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Abstract

This paper uses the insights from the Optimal Speed of Transition literature to inquire the causes of relatively higher unemployment rate in a transition context. We study whether local variation in unemployment rates is related to labor turnover. In addition, the paper aims to assess the relative impact of inflow and outflow from unemployment on the dynamics of the local unemployment rate. The empirical analysis is based on a newly available unique dataset from the employment registry of a transition economy (Poland), encompassing nine years of monthly data (from 2000 to 2008) at a county (poviat) level. We find that turnover, as well as inflows and outflows separately, are ceteris paribus positively related to the unemployment level. This general conclusion is robust to stratification, model specification as well as spatial effects. We find that elasticity is larger in the case of the inflow rate than for the outflow rate. Finally, we demonstrate that these effects are stronger in low unemployment regions.

Keywords:
regional unemployment; labor turnover; panel data; Poland

JEL:
C33; J63; P25; P52; R23

Introduction

Different theories suggest positive, negative or no relationship between labor market turnover and the unemployment rate. Optimal speed of transition model (Aghion and Blanchard, 1994) suggest that positive link between turnover and unemployment due to excessively fast restructuring processes. In addition, the so called Lilien hypothesis suggests that large turnover stems from sectoral shifts, which typically is associated with larger (structural) unemployment. Alternatively, New Economic Geography with the so-called Krugman hypothesis suggests that large labor market flows are a sign of greater labor market flexibility, thus efficient labor markets and low unemployment, *ceteris paribus*. Policy implications of these alternative hypotheses are different, because low turnover in high unemployment regions essentially necessitates supply side policies, whereas a positive relationship between labor market turnover and unemployment calls for interventions on the demand side as well. The aim of this paper is to empirically discriminate between these alternative theoretical hypotheses by exploiting the geographical differentiation of labor turnover and unemployment.

We use local level data encompassing nearly ten years of monthly observations (from 2000 to 2008) relative to 380 *poviats* (i.e. counties classified in the EU as LAU1 units) of a transition economy (Poland). To our knowledge, only few other countries have similar data, which makes this study the first one to implement a systematic analysis of the relationship between the geographical pattern of unemployment and that of the labor market dynamics. The length of the period that the data covers allows us to consider both times of considerable unemployment growth (2001-2003) and of the subsequent decrease (2005 onwards).

The estimates provide evidence of a positive coefficient on turnover, much larger for the inflow than for the outflow. Estimations are robust to the inclusion of spatial effects, a number of control variables, several stratifications and different types of estimation techniques. To adequately tackle the dynamic component of the data, we employ both fixed effect GLS panel data estimation with time controls and the alternative specifications of GMM. We also distinguish market driven from administrative flows and the results remain unaffected. Finally, to further verify the robustness of the results we also isolate the *poviats* where industrial restructuring has been more intense. We introduce a classification based on the share of private employment, employment in services and investment; and a stratification based on the level of employment in the first period of our sample We find that that the positive correlation between labor turnover and unemployment is universal across all the clusters and strata, but is quantitatively the strongest in the most industrialized clusters of *poviats* and strata with *lowest* unemployment.

The paper is structured as follows. In the next section motivation is briefly discussed, with some insights into the interplay between geography and unemployment in transition economies. Section 2 discusses the relevant theoretical foundations in detail as well as some available empirical evidence. Subsequently, we describe the dataset (Section 3) and the methodology (Section 4). Section 5 presents the analysis of the results. Concluding remarks and emerging policy implications are included in the final section.

1. A survey of the literature

The Aghion and Blanchard (1994) model can be used as a framework to study how labor market dynamics affects regional unemployment. Assume that the hiring rate is a bell-shaped function of unemployment. This non-linearity depends on the double effect of unemployment on hiring: on the one hand, with unemployment increasing there is greater competition for jobs and downward pressure on wages, which fosters private sector growth; on the other hand, though, unemployment raises the level of taxes per worker, to pay unemployment benefits, thus reducing profits. Assume also that the separation rate is a control variable, independent of unemployment. When the separation rate is above (below) the hiring rate, unemployment increases (reduces).

As Ferragina and Pastore (2008) and Pastore (2012) argue, this aggregate-level framework might also apply to local labor markets, provided that they are separated from each other by sufficiently low migration / commuting. Then, two alternative hypotheses are in order:

H_0: worker reallocation is independent of or correlates negatively with unemployment.

H_1: worker reallocation correlates positively with unemployment;

According to H_1, in high unemployment regions more jobs are destroyed and created at the same time. In the spirit of the model, this happens because each region has a specific rate of structural change, but other hypotheses are also possible, as later discussion shows. According to H_0, instead, the same aggregate shock has yielded different effects across regions. High unemployment regions have experienced unsuccessful structural change in the past, with a too high separation rate at the beginning, so that the unemployment rate exceeds its equilibrium level. Only at a later stage separation rates converge across regions.

In fact, the above hypotheses configure an empirical law to detect the case when unemployment is due to some region-specific shock (H_1) and when it is due to labor market rigidities (H_0). Policy implications are partly different. Whilst a low job finding rate essentially point to supply side policies in favor of the long-term unemployed, namely increasing labor market flexibility and/or educational reforms and active labor market policy; H_1 also requires interventions on the demand side. For instance, the government should reduce the rate of separation and/or increase the life expectancy of private businesses by removing the sources of structural change in high unemployment regions.

The empirical evidence available in the literature is neither large nor unambiguous. The main reason is the limited availability of suitable longitudinal data to measure labor market dynamics at a local level. In addition, the sign of the relation under consideration might change over time.

Robson (2001) finds no correlation between worker reallocation and unemployment across the UK macro-regions in the decade 1984-1994. Some authors (such as Boeri and Scarpetta 1996; Boeri 2000; the World Bank 2001; Rutkowski 2003) interpret the low rate of monthly labor turnover based on employment registry data of high unemployment regions in formerly transition countries as a consequence of low dynamism. Other studies find evidence in favor of H_1. For the UK, Armstrong and Taylor (1985) find that the male monthly inflow from the employment registry positively correlates to local unemployment. Newell and Pastore (2006) find a statistically significant correlation coefficient of 0.76 between the job separation rate computed with labor force survey data and the unemployment rate (years 1994-1997). Contini and Trivellato (2006), Naticchioni, Rustichelli and Scialà (2006) find the highest turnover rate in the traditionally high unemployment regions of Mezzogiorno.

The well-known Krugman (1994) hypothesis provides an explanation of H_0: greater labor reallocation would mean, in fact, lower frictional and long-term unemployment because of the spatially asymmetric impact of rigid labor market institutions. Extensive literature highlights, among others, the role of rigid wages and legislation protecting employment, non-employment subsidies and early retirement schemes (see, among others, Boeri 2000; World Bank 2001; Rutkowski and Przybila 2002; Funck and Pizzati 2002; 2003). Garonna and Sica (2000) find a negative association between the Lilien index of structural change and the unemployment rate in Italy: in particular, sectoral and interregional reallocations in Italy would reduce unemployment, rather than increasing it. Böckerman (2003) takes the same result for Finland as evidence of Schumpeterian "creative destruction".

In addition, H_0 can be seen also as the outcome of agglomeration economies in the New Economic Geography (NEG) literature. Epifani and Gancia (2005) is one of the first NEG models to propose an explanation of regional unemployment differentials in terms of agglomeration economies and internal labour migration. More recently, Francis (2009) has reached the same conclusion by endogenizing job separations: agglomeration induces in-migration, which causes both higher job creation and destruction rates in thicker markets. In-migration of high skill workers further increases productivity in low unemployment areas, favouring an increase in job creation higher than that in job destruction, which maintains low the local unemployment rate.

The policy implications of the Krugman and NEG explanations are radically different. Empirical evidence linking the lower degree of job / worker reallocation in high unemployment regions to labour market rigidities at a local level would require removing such rigidities. Policy implications of NEG models are complex. If the aim is reducing regional unemployment differentials, a policy tool would be to prevent the brain drain from peripheral to core regions. Traditional views according to which labour mobility is the key to generate convergence in unemployment rates are clearly challenged by this type of analysis. Indirectly, NEG models provide new support for policy aimed at increasing the capital and technological endowment of high unemployment regions.

A related issue is whether it is the inflow or the outflow rate to affect unemployment. Blanchard and Summers (1986) claim that a higher degree of cyclicality of the hiring rate is behind fluctuations in US unemployment. Burda and Wyplosz (1994) note that while some EU countries follow US trends, others, instead, have a cyclical firing rate. Layard, Nickell and Jackman (1991) summarize this research partly confirming the hypothesis that a low job finding rate is behind high unemployment rates, due to the increase in long-term unemployment and its persistent impact on average unemployment. Shimer (2007) proposes a new methodology to demonstrate that it is the evolution of the job finding rate - not the flow into unemployment – that reproduces the cyclicality observed in the unemployment rate. Other studies reach the opposite conclusion though (see, among others, Petrongolo and Pissarides, 2008; and Fujita and Ramey, 2009) [1].

1.1. The sources of worker reallocation

If H_1 holds true, what are the sources of the reallocation and why do they differ across regions? Several hypotheses have been raised:

[1] Hall (2007) Bachman, 2009, for Germany; and Strawinski, 2009, for Poland, subscribes to Shimer's view, while Petrongolo and Pissarides (2008), Elsby et al. (2009) and Fujita and Ramey (2009) suggest alternative explanations. Fujita and Ramey (2009) find that cyclical changes in the separation rate is negatively correlated with changes in productivity and move contemporaneously with them, whereas the job finding rate is positively correlated with and tends to lag after productivity, which is consistent with the Aghion and Blanchard (1994) theoretical framework adopted in this paper.

H_{11}: different sectoral shifts across regions (Lilien hypothesis);

Some sectors/regions experience a permanent reduction in labor demand that causes local unemployment. This type of analysis does not refer to structural change in the sense of the growth literature, which implies a reallocation of workers *across* sectors, but rather to *within* sectoral reallocation. Essletzbichler (2007, p. 22) notes that the latter is much greater than the former component of job reallocation, the difference depending on the degree of aggregation of the data.

Lilien (1982) found a positive correlation over time between the aggregate unemployment rate and the cross-industry dispersion of employment growth rates in the US. Most studies use some variation of the Lilien index[2].

H_{12}: aggregate disturbances with spatially asymmetric effects (Abraham and Katz hypotheses);

Abraham and Katz (1986) and a number of related studies (such as Neelin, 1987; Fortin and Araar, 1997) argue against the underlying assumption that sectoral shifts can take place independent of aggregate labor demand reductions[3]. To overcome these criticisms, the ensuing research in the field has pursued the aim of finding empirical ways of disentangling sectoral shifts and aggregate disturbances. Neumann and Topel (1991) elaborate a macroeconomic model where the equilibrium level of unemployment in a region depends on its exposure to the risk of within-industry employment shocks and on their degree of industrial diversity. Their approach has stimulated further research (see, for instance, Chiarini and Piselli 2000; and Robson 2009)[4]. Hyclak (1996, p. 655) reports a negative correlation of -0.72 between sectoral shifts and net job growth in a sample of 200 US metropolitan areas over the years 1976-1984. Holzer (1991) proposes the sales growth rates to disentangle shifts between and within local markets and find that the former have much greater impact than the latter.

[2] Among the available studies, it is worth mentioning Samson (1985) for Canada; Berg (1994), Barbone, Marchetti and Paternostro (1999), Newell and Pastore (2006) for Poland; Krajnyàk and Sommer (2004) for the Czech Republic; Robson (2009, p. 282) for the UK.

[3] There are sources of structural change that tend to be transitory and others that are permanent. The former include the opening up to international trade of new competitors and the introduction of new technologies causing some productions to go out of market. Structural and permanent 'weaknesses' of high unemployment regions, which cause their low competitiveness and attractiveness to investment from abroad, include: a) Low human and social capital endowment; b) High (organised) crime rates; c) Reduction in migration as an adjustment mechanism; d) Economic dependence on more developed regions; e) Poverty traps. For a more detailed analysis, see Caroleo and Pastore (2010).

4 The above discussion shows the existence of a clear link between Lilien's argument and Simon (1988) and Simon and Nardinelli (1992) hypothesis of a portfolio effect in the labour market (see for surveys Elhorst 2003, p. 735).

H_{13}: a crowding out of employed job seekers in low unemployment regions (Burgess hypothesis);

According to Burgess (1993), the greater worker reallocation in high unemployment regions is due to the lower job opportunities for unemployed job seekers in low unemployment regions (H_{13}). In these regions, in fact, the unemployed are crowded out by employed job seekers who are encouraged to search for better jobs. Consequently, one would observe a higher worker turnover in high unemployment regions simply because in these regions the unemployed who find jobs are a larger relative number with respect to their peers in low unemployment regions.

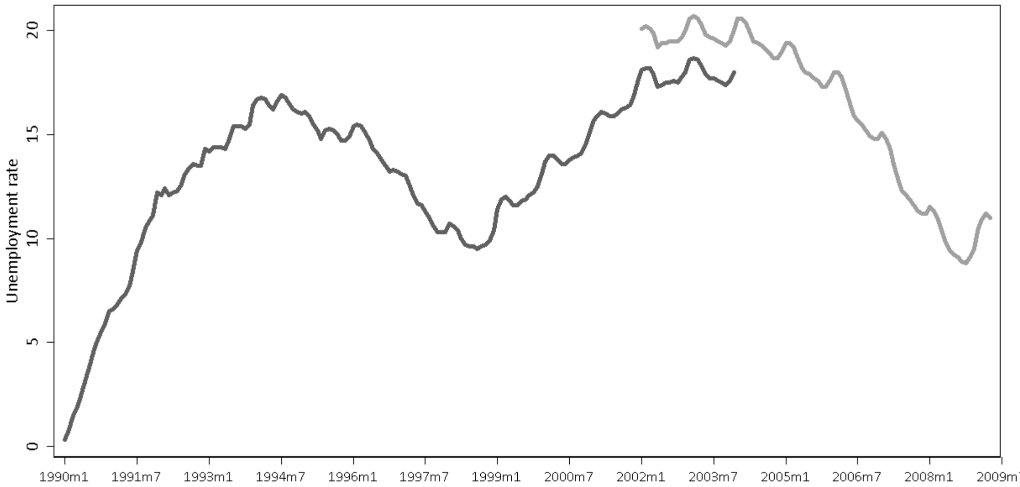
Van Ours (1995) and Broersma (1997) find only partial evidence of competition between employed and unemployed job seekers in the UK and the Netherlands. For the UK, Robson (2001) finds evidence of employed job seekers crowding out the unemployed especially in low unemployment regions. Burgess and Profit (2001) find that high unemployment levels in neighboring areas raise the number of local vacancies but lower the local outflow from unemployment. Eriksson and Lagerström (2006) study the Swedish Applicant Database and find evidence that unemployed seekers face a lower contact probability than employed job seekers.

It should be noted that no study compares the above hypotheses in a coherent empirical framework.

1.2. The context of Poland

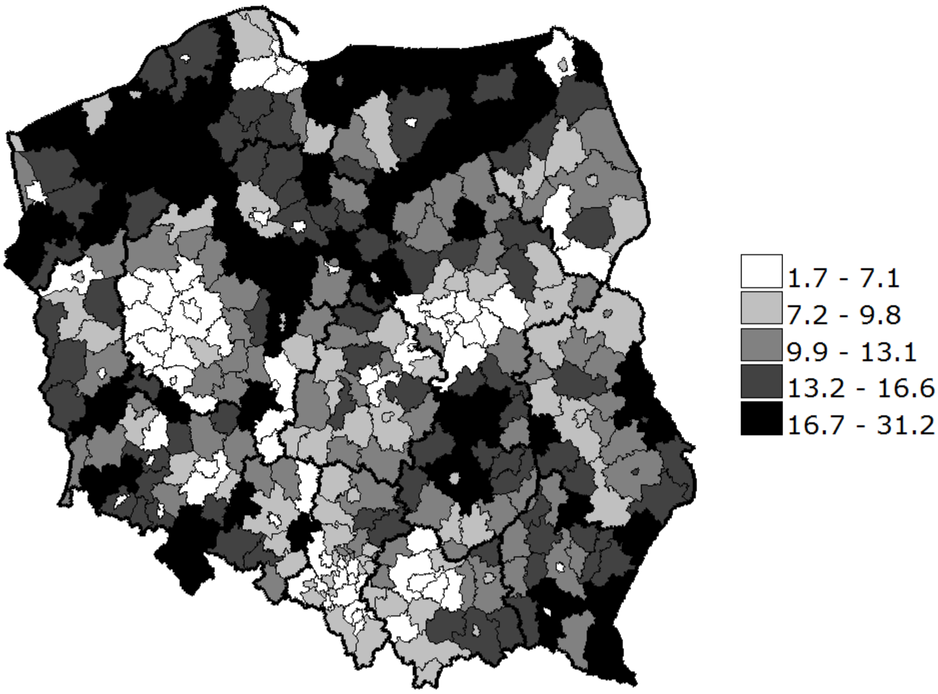
Transition from a centrally planned to a market economy typically involves massive layoffs and economic slowdown inhibiting vivid job creation. The situation in the early 1990s in Poland was no different, with the registered unemployment rate increasing up to 10% in just two years and since then never falling below this level (Figure 1) and wage levels falling down consequently as the Aghion and Blanchard (1994) model predicted (for an estimate of the downward pressure on wages exerted by increasing unemployment in the early 1990s, see Burke and Walsh, 2012). Professional and geographic mobility is very low, while transitory migration of approximately one million Poles to Ireland, Sweden, Norway, Germany, UK and other EU countries as of 2004 concerns predominantly those aged under-30 (80%) and with relatively high skills (17% of them have a university degree). Employment in agriculture still exceeds 17%, which is extremely high by European standards, while half of the registered unemployed live in the rural areas.

Figure 1. Unemployment rate evolution in Poland, 1990-2009.



Source: CSO. **Note:** In January 2004, new census data have yielded a lower size of the population and thus higher unemployment rate (by roughly 3.2 percentage points). In panel estimations time effect is removed so this adjustment plays no role in the estimations. In the GMM estimations additional control variable is introduced.

Figure 2. The regional distribution of the unemployment rates in Poland (averaged over 2000-2008)



Source: CSO. *Note:* The darker the shade, the higher the unemployment rate in percent.

Since the beginning of transition , unemployment has taken a strong geographic dimension. However, the differentiation at a regional level is surprisingly low (usually 3-5 percentage points), while within regional variation may be as high as 11-fold. As also the early literature has shown (Gorzelak, 1996), there has never been any obvious geographical pattern across *voivodships* or *poviats*: neither a North-South (like in Italy and the UK) nor an East-West (like in Germany) divide. Figure 2 shows that, although the highest unemployment *poviats* tend to locate in the North-West, West and South-East, some of the highest unemployment ones are neighboring some of the lowest ones.

This fact has encouraged the literature of the early 1990s to elaborate different classifications of Polish *voivodships* aimed at testing the impact of the industry structure inherited from the past communist era on the spatial distribution of unemployment. The basic assumption behind these research efforts followed from the contention that the transition hit most the regions abundant in inefficient manufacturing plants, where production was established and maintained as a result of political, rather than economic considerations. An index of industrial concentration was used to proxy the level of industrial development, while the share of employment in services, the level of infrastructure and of human capital proxied the current level of development (Gòra and Lehmann, 1995; Scarpetta, 1995; and Scarpetta and Huber, 1995; Lehmann and Walsh, 1999; Walsh, 2003). However, as Newell and Pastore (2006) argue, none of these classifications actually capture the distribution of labor market flows, which makes them only marginally informational about the sources of unemployment rate diversification.

2. Data

This paper employs data from three main sources: a) reporting of stocks and flows of registered unemployed by local labor offices (LLOs) for the Ministry of Labor and Social Affairs (ML&SA); b) the unemployment rate from the Central Statistical Office; and c) control variables from the Bank of Regional Data.

The first source provides the bulk of the data bank. It is very rich, as it refers to 380 *poviats* (i.e. counties classified in the EU as LAU1 units - 314 land counties and 65 city counties)[5] from January 2000 to December 2008. The length of the period that the data covers allows us to consider both times of considerable unemployment growth (2001-2003) *and* the subsequent decrease (2005 onwards). The data yields an overall number

[5] A poviat is the second-level unit of the local government and administration in Poland, equivalent to a county or a district (LAU1 in the EU classification, formerly NUTS4). A *poviat* is part of a larger unit or province called a *voivodship* (NUTS2 in the UE classification). In turn a *poviat* is usually subdivided into *gminas* (i.e. municipalities or communes). However the more important towns and cities function as separate counties in their own right, with no subdivision into *gminas* (the so-called city counties). Public employment services have *poviat* coverage with no separate service centres existing at a *gmina* level.

of 40,201 observations coming from monthly reports by each of the LLOs to ML&SA with detailed information about the stock of the unemployed as well as the size of the flows[6].

This dataset is a unique source of information for both the length and the detail. Although the labor force survey has quasi-panel dimension, which allows computing quarterly flows (Pastore and Socha, 2005), it does so only at a relatively aggregated NUTS2 level of 16 *voivodships*. However, for two main reasons a *voivodship* level analysis may not be satisfactory. First, the information content of regional aggregates is low, since *poviat* level unemployment rates exhibit neither stochastic nor *sigma* convergence to the *voivodship* averages, which suggests these are indeed diverging processes (Tyrowicz and Wójcik, 2011). Second, it is exactly at this local level that decisions regarding employment policy are taken today in Poland.

A shortcoming of working with *poviat* data, though, is that only few control variables are available. First, the stock of unemployed drawn from ML&SA data and the unemployment rate from CSO data have been used to compute the labor force (LF) size of *poviats*. The latter we use as a denominator to normalize stock and flow variables and hence make them quantitatively comparable.

Second, CSO provides the employment composition by broad sectors of activity, namely agriculture, industry and services. This data is available only annually and from 2003. The private ownership share in employment is also available annually for the same years. Moreover, annual data relative to private per capita fixed capital formation is available since 2002.

Finally, we obtained the annual data on personal income tax (PIT) revenues in *poviats* for 1999-2008. Since PIT is proportional to individual income, it can be taken as a proxy for per capita GDP, which is unavailable. However, tax data is not available for city *poviats*; while it is provided at an annual frequency for the land *poviats*. Unfortunately, since 2004 there has been a considerable increase in the proportion of PIT revenues assigned to local authorities, which blurs the comparison across years. To address this shortcoming as well as avoid difficulties induced by the nominal character of this variable, we standardize tax data year-wise. This approach still permits to explore the regional variation and eliminates the problems induced by the nature of this variable. Other potentially relevant information is reported only at the *voivodship* level.

2.1. Inflows and outflows

[6] Prior to reporting, data is aggregated in each LLO, thus this dataset does not permit individual level analysis.

The registry data includes information on two types of flows into and three types of flows out of the registry. The former allows the separation into a group that is registering for the first time (FT), and a group that is re-registering (RR). The data on the outflow permits to observe separately those who find a job (JF), those who are de-listed from the registry for administrative reasons (AD) and those who are temporarily attending active labor market schemes (AS). The total inflow rate in each *poviat* i at each point in time t is defined hence as a sum of all inflows over the labor force:

$$Inflow_{i,t} = \frac{FT_{i,t} + RR_{i,t}}{LF_{i,t}}, \tag{1}$$

whereas the total outflow rate is defined as a sum of all outflows over the labor force:

$$Outflow_{i,t} = \frac{JF_{i,t} + AD_{i,t} + AS_{i,t}}{LF_{i,t}}. \tag{2}$$

The turnover rate is then defined as a sum of the inflow and outflow.

$$Turnover_{i,t} = inflow_{i,t} + outflow_{i,t} \tag{3}$$

While it captures well the absolute dynamics in the labor market – as opposed to net flows – such measure is also "blind" to whether these are the inflows or the outflows that differ across units. To inquire which of the flows contribute more to the variation in the unemployment rate, we estimate the model both for the turnover as a whole and with separation of the inflows and the outflows. Finally, the unemployment rate is

$$unemployment\ rate_{i,t} = \frac{registered\ unemployed_{i,t}}{LF_{i,t}} \tag{4}$$

A reason of concern, when dealing with data from LLOs is that the overall flow might not be entirely related to the labor market dynamics, but to administrative reasons as well. There are three main reasons why individuals register with the LLOs: access to job offers, to unemployment benefits and to health insurance (covering all dependent family members). Only the unemployment benefit is temporary (usually 12 months, never exceeding 18 months) and some of the registered unemployed are not entitled to it at the time of their first registration[7]. Individuals ineligible for the unemployment benefit may apply to the social assistance institutions, which provide means tested

7 These groups include the youth without prior employment experience, individuals returning to the labour market after a prolonged period of inactivity and the handicapped.

benefits. Moreover, registration with the social assistance provides health insurance as well. Consequently, in fact, only weak incentives exist to maintain registration with the LLOs.

On the other hand, an unemployed person is obliged to demonstrate "willingness to undertake employment". There is no strict definition of what exactly is expected of the unemployed, but local internal regulations in the LLOs permit their representatives to remove individuals from the registry on various grounds[8]. For instance, some LLOs remove an unemployed if he/she refuses to accept a sequence of job offers, irrespective of their suitability, whereas in other *poviats* employers known for violating the labor code remain eligible to post their vacancies and even receive job creation subsidies or apprenticeship financing.

In addition, LLOs are temporarily or permanently subjected to incentives to abuse the discretionary power of "de-listing" for fiscal and organizational reasons. These incentives originate from the conflict between different financing schemes. On one hand, the higher is the number of registered unemployed, the larger is the state-level financing for active labor market policies. On the other hand, local authorities – who supervise public employment services and are obliged to bear the entire payroll and institutional expenses – occasionally, exert pressure to decrease headcount in the respective LLO as well as the number of registered unemployed for both financial and political reasons. At the same time, though, the majority of the individuals who are removed from the registry for administrative reasons re-register after a penalty period[9]. Either of these effects is likely to dominate temporarily in a particular *poviat*.

In addition, a minor but potentially pivotal part of the flows – although administratively driven – might in fact correspond to one’s individual labor market situation (e.g. discouraged workers stop reporting to the employment office and are thus de-listed, but within few months their situation may change inducing more effort to find a job, which implies a subsequent re-registration).

Summarizing, some of the movements into and out of the registry can be called *administratively driven flow* as distinguished from the *market-driven flow* and might affect the results. To take into account this possible source of bias, we distinguish turnover due MDF (=JF+FT, i.e. outflows to employment and first-time registrations, respectively) from turnover due to ADF (=AD+AS+RR, i.e. de-listings for administrative reasons, participation in activation schemes and re-registrations, respectively).

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[8] As a matter of fact, LLOs draft independently internal regulations, which serve as “interpretations” of the country-wide legislation. Consequently, there is considerable heterogeneity relative to how the legislation is being implemented.

9 The correlation coefficient between de-listings and re-registrations is of roughly 0.74 and highly statistically significant.

Of the ADF, re-registrations capture partly job losers and quitters who have been registered at any moment in time since 1994[10]. While participation in activation schemes is of minor scale (cfr. Table 1), it covers undoubtedly a group that is not working in the reporting month. Thus, to recognize that part of the flows is driven purely by administrative decisions (AD and AS), an additional, adjusted unemployment rate measure has been computed as:

$$unemployment\ rate^{A}_{i,t} = \frac{(registered\ unemployed_{i.t} - AD_{i.t} - AS_{i.t})}{LF_{i.t} - AD_{i.t} - AS_{i.t}}, \tag{5}$$

In fact, as Table 1 shows, while AS is of minor scale, the ADF is overall of considerable size. As a consequence, assuming that it correlates to the local unemployment rate with a different sign from the overall inflow and outflow, it might affect changes in the local unemployment rate in a way that is not related to the theoretical underpinnings of this study[11]. Consequently, we pay particular attention in the estimations to disentangling these two effects, to the extent that data quality permits it.

Table 1.Inflow and outflow components of the turnover

	Share in		
Flow	**inflows**	**outflows**	**turnover**
Administrative de-listing (AD)		0.411	0.119
Job finding (JF)		0.527	0.152
Re-registration (RR)	0.806		0.573
First-time registration (FT)	0.194		0.138
Activation schemes (AS)		0.063	0.018

Source: Own elaboration on ML&SA data.

2.2. Clusters of *poviats*

Considering the high heterogeneity of local units, it is crucial to verify the robustness of results to the potential clustering of *poviats* sharing similar structural characteristics. A typical way to address this problem in the spirit of Aghion and Blanchard (1994) would be to compute the Lilien Index (LI) and include it as a control variable. Unfortunately, there are no variables available at a *poviat* level to obtain LI for

[10] In 1994 the New IT system covering the unemployment services has been established, while subsequent modifications have built on this original database. Thus, unemployed registered ever since 1994 will appear as a re-registering individual, no matter what the reason for de-registration (administrative delisting, finding employment, etc.).

[11] The hypothesis underlying empirical testing certainly concerns market driven adjustment, rather than administrative factors.

the whole time span of the data[12]. While employing the index would reduce the sample to just two years (2004-2005), we may nonetheless use it as an index to detect which *poviats* experienced more structural adjustment. We then combine these results with additional data available for *poviats* and propose a type of stratification strategy.

While the values of LI are in general relatively high, we may discern the groupings of *poviats* with extreme and moderate scores. However, it would be rather reckless to assume that a value of LI over only two years is symptomatic of the whole period. We thus coupled this information with data on overall change in the structure of employment and ownership over a longer time span. For example, *poviats* which ranked among the lowest in service employment in 2003 and among the highest in 2008 have naturally undergone continuous significant structural change. On the other hand, *poviats* with the lowest share of private ownership, the lowest investment rates and the highest employment share in agriculture can be identified as relatively resistant to transition forces.

For these reasons, the stratification is based on four variables: the share of private firms in employment, the share of services and agriculture in employment and the investment intensity. The following groupings of *poviats* have been identified:

LAGGARDS - [44 *poviats*] with low private ownership (bottom 25%), high share of rural employment (top 25%) and low investment rate (bottom 25%)

IN TRANSITION – [74 *poviats*] with both high rural and service share in employment (top 25% in both)

PRIVATISED INDUSTRIAL – [66 *poviats*] with high private ownership (top 25%) and high industry contribution (top 25%)

Naturally, *poviats* "travel" across the quarters of variables distribution, while this migration is also endogenous to the labor market turnovers. Thus, we use the earliest available data (2003 for employment shares, 2002 for investment) which partially addresses the problem of the mutual reinforcing between structural change and labor turnover. In addition, these classifications are not mutually exclusive in the sense that the same *poviat* may belong to more than one group, while some *poviats* may appear in none of the groups. The purpose of this grouping, however, has not been to classify all the *poviats*, but rather to distillate those, who are more likely to expect larger (INDUSTRIAL, IN TRANSITION) or smaller (LAGGARDS) structural change.

To corroborate the adopted typology we report below the average values of Lilien Index for the available years within the identified clusters, Table 2. In all of the cases where relatively larger industrial restructuring is expected (IN TRANSITION,

[12] For the same reason we were unable to replicate the classifications of Gòra and Lehmann (1995); Scarpetta (1995); Scarpetta and Huber (1995); Lehmann and Walsh (1999) or Walsh (2003).

INDUSTRIAL), the Lilien Index is statistically larger than average. Moreover, for the LAGGARDS it is smaller. Consequently, the adopted stratification seems to reflect well the level of industrial restructuring.

Table 2. The Lilien Index by stratification group

Group	Mean	Max	Min	% of *poviats* above mean of total sample	T-test vis-à-vis total sample
Total sample	.055	.286	.002	-	-
Laggards	.062	.099	.022	27%	***
Transition	.068	.240	.013	41%	***
Industrial	.078	.197	.009	67%	***

Source: Own elaboration on ML&SA and CSO data. T-test for the equality of means reported, *** denote statistical significance at 1% level.

3. Methodology

According to H_0 in Section 1, large turnover is consistent with more flexibility and lower unemployment (frictional unemployment reduces faster). On the other hand, according to H_1, large turnover is consistent with more structural change and higher unemployment (structural unemployment is larger). The estimated model is:

$$unemployment\ rate_{i,t} = \alpha_i + \beta_i TURNOVER_{i,t} + \nu_t + \varepsilon_{i,t} \tag{6a}$$

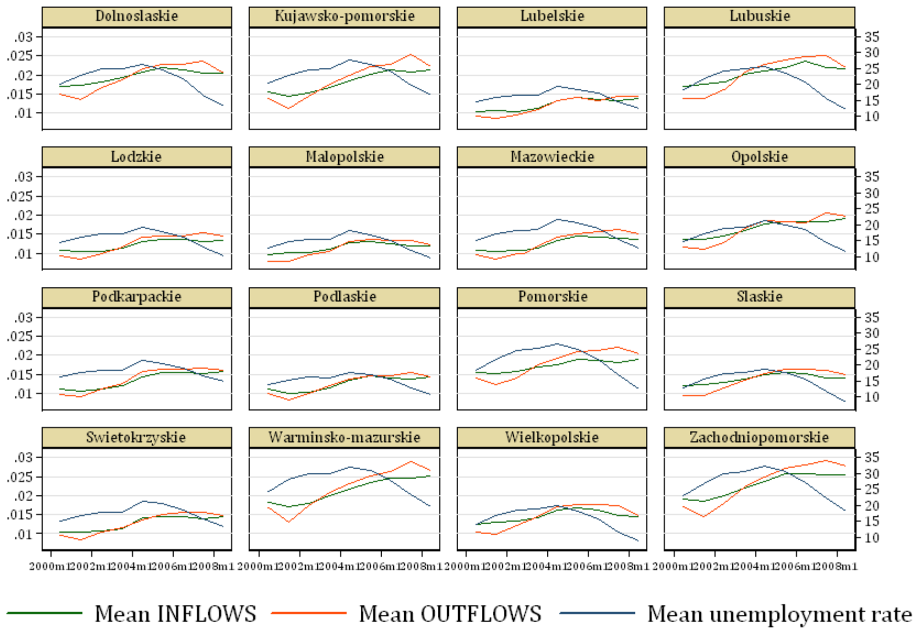
and, alternatively,

$$unemployment\ rate_{i,t} = \alpha_i + \beta_i^O OUTFLOWS_{i,t} + \beta_i^I INFLOWS_{i,t} + \nu_t + \varepsilon_{i,t} \tag{6b}$$

with the additional inclusion of $\gamma Control\ Variables_{i,t}$ in the augmented version of both equations. H_0 will then imply that all $\beta_i \leq 0$; against the H_1 of all $\beta_i > 0$. The correlation across time is an evident phenomenon – increase in outflows is ceteris paribus associated with increase in unemployment and the opposite is true for outflows, (Figure 3). However, *a priori* cross-sectional link between flows and the unemployment rate is undetermined.

There is a number of possible technical econometrics issues. The first one is the natural autocorrelation in the unemployment rate. A time fixed effect is used in this study, while we additionally assure robust Newey-West panel data estimator. For each point in time, this estimator will essentially allocate to the fixed effect the entire time specific component, allowing the model parameters to capture the variation that is attributable to the cross-section of *poviats*.

Figure 3. Unemployment, inflow and outflow rates by region (*voivodship*)



There are three additional possible weaknesses of this methodology, though. The first one is a bias attributable to the spatial effects associated with the labor market processes. For example, although a person is registered as unemployed in a high (low) unemployment *poviat*, geographically (s)he may be closer (further) to a dynamic, low unemployment *poviat* and thus have more(less) chances to obtain a job. Consequently, unemployment level in a *poviat* and its neighboring *poviats* encompasses also outcomes of individuals' geographical mobility, which necessitates spatial spillovers. Based on the adjacency of *poviats* we compute a typical spatial weights matrix [13]. We focus on the quantitatively most important source of the potential spatial effects - spatial lag dependence (Anselin, 1988). Spatial lag dependence can occur when there are spatially correlated omitted variables, spatially correlated aggregate variables or spatially correlated errors in variable measurement. *Ex ante* we cannot rule out any of these three sources of spatial error dependence, we thus adopt a geography weighted regression to the explanatory variables to account for potential bias in addition to the standard panel estimations.

Second, the model – being a single equation one – naturally involves explanatory variables that are not strictly exogenous. While spatial issues may result in a bias of the estimated coefficients – potential endogeneity may contribute to the inconsistency of the

[13] For each *poviat* we obtained the data on adjacency denoted by 1 in a a kxk matrix, where k=380 *poviats*. Each row (and column) in this matrix was subsequently normalized to unity, by dividing by its row (and column). This matrix was subsequently used to reweigh the values of the independent variables used in the estimations, cfr Anselin (1988).

estimated coefficients and potential heteroscedasticity implies that the estimated standard errors may be unreliable. There are several ways to handle the potential dynamic panel bias The regressands of particular interest – measures of turnover – are likely to be endogenous to the unemployment rate. It is known that LSDV does not address the potential endogeneity of other regressands[14], but conveniently Generalized Method of Moments (GMM) does so in this context[15]. The potential correlation between the error term and the individual effect makes the panel estimation inconsistent. Anderson-Hsiao (1981) estimator uses the second lag as an instrument after first-differencing the model to be estimated, while Arellano and Bond (1991) argue that model performance may be improved if additional lags are introduced. Additionally, Huber-White sandwich estimator of variance allows obtaining robust standard errors.

This estimation may be implemented as a less efficient – but also less demanding – IV model or in a two-step version offering more efficient estimators of standard errors. However, the moment conditions of this type of GMM estimator are only valid if serial correlation is not present in the idiosyncratic errors. In our results, there is no evidence of serial correlation in the first-differenced errors at order 2, so the moment conditions used are valid. Secondly, in order to perform two-step GMM estimation, the model needs to be overidentified. In fact, this requirement is satisfied in our model. Namely, the availability of the monthly data permits the use of multiple lags as instruments without a major loss in the sample size[16]. Consequently, as the best strategy, we obtain the classic Arellano-Bond (1991) GMM estimator, which uses moment conditions in which lags of the dependent variable and first differences of the exogenous variables are instruments for the first differenced equation[17].

The final attempt to tackle the consequences of endogeneity and the time-induced estimation flaws consists of a simple approach. Namely, we use only 2000 annual averages for the right-hand side variables (turnover as well as inflows and outflows) and 2008 annual averages for the dependent variable (unemployment rate). In addition, both

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[14] Comprehensive surveys of these estimators can be found for instance in Arellano and Honore (2001) or Blundell, Bond and Windmeijer (2000).

[15] In order to adequately establish the structure of the GMM estimation, we first estimate a simple dynamic model. This allows understanding better the dynamics of the process, thus yielding the boundaries for the structure of the estimation. As expected, the first lag of the dependent variable in the OLS regression is correlated with the fixed effects in the error term, creating dynamic panel bias (Nickel 1981). After accounting for the fixed effects in the model, the initial naive GLS regression demonstrates that the lagged dependent variable is positively correlated with the error, biasing its coefficient estimate upwards, and for the within groups, the opposite effect is observed.

[16] In fact, this would not have been possible with the annual data, because T (i.e. the number of periods) would have been relatively small (only ten years of observations). Implementing the Arellano-Bond estimator would effectively imply the loss of at least three years, i.e. nearly a half of our sample. Moreover, the requirement of overidentification would have been violated, necessitating the use of less efficient one-step estimator. Thus, we resort to monthly data only.

[17] To complete these estimations, we also employ the so-called SYS-GMM, as suggested by Arellano and Bover (1995) as well as Blundell and Bond (1998). This specification allows the use of first lags as additional instruments in the differenced equation. System GMM estimator is believed to obtain more precision and better finite sample properties thanks to using this additional lag, Doornik, Arellano and Bond (2002).

RHS and LHS variables have been standardized to asymptotically N(0,1) distribution. Consequently, we explore a cross-sectional dimension, without running the risk of endogeneity (LHS variables precede RHS by 8 years, while the level of absolute unemployment rate in 2000 and in 2008 were roughly comparable, see Figure 1).

Third and final technical problem is heterogeneity of an *a priori* unknown form[18]. It is possible that while we account for spatially driven heterogeneity and employ robust standard errors, there are also other sources of heterogeneity that prevail. To address this issue we propose two additional estimations. First, obtain estimates separately by the decimal groups of the unemployment rate to capture the heterogeneity attributable to the severity of the local labor markets situation. Second, clustering of *poviats* based on industrial restructuring provides another way to check if heterogeneity substantially influences the standard errors obtained for the total sample.

4. Results

This section is organized in three parts: (i) description of data properties; (ii) estimates for the overall sample and (iii) robustness checks. The robustness checks are based on spatial lag inclusion as well as clustering of *poviats* to account for potential distributional effects associated with the unemployment rate and clustering of *poviats* to account for the structural differences among them.

4.1. Data properties

Table 3 in the Appendix supplies averages over the entire period. "Industrial" *poviats* include the largest stock of unemployed but the lowest unemployment rate, which suggests that these are relatively large local labor markets – virtually all city *poviats* and other densely populated and urbanized *poviats* – with a more dynamic economy. As expected, the *poviats* "lagging behind" include some of the least densely populated regions with the highest unemployment rate. The "transition" cluster is more similar to the "laggards" than the "industrial".

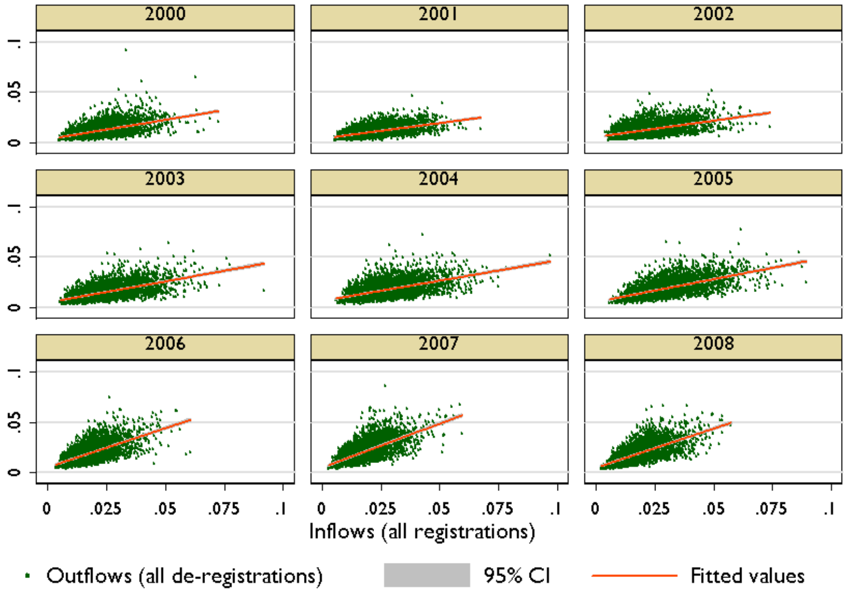
Panel (a) of Figure 4 provides scatters of inflow and outflow rates by year for all *poviats*. Both components of labor turnover present a high degree of variation, over time and across units. Nonetheless, they positively correlate with each other in every year. This depends on the nature itself of labor market dynamics, which always tends to fluctuate around some equilibrium unemployment level. Nonetheless, at a careful glance, the slope of the scatters appears to be flatter (steeper) when the unemployment

[18] Throughout all the estimations heteroscedasticity consistent Newey-West standard errors estimation is used. Technically speaking, we use an adequate adaptation of the initial Newey-West variance matrix estimator that is relevant for a particular model.

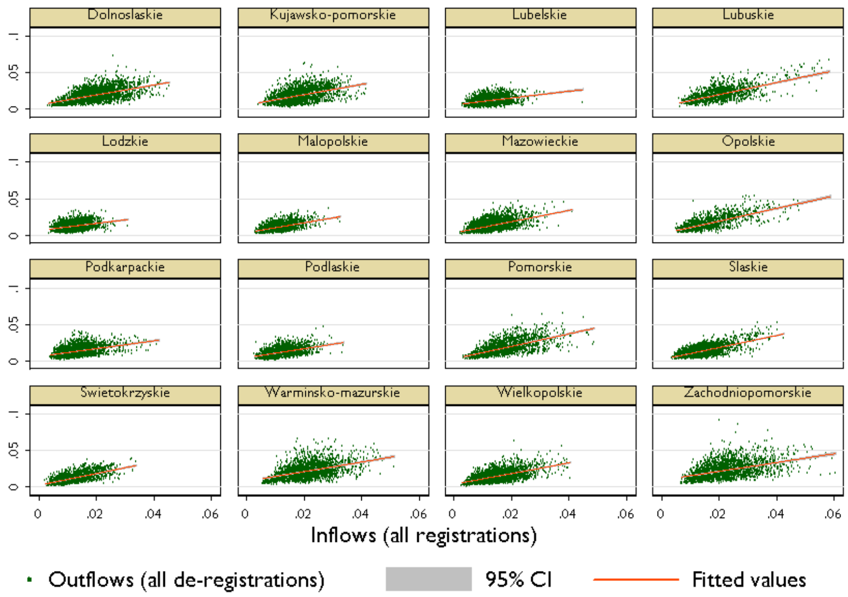
rate is increasing (reducing). Overall, this is as if it was not the gap in inflow or outflow rates, but the gap in both flows, or in the turnover rate, as suggested in the theoretical analysis of section two, that correlates with the gap in unemployment rates. Panel (b) of Figure4 shows the same variables as in panel (a), but organized by *voivodship*. Again, the correlation is always positive, although with different slopes.

Figure 4. Scatter of monthly inflow and outflow rates by year and *voivodship*

Panel (a)



Panel (b)



4.2. Results of the estimations

Table 4 in the Appendix reports the results of the time fixed effect panel GLS estimator with robust standard errors. All the variables are in logarithms and therefore the coefficients measure elasticities. All the estimations are performed on the raw (columns from 1 to 7) and adjusted data (columns from 8 to 14). As described in Section 3, the former are the originally reported unemployment rate as well as the turnover rate, whereas the adjusted data do not take into account the administratively de-listed (see equations 3a and 3b). In addition to the specification using labor turnover only as the regressor of interest (columns 1 and 8), the following ones disentangle labor turnover in different components: (i) inflow and outflow (columns 2 and 9); (ii) components of the flow (columns 3 and 10); (iii) market and administratively-driven flow (columns 7 and 14). The following columns – from 4 to 6 and from 11 to 13 – include also the available control variables.

The results show a consistent positive and statistically highly significant coefficient for the rate of labor turnover and also for inflows and outflows in both the raw and adjusted data. The positive coefficient of outflows catches the correlation between above average unemployment rate and above average outflows, confirming that in fact what matters while explaining the cross-section dimension of variation in unemployment rates is the overall degree of turnover, rather than the size of the outflow.

The size of the estimated elasticity is consistent across specifications, but slightly lower in the case of adjusted data. This suggests that administratively driven outflows contribute negatively to the unemployment rate and, considering their large size, this is indication for policy makers that registered unemployment might partly be affected by the behavior of LLOs. *Ceteris paribus*, across all specifications on the raw data elasticity of the AD variable is significantly negative, although the point estimator is fairly low. This is circumstantial evidence that LLOs use the AD flow to artificially "adjust" the unemployment rate especially in high unemployment regions[19].

The differential between the coefficients of inflow and outflow shrinks when we move from raw to adjusted data. Larger responsiveness of the unemployment rate towards inflows may stem from two sources. First, we are not exploring the time dimension but the cross-sectional dimension, which implies regional differentiation of

[19] Given the implicit incentives in the financing scheme, this problem should be particularly severe there. The pressure to deliver achievements in the fight against unemployment is higher, but at the same time the risk of losing state funds for active labour market schemes are much lower, since financial allocations are proportional to the relative situation of *poviats*. Thus, if administrative adjustments do not improve the official indicators to an extent sufficient for changing the ordering of *poviats* in the regional rankings, the loss in available financing may indeed be marginal. Moreover, demonstrating reduction in the headcount of the unemployed may indeed be a way to justify the expenditure of public resources.

the unemployment rates across *poviats* is driven more by the asymmetric response to economic shocks exhibiting in the increases of the unemployed pool rather than by the recovery outflows from the registry. This finding is consistent with Armstrong and Taylor (1985). Second, *poviats* with higher unemployment rate are typically those with larger shares of long-term unemployed, who tend to drop out of the registry and re-register more frequently than other unemployed. This assertion is partly confirmed by the change in estimators when adjusted data are analyzed.

It is even further corroborated by the analysis of flows separately. There is naturally a consistently negative contribution from the administrative de-listing (AD) and – quantitatively minor – from the flows into activation measures (AS). This confirms that de-listings are used to reduce unemployment. In addition, the flow to activation is marginally greater the higher is the local unemployment rate. On the other hand, market driven flows of job finding (JF) and first time registrations (FT) have both a positive sign and are of a comparable size. This finding remains essentially the same for the adjusted unemployment rate and flows, with comparable elasticity. Consequently, markets with larger market-driven turnover confirms H_1. Also re-registrations contribute positively to unemployment.

The inclusion of the control variables does not alter the findings. The coefficient of labor turnover is somewhat reduced, confirming that the controls used do have an impact on the relationship between unemployment and labor turnover. The coefficients of the control variables are as expected. Higher capital availability relative to the rest of the country tends to be associated to lower than average unemployment. On the other hand, the service sector seems to provide less stable jobs than industry or agriculture, thus yielding higher turnover and unemployment rate. The relative wealth, as proxied by the standardized tax revenues, seems to be associated with higher unemployment rates, *ceteris paribus*. However, this finding is also a consequence of the fact that tax data are not available for the city *poviats*. It thus seems that among the land *poviats*, higher wealth is associated with larger labor market dynamics and thus higher unemployment rate[20].

To evaluate empirically the severity of endogeneity, we employ alternative GMM specifications (Table 5 in the Appendix). Naturally, GMM focuses more on the “within” or time-dimension, but it also provides a reliable estimate of how the GLS estimators may be biased vis-à-vis this dimension.

GMM estimators differ considerably in size, but are consistent. Namely, *over time* the coefficient for outflows is both significant and negative, while inflow remains positive. However, it seems that instruments – lags and differences of turnover, inflows

[20] Specific results for only city *poviats* are also in line with the main findings. Detailed results available upon request.

and outflows in respective specifications – have relatively low power, in capturing the cross-sectional dimension. Thus, it seems that GMM – both system and difference specifications – tackle well the time-dimension, but not necessarily the cross-sectional variation.[21]. Nonetheless, GMM results demonstrate – mainly by exploring the cross-sectional dimension of the data – that turnover as well as both inflows and outflows are positively correlated to the unemployment rate. This relationship is robust to the inclusion of other control variables as well as measure of labor market flows and unemployment rate. In the reminder of this section we verify if these results are susceptible to spatial phenomena, urbanization, statistical deficiencies or outliers.

4.3 Robustness check: spatial analysis

We verify if the results are robust to the inclusion of spatial controls in Table 6 in the Appendix. In fact, both the size and the sign of the estimators on turnover as well as inflows and outflows – remain essentially unaffected by the inclusion of spatial controls. Nonetheless, the data support the existence of spatial effects as well. We find a positive spatial lag of turnover on original data and negative spatial lag of this variable on adjusted data. This seems to suggest that when public employment services discretion is controlled for, if surrounded by high turnover *poviats,* a local labor market is characterized by lower unemployment rate. In fact, this is consistent with intuition which suggests that more dynamic labor markets surrounding a particular location contribute to lowering its unemployment rate.

Spatial effects of inflows are negative and significant, suggesting that with the increasing inflows in the neighboring regions, unemployment rates tend to decrease. This effect is counterintuitive, but seems to be driven by metropolises. In the case of large cities, reductions in job demand are equivalent to either overall job destruction or a shift of demand towards cheaper workers inhabiting the surrounding *poviats*. However, when large cities are no longer included in the estimation (column 5 of Table 6), the spatial effect is significant and conforms to the intuition of unemployment increases spilling over the entire area.

The spatial effects of outflows, on the contrary, seem to be independent of the metropolises effects. Namely, for adjusted data it is insignificant, whereas the original

[21] What follows is that the negative consequences of the autocorrelation induced by the time dimension of the data are effectively reduced – if not removed – due to the large size of our sample, whereas unit-driven heteroscedasticity is better tackled by the robust GLS estimator than the GMM (even with the correction for robust variance covariance estimator in both one-step and two-step Arellano-Bond estimations). Nonetheless, we find again that the estimator of the inflows coefficient is again larger than the one of the outflows in a statistically significant manner, which further corroborates the findings discussed earlier In fact, as expected, in all cases the specification proves to provide consistent estimators. Namely, the null hypothesis of autocorrelation is not rejected at order 1, but is rejected at higher orders. Moreover, in the standard Sargan test the null hypothesis concerning the validity of overidentifying restrictions (i.e. that the population moment conditions are correct) has not been rejected, either.

data suggest positive and significant estimators, which is consistent with the anecdotal evidence that LLOs refuse to share collected vacancies and information on job creation. Moreover, the fact that adjusted data no longer lend support to spatial effects seems to suggest a spurious relationship (due to administrative delisting).

4.4 Robustness check: urbanization

Considerable heterogeneity exists across *poviats*. Relatively fast urbanization combined with a massive shift towards services could be one such dimension that requires empirical tackling. The most obvious way to do that would be to consider separately city and land *poviats*. Labor market adjustment might have differed considerably in large, dynamic agglomerations, as opposed to remote land counties, whose development was in general slower.

The results demonstrate that, despite some differences, H_0 is rejected in favor of H_1 even controlling for potential urbanization effects, Table 7 in the Appendix. Differences between raw and adjusted measures are similar for city and land *poviats*. The main difference concerns the effects of non-market factors: the unemployment rate is more responsive to institutional turnover as well as to re-registrations in the case of land counties. This finding conforms with the intuition that less dynamic labor markets are more subject to policies, whereas dynamic agglomerations have stronger market forces to drive the processes. However, signs and magnitudes are comparable across agglomerations and land counties.

The split between city and land counties is rather mechanical while mirroring the administrative status. In the following section, the stratification is based on employment and production status.

4. 5. Robustness check:–unobserved heterogeneity

Since the data set is so rich, stratification or grouping permits exploring further the cross-sectional variation and does not hazard the statistical quality of the findings. Here, we verify whether results are driven by specific types of *poviats*. We implement two robustness checks: (i) stratification and (ii) deciles of the unemployment distribution. First, we inspect differences in the estimated point coefficients across the clusters of *poviats* mentioned above. Tables 8 and 9 in the Appendix report the results for the two preferred specifications, including additionally the spatial controls.

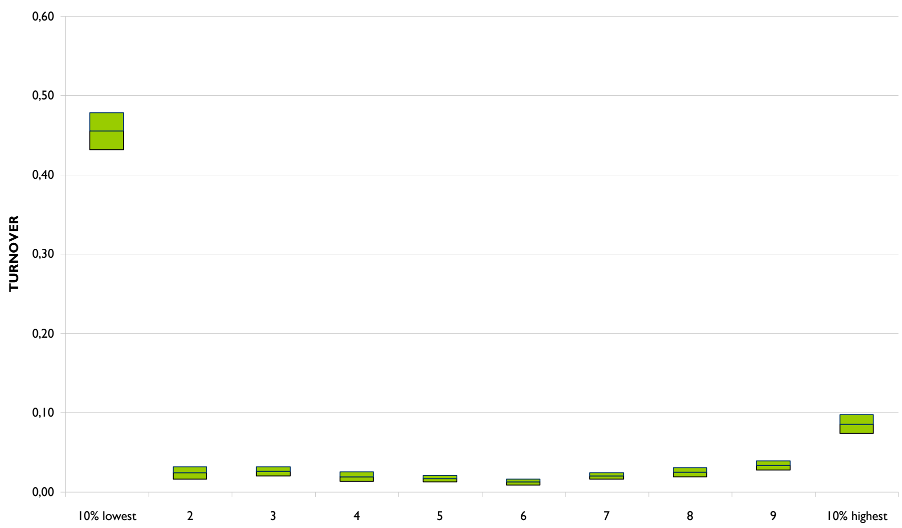
The stratification analysis reveals that in fact elasticity estimators are consistent and of the same sign irrespective of the grouping – the differences concern only the size of the estimator. Controlling for spatial dependence does not alter these findings. More specifically, elasticities are the largest in the INDUSTRIAL cluster, where industrial restructuring is expectedly the highest. Not surprisingly, considering the way clusters are defined, the coefficient of the service sector employment variable is not statistically significant. The difference between the estimators of the inflows and the outflows elasticities is no longer as large as earlier. Moreover, the differences between labor market turnover and institutional turnover is largest for the INDUSTRIAL cluster. Finally, “active de-listing” seems to be particularly at play in these *poviats*, where institutional turnover exhibits a negative elasticity.

4.6. Robustness check: outliers

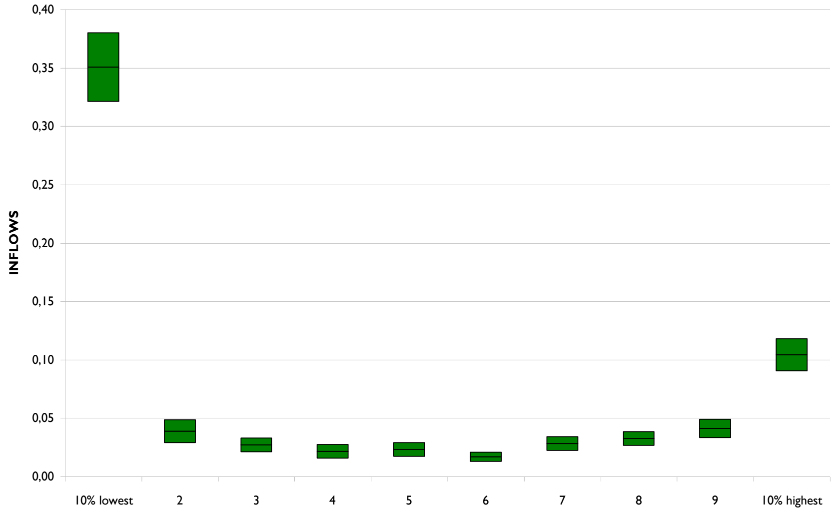
To account for potentially diverse effects among low and high unemployment regions, we use stratification on the unemployment distribution. We estimate the coefficients of interest at different deciles of the distribution of *poviat* unemployment rates at the beginning of the analyzed period. In fact, *poviats* rarely change these decimal groups (Tyrowicz and Wójcik, 2010a).

Figure 5. Point estimators (elasticities) by the decimal groups

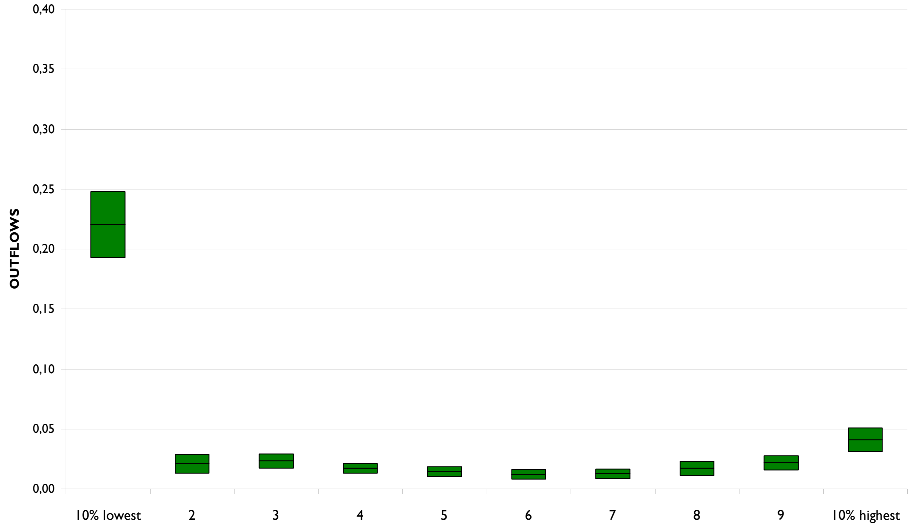
Panel (a)



Panel (b)



Panel (c)



Note: Point estimators were obtained for decimal groups in separate estimations for each group. The values are obtained from estimation like the one presented in column 2 of Table 4. *Source:* Own elaboration.

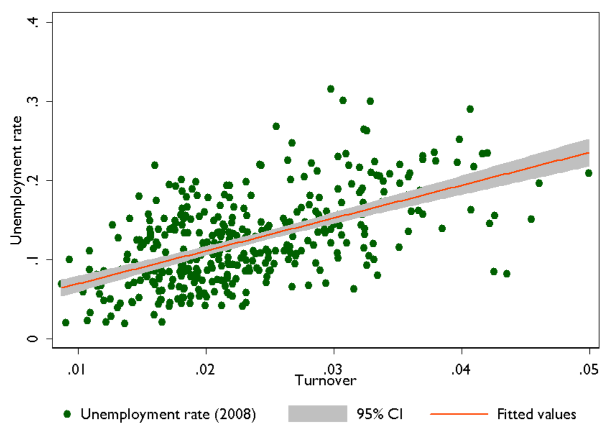
Panel (a) of Figure 5 displays the estimated elasticity and confidence interval (shaded area) on the turnover. The panels (b) and (c) contain the elasticities for inflows and outflows, respectively. Clearly, all the coefficients are statistically significant and of the same – positive – sign. However, the effect is much stronger among the *poviats* with the lowest unemployment rate and the difference in the size of the estimated coefficient is statistically significant between the lowest unemployment decimal group and the rest of the sample for all the estimators. This finding is in a sense intuitive – in the low unemployment regions the current changes in job creation and destruction give a more decisive contribution to unemployment. In the regions with higher unemployment rates, the cumulated stock of unemployed is actually large enough to make the flows quantitatively less important for determining the unemployment rate. Thus, although the strength of the effect is visibly different along the distribution of unemployment, it is also consistently of the same sign and statistically significant for all deciles.

One additional – and final – attempt to verify the reliability of the results consisted of plotting the variables of interest (i.e. turnover, inflows and outflows) as recorded in 2000 (annual averages) against the unemployment rate at the end of the time span available for the analysis (i.e. the annual averages for 2008). In fact, the aggregate unemployment levels in 2000 and in 2008 were fairly similar, but doubled in between these time boundaries.

Figure 6 displays the scatter plots of the unemployment rate in 2008 on the vertical axis against the turnover (panel a), inflows (panel b) and outflows (panel c) by *poviats*. Each of the graphs is consistent with the statistical findings reported earlier. Namely, *poviats* with relatively larger turnover, inflow and outflow in 2000 are characterized by relatively larger unemployment rate in 2008. This finding also further undermines the reliability of the GMM estimates – the negative sign of the outflows and turnover estimators seems to find little justification in the graphical analysis of the data.

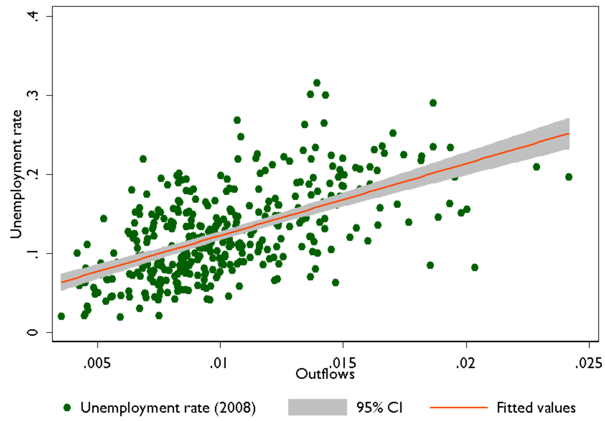
Figure 6. Scatter plot of turnover, inflows and outflows in 2000 against the unemployment rate in 2008 by poviats

Panel (a)



Panel (b)

Panel (c)



Note: Figure displays the scatter plots of the unemployment rate in 2008 on the vertical axis against the turnover (panel a), inflows (panel b) and outflows (panel c) in 2000; annual averages.

Concluding remarks

The empirical analysis of this paper builds on Aghion and Blanchard (1994). The previous literature brings to the fore different hypotheses as to the link between local labor market dynamics – as proxied by the turnover rate – and the unemployment rate. Causality seems evident in the case of the time link between unemployment and labor market flows. Inflows exceeding outflows yield growing unemployment. However, this general contention does not necessarily translate to a cross-sectional dimension. Indeed, if higher turnover is a sign of more flexibility, lower unemployment rates should be expected. In this paper an attempt was made to quantitatively verify the cross-sectional empirical pattern linking the labor market turnover and the unemployment rate using a rich dataset encompassing nearly 10 years of monthly data at a policy relevant level of a *poviat* (county) in Poland. We find a statistically significant and economically large positive estimator on turnover as a whole as well as its components: inflows and outflows.

Earlier literature finds that there is no clear spatial pattern of unemployment in Poland, while unemployment differentials are extremely high and persistent. Our findings provide some insights into why it may be so: spatial effects are statistically significant, but quantitatively smaller than general estimators. We also contribute by lending support to the assertion that the larger is the labor market dynamics in the local labor markets, the higher is the unemployment rate. This finding is in stark contrast to the general belief that high unemployment regions tend to be the stagnant ones. Correcting for the participations rates (i.e. accounting for over-employment in agriculture) we find that the stagnant counties enjoy, *ceteris paribus*, lower unemployment rates. These results are robust to the inclusion of the additional control variables such as the investment rate and the share of employment in the service sector.

The aim of this paper has not been to "explain" the level of unemployment or even to find the roots of persistent unemployment differentials. Instead, rooted in the optimal speed of transition literature, the data was used to check if structural change could be considered the root cause for why unemployment remains persistently high in Poland when compared to other regions. A number of policy-related explanations failed to accommodate fully the unstable high unemployment equilibrium, as suggested by Aghion and Blanchard (1994) model. In fact, the evidence presented in this paper seems to show that yet in the 2000s excessively fast privatization has been the main reason for relatively higher unemployment in Poland. The findings of this paper further corroborate the literature that emphasizes the role of the mechanisms suggested by the Aghion and Blanchard (1994) model, such as, for instance, Burke and Walsh (2012), but refer to much more recent data and thus point to the lasting effects of inadequate policy.

One potential explanation for the findings presented in this paper seems to follow from a nonlinearity – if the relationship between turnover and unemployment was to be inverted U-shaped, our results could follow from encompassing mostly observations from just "one range" of the bell. However, the separate estimates for city and land *poviats*, stratification across the labor force and productive composition and along the whole distribution of the unemployment suggest that indeed the phenomenon suggested by Aghion and Blanchard (1994) is universal and cannot be explained by one specific type of labor market adjustments (e.g. the collapse of the state farms or large scale state enterprises in monopsonistic setting).

The policy implications of our findings are far reaching. In fact, providing empirical evidence in support of the optimal speed of transition model suggests that the key source of the unemployment is too fast restructuring on the onset of transition. In this context, first and foremost, it seems that instead of policies addressing the supply side (i.e. the concept of the unemployed mismatched geographically or occupationally to the needs of the employers), intensive policies towards the demand side should be enforced. More specifically, high non-wage labor costs successfully deterred job creation, encouraging scarce use of labor. Whether or not labor costs continue to be high now may actually be irrelevant if that behavioral pattern is rooted into private sector decisions. These results effectively call for employment subsidies and consistent cushioning of the subsequent structural changes. In addition, support is lent to private or state investment high unemployment high turnover *poviats*.

Indirectly, these finding may also be interpreted as evidence of the inefficiency of local labor market institutions, whose role should be to smoothen the job-to-job as well as unemployment-to-job flows.

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Appendix of Tables and Figures

Table 3. Descriptive statistics by group of *poviat*

Variable	Full sample	Laggards	Transition	Industrial
Unemployed registering	566.68	394.69	379.90	862.22
(flow)	[422.41]	[269.71]	[229.12]	[661.56]
Unemployed who got employed this month - JF	268.74	181.59	176.28	375.77
(flow)	[210.35]	[141.85]	[123.25]	[321.14]
No of unemployed	6 922.39	5 684.82	5 405.76	9 763.32
(stock)	[5227.87]	[3834.46]	[3277.77]	[8229.32]
No of unemployed, previously registered - RR	416.61	296.33	283.90	614.86
(flow)	[293.30]	[214.31]	[183.58]	[434.92]
No of delisted unemployed - AD	192.20	127.15	125.61	328.05
(flow)	[179.45]	[97.57]	[89.26]	[268.93]
No of unemployed, first time registered - FT	150.07	98.36	96.00	247.37
(flow)	[168.92]	[77.73]	[68.62]	[275.48]
No of unemployed, in activation schemes - AS	102.08	80.40	78.10	134.16
(flow)	[104.69]	[78.3089]	[71.64]	[147.54]
Labor force [computed]	43 218	33 797	32 941	73 396
(stock)	[58286.38]	[18196.74]	[15952.96]	[71876.52]
Service share in employment	0.403	0.220	0.229	0.586
(stock, % of working population)	[.14	[.041]	[.039]	[.13]
Fixed capital formation per capita	- 0.000	- 0.642	- 0.463	0.589
(standardized)	[.99]	[.07]	[.44]	[1.24]
Per capita tax revenues	- 0.000	-0.879	- 0.743	1.376
(standardized)	[.99]	[0.26]	[0.36]	[0.77]
Unemployment rate [%]	18.66	16.60	16.49	15.49
	[7.53]	[5.42]	[5.46]	[6.06]
Adjusted unemployment rate [%]	18.26	16.29	16.17	15.05
	[7.51]	[5.41]	[5.43]	[6.04]
Inflows (FT+RR/LF) [%]	1.540	1.180	1.190	1.380
	[.0069]	[.0048]	[.0048]	[.005]
Outflows (JF+AS+AD/LF) [%]	1.560	1.180	1.210	1.350
	[.0083]	[.0059]	[.006]	[.0058]
Turnover (inflows + outflows) [%]	3.100	2.360	2.390	2.730
	[.0138]	[.0093]	[.0095]	[.0099]
Adjusted outflows (JF/LF) [%]	1.060	0.810	0.820	0.830
	[.0065]	[.0048]	[.0048]	[.0041]
Adjusted inflows (FT/LF) [%]	0.380	0.290	0.300	0.360
	[.0019]	[.0014]	[.0014]	[.0017]
Adjusted turnover	1.440	1.100	1.120	1.200
(adjusted inflows + adjusted outflows) [%]	[.0072]	[.0052]	[.0053]	[.0046]
Number of observations	40 202	4 663	7 843	6 993

Notes: Standard deviations in brackets. Each observation is an average computed on the entire sample period.

Source: Own elaboration on ML&SA and CSO data.

Table 4. Estimations results, unemployment rate (raw and adjusted) as determined variable

	Raw data							Adjusted data						
Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Turnover	0.8479***			0.7723***				0.7515***			0.6381***			
	[0.003]			[0.004]				(0.004)			(0.004)			
Inflows		0.5926***			0.5628***				0.1230***			0.1950***		
		[0.005]			[0.005]				(0.004)			(0.005)		
Outflows		0.2676***			0.2301***				0.5994***			0.4677***		
		[0.005]			[0.005]				(0.003)			(0.003)		
AD			-0.1146***			-0.0713***								
			[0.004]			[0.003]								
JF			0.1672***			0.1247***				0.1819***			0.1305***	
			[0.006]			[0.006]				(0.006)			(0.006)	
FT			-0.4208***			-0.2771***				-0.4756***			-0.2992***	
			[0.005]			[0.005]				(0.005)			(0.005)	
RR			0.3898***			0.3514***								
			[0.007]			[0.007]								
AS			0.0201***			0.0114***								
			[0.002]			[0.002]								
Institutional turnover							0.4949***							0.0733
							[0.004]							(0.086)
Market turnover							0.2756***							0.7147***
							[0.003]							(0.078)
Tax revenues				-0.0837***	-0.0855***	-0.0635***	-0.1011***				-0.1145***	-0.1115***	-0.0736***	-0.8085*
				[0.001]	[0.001]	[0.003]	[0.001]				(0.002)	(0.002)	(0.003)	(0.478)
Investment				-0.0141***	-0.0140***	-0.0440***	-0.0117***				-0.0193***	-0.0188***	-0.0450***	-26.8408
				[0.001]	[0.001]	[0.002]	[0.001]				(0.002)	(0.002)	(0.002)	(31.701)
Services				0.3008***	0.2569***	1.1368***	0.3165***				0.6840***	0.6477***	1.1492***	-92.5368
				[0.015]	[0.015]	[0.023]	[0.015]				(0.019)	(0.019)	(0.023)	(264.730)
Constant	1.2550***	1.9069***	-2.4741***	0.9069***	1.5569***	-3.2346***	1.3374***	1.4799***	1.7362***	-2.4580***	0.7698***	1.3206***	-3.2827***	30.3561
	(0.011)	(0.014)	(0.021)	[0.023]	[0.025]	[0.027]	[0.018]	(0.016)	(0.022)	(0.022)	(0.028)	(0.034)	(0.029)	(89.797)
Number of observations	39,838	39,838	39,185	33,090	33,090	32,527	33,090	39,838	39,838	39,838	33,090	33,090	33,090	33,090
R2 within	0.684	0.688	0.294	0.716	0.726	0.425	0.721	0.567	0.593	0.271	0.605	0.619	0.414	0.493

Note: Monthly data, annual and monthly dummies included. Time fixed effect panel GLS estimator with robust standard errors. Tax data only available for land *poviats*,

Table 5. Estimation results, unemployment rate as a determined variable, monthly data

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Turnover	-0.0330	-0.0329			-0.0332*	-0.0332*		
	(0.049)	(0.020)			(0.017)	(0.018)		
- first lag	-0.0150	-0.0150			-0.0222	-0.0222*		
	(0.045)	(0.030)			(0.037)	(0.034)		
Inflows			0.0760***	0.0761***			0.0814***	0.0815***
			(0.028)	(0.001)			(0.019)	(0.001)
- first lag			-0.0163	-0.0163***			-0.0113	-0.0113***
			(0.057)	(0.001)			(0.010)	(0.001)
Outflows			-0.0677*	-0.0677***			-0.0678***	-0.0678***
			(0.040)	(0.001)			(0.017)	(0.001)
- first lag			-0.0056	-0.0056***			-0.0021	-0.0021
			(0.065)	(0.001)			(0.016)	(0.001)
Constant	-0.2176	-0.2174***	-0.0839	-0.0839***	-0.1927*	-0.1926***	0.0031	0.0032
	(0.275)	(0.013)	(0.202)	(0.008)	(0.101)	(0.009)	(0.099)	(0.004)
No of observations	31,902	31,902	31,902	31,902	33,035	33,035	33,035	33,035
Model	Arellano-Bond				Andersen-Hasiao			
	Two-step	One-step	Two-step	One-step	Two-step	One-step	Two-step	One-step

Note: Each estimation includes up to 6 lags for unemployment and up to 4 lags for independent variables, (computational constraints prohibited including further lags). In addition, Andersen-Hsiao estimators also include lagged second differences of dependent and independent variables as instruments. Robust standard errors. Statistics for Sargan test and identification test computed robustness correction (as only possible in Stata11). Lags of unemployment significant, not-reported, available upon request.

Table 6. Spatial regressions, unemployment rate as determined variable, spatial lag model with weights based on adjacency.

Variables	Raw data						Adjusted data		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Turnover	0.8088***						0.9159***		
	(0.004)						(0.010)		
- spatial lag	0.0730***						-0.1065***		
	(0.005)						(0.010)		
Inflows		0.5866***			0.5087***			0.6673***	
		(0.006)			(0.008)			(0.016)	
- spatial lag		-0.0491***			0.0962***			-0.0992***	
		(0.010)			(0.012)			(0.017)	
Outflows		0.2413***			0.1841***			0.2645***	
		(0.005)			(0.006)			(0.014)	
- spatial lag		0.1044***			0.0829***			-0.0147	
		(0.009)			(0.010)			(0.016)	
Market turnover			0.2465***			0.2237***			0.4754***
			(0.008)			(0.007)			(0.010)
- spatial lag			0.0492***			0.0152			-0.0787***
			(0.015)			(0.013)			(0.012)
Institutional turnover			0.3650***			0.3866***			0.4494***
			(0.012)			(0.009)			(0.011)
- spatial lag			0.2078***			0.2741***			-0.0119
			(0.018)			(0.015)			(0.012)
AD				-0.0993***					
				(0.004)					
- spatial lag				-0.0881***					
				(0.007)					
JF				0.1173***					
				(0.007)					
- spatial lag				0.0713***					
				(0.011)					
FT				-0.2779***					
				(0.006)					
- spatial lag				-0.2954***					
				(0.008)					
RR				0.2470***					
				(0.008)					
- spatial lag				0.4571***					
				(0.012)					
AS				0.0151***					
				(0.002)					
- spatial lag				0.0230***					
				(0.004)					
Services					0.2222***	1.0148***	0.0262	0.0211	-0.0484***
					(0.023)	(0.059)	(0.020)	(0.019)	(0.018)
- spatial lag					0.0026				
					(0.012)				
Investment					-0.0143***			0.0042*	0.0066***
					(0.001)			(0.002)	(0.002)
- spatial lag					-0.0066***				
					(0.002)				
Taxes					-0.0616***				
					(0.004)				
- spatial lag					-0.1069***				
					(0.004)				
Constant	1.0551***	1.3709***	2.0032***	-3.4365***	1.9088***	1.8337***	1.0095***	1.6135***	1.5454***
	(0.069)	(0.015)	(0.018)	(0.033)	(0.059)	(0.053)	(0.043)	(0.050)	(0.045)
No of observations	38,537	38,537	36,465	36,465	23,505	7,661	6,847	6,847	6,847
R2 within	0.683	0.687	0.363	0.730	0.669	0.641	0.663	0.669	0.697

Table 7. Estimation results, urbanization, unemployment rate as determined variable

Variable	Large cities (*city poviats*)						Land poviats					
	Raw data			Adjusted data			Raw data			Adjusted data		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Turnover	0.8030***			0.7346***			0.8130***			0.6736***		
	(0.009)			(0.014)			(0.006)			(0.011)		
Inflows		0.5937***			0.1235***			0.5856***			0.1033***	
		(0.017)			(0.011)			(0.012)			(0.011)	
Outflows		0.2252***			0.5864***			0.2478***			0.5362***	
		(0.017)			(0.011)			(0.011)			(0.008)	
Investment	-0.0546***	-0.0526***	-0.0481***	-0.0935***	-0.0879***	-0.1937***	-0.0350***	-0.0354***	-0.0369***	-0.0493***	-0.0465***	-0.0617***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Services	-0.1555***	-0.1365***	-0.1764***	-0.3115***	-0.2761***	-0.8278***	-0.1758***	-0.2294***	-0.2250***	0.0659***	0.1239***	0.7887***
	(0.026)	(0.027)	(0.024)	(0.040)	(0.038)	(0.037)	(0.021)	(0.021)	(0.021)	(0.024)	(0.025)	(0.040)
Market turnoveor			0.4262***						0.2332***			
			(0.020)						(0.011)			
Institutional turnover			0.3972***						0.5659***			
			(0.010)						(0.008)			
JF						0.2359***						0.1408***
						(0.027)						(0.010)
FT						-0.3369***						-0.3636***
						(0.015)						(0.011)
RR						0.1346***						0.3595***
						(0.021)						(0.013)
Constant	1.0913***	1.7066***	1.5630***	1.5417***	1.7941***	-1.8397***	1.2176***	1.8997***	1.6548***		1.3034***	-3.1683***
	(0.044)	(0.048)	(0.029)	(0.039)	(0.053)	(0.057)	(0.032)	(0.036)	(0.022)		(0.052)	(0.046)
Number of observations	6,748	6,748	6,748	6,748	6,748	6,748	33,090	33,090	33,090		33,090	33,090
R2 within	0.723	0.727	0.752	0.673	0.698	0.475	0.684	0.693	0.676		0.570	0.394

Note: Time fixed effect panel GLS estimator with robust standard errors.

Table 8. Estimation results, stratification, unemployment rate as determined variable with spatial correction

Variables	Laggards			Transition			Industrial		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Turnover	0.6810***			0.6725***			0.9159***		
	(0.010)			(0.008)			(0.010)		
- spatial lag	0.1748***			0.2695***			-0.1065***		
	(0.017)			(0.013)			(0.010)		
Inflows		0.5409***			0.5305***			0.6673***	
		(0.013)			(0.011)			(0.016)	
- spatial lag		0.0954***			0.1700***			-0.0992***	
		(0.025)			(0.020)			(0.017)	
Outflows		0.1764***			0.1801***			0.2645***	
		(0.011)			(0.009)			(0.014)	
- spatial lag		0.0562***			0.0840***			-0.0147	
		(0.021)			(0.017)			(0.016)	
Market turnover			0.2465***			0.2237***			0.4754***
			(0.008)			(0.007)			(0.010)
- spatial lag			0.0492***			0.0152			-0.0787***
			(0.015)			(0.013)			(0.012)
Institutional turnover			0.3650***			0.3866***			0.4494***
			(0.012)			(0.009)			(0.011)
- spatial lag			0.2078***			0.2741***			-0.0119
			(0.018)			(0.015)			(0.012)
Constant	1.0551***	1.7613***	1.4581***	1.5373***	2.3273***	1.8337***	1.0095***	1.6135***	1.5454***
	(0.069)	(0.077)	(0.063)	(0.051)	(0.059)	(0.053)	(0.043)	(0.050)	(0.045)
Services	0.8099***	0.7301***	1.2703***	0.6427***	0.5779***	1.0148***	0.0262	0.0211	-0.0484***
	(0.077)	(0.076)	(0.076)	(0.061)	(0.059)	(0.059)	(0.020)	(0.019)	(0.018)
Investment	-0.2702***	-0.2403***	-0.3391***	-0.0479***	-0.0442***	-0.0380***	0.0026	0.0042*	0.0066***
	(0.043)	(0.041)	(0.038)	(0.006)	(0.006)	(0.007)	(0.002)	(0.002)	(0.002)
No of observations	4,484	4,484	4,484	7,661	7,661	7,661	6,847	6,847	6,847
R2 within	0.641	0.666	0.669	0.649	0.669	0.641	0.663	0.669	0.697

Table 9. Estimation results, stratification, unemployment rate as determined variable

Variables	Laggards			Transition			Industrial		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Turnover	0.7433***			0.7622***			0.8809***		
	(0.009)			(0.007)			(0.009)		
Inflows		0.5760***			0.5886***			0.6283***	
		(0.012)			(0.010)			(0.014)	
Outflows		0.1962***			0.2079***			0.2658***	
		(0.011)			(0.009)			(0.013)	
Market turnover			0.2364***			0.2202***			0.4407***
			(0.007)			(0.006)			(0.009)
Institutional turnover			0.4669***			0.4878***			0.4576***
			(0.009)			(0.008)			(0.008)
Services	0.8107***	0.7560***	1.1806***	0.5065***	0.4557***	0.8006***	-0.0242	-0.0291	-0.0754***
	(0.078)	(0.076)	(0.075)	(0.061)	(0.060)	(0.059)	(0.019)	(0.019)	(0.018)
Investment	-0.2177***	-0.1884***	-0.3046***	-0.0581***	-0.0533***	-0.0543***	-0.0063***	-0.0052**	0.0002
	(0.043)	(0.042)	(0.039)	(0.006)	(0.005)	(0.007)	(0.002)	(0.002)	(0.002)
Constant	0.6728***	1.3625***	0.8005***	0.9000***	1.6113***	1.0523***	1.2955***	1.9693***	1.8191***
	(0.048)	(0.051)	(0.044)	(0.036)	(0.040)	(0.035)	(0.040)	(0.045)	(0.035)
No of observations	4663	4663	4663	7843	7843	7843	6969	6969	6969
R2 within	0.625	0.651	0.644	0.623	0.646	0.609	0.664	0.670	0.696

Note: Time fixed effect panel GLS estimator with robust standard errors.

Figure 7. Turnover as a share of labor force (averaged over 2001-2008)

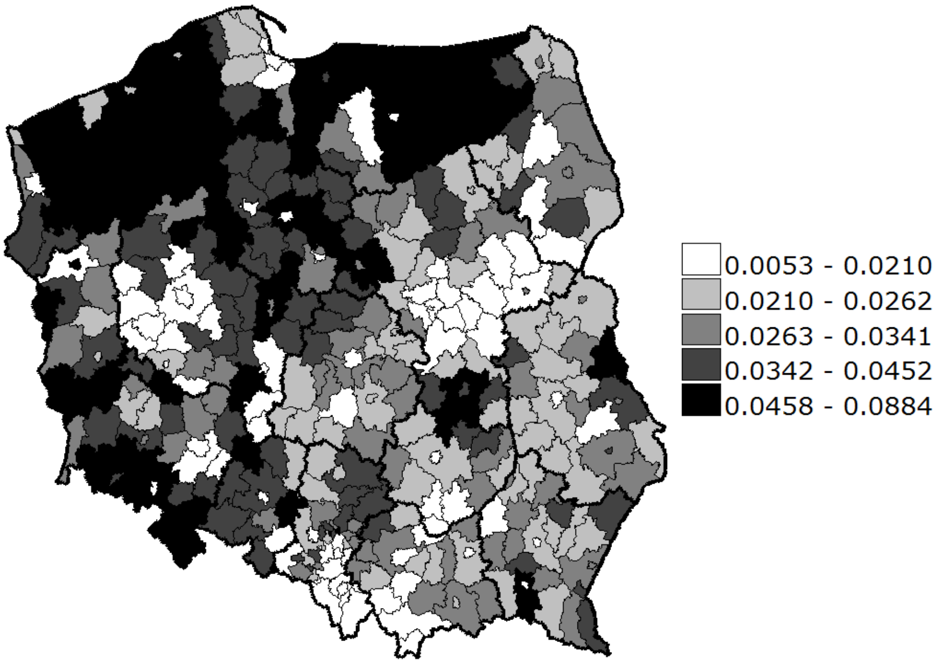


Figure 8. Lilien Index

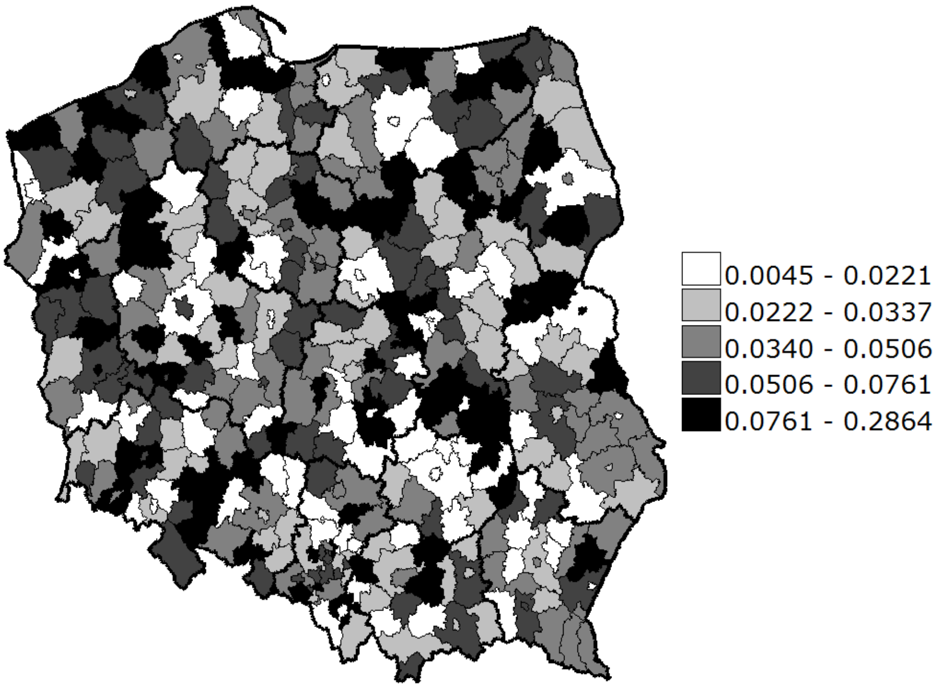
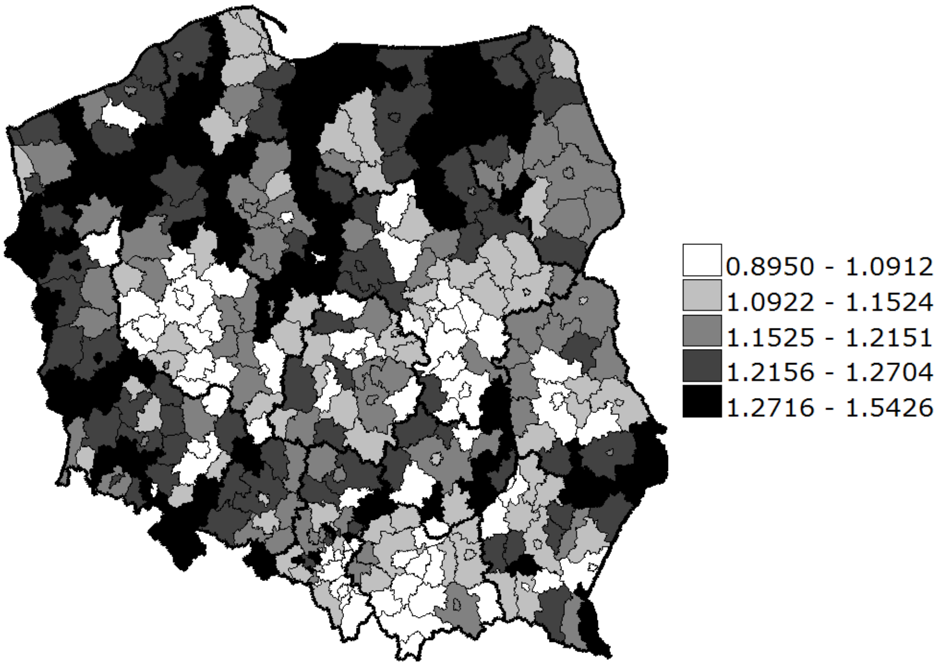


Figure 9. Ratio of institutional flows over market driven flows



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