compared with the basic specification: three times higher when dealing with at least three transitions (Table 5, column 1a & 1b), and four times higher when dealing with at least five transitions (Table 5, column 3a & 3b). These results hold after controlling for sample selection for the two thresholds (three and five exits among the peer group) by using the Heckman two-step procedure (column 2a, 2b 4a, 4b).

Table 5: Restriction to frequent exits in the peer group in *t-1*

	Dependent variable: Welfare-to-work transitions							
	five closest post codes				**ten closest post codes**			
	At least three exits in *t-1* among the peer group		At least five exits in *t-1* among the peer group		At least three exits in *t-1* among the peer group		At least five exits in *t-1* among the peer group	
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)
Same postcode	0.0066***	0.0066***	0.0091***	0.0092***	0.0055***	0.0056***	0.0084***	0.0085***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Characteristics of individual i, j	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Local labour market F.E.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Years F.E.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Postcodes Group F.E.	inc.	inc.			inc.	inc.	inc.	inc.
Inv. mills ratio (3 exits)	-	0.1986***	-	-	-	0.1921***	-	-
		(0.020)				(0.020)		
Inv. mills ratio (5 exits)	-	-	-	0.1877***	-	-	-	0.1644***
				(0.028)				(0.024)
Constant	0.0298***	-0.2499***	0.0271***	-0.2947***	0.0286***	-0.2544***	0.0216**	-0.2754***
	(0.008)	(0.029)	(0.008)	(0.049)	(0.009)	(0.032)	(0.010)	(0.045)
Observations	1,782,917	1,782,917	833,072	833,072	2,465,107	2,465,107	1,098,480	1,098,480
R^2	0.026	0.027	0.026	0.027	0.016	0.018	0.019	0.020

Source: SPAFIL data, authors' computation.
Characteristics of individual i and j include age, gender, number of children and years of experience in the national labour market.
Standard errors in brackets are clustered at the postcodes group level.
****, **, * indicate significance at the 1, 5 or 10% level.*
The selection bias induced by focusing on at least three or five exits among the peer group in t-1 is controlled for by the inclusion of the inverse Mills ratio, which is defined as $\phi(W\pi)/\Phi(W\pi)$ where Φ is the cumulative normal density and ϕ is its p.d.f. In practice, we use the Heckman two-step procedure to control for selectivity bias. Household wages are used as exclusion restriction, as these are expected to greatly affect participation in social assistance.

Robustness and falsification test

Despite the robustness of our results, further assessments of the specifications remain to be carried out (Table 6). Among other things, remaining variations within the groupings of postcodes and at the scale of the pairs may still bias the results due to sorting of individuals based on unobservable factors, and interactions of pairs according to unobservable factors. Individuals' skills are one important unobservable factor to be noted in our case. On the one hand, individuals may be assumed to sort by place of residence according to their skills; on the other hand, skills are likely to mediate moving into the labour market.

Table 6: Further assessment of the specification: falsification tests and control for individual and dyads fixed effects

	Dependent variable: Welfare-to-work transitions							
	five closest postcodes				**ten closest postcodes**			
	(fals. 1) (1a)	(fals. 2) (2a)	i, j F.E. (3a)	Dyads F.E. (4a)	(fals. 1) (1b)	(fals. 2) (2b)	i, j F.E. (3b)	Dyads F.E. (4b)
Same postcode	0.0001	-0.0010	0.0026***	0.0023***	-0.0006*	-0.0012**	0.0027***	0.0026***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Char. of individual i, j	inc.	inc.	-	-	inc.	inc.	-	-
Years F.E.	inc.	inc.	inc.	inc.	inc.	inc.	inc.	inc.
Postcodes Group F.E.	inc.	inc.	-	-	inc.	inc.	-	-
Individual i, j F.E.	-	-	inc.	-	-	-	inc.	-
Dyads F.E.	-	-	-	inc.	-	-	-	inc.
Constant	0.0024	0.0562***	0.4317	-0.1905*	0.0019	0.0371***	0.0892	-0.2287***
	(0.005)	(0.012)	(0.491)	(0.109)	(0.003)	(0.014)	(0.364)	(0.077)
Observations	1,781,630	923,999	3,459,051	3,458,989	2,468,569	1,957,135	4,916,873	4,916,855
R^2	0.005	0.013	0.211	0.225	0.004	0.012	0.184	0.196

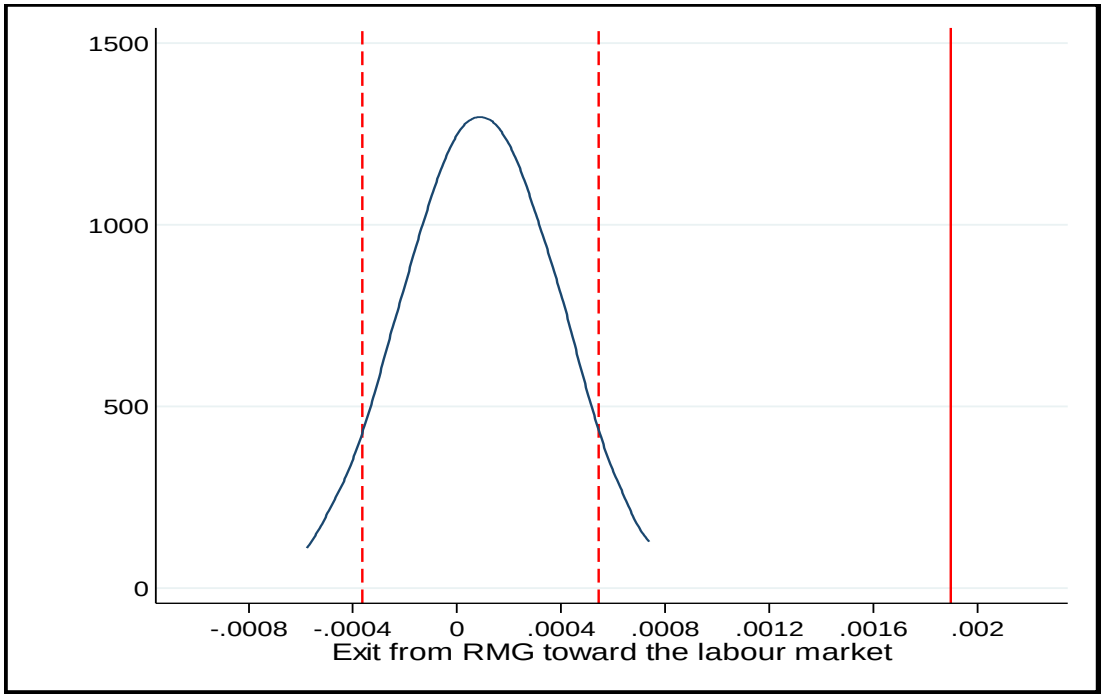
Source: SPAFIL data, authors' computation.
Characteristics of individual i and j include age, gender, number of children and years of experience in the national labour market.
Standard errors in brackets are clustered at the postcodes group level.
****, **, * indicate significance at the 1, 5 or 10% level.*

We carry out a first falsification test by examining potential interactions of RMG beneficiaries likely to move into the labour market, and 'wrong' peers; that is, RMG beneficiaries exiting from RMG, but not into the labour market. While these two transitions are prone to being affected by similar remaining variations, induced by sorting due to unobservables, they are likely to be supported by different explanatory factors specific to these two types of exit. The non-significance of the falsification test for both groupings of postcodes (column 1a, 1b) tends to support the second assumption. We find that factors supporting moving from RMG into the labour market and other moves out of RMG are not related. However, such a test is not sufficient to rule out the first assumption completely.

In line with Grossman and Khalil (2020), we therefore carry out a second falsification test to rule out the first assumption; that is, potential remaining variations within the grouping of postcodes. For this purpose, within all the pairs we randomly allocate the individuals likely to take advantage of the peer effect to another postcode within their grouping of postcodes. Based on this setup, the potential impact of the

falsification variable 'sharing a postcode' will relate to the remaining variations within the grouping of postcodes we want to test (column 2a, 2b). We run this falsification test on all the pairs of RMG beneficiaries 100 times for the larger grouping of postcodes (see Figure 3). Results for a similar falsification test for the five closest postcodes can be provided on request. The result provides clear evidence of any substantial remaining variation likely to bias our result when applying our identification strategy.

Figure 3: Second falsification test: Interaction with a peer located in a random postcode



Source: SPAFIL data, authors' computation.
Note: Falsification estimates corresponding to interactions with a peer located in a random postcode within their own grouping of postcodes are depicted on the left by a kernel distribution function applied to 100 random draws of every peer. The dotted line describes the 95th percentile range of this distribution. The true postcode allocation of the peers is depicted on the right by the straight line.

To further control for variations within the pairs, we first apply individuals fixed effects for individuals *i* and *j* (3a, 3b), before introducing dyads fixed effects (4a, 4b). The results are reasonably close when applying these two strategies. Despite this similarity, the peer effect only appears higher for the largest grouping of postcodes (in line with basic expectations) when applying the dyads fixed effects.

The mediating effect of citizenship

To complete these findings, we examine further the interactions between pairs of RMG beneficiaries *i* and *j* according to their citizenship (Table 7). In practice, we focus on the ten postcodes grouping, as this offers further opportunities for interactions. In line with

Bertrand *et al.* (2000), we assume that interactions are more likely to take place among individuals with the same citizenship. This is because sorting of individuals by citizenship will lower the costs of linking and increase the opportunity to meet. The results are in line with our expectations, but only for relatively large and homogenous groups of RMG beneficiaries, such as Luxembourg natives and Portuguese. Members of each of these groups appear to interact negatively with the transition of members of another relatively large group: respectively the Portuguese (for the Luxembourg natives) and the other EU-15 (for the Portuguese). As could be expected, interactions are not positive and significant among the relatively large but heterogeneous group of non-Europeans, including mainly Americans, Asians and Africans. The combination of these results therefore suggests some form of homophily among these large groups of RMG beneficiaries, as far as they are homogeneous enough. In contrast to the results for large groups, positive interactions between pairs of RMG beneficiaries belonging to different medium-sizes citizenship groups—(i.) non-native Luxembourg and French, and (ii.) citizens from other EU-15 countries and French—stand out. These results suggest some complementarity between RMG beneficiaries belonging to medium-sized citizenship categories at the postcode group level. At this level, it may appear profitable to enlarge the scope of cooperation with people from other large enough groups with the aim of increasing job opportunities. Indeed, the number of people moving from welfare to work is relatively restricted when focusing only on others from their own group (see appendix Graph 1, for the distribution of RMG beneficiaries by the grouping of the ten closest postcodes).

This result holds, despite the fact that these individuals may have different mother tongues. However, it should be noted that a large proportion of the resident population has some practical knowledge of different languages.[29] To complete this examination of interactions according to RMG beneficiaries' citizenship, we focus on the smallest groups within the postcodes groupings, comprising Belgians and Germans. Individuals from these two small groups do as well appear to interact together positively despite their small size.

[29] According to the QVT survey (2013), 77.9% of the foreign workforce speak at least two languages, in the worst case with some difficulty in one of them. This proportion drops to 44.7% when focusing on people employed in the least-skilled professions: workers and unqualified employees, unskilled workers in the construction and manufacturing industry, and unqualified service and sales employees (door staff, window cleaners, etc.).

Table 7: Interactions of dyads by citizenship

t-1 \ t	Native Lu	Non-native Lu	Pt	Fr	Be	De	Other EU-15	Extra-EU
Native Lu	0.003***	0.003	-0.002**	-0.002	0.007	0.007	-0.003	0.000
	(0.0009)	(0.0021)	(0.001)	(0.0023)	(0.0053)	(0.0102)	(0.0051)	(0.0015)
	3,839,338	*2,715,910*	*3,671,714*	*2,251,805*	*846,209*	*630,831*	*1,576,312*	*3,147,295*
Non- native Lu	-0.003*	-0.003	-0.002	0.016**	-0.003	0.024*	0.025	-0.002
	(0.0015)	(0.0059)	(0.0027)	(0.0075)	(0.0216)	(0.0141)	(0.0156)	(0.0021)
	2,201,475	*2,241,618*	*2,255,117*	*1,668,132*	*581,595*	*392,819*	*1,097,641*	*2,101,698*
Pt	-0.001	-0.003	0.006***	0.004	-0.005	-0.018	-0.006**	-0.001
	(0.0009)	(0.0027)	(0.0016)	(0.0025)	(0.0109)	(0.0115)	(0.0028)	(0.0016)
	3,833,295	*2,980,773*	*4,008,398*	*2,464,579*	*943,969*	*640,993*	*1,719,633*	*3,402,958*
Fr	-0.002	-0.006	-0.005**	-0.004	-0.002	-0.038*	-0.003	-0.007
	(0.0018)	(0.0045)	(0.0022)	(0.0064)	(0.0127)	(0.0203)	(0.0051)	(0.0054)
	1,467,361	*1,178,415*	*1,493,003*	*1,493,526*	*397,774*	*310,401*	*888,590*	*1,391,423*
Be	0.000	0.028	-0.001	0.002	0.022	0.003	0.028	-0.001
	(0.003)	(0.0254)	-0.0035	(0.0077)	(0.0262)	(0.0067)	(0.0271)	(0.0038)
	601,533	*503,784*	*598,437*	*386,623*	*426,514*	*167,538*	*312,613*	*552,839*
De	0.003	-0.001	0.01	-0.002	0.007*	0.009	0.002	0.000
	(0.0032)	(0.0022)	(0.0076)	(0.0051)	(0.0038)	(0.0134)	(0.0024)	(0.003)
	427,336	*274,927*	*413,725*	*276,949*	*96,186*	*394,954*	*189,667*	*352,598*
Other EU-15	0.000	0.009	-0.006**	0.017*	-0.013*	-0.008	0.006	-0.008*
	(0.0023)	(0.0085)	(0.0029)	(0.0102)	(0.0067)	(0.0085)	(0.0117)	(0.0047)
	959,298	*736,108*	*952,151*	*713,045*	*258,229*	*124,676*	*891,729*	*867,170*
Extra-EU	-0.002	0.001	0.001	0.000	-0.002	0.022	0.003	-0.001
	(0.0013)	(0.0047)	(0.0015)	(0.0031)	(0.0099)	(0.0244)	(0.0065)	(0.0019)
	2,867,987	*2,360,628*	*2,925,248*	*2,017,810*	*737,518*	*530,175*	*1,380,624*	*2,952,830*

Source: SPAFIL data, authors' computation.
All the regressions include the same set of controls used in the base model and reported in Table 4, column 3b.
Standard errors in brackets are clustered at the postcodes group level.
****, **, * indicate significance at the 1, 5 or 10% level.*
Number of observation of the pairs at the grouping of postcodes are shown in italics.
Note: Other EU-25 are not reported due to small number of observations within some pairs of RMG beneficiaries.

7. Conclusion

This paper analyses neighbourhood effects in welfare-to-work transitions in Luxembourg. To identify these effects, we developed a strategy inspired by Bayer *et al.* (2008) taking advantage of random variation at a very local level, induced mainly by the constraints of the housing market. In addition, we controlled for potential reverse

causality and the reflection problem, by taking advantage of longitudinal data with respect to individuals' place of residence.

Individuals likely to move from welfare into work appear to follow the behaviours of their direct neighbours, suggesting peer effects among welfare recipients. Their transitions are also mediated by the characteristics of their direct neighbours, including citizenship. On the one hand, the impact of selected characteristics of the neighbours suggests that social norms/stigma prevail over the support for welfare recipients to find a job. On the other hand, local diversity according to the citizenship of the neighbours appears negatively related to welfare exit; a result contrasting with previous empirical evidence negatively linking diversity and public expenditure (e.g. Alesina *et al.*, 1999). This effect appears driven by large-sized groups of migrants overrepresented among welfare recipients (a specificity of our case study), in line with so-called racial group loyalty (Luttmer, 2001). The effects of diversity and citizenship at least partially remain when we control for other characteristics of the neighbours, reflecting among other things social norms/stigma. Accordingly, our results suggest the prevailing incidence of social norms and/or stigma over the support of welfare recipients to find a job through informal contacts and the remaining effect of in-group incentives, when dealing with the overall set of neighbours.

The focus on pairs of welfare recipients (RMG beneficiaries) among neighbours provides further opportunities to identify peer effects on welfare-to-work transitions, and to show that these effects are linearly related to the proportion of local RMG beneficiaries. Further examinations of pairs of RMG beneficiaries highlight the contrasting influence of the citizenship of these pairs on their transition into employment. While individuals from the two main citizenship groups (Luxembourg natives and Portuguese) appear to enhance their transitions by interacting with other RMG beneficiaries having the same citizenship, individuals belonging to medium-sized citizenship groups (French, and Luxembourg non-natives) foster their transitions by interacting with RMG beneficiaries from other medium-sized citizenship groups (other EU-15 citizens). This latter result therefore supports some complementarity across citizenship, despite the fact that people with different characteristics are less likely to meet (McPherson *et al.*, 2001) and furthermore that they usually do not share the same mother tongue. The realized interactions between mainly low-skilled workers, who are overrepresented among RMG beneficiaries, seem relatively productive, enlarging the

scope of opportunities in the labour market. This result is in line with theoretical findings from de Marti and Zenou (2017), highlighting that inter-community interactions may prevail over intra-community interactions for different equilibrium configurations.

As just said, a key finding of our study is the prevalence of the norms effects over information spillover regarding job opportunities. Analysing first the sensitivity of this result to the specificity of the RMG scheme and secondly extending the analysis to other disadvantaged populations constitute then future steps of the analysis. Regarding the scheme, our conclusion is obtained in the framework of the RMG whose design is known for providing low incentives to work (see OECD 2012 and Fusco *et al.* 2021). These low work incentives may affect negatively a beneficiary's proactive behavior to collect information, from among other their neighbours, regarding job opportunity; such proactive behaviors leading at the end to positively affect their welfare-to-work transitions. As, the RMG has been replaced in 2019 by the REVIS (*Revenu d'Inclusion Sociale)* whose aim was specifically to reduce the disincentive effect to work arising from the RMG design, further analysis of this program could provide the opportunity to assess the design effect of the RMG. Finally, focusing on other disadvantaged subgroups not affected by the RMG scheme, such as the unemployed, may highlight different mechanisms that the ones we found. For example, Jahn and Neugart (2020) provide evidence that information spillovers among neighbours prevail over the social norms effects for unemployment-to-work transitions. These elements constitute future lines of research.

8. References

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Appendix:

Table A1: sample size, by gender and year

Year	Women	Men	Total
2001	222347	219282	441629
2002	224856	222144	447000
2003	227719	225459	453178
2004	230423	228218	458641
2005	232929	231019	463948
2006	235071	233396	468467
2007	238721	236751	475472
2008	242691	240997	483688
2009	246079	244038	490117
2010	250139	248602	498741
2011	255036	254084	509120
2012	258157	257355	515512
2013	259286	258471	517757
2014	260165	259272	519437
2015	261289	260532	521821
Total	**3659951**	**3619620**	**7264528**

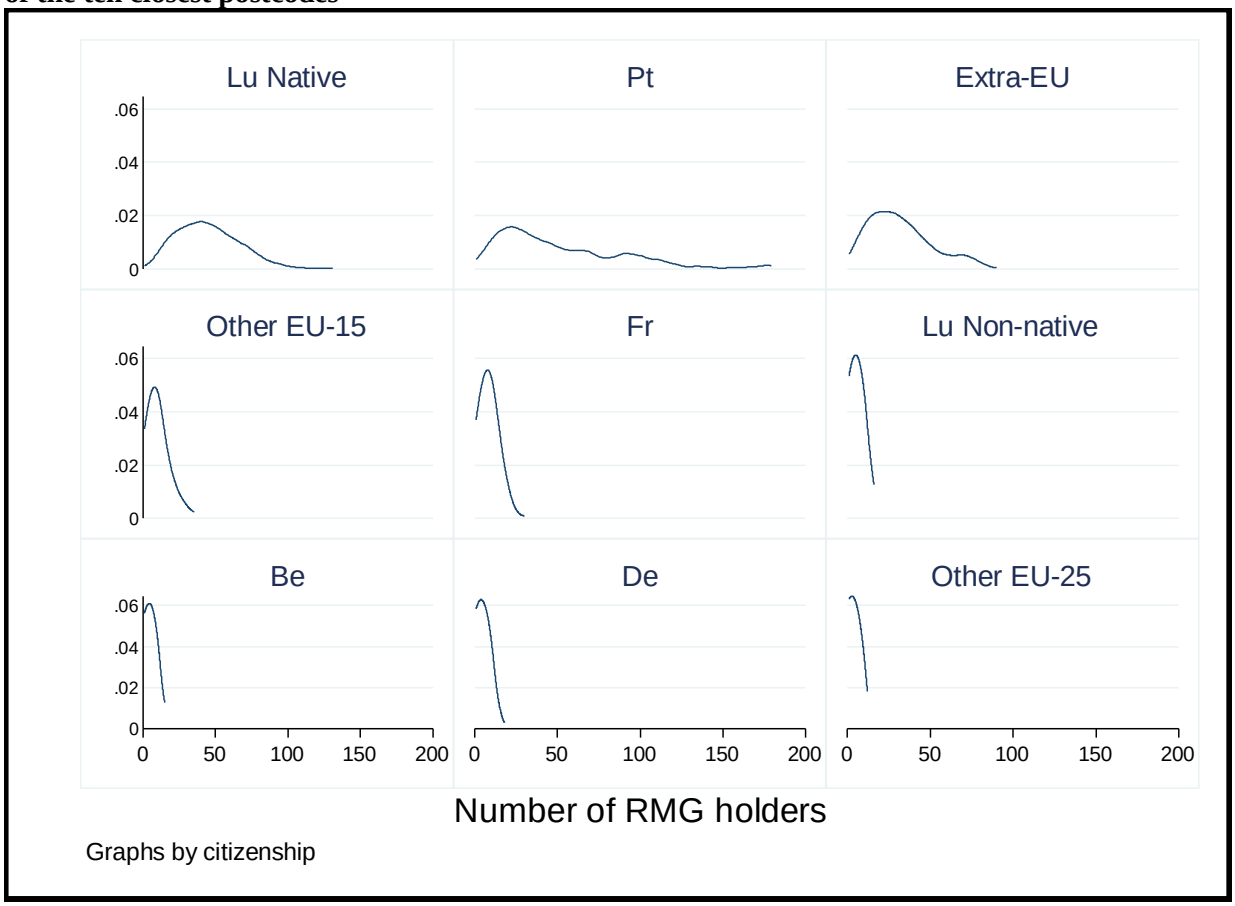
Source: SPAFIL data, authors' computation.

Table A2: Citizenship by year and welfare status

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Native Lu															
% pop	62.1	61.1	60.1	59.2	58.2	57.3	56.2	54.8	53.9	52.9	51.7	50.4	49.5	48.6	47.7
% RMG	59.4	55.6	51.7	48.6	46.5	45.1	44.1	42.6	38.8	35.4	33.9	32.2	30.7	29.2	27.7
Non-Native Lu															
% pop	0.7	0.9	1.1	1.4	1.6	1.9	2.2	2.5	4.2	5.1	5.7	6.3	6.8	7.5	8.1
% RMG	0.8	1.4	1.9	2.1	2.6	2.9	3.5	4.0	6.1	6.6	6.9	7.1	7.1	7.4	8.1
Pt															
% pop	14.3	14.7	15.2	15.6	16.1	16.6	17.0	17.4	17.1	17.1	17.4	17.6	17.7	17.6	17.4
% RMG	13.5	15.5	18.1	20.3	21.7	23.2	23.3	23.5	25.7	27.3	28.1	29.3	30.0	30.1	29.3
Fr															
% pop	4.6	4.7	4.8	4.9	5.0	5.2	5.4	5.6	5.7	5.8	5.9	6.0	6.2	6.3	6.4
% RMG	4.3	4.4	4.6	4.9	5.1	5.1	5.2	5.2	5.3	5.3	5.5	5.5	5.4	5.5	5.5
Be															
% pop	3.3	3.4	3.4	3.3	3.3	3.3	3.2	3.2	3.1	3.1	3.1	3.1	3.1	3.1	3.1
% RMG	1.7	1.8	2.0	2.1	2.1	2.0	2.0	2.1	2.0	2.0	2.0	2.0	2.1	2.1	2.2
De															
% pop	2.0	2.0	2.0	2.1	2.1	2.1	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.0	2.0
% RMG	2.0	2.0	2.0	1.9	1.9	1.9	1.9	2.1	1.9	2.0	2.1	2.0	2.0	2.0	1.9
Other EU-15															
% pop	7.3	7.3	7.2	7.1	7.1	7.1	7.1	7.1	6.8	6.6	6.6	6.6	6.7	6.7	6.8
% RMG	6.4	6.5	6.1	5.9	5.9	5.7	5.6	5.6	5.3	5.1	5.0	5.3	5.3	5.4	5.9
Other EU-25															
% pop	0.3	0.3	0.4	0.5	0.5	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.1	1.2	1.2
% RMG	0.2	0.3	0.2	0.3	0.4	0.4	0.4	0.5	0.5	0.7	0.8	0.8	0.9	1.0	1.1
Extra-EU															
% pop	5.4	5.6	5.8	6.0	6.1	6.1	6.2	6.4	6.3	6.3	6.6	6.8	6.9	7.0	7.3
% RMG	11.6	12.5	13.5	13.8	13.9	13.7	14.0	14.5	14.3	15.5	15.6	15.8	16.4	17.2	18.3

Source: SPAFIL data, authors' computation.

Figure A1: Kernel distribution of the number of RMG beneficiaries by citizenship and grouping of the ten closest postcodes



Source: SPAFIL data, authors' computation.

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