Regional Resilience through Resilient Neighbourhoods?

measuring and assessing resilience using grid-level data in the Warsaw region

Monika Kot, Martin Andersson, Katarzyna Kopczewska, Maria Kubara

Abstract

Regional economic resilience is increasingly recognised as a multi-dimensional and spatially uneven process, yet most studies treat regions as homogeneous units in empirical analyses. This paper adopts a sub-regional perspective on resilience by examining how resilience emerges from local industrial structures and firm dynamics at the sub-regional scale. Leveraging geo-referenced firm-level data, we develop a Local Industrial Resilience Index (LIRI) that measures resilience at a 2 × 2 km grid scale across the Warsaw metropolitan region (Mazowieckie Voivodeship, Poland) over the period 2012–2021. Using firm survival and birth data from the Polish business register, combined with measures of local specialisation, diversity, concentration, and related variety, we show that related variety is a key driver of local resilience, fostering both firm survival and adaptive renewal, while high sectoral concentration consistently undermines resilience. Resilience does not follow a simple core–periphery pattern, underscoring the need to move beyond aggregate regional indicators. Overall, our findings demonstrate that regional resilience is an emergent property of localised industrial ecosystems.

Key words: local resilience, firm resistance, firm renewal, reorientation capacity,

JEL Code: O31, O33, R12

1. INTRODUCTION

Regional economic resilience has emerged as a significant line of research in urban and regional economics, economic geography as well as regional science. Why some regions manage to withstand and adapt to economic shocks attract interest from researcher in different fields and is a key issue in debates on regional development and policy (Martin & Sunley 2015, Christopherson, Michie, & Tyler, 2010; Hudson, 2010; Sutton et al., 2023). In analyzing determinants of regional resilience, most empirical studies to date turn to regional data that treats a region as a single data point and infer determinants of resilience from cross-regional variance. A growing literature on the micro-geography of economic activity yet shows that the internal geography of regions is relevant in explaining regional economic outcomes (Andersson et al., 2016, Rosenthal & Strange, 2003, Arzaghi & Henderson, 2008; Kopczewska et al., 2024). We integrate perspectives from the literature on micro-geography in the analysis of regional resilience and move beyond the typical region-level approach. Leveraging grid-data on firms, we measure and assess determinants of resilience at a 2 km x 2 km cell level across the Warsaw metropolitan region (Mazowieckie Voivodeship NTS2 in Poland).

Background and motivation

Interest in resilience was catalysed by the 2008–2009 financial crisis, which revealed that some regions were severely hurt while others proved more resistant or quick to recover (Martin, 2012; Sensier, Bristow, & Healy, 2016). These stark spatial disparities in downturn and recovery rates highlighted the relevance of issues related to why some regions can better withstand and bounce back from major shocks than others (Martin & Sunley, 2015; Di Caro & Fratesi, 2018). In short, regional resilience has became a key issue in debates on regional development and policy (Christopherson, Michie, & Tyler, 2010; Hudson, 2010; Sutton et al., 2023).

Despite the growing use of the term, conceptualising regional economic resilience has proven challenging. Early contributions noted that resilience was often underdefined or even a "fuzzy" concept (Markusen, 1999; Martin & Sunley, 2015), with multiple meanings in literature spanning engineering and ecological analogies. Many economic geographers have argued for an evolutionary perspective on regional resilience, moving beyond the idea of simply "bouncing back" to a pre-shock equilibrium (Simmie & Martin, 2010; Hassink, 2010; Boschma, 2015). An evolutionary approach emphasizes long-term adaptive capacity – the ability of a region's firms and institutions to adapt or transform in response to shocks by renewing their economic structure (Boschma, 2015; Pendall, Foster, & Cowell, 2010).[1]

[1]For example, Boschma (2015) conceptualises regional resilience as not only recovery, but also the region's capacity to reconfigure its industrial and institutional base and develop new growth paths after a shock. Similarly, Martin (2012) and Martin and Sunley (2015) contend that a region's resilience entails a combination of resistance (the ability to withstand immediate shock impacts), recoverability (the speed and extent of recovery), and re-orientation or renewal (the degree of structural change or reinvention in the aftermath).

One important insight from this literature is the notion of a trade-off between short-term adaptation (robustness in absorbing a shock) and long-term adaptability (the capacity to evolve). Truly resilient regions must somehow achieve both (Pike, Dawley, & Tomaney, 2010; Hassink, 2010; Boschma, 2015). The literature has advanced and recent reviews find that regional economic resilience is now a well-developed multi-dimensional concept, involving dynamic processes at multiple temporal and spatial scales (Evenhuis, 2017; Hu & Hassink, 2020; Sutton et al., 2023). Yet, consensus on certain aspects (e.g. how to best measure resilience, or the relative importance of various determinants) remains elusive, keeping the concept both complex and continually evolving.

A substantial body of empirical research has emerged, identifying the determinants of regional resilience and explaining why some places fare better than others during crises. A key theme in this literature is the role of industrial structure and diversification. Regions with more diverse economies are often found to be more resilient, since diversity provides a broader shock absorber and greater potential for post-shock reorientation (Frenken, Van Oort, & Verburg, 2007; Bristow & Healy, 2014). Much of the literature emphasises the distinction between related variety (diversification into industries that share complementary capabilities) and unrelated variety (a broader mix of very different industries). Both forms of variety can enhance adaptability: related variety fosters knowledge spillovers and incremental innovation, while unrelated variety reduces vulnerability to sector-specific shocks (Boschma, 2015; Xiao, Boschma, & Andersson, 2018).

This paper departs from the idea that regional resilience is inherently spatially nuanced and multi-scalar. Many studies of resilience compare regions as single data points, but there is growing recognition that intra-regional geography – the micro-geography of economic activity – can influence regional economic outcomes (Andersson, Klaesson, & Larsson, 2016, Rosenthal & Strange, 2003, Arzhaghi & Henderson, 2008). Literature on the attenuation of agglomeration economies demonstrates that agglomeration externalities operate strongly at very local scales (on the order of 1 km neighbourhoods), decaying sharply with distance (Andersson et al., 2019, Lavoratori & Castellani, 2021). This implies that where firms are located within a region may matter greatly for their performance and resilience potential. Different neighbourhoods within the same region often have very different industry structures and innovation capacities, and thus likely exhibit unequal resilience to shocks. It is possible for a severe crisis to leave only a mild imprint on the region's aggregate indicators, while inflicting heavy losses on specific localities, even as other areas remain relatively unscathed. Likewise, two regions with similar aggregate characteristics might differ in resilience depending on how their economic activity is spatially organized internally. In short, a region's overall resilience is an emergent outcome of the resilience of its constituent communities and economic clusters. Neglecting this intra-regional heterogeneity can obscure important vulnerabilities (or strengths) and lead to misinformed policy. Regional resilience can from this perspective be seen, not as a uniform trait, but as emerging from a nested hierarchy of factors – from the firm and neighbourhood level up to the regional and national context (cf. Sutton et al., 2023).

Contribution

Against this backdrop, the present paper provides a sub-regional analysis of economic resilience. We move beyond the typical region-level approach by examining resilience at the neighbourhood scale. Leveraging grid-data on firms, we measure resilience for each 2×2 km cell across the Warsaw metropolitan region (Mazowieckie Voivodeship in Poland). Building on recent conceptual developments in the resilience literature, we define resilience in a multidimensional way encompassing four complementary modes – resistance, recovery, renewal, and reorientation– which we term the "4R" framework. This framework is inspired by evolutionary thinking (cf. Martin, 2012), which views resilience as a process involving multiple phases or capacities.

In our operationalisation, resistance refers to the immediate ability of the local economy to withstand a shock (as measured by the survival rate of firms during the crisis period). Recovery denotes the speed and extent of the post-shock rebound, captured in part by the rate of new firm formation as economies reopen or adjust. The renewal dimension reflects path-dependent adjustment – the degree to which a neighbourhood resumes growth through its existing economic structure, e.g. via expansion or diversification within related industries (leveraging local related variety). Finally, reorientation gauges longer-term transformation, indicated by the emergence of unrelated new activities that signal a break from the pre-shock specialisation (entry of firms in industries with no prior local presence). By combining these four aspects into a composite index, we aim to capture the multidimensional nature of resilience that balances stability and adaptability at the local level. In essence, the 4R index aims to empirically operationalize the balance between short-term robustness (resistance) and longer-term adaptability (renewal and transformative reorientation) in a fine-grained spatial context. Using this 4R framework, we construct and analyze a grid-level resilience index for the Warsaw region over the period 2012–2021.

Main findings

Our findings show the relevance of a sub-regional analyses and align with evolutionary-economic arguments that related diversification provides an adaptive buffer by enabling the recombination of existing competencies into new activities. Sub-regional neighbourhoods rich in related variety appear to be in a better position to foster renewal, corroborating evidence from other regions that related and unrelated variety bolster resilience (especially for facilitating new growth in knowledge-intensive industries post-shock).

While the metropolitan core of Warsaw exhibits the highest resilience scores, we find that several medium-sized towns in the wider region also display notable resilience potential. By contrast, many peripheral rural or mono-industrial grids show consistently low resilience, reflecting their limited ability to generate or attract new economic activities beyond their existing specialisation paths. Such spatial disparities confirm that resilience is not simply a function of urban scale or sheer density of firms; rather, it hinges on the composition and interconnectedness of the local economic structure in each place. Specifically, grids that had higher initial diversity and, importantly, greater related variety (i.e. a mix of industries with complementary capabilities) in 2012 fared significantly better in terms of both firm survival and new firm creation during 2012–2021. Overall, our analyses supports the evolutionary economic geography perspective – related variety fosters adaptive resilience by enabling the recombination of existing competences into new activities. Conversely, grids dominated by a single sector exhibited weaker renewal and higher vulnerability to structural decline, consistent with path dependency and lock-in effects.

2. RESILIENCE, TECHNOLOGY FIRMS AND SUB-REGIONAL ANALYSIS

Our analysis builds on the resilience from the perspective of resistance, recovery, renewal and reorientation (4R) and is based on data on technology-based firms linked to sub-regional grid data in Poland. This section provides a short background and motivation of the perspective (4R), data as well as the sub-regional level of the data.

2.1. Resilience – resistance, recovery, renewal and reorientation

Resilience is defined as the capacity of places to absorb shocks, adapt, and reorganize without sacrificing their long-term development potential (Martin, 2012; Boschma, 2015). Studies have shown that resilience is closely connected to future growth trajectories of places: some economies recover to their previous path, others stagnate, while some manage to reinvent themselves entirely.

Rather than a one-dimensional return to a pre-shock equilibrium the evolutionary perspective considers resilience as an adaptive process in which regional economies may continue along existing paths, become locked into declining structures, or create new ones (Simmie & Martin, 2010; Martin & Sunley, 2015). Regions thus display different trajectories: some get stuck in lock-in, others show path-dependent renewal, and some demonstrate reorientation capacity that enables transformational change. Over the past decade, this evolutionary perspective has transformed into a multi-dimensional view of resilience, distinguishing short-run responses - resistance and recovery - from longer-term adaptive capacity - renewal and reorientation (Martin, 2012; Bailey & Turok, 2016).

Resistance captures the immediate impact of a shock, typically measured by the depth of decline in output or employment relative to an expected baseline (Fingleton, Garretsen, & Martin, 2012). Evidence from UK and European regions shows that resistance levels differ across regions, while the magnitude of reactions can be often explained by industrial composition: diversified economies tend to resist shocks better, while specialised ones suffer deeper declines (Martin, 2012). Related variety further enhances resistance by buffering shocks across complementary industries (Frenken, Van Oort, & Verburg, 2007).

Recovery denotes the speed and extent of rebound toward - or beyond - the pre-shock trajectory. Recovery can diverge from resistance: some places that resist strongly recover slowly, while others that are hit hard rebound quickly (Martin & Gardiner, 2019). The literature highlights that recovery is less dependent on the local sectoral structure, and is vastly shaped by institutional capacity, human capital, and connectivity, which condition how quickly resources can be reallocated (Bristow & Healy, 2014; Giannakis & Bruggeman, 2017). In turn – recovery is the element of resilience least dependent on the pure market forces and local business composition.

Renewal represents the replenishment of economic activity through new firm entry, investment, and upgrading. It is often path-dependent, as regions tend to diversify into activities related to their existing base where knowledge proximity supports recombination and spillovers (Boschma & Frenken, 2011; Neffke, Henning, & Boschma, 2011). Renewal thus depends not only on the quantity of new entry but also on its relatedness to the existing sectoral composition of a place: coherent diversification strengthens resilience, while entry into unrelated but fragile niches may not. Empirical evidence shows that technological coherence enhances adaptive performance during crises (Rocchetta & Mina, 2019).

Reorientation denotes the ability to shift into unrelated activities, opening up new growth paths when established ones are disrupted (Simmie & Martin, 2010; Boschma, 2015). This capacity for transformation is particularly relevant in regions facing deep structural changes such as green or digital transitions. While riskier than renewal, reorientation reduces vulnerability to sector-specific shocks and underpins long-term adaptability. Recent work shows that the structure and connectivity of regional knowledge and industry networks strongly influence this capacity (Tóth et al., 2022).

Decomposing resilience into resistance, recovery, renewal, and reorientation clarifies that places may be resilient in some respects but not in others (Martin, 2012; Martin & Sunley, 2015). It also maps these phenomena cleanly onto testable mechanisms: (i) structural exposure (resistance), (ii) capacity to rebound (recovery), (iii) path-dependent branching (renewal), and (iv) new path creation (reorientation). The contemporary literature further urges operationalizations that link these dimensions to measurable, micro-founded outcomes rather than treating resilience as a single index (Sutton et al., 2023). Such a decomposition also aligns with ongoing debates in Europe on industrial policy and place-sensitive interventions, which require understanding not only where shocks hit hardest, but where and how local economies regenerate and transform in the aftermath.

2.2. Technology-based Firms and Industrial Resilience

Regional resilience is conditioned by firms and their capacities in a region. Their responses to shocks, when aggregated, define the regional trajectory of decline, recovery, or transformation. Firms are thus the primary local drivers of resilience, but technology firms stand out because of their innovation capacity, digital orientation, and networked character. This perspective has led many scholars to look closely at technology-based firms as a special case, investigating whether their characteristics make them more resilient than others.

Emerging evidence suggests that technology-based firms are more likely than other types of firms to be resilient across the four key dimensions. In terms of resistance, studies show that technology-based firms are better able to withstand shocks because of their deployment of digital tools, advanced supply chain management, and diversification of markets (Li et al., 2022; Spieske & Birkel, 2021). They also display stronger recovery capacities, using absorptive capabilities, IT-enabled learning, and digital coordination to restore functions more quickly than non-tech firms, thereby helping stabilize not only themselves but also their suppliers and local partners (Cui et al., 2022; Basit et al., 2024; Gu et al., 2020). When it comes to renewal, technology-based firms are often the pioneers of product and process innovation, business model change, and related diversification, which enables them to “bounce forward” after crises and stimulates adaptive renewal in their regional contexts (Neffke, Henning, & Boschma, 2011; Rocchetta & Mina, 2019; Tian & He, 2025). Finally, technology-based firms contribute to reorientation, as their technological diversity and digital maturity allow them to pivot into unrelated activities and pioneer new growth paths, especially during transitions such as digitalization and the green economy (Forliano et al., 2022; Ran et al., 2024; Tóth et al., 2022).

Despite a focus on technology-based firms above, it should be acknowledged that low- and medium-tech firms (LMT) also can boost their resilience when connected to technological ecosystems. LMT firms often rely on technology transfer, modest digital adoption, and external knowledge networks to adapt. Their absorptive capacity and openness to collaboration are critical in peripheral regions, where they provide the backbone of employment and incremental innovation (Simms & Frishammar, 2024; Guo, 2024; Zouaghi et al., 2018; Hansen & Winther, 2011; Gornig & Schiersch, 2024). This highlights that resilience-enhancing effects of technology are not confined to frontier firms but extend across the industrial spectrum.

Taken together, the discussion above suggest that technology-based firms are resilient actors, and their resilience can in turn enhance the resilience of the regions in which they are embedded. If regional resilience is indeed the sum of local firm dynamics, then understanding how the presence and activity of technology firms contribute to resilience at fine geographical scales becomes essential.

2.3. Towards Local Measurement of Industrial Resilience

While the literature has advanced our understanding of resilience and demonstrated the distinctive resilience of technology firms at the micro level, most empirical studies remain focused on the regional scale (NUTS2 or NUTS3). This perspective overlooks the micro-geographies where resilience is produced: the neighbourhoods, industrial districts, and entrepreneurial ecosystems where firms survive, die, or emerge. As Martin (2012) argued, fully explaining resilience requires analyzing the adjustments of firms and workers at the local level, yet systematic measures of resilience at such fine scales are still missing.

Moreover, many existing studies tend to focus on firm-level resilience in isolation, without tracing how the presence of resilient firms - particularly technology firms - aggregates into regional outcomes. Since regional resilience is the outcome of firm behaviour, the issue of how local concentrations of technology firms contribute to resilience remains a crucial research gap. Addressing this question is crucial for both advancing the theory of adaptive resilience and informing place-sensitive industrial policy, particularly in identifying which localities are self-sufficient, which are locked into decline, and which could benefit most from targeted interventions.

Against this backdrop, our study introduces the Local Industrial Resilience Index (LIRI), a novel approach to capturing resistance, recovery, renewal, and reorientation at the scale of 4 km². We specifically test whether the presence of technology firms - broadly defined to include high-, medium-, and low-tech industries - helps explain variation in local resilience, thereby linking the micro-level resilience of firms with the adaptive capacity of places.

3. METHODOLOGY AND DESCRIPTIVE STATISTICS

3.1 Integrating perspectives: a Local Industrial Resilience Index (LIRI)

We introduce a new measure - Local Industrial Resilience Index (LIRI). It is a low-granulation grid-based metric to capture quantitative and structural entrepreneurship dynamics in multidimensional way. It combines survival and birth rates of firms with a sectoral structure of new firms – whether they are related or unrelated to previously existing sectors. The construction of LIRI is a multi-step procedure as presented below.

STEP 1: Put firms on a grid (e.g. 2 km ×2 km). Use geo-located individual point data for firms with information on their ID (e.g. registration number), sectoral and technological involvement (e.g. NACE2 code). Assign each firm to a grid (cf. Kopczewska, 2025). Use data from two periods (starting and ending) to determine how many and which firms survived, appeared and disappeared.

STEP 2: Describe each grid cell in a starting year. For every grid cell *g*, count firms by sector and compute specialisation, diversity, concentration and related variety indices. Those metrics will be used as explanatory variables in regression that explain survival and birth of firms in the STEP 5. We use the following metrics:

a) Krugman Dissimilarity Index KDI (Krugman, 1991, Kopczewska et al. 2017) for the specialisation of the grid cell:

$$KDI_g = \sum_{i=1}^{s} \left| \frac{n_{i,j}}{\sum_{i=1}^{s} n_{i,j}} - \frac{\sum_{j=1,i}^{g} n_{i,j}}{\sum_{i=1}^{s} \sum_{j=1}^{g} n_{i,j}} \right| \tag{1}$$

where *n* is the number of firms in given sector *i* (from 1 to *s*) in given grid cell *j* (from 1 to *g*). The metric is based on the standard error concept and measures the standard error of industry shares. It is the total by *s* sectors (industries), summing up the differences between the share of firms in a given sector *i* in a given grid cell *j* and the share of firms in a given sector in all grid cells (the whole reference area). The total is for the absolute values (| |) of differences. The minimum value is 0 (local structure is fully consistent with the regional one), the maximum is $2 \cdot (n-1)/n$. The higher the Krugman dissimilarity KDI_j index value, the stronger the deviation of local economic structure from the average reference structure. This overrepresentation of firms in a given sector is called specialisation.

b) Shannon entropy H (Shannon, 1948, Horowitz and Horowitz, 1968) for the diversity of the grid cell g:

$$H_g = -\sum_{i=1}^{s} p_{i,j,ref\_j} \cdot ln\,(p_{i,j,ref\_j}) \tag{2}$$

where p_{i,j,ref_j} is the proportion of firms in given sector i in all firms established in a given grid cell j. Shannon entropy H is summing the products $p*ln(p)$ over sectors within single grid cell. There is no reference to the global business structure. The Shannon's H is maximum in case of equal shares of all sectors (all $p_{i,j} = 1/s$) and takes the value $H_{max} = -s \cdot \left({}^{1}/_{s}\right) \cdot ln\, {}^{1}/_{s} = \ln s$. The minimum of Shannon's H (H_{min}=0) is available only in the case of full concentration of firms in one single industry, $p = 1/1$. The higher the value, the less specialised business structure.

c) Herfindahl-Hirschman index HHI for the concentration in the grid cell:

$$HHI_g = \sum_{i=1}^{s} (p_{i,j,ref\_g})^2 \tag{3}$$

where p_{i,j,ref_g} is the proportion of firms in given sector i to all firms from this sector in whole territory (all grids g). The total of sectoral shares for one sector in all grid cells equals 1. For s sectors, total of all shares equals s. Therefore, HHI_g in a particular grid may be between 0 and s ($0<HHI_j<s$)[2]. The higher the HHI, the stronger concentration of market power within a particular grid.

d) related variety for the co-locations in the grid cell – begin with the relatedness matrix R in a starting year, sized s×s sectors. For each pair of sectors compute co-occurrence (co-location) ratio:

$$R_{i,s} = \frac{\left({}^{\#cells\ with\ sectors\ i\ and\ s}/_{\#cells}\right)}{\left({}^{\#cells\ with\ sector\ i}/_{\#cells}\right) \cdot \left({}^{\#cells\ with\ sector\ s}/_{\#cells}\right)} \tag{4}$$

Symmetrize and scale this matrix R to [0,1], by $R_{i,s}$=min(1, max(0, log$R_{i,s}$ / max(logR)) to obtain $R'_{i,s}$, while fixing the diagonal elements at zero, as self-relatedness (co-location of the same sector) does not contribute to inter-sectoral variety. Use this scaled relatedness matrix $R'_{i,s}$ values as a correction factor in calculating the related variety RV_g index in each grid cell:

[2] Alternative reference values are problematic: if p is defined as in Shannon entropy (within grid cell only), both indicators are correlated and there is no further information included in HHI; if shares are referred to total number of firms n in a region, then p is 1/n.

$$RV_g = \sum_{i=1}^{s} p_{g,i} \cdot p_{g,s} \cdot R'_{i,s} \tag{5}$$

where $p_{g,i}$ and $p_{g,s}$ are shares of sectors *i* and *s* in particular grid cell *g*. The related variety RV_g index computes the product of shares of both sectors within each grid cell, corrected by values from relatedness matrix. It is a total of products for each pair of different sectors.

STEP 3: Describe the dynamics between a starting and ending year in each grid cell *g*. Calculate the following metrics of changes:

$$survival.rate_g = \frac{\#survived.firms_g}{\#firms_{g,starting\_year}} \tag{6}$$

$$death.rate_g = \frac{\#died.firms_g}{\#firms_{g,starting\_year}} \tag{7}$$

$$birth.rate_g = \frac{\#new.firms_g}{\#firms_{g,starting_{year}}} \tag{8}$$

STEP 4: For each grid identify the sectors of births. Compute industrial transformative emergence signals, which are expressed as two complementary measures: (path-dependent) *renewal* and *reorientation*.

The ***renewal*** indicator measures the degree to which new firm births are related to the existing industrial structure. For each grid cell *g*, first compute new sectors' relatedness to the grid's incumbent sectors as $R'_{g,s}$ = weighted average of sectors' relatedness to all sectors already present in grid *g*, using the scaled relatedness matrix $R'_{i,s}$. The grid-level renewal index is then obtained as the birth-weighted average of these relatedness values across all birth sectors:

$$renewal_g = \frac{\sum_s R'_{g,s} \cdot births_{g,s}}{\sum_s births_{g,s}} \tag{9}$$

where $births_{g,s}$ is the number of newly established firms in sector *s* within grid *g*.

The ***reorientation*** indicator captures the extent of diversification into unrelated sectors, defined as the share of births occurring in sectors weakly related to the grid's existing structure:

$$reorientation_g = share\ of\ births\ with\ R'_{i,s} < \tau \tag{10}$$

where τ is a threshold indicating unrelatedness. Unrelated sectors are those for which the values in the scaled relatedness matrix $R'_{i,s}$ are below some threshold τ (e.g. $R'_{i,s} < 0.3$). Both values, *renewal* and *reorientation*, must be further normalised (z-score).

STEP 5: Run the regressions to obtain resilience signals from residuals. Estimate two models for different dependent variables: a) a binomial model for the number of surviving firms, and b) a count model (Poisson or Negative Binomial) for the number of newly established firms (births). The explanatory variables are the indices created in STEP 2: diversity (entropy *H*), specialisation (Krugman Dissimilarity Index *K*), concentration (Herfindahl-Hirschman Index *HHI*), Related Variety (*RV*) and business intensity in starting year (a number of firms *N* per capita) in a grid cell. Models are as follows:

$$Survivors(g) \sim \alpha + \beta_1 \cdot H(g) + \beta_2 \cdot K(g) + \beta_3 \cdot HHI(g) + \beta_4 \cdot RV(g) + \beta_5 \cdot N(g) + \varepsilon \tag{11}$$

$$Births(g) \sim \alpha + \beta_1 \cdot H(g) + \beta_2 \cdot K(g) + \beta_3 \cdot HHI(g) + \beta_4 \cdot RV(g) + \beta_5 \cdot N(g) + \varepsilon \tag{12}$$

For each model get the fitted values for each grid cell (*expected survivors(g)* and *expected births(g)*). Calculate two metrics of resilience, *resistance* and *recovery*, based on actual and expected number of survivors and births.

$$Resistance(g) = (actual\ survivors(g) - expected\ survivors(g)) / sd(actual\ survivors) \tag{13}$$

$$Recovery(g) = (actual\ births(g) - expected\ births(g)) / sd(actual\ births) \tag{14}$$

There is no model for “exits”, because they are already included in the survival count (exits are 1-*survival.rate*), so the information is already preserved. As the index is focused on a resilience, the major interest is in “who stayed” and “who is new”.

STEP 6: Build the *Local Industrial Resilience Index (LIRI)*. It is composed of four components: *renewal and reorientation* from STEP 4 and resistance and recovery from STEP 5. It is expressed as the weighted average of those components:

$$LIRI(g) = (Resistance(g) + Recovery(g) + 0.5 \cdot Renewal(g) + 0.5 \cdot Reorientation(g)) / 3 \tag{15}$$

The higher the LIRI, the more resilient grid cell and more adaptive to changing conditions. The construction based on difference between empirical and predicted values allows for controlling economic structure of local ecosystem. By including the explanatory variables, the index is free from the impact of those factors.

Interpretation of LIRI goes in three groups: negative values, positive values and values around 0 (Tab.1).

- **LIRI >0:** A positive LIRI indicates that a region's industrial system has *recovered from adverse shocks* or *maintained growth* despite them. These regions demonstrate strong adaptive and regenerative strength - they not only absorb disturbances but convert them into opportunities for renewal. From a policy perspective, positive LIRI reflects forward-looking industrial ecosystems where capabilities, diversity, and connectedness translate into sustained post-shock recovery and long-term competitiveness.

- **LIRI<0:** A negative LIRI signals that the industrial base has *contracted or failed to recover* following disruption. It denotes low absorptive capacity and weak resilience, often arising from structural dependence, concentration, or insufficient renewal mechanisms. Negative LIRI thus marks structural vulnerability - the system amplifies shocks instead of absorbing them. Industrial policy here should prioritize stabilization and diversification, enhancing the foundations of resilience rather than merely promoting growth.

- **LIRI~0:** LIRI values close to zero describe regions that are *neither clearly resilient nor clearly vulnerable*. These areas maintain industrial activity without pronounced loss or gain - a fragile equilibrium. They may have weathered shocks without collapse but have not transformed or adapted sufficiently to build long-term resilience. Policy attention for these regions should focus on strengthening adaptive mechanisms - supporting innovation, inter-sectoral linkages, and upgrading of local capabilities, to shift them toward positive resilience trajectories.

Table 1: Interpretation of LIRI values

LIRI values	**Interpretation**	**Systemic condition**	**Policy focus**
LIRI > 0	Adaptive & regenerative resilience	System absorbs and transforms shocks	Support scaling, innovation, and knowledge recombination
LIRI ≈ 0	Transitional / fragile stability	System survives but lacks adaptive renewal	Stimulate firm dynamism and knowledge flows
LIRI < 0	Structural vulnerability	System exposed, fails to recover	Strengthen survival, diversification, and competition

3.2 Operationalization

We operationalize the Local Industrial Resilience Index (LIRI) at the scale of 2 km x 2 km grid cells in the Mazovian region. This fine spatial granularity enables us to capture the micro-geographies of entrepreneurship that remain hidden at broader regional levels. The area of the region is 35.579 km^2 which is equivalent to 9,320 grids and the central city is Warsaw, capital city of Poland. It is inhabited by ca. 5.5 million people. The analysis is based on firm-level data from the official Polish business register (REGON) in years 2012 and 2021. Firms are classified by sector (NACE 2-digit), size class and by technological involvement (tech and non-tech). In the starting year (2012), the dataset covers approximately 989,000 firms, and 4.3% are active in technology-intensive sectors (medium-tech, high-tech, or high-tech knowledge-intensive). In the end period (2021) the dataset includes 1,113,000 firms. Compared to 2012 there were 429,507 new firm births and 288,882 exits. Only 15% of grid cells is empty (no firms registered). Tab.2 describes the variables that were constructed for each grid cell and were used in further analysis. Appendix 1 reports descriptive statistics of those variables.

Table 2: Variables used in the study for each grid cell

Variable	Data used for calculation	Role of variable
Krugman Dissimilarity Index KDI	Number of firms in grids by sectors in starting year (2012). K is calculated as in eq.1.*	It averages (in grid cells) by sectors the differences between local (grid) and global (region) business structure. It measures the uniqueness of local business structure compared with general pattern. The higher the value the more different local structure from the global one.
Shannon entropy H	Share of firms in grids by sectors in starting year (2012). H is calculated as in eq.2.*	It averages the local (in grid) internal sectoral shares without reference to global pattern. It measures the internal inequality (diversity) of sectoral division. The higher the value the more similar shares of all sectors within the grid cell.
Herfindahl-Hirschman index HHI	Share of firms in grids by sectors in starting year (2012). H is calculated as in eq.3.*	It sums up in grid cell the sectoral global shares of firms. It measures the local degree of concentration of firms. The higher the value, the stronger the concentration of firms within the grid cell, in reference to overall business saturation.
(Scaled) relatedness matrix R’	For each pair of sectors, share of co-occurrence related to product of individual occurrence chances. Scaled matrix.	It measures the global (regional) pattern of co-occurrence of sectors on a grid level, by counting grids in which both sectors and single sectors appear. The higher the value, the more frequent co-occurrence of two sectors.
Related variety RV	Share of firms in grids by sectors in starting year (2012). H is calculated as in eq.4-5. It is standardised to [0,1] internally.	It starts as a product of sectoral shares within each grid cell (summing up to 1) to express the local co-occurrence of sectors. It is then corrected with relatedness matrix which measures the co-occurrence on global level. The higher the value the more related two sectors – on local and global level.
Survivors Births	Number of firms within grid cell that survived or appeared compared with starting year (2012).	It measures the volume of business dynamics (within a grid cell) in absolute terms, without any reference to global pattern. The higher the value the more intensive trend.

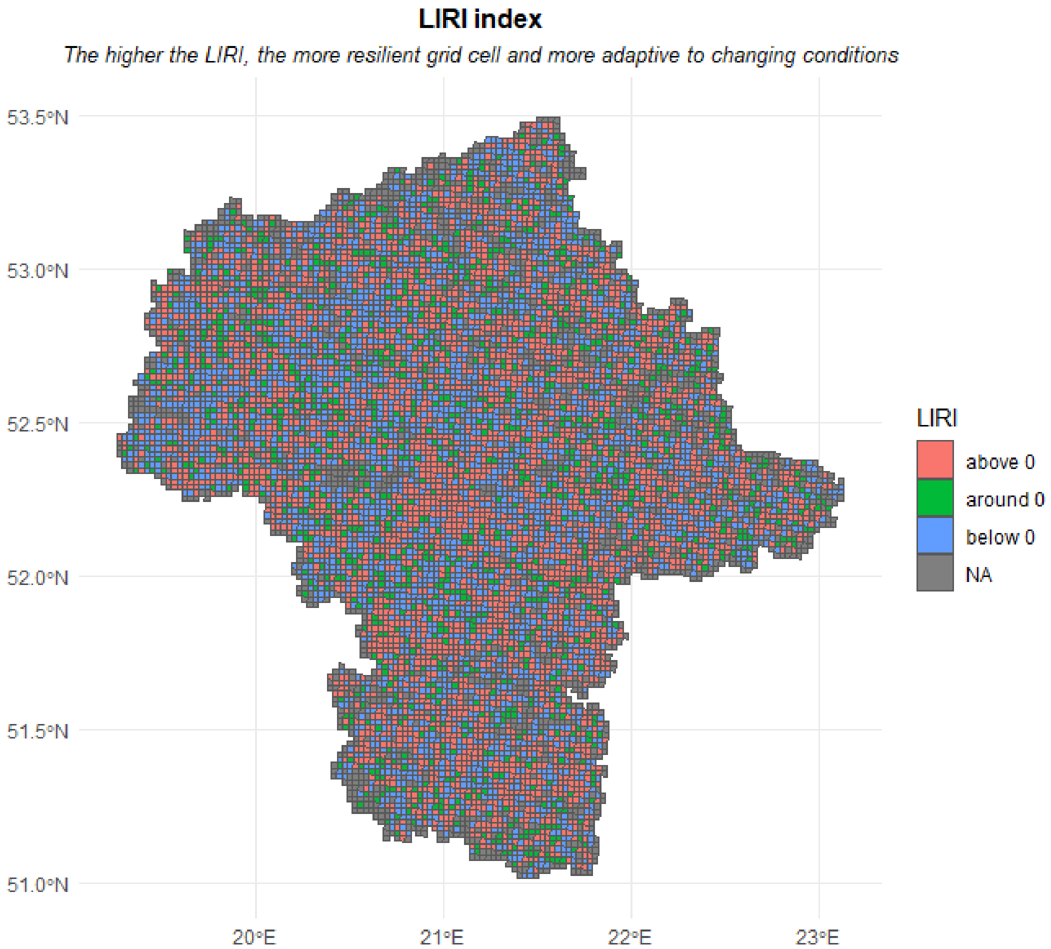
Survival rate Death rate Birth rate	Number of firms within grid cell that survived, exited or appeared related to the total number of firms in starting year (2012). It is calculated as in eq.6-8.	It measures the local dynamics of business (within a grid cell) in relative terms, without any reference to global pattern. The higher the value the more intensive trend.
Firms per capita	Total number of firms divided by total number of people within each grid cell, in starting year (2012)	It measures the local business potential in relation to local capacity. The higher the value, the more firms per inhabitant.
Renewal Reorientation	Average within grid cell of values from the scaled relatedness matrix, calculated for birth sectors only for selected sectors. It is z-score normalized.	It measures the degree of local births in commonly co-occurring sectors (renewal) or non-co-occurring sectors (reorientation). The higher the value, the more firms appear in typically related (or unrelated) sectors.
Expected survivors Expected births	Fitted values for each grid cell from econometric count models - binomial model (survivors) and Poisson model (births).	Observed numbers of survivors or births are explained in an econometric model with firms per capita, related variety RV, Shannon entropy H, Herfindahl-Hirschman Index HHI and Krugman Dissimilarity Index KDI
Resistance Recovery	Normalised value of survivors and births, calculated as (obs-exp)/sd(obs)	It measures the surplus or shortage of firms that survived (resistance) or appeared (recovery) (observed values) compared with the expected values (fitted) from the regression model. The values around 0 indicate intensity as in global trend.
LIRI	Average of resistance, recovery, renewal and reorientation for each grid cell	It measures the resilience of cells and adaptability to shocks and new conditions. The higher the value, the stronger resilience.
Relative location**	Set of continuous variables indicating a distance between grids and cities Set of dummy variables indicating if grid is in a given radius from cities	Continuous variables indicating distance from a grid cell to the closest city from given category (core, midsize, regional, local big, local small) Set of 15 dummy variables – binary variables if particular grid cell is located in a radius of 10, 25 or 50 km from a city of a given category (core, midsize, regional, local big, local small)
Technological firms	Set of variables that indicate if there are technological firms within grid cell	It is measured as a share of technological firms (share_tech) in starting (2012) and ending (2021) year and a dummy variable (if_tech) if a grid cell contains a technological firm in starting (2012) and ending (2021) year. The higher the values, the stronger technological environment.
Big firms	Dummy variable that indicate if there is a big firms within grid cell	It measures the existence of big firms (500+) within a grid.

** In designing the construction of LIRI we tested the [0,1] normalized values of these measures but there was no changes in outcomes. We decided to keep non-normalized values for comparability with results in literature.*
*** Those variables were tested in model specifications but never appeared significant determinants of LIRI, so finally they do not appear in a study*

3.3 LIRI statistics and distributions

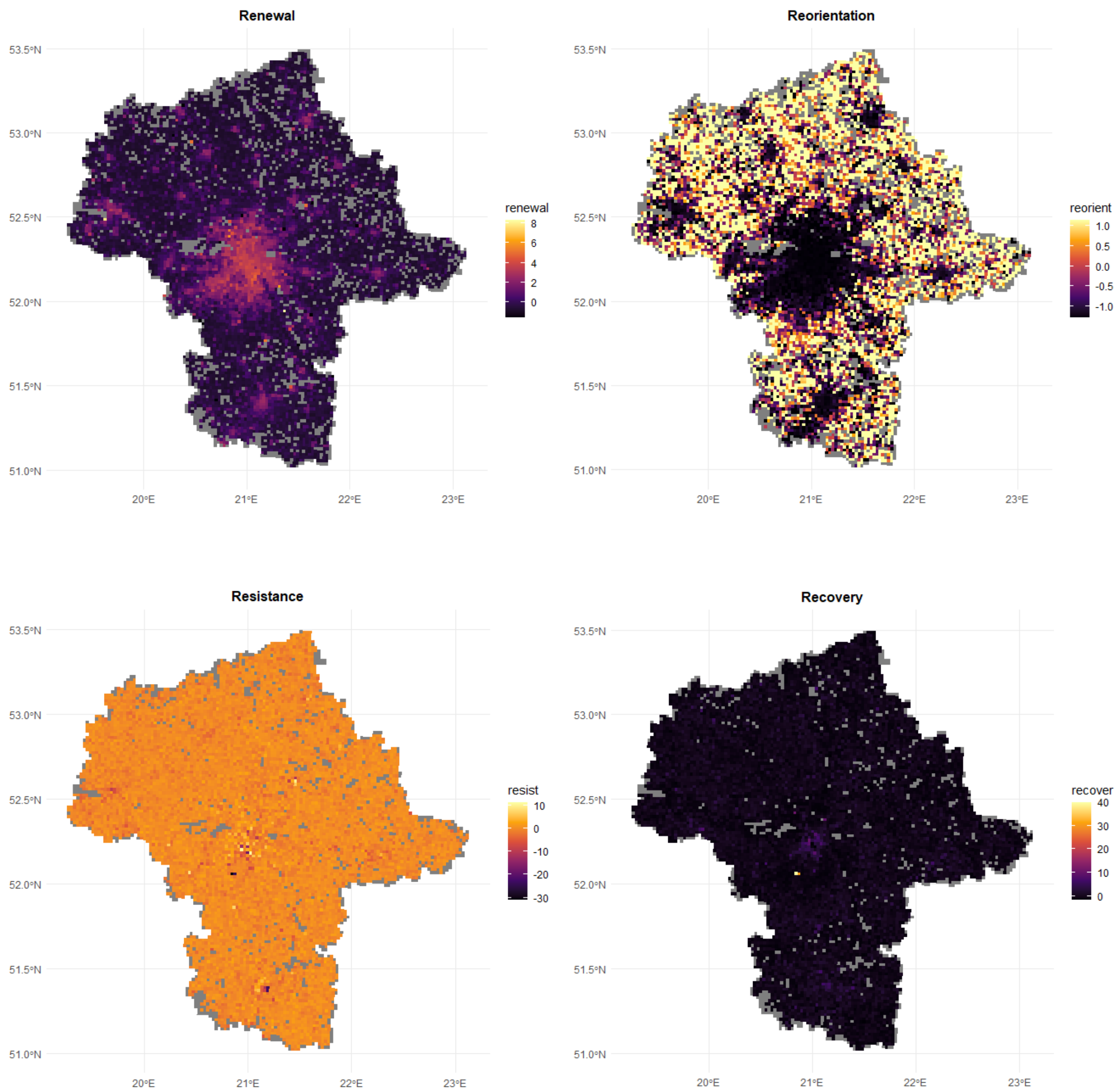
Figure 1 shows that there is no clear core-periphery pattern or clustering. The neighbourhood similarity (spatial autocorrelation) is very weak (Moran's I=0.089). Both positive, zero and negative values of LIRI appear over the whole territory of the region. The cross-sectional distribution of LIRI values is balanced, there are 3466 cells with LIRI>0.1, 3048 cells with LIRI<(-0.1), 1269 cells with values around 0 (-0.1<LIRI<0.1) and 1537 NA values. This high grid-level variability indicates that resilience is a local phenomenon.

Figure 1: LIRI index for 2 km x 2 km grids



The four metrics that build the LIRI have diverse spatial distributions (Fig.2). Renewal and reorientation follow a core-periphery pattern and behave oppositely in the sense that places with higher renewal mostly have lower reorientation (Person corr=-0.72). Resistance and recovery do not reveal a clear spatial pattern, and they also behave rather oppositely (Person corr=-0.18). Other composites are not related (Pearson corr<|0.06|). The average of those four components, i.e. LIRI, does not follow any clear spatial pattern.

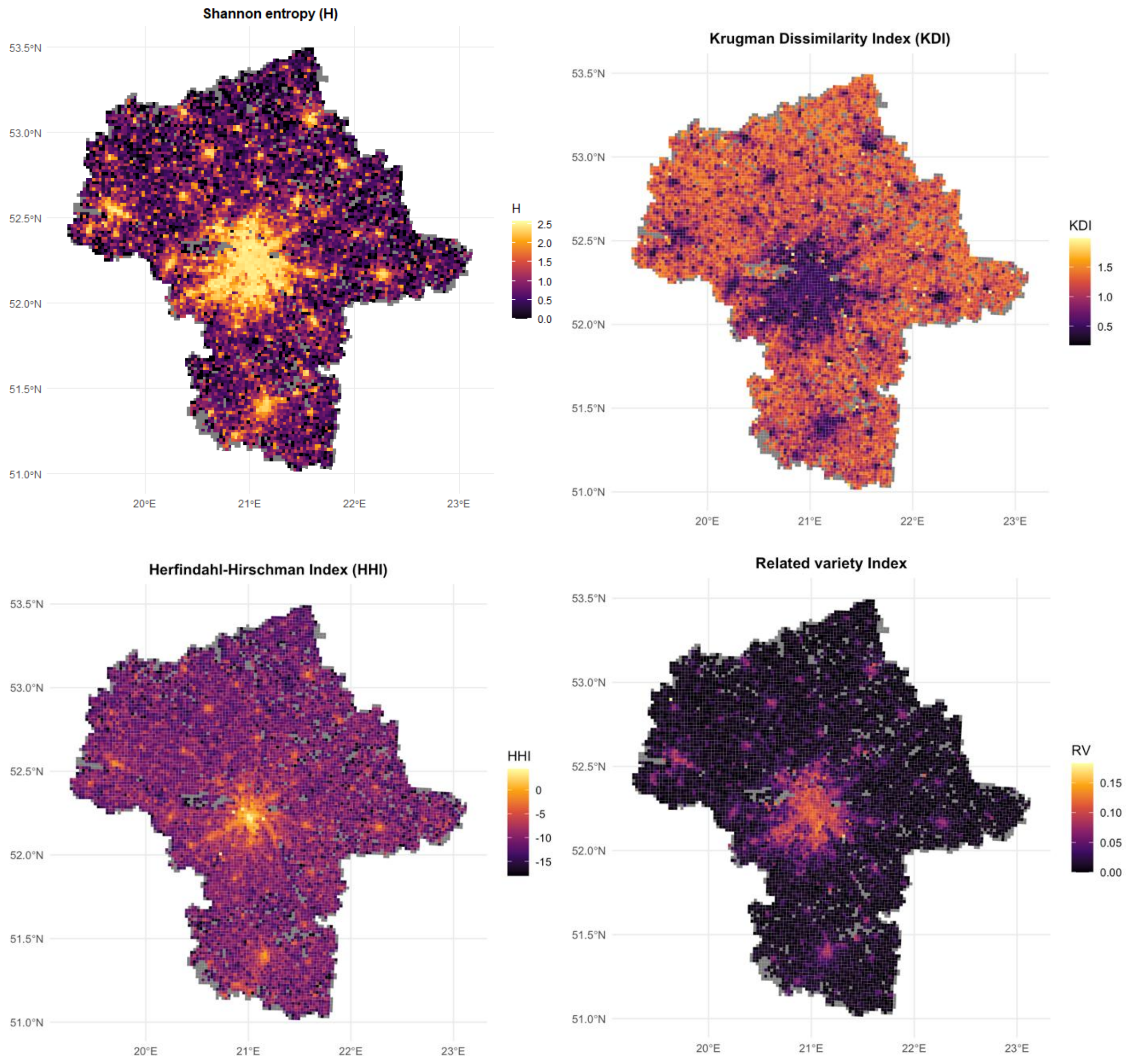
Figure 2: Major components of LIRI: a) renewal, b) reorientation, c) resistance, d) recovery



4. ECONOMETRIC ANALYSIS – determinants of LIRI

The previous section highlights a huge diversity of LIRI (Fig.1) across areas in Poland. Figure 3 below presents the distributions of the metrics for LIRI, mainly diversity, specialisation, market concentration and related variety, that were used as control variables in binomial and Poisson regression to explain the counts of survivors and births (see Section 3). They are the highest in metropolitan areas and much lower in peripheral locations (Fig.3). Urban cores and medium-sized towns tend to be more diversified, while peripheral rural areas display stronger specialisation. Related variety peaks in intermediate-density areas, suggesting that co-location of related industries extends beyond the metropolitan core. These patterns are broadly consistent with theory of agglomeration externalities. The question is how much these metric impacts the values of LIRI.

Figure 3: Major drivers of LIRI: a) diversity (entropy), b) specialisation (Krugman Dissimilarity Index), c) market concentration (HHI), d) related variety



To assess drivers of LIRI, we build three models for LIRI at the grid level. Our first two models are binary choice models: for negative values of LIRI (y=1 for LIRI<(-0.1) and y=0 other cases) and for positive values of LIRI (y=1 for LIRI>0.1 and y=0 in other cases). The third models is a linear model for continuous values of LIRI (y=LIRI). All three models have the same set of explanatory variables and are presented below (eq.16):

$$LIRI_g = \beta_0 + \beta_1 \cdot population_g + \beta_2 \cdot if.tech.firm_g + \beta_3 \cdot if.big.firm_g + \beta_4 \cdot survival\_rate_g + \beta_5 \cdot birth\_rate_g + \beta_6 \cdot KDI_g + \beta_7 \cdot entropy\_H_g + \beta_8 \cdot HHI_g + \beta_9 \cdot related\_variety_g + \beta_{10} \cdot firms\_per\_capita_g + \varepsilon_g \quad (16)$$

All models were estimated as non-spatial econometric regressions, as the spillover effects were insignificant. Regression results are presented in Tab.3.

Taken together, our three models describe factors associated with negative, positive, and continuous domains of LIRI. Coefficients in probit for negative LIRI are interpreter as a probability of negative outcome as decline or deterioration. For a positive LIRI, it is a probability of positive outcome as growth or improvement. In the OLS model for continous LIRI, it is a magnitude and direction of overall LIRI performance. These three perspectives reveal not only whether a variable matters, but also how to what extent it is related to 'good' and 'bad' outcomes, and whether the average effect (OLS) hides nonlinearities. In general, most variables are significant and directionally consistent, but their magnitudes differ. Negative and positive probit coefficients are of opposite sign, as expected, but often unequal in size. The OLS results sit between them - confirming the same directional tendencies but blending asymmetric effects. This shows the system is not symmetric: the determinants of downturns (LIRI−) and upturns (LIRI+) are different in strength.

Table 3: Regression results

Variable	Probit LIRI−	Probit LIRI+	OLS LIRI (continous)	Interpretation & Asymmetry
Intercept	+24.86***	−18.99***	−5.64***	Strong baseline asymmetry — negative outcomes are more structurally

				unlikely; positives require favorable conditions.
Population (popul.K)	−0.210***	+0.164***	+0.072***	Larger populations stabilize regions, they reduce risk of negative LIRI and promote positives; effect slightly stronger on downturn prevention (asymmetric resilience).
Technological firm (if_tech_21)	−0.531***	+0.510***	+0.166***	Balanced, nearly symmetric: tech presence both shields from negatives and fosters positives; strong bidirectional stabilizer.
Big firm presence (if_big_21)	−0.014 (ns)	+0.378**	+0.140***	Asymmetric pro-cyclical: big firms mainly drive positive LIRI, but don’t protect from declines — they amplify booms, not cushion busts.
Survival rate (surv_rate)	−22.46***	+17.34***	+4.43***	Highly asymmetric stabilizer: firm survival is much more effective in preventing negatives than in generating strong positives — a defensive mechanism.
Birth rate (birth_rate)	−2.98***	+1.65***	+0.57***	Entrepreneurial dynamics act asymmetrically: new firm entry mitigates decline more than it drives growth — adaptive regeneration.
Krugman Dissimilarity (KDI)	−2.59***	+1.40***	+0.93***	Structural diversification cushions downturns more than it accelerates growth; acts as insurance against negative specialisation.
Entropy (H)	−1.90***	+1.25***	+0.54***	Diversity and complexity protect against negative outcomes and promote positives, but with stronger stabilizing (defensive) effects.
HHI (concentration)	+59.96***	−49.74**	−33.02***	Symmetric but adverse: higher concentration increases risk of decline and reduces chance of growth. Classic destabilizer.
Related variety (RV)	−18.42***	+16.04***	+2.91***	Nearly symmetric: regional knowledge relatedness fosters positive dynamics and shields from negative ones. Strong structural stabilizer.
Firms per capita (firms.pc.21)	−0.465*	+0.826***	+0.394***	Pro-cyclical asymmetry: density of firms boosts positives more than it prevents negatives — indicates agglomeration economies matter more in expansions.
R2 (R2 McFadden for probit)	0.466	0.344	0.543	Goodness of fit of models in cross-sectional data is good.
N obs	7783	7783	7783	Number of non-empty grid cells

Variables like population, surv_rate, birth_rate, KDI, H, and RV show larger coefficients in the negative model than in the positive model. This may be interpreted as that they shield regions from downturns more effectively than they generate exceptional upswings. On the other hand, variables like if_big_21 and firms.pc.21 show stronger positive than negative responses. This suggests that they are pro-cyclical - important in booms but less relevant (or even ineffective) in avoiding declines. Additionally, one can see balanced forces as if_tech_21 and RV, that are roughly symmetric. They play the role of dual stabilizers that promote long-run balanced growth and reduce downside risk. Finally, there is one destabilizer, HHI, that has consistently opposite effect. It shows that concentration increases vulnerability and suppresses growth and it plays a role of a hallmark of structural fragility. The OLS results confirm the average direction of each effect: positive OLS coefficients (population, tech, diversity, survival, RV) correspond to growth-enhancing or stabilizing influences, while negative OLS coefficient for HHI confirms destabilizing market concentration. However, OLS *smooths out* the asymmetry seen in the probit models (e.g. surv_rate with a much larger magnitude effect in preventing negatives than in boosting positives and with moderate OLS average value or variables as if_big_21 and firms.pc.21 that seem beneficial in OLS, but probits reveal their one-sided, pro-growth asymmetry. Thus, the continuous model underestimates nonlinear behavior — the economy reacts more strongly to shocks on one side (negative) than on the other (positive).

To conclude, stabilizing variables (population, survival, diversity) have stronger effects in preventing negative LIRI. Large firms and density matter more in expansion and growth that depends on structural scale and clustering, not on the same factors that ensure stability. Concentration (HHI) consistently harmful on both sides and the lack of competition undermines both resilience and dynamism. Finally, there is an asymmetry between LIRI− and LIRI+ probits, with OLS in-between what highlights that the regional system is nonlinear: downturns and upturns are governed by different mechanisms. This duality suggest that there may be a need for complementary policy instruments: one set to stabilize and another to accelerate.

5. SUMMARY AND CONCLUSIONS

The Local Industrial Resilience Index (LIRI) offers a novel and empirically validated framework for quantifying resilience at a fine geographical scale. By integrating four interrelated dimensions— resistance, recovery, renewal and reorientation — it aims to capture both the immediate and adaptive responses of industrial systems. The results demonstrate that resilience is inherently asymmetric: regions that resist shocks are not necessarily those that lead in recovery. Understanding this asymmetry enables policymakers to design more nuanced strategies for building sustainable and adaptive industrial ecosystems. LIRI thus contributes to the emerging agenda of evidence-based, place-sensitive industrial policy, providing a foundation for monitoring resilience under the evolving pressures of digital and green transitions.

The results for the Mazowieckie region show that resilience is highly uneven across space: while the metropolitan core of Warsaw exhibits the highest LIRI values, several medium-sized towns also display notable resilience potential, often linked to diversified industrial structures and strong related renewal. Conversely, many peripheral or mono-industrial areas show low LIRI scores, reflecting their limited ability to generate or attract new activities beyond existing specialisation paths.

These findings confirm that resilience is not simply a function of urban scale or firm density but depends critically on the composition and connectivity of local knowledge bases. Grids with higher diversity and related variety in 2012 performed better in terms of both firm survival and renewal during 2012–2021. This supports the evolutionary economic geography perspective that *related variety fosters adaptive resilience* by enabling recombination of existing competences into new activities. Conversely, grids dominated by a single sector exhibited weaker renewal and higher vulnerability to structural decline, consistent with path dependency and lock-in effects. The LIRI thus empirically operationalizes the balance between *stability* (resistance) and *adaptability* (renewal and transformation) at a fine spatial resolution.

From a policy perspective, these patterns suggest a shift from traditional sectoral or firm-centric policies toward ecosystem-oriented, place-based strategies. Regional authorities should prioritize related diversification - policies that strengthen linkages between technologically or cognitively proximate sectors, through targeted support for inter-firm cooperation, shared infrastructure, and cluster-based innovation programs. Policies in high-LIRI areas should focus on maintaining network connectivity and avoiding lock-in, for example by encouraging cross-sector partnerships and mobility of skills. In low-LIRI or structurally vulnerable areas, transformational policies are needed to create new growth paths: supporting entrepreneurship in emerging sectors, investing in digital and transport infrastructure, and fostering knowledge inflows from urban centers or universities. Finally, the LIRI can serve as a diagnostic and monitoring tool for regional development agencies, allowing them to identify resilience "hotspots" and "coldspots," assess the impact of shocks, and evaluate the effectiveness of smart specialisation strategies over time.

In summary, the LIRI demonstrates that local industrial resilience emerges from the interplay between diversity, relatedness, and innovation dynamics rather than from sectoral dominance or sheer scale. Policies that enhance these relational and cognitive dimensions are more likely to build durable, adaptive local economies capable of both resisting shocks and evolving toward new trajectories of growth.

Financing: The paper is a part of the project "Tandems for excellence" financed within IDUB programme (Inicjatywa Doskonałości – Uczelnia Badawcza / Initiative of Excellence – Research University) at the University of Warsaw, Poland.

Data availability and reproducibility: The full R code for this study is available at RPubs at: https://rpubs.com/Monika_Kot/LIRI.

References:

Andersson, M., Klaesson, J., & Larsson, J. P. (2016). How local are spatial density externalities? Neighbourhood effects in agglomeration economies. *Regional studies*, *50*(6), 1082-1095.

Andersson, M., Larsson, J. P., & Wernberg, J. (2019). The economic microgeography of diversity and specialization externalities–firm-level evidence from Swedish cities. *Research Policy*, *48*(6), 1385-1398.

Arzaghi, M., & Henderson, J. V. (2008). Networking off madison avenue. *The Review of Economic Studies*, *75*(4), 1011-1038.

Bailey, D., & Turok, I. (2016). Resilience revisited. *Regional Studies*, *50*(4), 557-560.

Basit, A., Wang, L., Javed, A., Shoaib, M., & Aslam, M. (2024). Impact of digital technologies on manufacturing firm resilience during COVID-19 pandemic: a PLS-SEM and artificial neural network analysis. *Journal of Manufacturing Technology Management*.

Boschma, R. (2015). Towards an evolutionary perspective on regional resilience. *Regional Studies, 49*(5), 733–751.

Boschma, R., & Frenken, K. (2011). The emerging empirics of evolutionary economic geography. *Journal of economic geography*, *11*(2), 295-307.

Bristow, G., & Healy, A. (2014). Regional resilience: an agency perspective. *Regional studies*, *48*(5), 923-935.

Christopherson, S., Michie, J., & Tyler, P. (2010). Regional resilience: theoretical and empirical perspectives. *Cambridge journal of regions, economy and society*, *3*(1), 3-10.

Cui, L., Wu, H., Wu, L., Kumar, A., & Tan, K. (2022). Investigating the relationship between digital technologies, supply chain integration and firm resilience in the context of COVID-19. *Annals of Operations Research*, 1 - 29.

Di Caro, P., & Fratesi, U. (2018). Regional determinants of economic resilience. *The Annals of Regional Science*, *60*(2), 235-240.

Evenhuis, E. (2017). Institutional change in cities and regions: A path dependency approach. *Cambridge Journal of Regions, Economy and Society*, *10*(3), 509-526.

Fingleton, B., Garretsen, H., & Martin, R. (2012). Recessionary shocks and regional employment: Evidence on the resilience of UK regions. *Journal of Regional Science, 52*(1), 109–133.

Forliano, C., Orlandi, L., Zardini, A., & Rossignoli, C. (2022). Technological orientation and organizational resilience to Covid-19: The mediating role of strategy's digital maturity. *Technological Forecasting and Social Change,* 188, 122288 - 122288.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies, 41*(5), 685–697.

Giannakis, E., & Bruggeman, A. (2017). Determinants of regional resilience to economic crisis: A European perspective. *European Planning Studies, 25*(8), 1394–1415.

Gornig, M., & Schiersch, A. (2024). Agglomeration economies: different effects on TFP in high-tech and low-tech industries. *Regional Studies*, 58, 1999 - 2010.

Gu, M., Yang, L., & Huo, B. (2020). The impact of information technology usage on supply chain resilience and performance: An ambidexterous view. *International Journal of Production Economics*, 232, 107956 - 107956.

Guo, P. (2024). Digital Infrastructure and Firm Resilience: Evidence from China. *Emerging Markets Finance and Trade*, 61, 1342 - 1359.

Hansen, T., & Winther, L. (2011). Innovation, regional development and relations between high- and low-tech industries. *European Urban and Regional Studies*, 18, 321 - 339.

Hassink, R. (2010). Regional resilience: a promising concept to explain differences in regional economic adaptability?. *Cambridge journal of regions, economy and society*, *3*(1), 45-58.
Horowitz, A., & Horowitz, I. (1968). Entropy, Markov processes and competition in the brewing industry. *The Journal of Industrial Economics*, 196-211.
Hu, X., & Hassink, R. (2020). Adaptation, adaptability and regional economic resilience: A conceptual framework. In *Handbook on regional economic resilience* (pp. 54-68). Edward Elgar Publishing.
Hudson, R. (2010). Resilient regions in an uncertain world: wishful thinking or a practical reality?. *Cambridge Journal of Regions, Economy and Society*, *3*(1), 11-25.
Kopczewska, K. (2025). *Modelling Spatial Density: Data, Methods, and R Applications in Statistics, Econometrics, and Machine Learning*. Oxford University Press.
Kopczewska, K., Churski, P., Ochojski, A., & Polko, A. (2017). *Measuring regional specialisation: A new approach*. Springer.
Kopczewska, K., Kubara, M., & Kopyt, M. (2024). Population density as the attractor of business to the place. *Scientific Reports*, 14(1), 22234.
Krugman, P., 1991. *Geography and Trade*. MIT Press.
Lavoratori, K., & Castellani, D. (2021). Too close for comfort? Microgeography of agglomeration economies in the United Kingdom. *Journal of Regional Science*, *61*(5), 1002-1028.
Li, L., Wang, Z., Ye, F., Chen, L., & Zhan, Y. (2022). Digital technology deployment and firm resilience: Evidence from the COVID-19 pandemic. *Industrial Marketing Management*, 105, 190 - 199.
Markusen, A. (1999). Four structures for second tier cities. *Second tier cities: Rapid growth beyond the metropolis*, 21-42.
Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography, 12*(1), 1–32.
Martin, R., & Gardiner, B. (2019). The resilience of cities to economic shocks: A tale of four recessions (and the challenge of Brexit). *Papers in Regional Science, 98*(4), 1801–1833.
Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of Economic Geography, 15*(1), 1–42.
Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths. *Economic Geography, 87*(3), 237–265.
Pendall, R., Foster, K. A., & Cowell, M. (2010). Resilience and regions: building understanding of the metaphor. *Cambridge journal of regions, economy and society*, *3*(1), 71-84.
Pike, A., Dawley, S., & Tomaney, J. (2010). Resilience, adaptation and adaptability. *Cambridge journal of regions, economy and society*, *3*(1), 59-70.
Ran, R., Zhang, J., Yang, X., & Chen, Y. (2024). Can technological diversity drive firm resilience? Evidence from Chinese listed firms. *Journal of Business Research.*
Rocchetta, S., & Mina, A. (2019). Technological coherence and the adaptive resilience of regional economies. *Regional Studies, 53*(2), 209–221.
Rosenthal, S. S., & Strange, W. C. (2003). Geography, industrial organization, and agglomeration. *review of Economics and Statistics*, *85*(2), 377-393.
Sensier, M., Bristow, G., & Healy, A. (2016). Measuring regional economic resilience across Europe: Operationalizing a complex concept. *Spatial Economic Analysis*, *11*(2), 128-151.
Simmie, J., & Martin, R. (2010). The economic resilience of regions: Towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society, 3*(1), 27–43.
Simms, C., & Frishammar, J. (2024). Technology transfer challenges in asymmetric alliances between high-technology and low-technology firms. *Research Policy*.
Shannon, C. E. (1948). A mathematical theory of communication, The Bell System Technical Journal 27: 379-423 and 623–656. Mathematical Reviews (MathSciNet): MR10, 133e.
Spieske, A., & Birkel, H. (2021). Improving supply chain resilience through industry 4.0: A systematic literature review under the impressions of the COVID-19 pandemic. *Computers & Industrial Engineering*, 158, 107452 - 107452.
Sutton, J., Arcidiacono, A., Torrisi, G., & Arku, R. N. (2023). *Regional economic resilience: A scoping review*. Progress in Human Geography, 47(2), 1–33.
Tian, S., & He, Y. (2025). The impact of digital industry development on regional economic resilience: Evidence from China. *PLOS ONE*, 20.

Tóth, G., Elekes, Z., Whittle, A., Lee, C., & Kogler, D. F. (2022). Technology network structure conditions the economic resilience of regions. *Economic Geography, 98*(4), 355–378.

Xiao, J., Boschma, R., & Andersson, M. (2018). Industrial diversification in Europe: The differentiated role of relatedness. *Economic Geography*, *94*(5), 514-549.

Zouaghi, F., Sánchez, M., & Martinez, M. (2018). Did the global financial crisis impact firms' innovation performance? The role of internal and external knowledge capabilities in high and low tech industries. *Technological Forecasting and Social Change*.

Appendix

Appendix 1

The table below (Table A1) presents the descriptive statistics of the analysed dataset. The statistics were calculated for grid cells (2 km x 2 km), for REGON data between years 2012-2021.

Table A1: Descriptive statistics of variables used in the study for each grid cell

	mean	sd	min	Q1	median	Q3	max
LIRI	0.029	0.590	-7.245892804	-0.3182948	0.037809	0.33424	7.15
KDI	1.048	0.310	0.178840932	0.8773528	1.115584	1.27576	1.99
H	0.972	0.647	0.000000000	0.5026834	0.827532	1.32966	2.59
HHI	0.064	1.745	0.000000015	0.0000082	0.000032	0.00014	83.50
RV	0.018	0.023	0.000000000	0.0050877	0.009456	0.02048	0.18
surv_rate	0.852	0.116	0.000000000	0.7969734	0.875000	0.93103	1.00
birth_rate	0.254	0.231	0.013888889	0.1272727	0.200000	0.31818	8.00
popul.K	0.698	2.869	0.001000000	0.1070000	0.174000	0.31900	51.59
firms.pc.21	0.228	0.119	0.004291845	0.1587302	0.213333	0.27931	4.00
if_tech_21	0.322	0.467	0.000000000	0.0000000	0.000000	1.00000	1.00
if_big_21	0.034	0.181	0.000000000	0.0000000	0.000000	0.00000	1.00
below0	0.392	0.488	0.000000000	0.0000000	0.000000	1.00000	1.00
above0	0.445	0.497	0.000000000	0.0000000	0.000000	1.00000	1.00

Appendix 2

This appendix presents the details of estimation of LIRI in STEP 5 of the procedure. Both presented models were to estimate the expected values of survival and birth, that were further used in constructing LIRI. Table A2 presents the results of binomial model for survival of firms, while Table A3 reports the results of Poisson model for births of firms.

Table A2: Binomial model for survival of firms

```
Call:
glm(formula = cbind(survivors_total, exits_total) ~ firms_per_person +
     RV + H + HHI + KDI, family = binomial, data = full_grids_1)

Coefficients:
                 Estimate Std. Error z value             Pr(>|z|)
Intercept)       4.30858    0.06813   63.24 < 0.0000000000000002 ***
firms_per_person -0.52003    0.02544  -20.44 < 0.0000000000000002 ***
RV                1.75969    0.25689    6.85     0.00000000000739 ***
H                -1.39084    0.02935  -47.39 < 0.0000000000000002 ***
HHI               2.34850    0.19951   11.77 < 0.0000000000000002 ***
KDI              -0.90688    0.04154  -21.83 < 0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

     Null deviance: 79829  on 8607  degrees of freedom
```

```
Residual deviance: 17689  on 8602  degrees of freedom
AIC: 42611

Number of Fisher Scoring iterations: 4
```

Table A3: Poisson model for births of firms

```
Call:
glm.nb(formula = new_firms_total ~ firms_per_person + RV + H +
    HHI + KDI, data = full_grids_1, init.theta = 1.743913628,
    link = log)

Coefficients:
                 Estimate Std. Error z value            Pr(>|z|)
(Intercept)       3.56281    0.17286  20.611 <0.0000000000000002 ***
firms_per_person  2.45819    0.07422  33.118 <0.0000000000000002 ***
RV               36.89460    0.95440  38.658 <0.0000000000000002 ***
H                -0.15064    0.07295  -2.065              0.0389 *
HHI              51.31378    5.00582  10.251 <0.0000000000000002 ***
KDI              -2.26921    0.11044 -20.547 <0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(1.7439) family taken to be 1)

    Null deviance: 58960.9  on 8607  degrees of freedom
Residual deviance:  9364.2  on 8602  degrees of freedom
AIC: 54528

Number of Fisher Scoring iterations: 1
               Theta:  1.7439
           Std. Err.:  0.0327
  2 x log-likelihood:  -54513.5510
```

Appendix 3

This appendix presents the regression results for models explaining LIRI. Table A4 reports three models: probit for negative LIRI (dummy dependent variable, y=1 for LIRI<(-0.1) and y=0 elsewhere), probit for positive LIRI (dummy dependent variable, y=1 for LIRI>0.1 and y=0 elsewhere) and OLS for continuous values of LIRI.

Table A4: Regression results – determinants of LIRI

```
==========================================================
                 Probit LIRI-   Probit LIRI+  OLS LIRI all
                -------------  -------------  ------------
                Model 1        Model 2        Model 3
----------------------------------------------------------
(Intercept)        24.859 ***    -18.988 ***    -5.636 ***
                   (0.665)        (0.557)       (0.108)
popul.K            -0.210 ***      0.164 ***     0.072 ***
                   (0.022)        (0.017)       (0.002)
if_tech_21         -0.531 ***      0.510 ***     0.166 ***
                   (0.054)        (0.047)       (0.012)
```

```
  if_big_21          -0.014          0.378 **      0.140 ***
                     (0.130)        (0.120)       (0.031)
  surv_rate         -22.456 ***     17.341 ***     4.430 ***
                     (0.505)        (0.413)       (0.056)
  birth_rate         -2.977 ***      1.646 ***     0.572 ***
                     (0.181)        (0.137)       (0.023)
  KDI                -2.593 ***      1.400 ***     0.928 ***
                     (0.270)        (0.248)       (0.057)
  H                  -1.896 ***      1.246 ***     0.537 ***
                     (0.174)        (0.155)       (0.038)
  HHI                59.956 ***    -49.744 **    -33.024 ***
                    (13.531)       (15.277)       (2.752)
  RV                -18.419 ***     16.038 ***     2.913 ***
                     (2.761)        (2.410)       (0.570)
  firms.pc.21        -0.465 *        0.826 ***     0.394 ***
                     (0.196)        (0.171)       (0.040)
  -----------------------------------------------------------
  AIC               5581.234       7038.935
  BIC               5657.791       7115.492
  Log Likelihood  -2779.617      -3508.468
  Deviance          5559.234       7016.935
  Num. obs.         7783           7783          7783
  R^2                                              0.544
  Adj. R^2                                         0.543
  ===========================================================
  *** p < 0.001; ** p < 0.01; * p < 0.05
```

Appendix 4

This appendix presents the relative location of grids to cities within the region. This relative location to cities was derived using real locations of 39 cities in the Mazovian NUTS2 region (*województwo mazowieckie*), Poland (Table A5). They were grouped into 5 population size: core 1mln+ (1 city), midsize 100K+ (2 cities), regional 50K+ (4 cities), local big 30K+ (9 cities), local small 15-30K (23 cities). Each grid was checked if it is located in a radius of 10, 25 and 50 km from the center of each city. In modelling we were checking the two types of variables:

A) Continuous variables – distance from a grid cell to the closest city from given category (core, midsize, regional, local big, local small)
B) Set of 15 dummy variables – binary variables if particular grid cell is located in a radius of 10, 25 or 50 km from a city of a given category (core, midsize, regional, local big, local small)

Table A5: Cities located in NUTS2 Mazovian region included in the analysis

Group	ID	City	Population	Longitude	Latitude
Core city	1	Warszawa	1 729 119	21.06119	52.23294
Midsize cities	2	Radom	217 834	21.01389	51.4152
	3	Płock	122 572	19.64501	52.53549
Regional cities	4	Siedlce	76 585	22.14144	52.16167
	5	Pruszków	59 796	20.66378	52.17202
	6	Legionowo	54 246	20.90458	52.40488

	7	Ostrołęka	52 792	21.51907	53.07745
Local big cities	8	Piaseczno	45 270	20.88196	52.07337
	9	Otwock	45 073	21.21945	52.11633
	10	Ciechanów	44 673	20.54715	52.87107
	11	Żyrardów	41 056	20.40536	52.05526
	12	Mińsk Mazowiecki	40 028	21.52169	52.17917
	13	Wołomin	37 418	21.20118	52.34264
	14	Sochaczew	37 333	20.1092	52.23635
	15	Ząbki	32 376	21.07776	52.29252
	16	Mława	30 893	20.31333	53.13291
Local small cities	17	Grodzisk Mazowiecki	29 988	20.59806	52.10513
	18	Marki	29 395	21.04995	52.33716
	19	Nowy Dwór Mazowiecki	28 361	20.42122	52.43413
	20	Wyszków	27 205	21.41228	52.5923
	21	Piastów	22 862	20.77894	52.18553
	22	Ostrów Mazowiecka	22 770	21.85631	52.80713
	23	Płońsk	22 435	20.32957	52.62666
	24	Kobyłka	21 132	21.16377	52.34008
	25	Józefów	20 013	21.08495	52.12857
	26	Sulejówek	19 385	21.24671	52.24465
	27	Pionki	19 286	21.41105	51.47252
	28	Pułtusk	19 229	21.04836	52.70321
	29	Gostynin	19 026	19.33104	52.42421
	30	Sokołów Podlaski	18 730	22.19902	52.41285
	31	Sierpc	18 468	19.63032	52.85337
	32	Kozienice	18 150	21.50136	51.58732
	33	Zielonka	17 434	21.07706	52.293
	34	Konstancin-Jeziorna	17 371	21.07058	52.08389
	35	Przasnysz	17 337	20.84989	53.01855
	36	Garwolin	17 160	21.58779	51.89536
	37	Łomianki	16 632	20.85897	52.33345
	38	Grójec	16 430	20.83774	51.86819
	39	Milanówek	16 427	20.63528	52.12485