BUILDINGS & CITIES

RESEARCH

ubiquity press

Non-domestic building stock: linking dynamics and spatial distributions

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ABSTRACT

In contrast to domestic buildings, the drivers influencing the stock dynamics (construction subtracted by demolition) of non-domestic buildings (NDB) have not yet been researched on a use-class basis. For the first time, due to elaborated data sets on construction and demolition of NDB in Germany, an in-depth analysis of causal relationships is provided at a subnational level. This paper investigates the cause–effect relationships between influencing variables and stock dynamics of the three quantitatively most relevant use classes of the German NDB stock: office buildings, industrial buildings and warehouses. Influencing variables on the development of the stock were first identified by means of expert interviews. Regions with high construction dynamics were identified. Within these highly dynamic regions, construction activity was correlated with influencing variables. A principal component analysis was used to examine the explanatory power of underlying, use-class-specific components of the variable set. The results show the particular importance of employment-related variables. They combine demographic, economic and wealth-related influences and allow for a distinction to be made in relation to functional non-domestic-use classes. For the first time, this confirms that different use classes of NDB are characterised by different influencing variables, and that these variables recur to uncorrelated overarching drivers.

PRACTICE RELEVANCE

This study identifies the drivers of NDB stock dynamics. These drivers can be used to estimate future changes of the NDB stock on different scales. The linkages to specific use-class drivers allow new understandings of stock dynamics for office, industrial and warehouse buildings at a regional level. This has potential application to circular economy approaches as the results of this research can be applied at city levels. This study can provide a clearer understanding of future construction material volumes and their respective recycling capacities. The same is applicable for research on stock-driven land demand. This study can contribute to the broader discussion on the future development of the non-residential building stock and the resulting environmental impacts due to land use, energy and material consumption or CO_2 emissions.

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KEYWORDS:
building stock; buildings; construction rate; demolition; non-domestic buildings; planning; scenario planning; service life; spatio-temporal; trend analysis; Germany

TO CITE THIS ARTICLE:
Kretzschmar, D., & Schiller, G. (2023). Non-domestic building stock: linking dynamics and spatial distributions. *Buildings and Cities*, 4(1), pp. 727–748. DOI: https://doi.org/10.5334/bc.357

DOI: 10.5334/bc.357

1. INTRODUCTION

The construction and operation of buildings accounts for around 38% of energy-related CO_2 emissions (IEA 2020: 4), 40% of waste production and 40% of global resource consumption (Becqué *et al.* 2016: 20). The stock dynamics of buildings—*i.e.* the cycles of construction, demolition and new construction of buildings—are becoming shorter (Hassler & Kohler 2004). Regarding the new construction of buildings, the United Nations (UN) estimates that, by 2070, floor area in buildings will double from current levels (UNEP & IEA 2017: 3). It is estimated that those additions:

> are equivalent to adding a city the size of Paris to the world every week.
>
> (IEA 2020: 160)

Concerning the building stock in Germany, about half of the usable floor area is accounted for by non-domestic buildings (NDB) (Ortlepp *et al.* 2015: 853).

In terms of demolition of buildings, NDB have a demolition rate that is 4–13 times higher than domestic buildings (DB) (Bradley & Kohler 2007: 535; Huuhka & Lahdensivu 2016: 78; Huuhka & Kolkwitz 2021: 5), and the cycles of demolition and new construction are significantly shorter for NDB compared with DB (Hassler & Kohler 2011: 26). NDB are subject to a much faster change of use requirements (Thomson & van der Flier 2011: 354). This contributes to lower survival probabilities and lower average life spans of NDB (Aksözen *et al.* 2017: 266).

Despite their great importance, NDB have received significantly less attention in the past compared with DB (Bradley 2017: 1). With regards to Germany, this is particularly true for information on the locations of NDB, their material composition, distribution across use and age classes, and information on ownership, rents, costs as well as vacancies (Clausnitzer *et al.* 2014). Germany does not have a nationwide building register (Körner *et al.* 2019: 82). Information on the stock of NDB is not publicly available (BBSR 2016: 3). Similar data gaps exist in other European countries (Stein *et al.* 2012), except for the UK, where tax and survey data allow for estimations of the NDB stock at an urban scale (Bruhns & Wyatt 2011: 225; Taylor *et al.* 2014; Steadman *et al.* 2020).

The NDB stock is very heterogeneous, ranging from buildings for public services such as schools and hospitals to commercial buildings, *e.g.* factories, office buildings and warehouses. Bruhns (2008: 2) argued that the:

> diversity of the NDB is one of the major underlying factors in the lack of comprehensive data.

The NDB stock can be differentiated, *e.g.* along building functions, age classes, ownership structures and building forms (*e.g.* Bruhns 2008; Schebek *et al.* 2017; D'Agostino *et al.* 2017, Kretzschmar *et al.* 2019). In some sectors of the NDB stock, the morphological, constructive and functional diversity is significantly higher compared with the domestic stock (Kohler *et al.* 2009: 451), which makes a comprehensive cadastre of the stock challenging (Kretzschmar *et al.* 2021a). In addition, some difficulties arise from mixed building use (Evans *et al.* 2017; Gao *et al.* 2013: 2349). Statistics often address dominant building activity and do not consider other activities within NDB. Thus, information about the true shape of the building stock is scarce.

Due to this lack of data, little is known so far about cause–effect relationships between NDB stock dynamics and certain influencing factors, 'the causes, or drivers, of stock accumulation' (Fishman *et al.* 2015: 77). While changes in the domestic stock can be explained by demographic and behavioural influences such as population development, the change in the number of households (Kavgic *et al.* 2010: 1685; Sandberg *et al.* 2016: 28) as well as the behaviour-dependent housing desires of households (Müller 2006: 144) and changes in infrastructure stocks are correlated to economic growth, affluence and urbanisation (Han *et al.* 2018, Zhang *et al.* 2019), knowledge of the drivers of the NDB stock is scarce in the recent literature (Lanau *et al.* 2019: 8510). It seems plausible that the drivers of NDB dynamics differ significantly from those of the domestic sector (Sartori *et al.* 2008: 425).

Accurate information on shifts in the dynamics of the NDB stock and the underlying causes are, however, essential for a comprehensive understanding of the built environment and its future challenges (Lanau *et al.* 2019). Due to its heterogeneity, it seems advisable to differentiate the NDB according to functional use classes, spatial contexts as well as related drivers. This would enable forecasts of the dynamics of certain use classes comparable with the domestic stock, and could enhance our understanding regarding urban mining or questions of energy consumption. Apart from those obvious benefits, knowledge about cause–effect relationships between the NDB dynamics and external drivers could open new possibilities for a more informed assessment of building stock models (Bischof & Duffy 2021: 19), which in turn could support the development of dynamic building simulations, predicting future performance of stocks and buildings (Steadman *et al.* 2020: 115). The release of the statistics of building construction by the German Research Data Centres now makes available for the first time detailed information on building types, building ownership and spatial distribution of non-domestic construction at a community level in Germany. This provides a new base of information on building dynamics and their characteristics (Kretzschmar *et al.* 2021a).

The aim of this paper is to identify the cause–effect relationships between external drivers and the stock dynamics of the three most relevant use classes of the German NDB stock in terms of stocks and flows quantity (office buildings, industrial buildings and warehouse buildings).[1]

This paper is structured as follows. The study design and methods presented link the influencing variables by use type to the spatial distribution patterns of NRB construction dynamics. An expert survey is then used to identify a preliminary selection of hypothetical influencing variables. A data analysis of the stock dynamics is created to differentiate non-domestic construction activity at a subnational level. Correlation statistics are then used to indicate interdependencies between the stock dynamics and their influencing variables. A factor analysis is then employed to identify the underlying latent drivers for each use class.

2. METHODOLOGY

The present analysis follows a parallel mixed-methods approach. First, guided expert interviews are used to identify possible cause–effect relationships. These cause–effect relationships are then examined independently by quantitative methods, differentiating these effects in terms of content, space and time. The qualitative strand serves to identify influencing variables (independent variables), while the quantitative strand examines the impact of these variables on the dynamics of NDB construction (dependent variables). For this purpose, suitable spatio-functional submarkets were delimited. Subsequently, variables for mapping these influencing variables were compiled by means of secondary data analysis, which were then examined for their effect on the locally surveyed NDB construction activity. The supplemental data online provide further background information about the different quantitative data techniques.

2.1 RESEARCH DESIGN

The research design has three main strands: (i) the identification of appropriate spatial clusters of construction dynamics, (ii) the detection of spatio-temporally differentiated correlations and (iii) the further examination of those correlations with use-class-specific drivers of construction dynamics identified by means of principal component analysis (Figure 1).

The first strand (i) uses a data set on office, industrial and warehouse stock dynamics from 2000 to 2015 (*i.e.* new construction and demolition data) obtained from the German Research Data Centre (RDC) (2018).[2] A previously performed typological frequency analysis of major-use classes identified office, industrial and warehouse buildings as the most important use classes, as those were considered by most of the typologies under review (Kretzschmar *et al.* 2019). The RDC data set provides figures on new construction and demolition for all municipalities in a harmonised and summarised form. A total of around 3.8 million individual construction measures (new construction, conversion, reuse, partial demolition, demolition) are recorded in this data set, allowing the measurement of stock dynamics on nuanced spatial and functional scale.

Stock dynamics are defined here as new construction (including net changes in conversions and reuse measures) subtracted by demolitions within a given district, year and use class. Thus, the cumulative data set contains 18,045 cases for all 15 years, 401 districts and three use classes. Due to data protection obligations, only aggregated information can be published.

By means of cluster analysis of the average stock dynamics at the district level, it was possible to identify particularly dynamic districts for all three use classes.

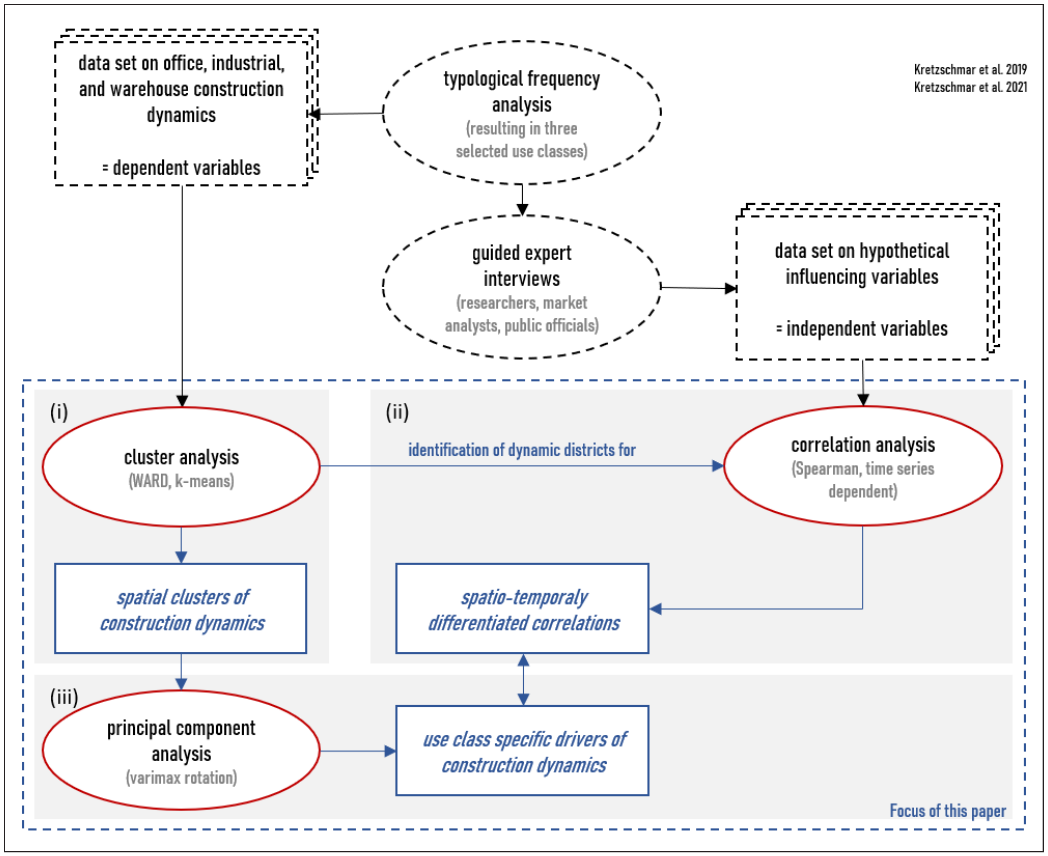

Figure 1: Study design showing research strands (i), (ii) and (iii).

The second research strand (ii) investigates spatio-temporally varying correlations between stock dynamics and their respective influencing variables. Here, hypothesis-based cause–effect relationships on the dynamics of non-domestic construction were obtained from expert interviews. Real estate researchers were asked to make statements about hypothetical influencing variables for the use classes of office, industrial and warehouse buildings (for a full list of experts, see ***Table S10*** in the supplemental data online). Depending on the expertise of the respondent, some experts were asked about one certain use classes, while others were able to make statements about all three use classes. Interviews with real estate experts, researchers and state-employed experts in public service were conducted (n = 11). Influencing variables were sorted along their degree of operationalisation, roughly distinguishing between influences for which the experts themselves named suitable operationalisation variables (influencing variables) and non-operationalised influences. The latter were then supplemented by the authors with suitable variables for measurement, although lack of data access made further analysis impossible in some cases (Table 1). As a result, hypothetical influencing variables (independent variables) were identified. Those were correlated with stock dynamics of office, industrial and warehouse buildings, respectively (dependent variables), focusing solely on dynamic districts previously identified in the first research strand (i), delivering spatio-temporally differentiated correlation coefficients for all three building types.

The third research strand (iii) verifies those results by means of PCA, moving away from the individual variables to an aggregated information of underlying drivers of stock dynamics using correlated information to form few, but uncorrelated, drivers. Here the complete data set of all temporal single values of the influencing variables in dynamic districts is used. These variables are condensed to their underlying cross-variable components of stock change within a single, holistic multivariate analysis. In the end, use-class-specific, uncorrelated drivers of construction dynamics are obtained.

2.2. DATA SETS ON INFLUENCING VARIABLES

Table 1 gives an overview of the identified hypothetical influencing variables for each use class, as well as the data samples used to operationalise those variables. The experts named 35 influences and influencing variables across all use classes. However, due to a lack of data, only 21 influencing variables could be considered in our analysis. Table 1 indicates both obtained data sets as well as variables that could not be supported by the data.

2.3 MULTIVARIATE ANALYSIS METHODS

It is assumed that the correlation between influencing variables and the stock dynamics of a use class is particularly evident in regions with high stock dynamics of the respective use class. Therefore, regions were differentiated for office, industry and warehouse dynamics using *cluster analysis*. First, annual averages of stock dynamics along the three use classes were calculated for so-called districts (see the supplemental data online).[3] To exclude the high proportion of small-scale building renovations, conversions and re-registrations, construction completions with a floor space of less than 2500 m^2 were not considered in this step. Following an approach from Wiersma *et al.* (2021) for the German DB stock, a combination of Ward and *k*-means was chosen to extract suitable clusters (for a more in-depth methodological discussion, see Steinley & Brusco 2007, and Vendramin *et al.* 2010). Ward was used to identify cluster centroids, since the approach guarantees high internal homogeneity within clusters while simultaneously delivering high external heterogeneity of clusters. Those cluster centroids where then used as starting points for *k*-means, eliminating problems with local optima in the algorithm and ensuring a plausible assignment of cases to certain clusters. Cluster analyses require a standardisation of the incoming variables. To ensure comparability between use classes and districts, dynamics data sets for all three use classes were set in relation to the number of inhabitants of the respective district and then *z*-standardised over all cases. Linear discriminant analysis was used to validate the results, because this method verifies the classification of elements into already given groups using an estimation function to determine the total dispersion between and within clusters.

After the identification of clusters with high-use class-specific dynamics, *correlation analysis* was used to check for interdependencies between those dynamics and the identified influencing variables. Since the visual quantile–quantile plots do not indicate a normal distribution for all variables, Spearman's rank correlation coefficient was used, allowing correlation analysis for sets of variables that are not normally distributed. To determine the correlation over time, all variables were subtracted with the respective value of the previous year to obtain the change in amplitude (change data set). Individual district data were then cumulated along their cluster affiliation, mitigating local extremes of construction activity in individual districts. This cumulative time series of annual use-class-related stock dynamics was then correlated against the respective set of influencing variables (Table 1). To search for the effects of a temporal offset, a time lag of one year was considered for all influencing variables so that correlations were calculated for time series running in parallel with stock dynamics (t) and for dependent variables leading ($t + 1$) and lagging ($t - 1$) the independent variable. As building construction activity is subject to strong annual fluctuations, the time series of all dependent and independent variables were smoothed using a moving average of two consecutive years. In combination with the one-year time lag, a three-year maximum response time frame is used, in accordance with estimations of average time-to-build and time-to-plan gestation lags for NDB construction (Millar *et al.* 2016).

Table 1: Hypothetical influencing variables according to expert survey by use class and data availability

Note: GVA = gross value added.

USE CLASS	INFLUENCE	INFLUENCING VARIABLE	DATA SOURCE	ABBREVIATION
Non-domestic sector in general	Building land	Purchase values for land ready for building	Expert committees for real estate values	*Land_price*
	Economic development	Gross domestic product	National accounts of the federal and state governments	*GDP*
	Population development	Inhabitants by six age classes	National accounts of the federal and state governments	*Population_0_18* *Population_18_25* *Population_25_30* *Population_30_50* *Population_50_65* *Population_65+*
		Migration by six age classes	Federal statistical office	*Net_migration_0_18* *Net_migration_18_25* *Net_migration_25_30* *Net_migration_30_50* *Net_migration_50_65* *Net_migration_65+*
		Number of births	Federal statistical office	*Births*
	Construction cyclicity	Construction of single-family homes	Federal statistical office	*SFH_const*
		Construction of multifamily houses	Federal statistical office	*MFH_const*
		Construction of domestic floor space	Federal statistical office	*Floor_space_dom*
	Population wealth	Gross wage per hour	National accounts of the federal and state governments	*Wages/hour*
		Employee compensation per employee and hour	National accounts of the federal and state governments	*Wages/employee/hour*
	Construction capacity	Construction sector employees	National accounts of the federal and state governments	*Employees_constr*
		GVA in the construction sector	National accounts of the federal and state governments	*Gross_value_added_constr*
	Construction costs	–	Not available at the district level	–
	(Alternative) yield	–	Not available at the district level	–
	Building conditions	–	No data available	–

(Contd.)

USE CLASS	INFLUENCE	INFLUENCING VARIABLE	DATA SOURCE	ABBREVIATION
	Vacancies	–	Not all districts available	–
	Image	–	No data available	–
	Rent	–	No data available	–
Office buildings	Office employment	Office employees	Empirica research and consulting	*Office_employees*
		Employees in the tertiary sector (three subtypes)	National accounts of the federal and state governments	*Employees_tertiary_1* *Employees_tertiary_2* *Employees_tertiary_3*
	Economic development	GVA in the tertiary sector (three subtypes)	National accounts of the federal and state governments	*Gross_value_added_ter_1* *Gross_value_added_ter_2* *Gross_value_added_ter_3*
	Public financial balance	–	Not available at the district level	–
	Economic sentiment indicators	–	Not available at the district level	–
Industrial buildings	Industrial employment	Manufacturing employees	Federal statistical office	*Manufacturing_employees*
		Manufacturing workers	Federal statistical office	*Manufacturing_workers*
		Secondary sector employees	National accounts of the federal and state governments	*Employees_secondary*
	Density of industrial enterprises	Number of manufacturing companies	National accounts of the federal and state governments	*Manufacturing_companies*
	Economic development	GVA in the secondary sector	National accounts of the federal and state governments	*Gross_value_added_sec*
	Capacity utilisation	–	Not available at the district level	–
	Historic industrial affiliation	–	No data available	–
Warehouse buildings	Warehouse employment	Logistics employees	Federal employment agency	*Logistics_employees*
	Share of e-commerce	–	Not available at a district level	–
	Motorway connection	–	Not available on a yearly basis	–
	Political inclination towards logistics	–	No data available	–
	Import and export volumes	–	Not available at a district level	–

Finally, to test the hypothesis of independent influencing drivers for all three use classes, underlying principal components of all influencing variables were identified via principal component analysis (PCA). This technique compresses data by reducing the number of variables in multivariate data sets. The goal is to obtain a smaller set of variables, known as principal components (PCs), which still capture most of the variance in the data set. Importantly, the PCs are uncorrelated with each other. Each PC is created as a linear combination of the original variables via so-called loadings. Using the previously processed change data set from 2001 to 2015 and information on strongly correlated influencing factors, a PCA with varimax rotation was performed. This rotation method attempts to maximise the variance within a factor so that large loadings become even larger and small loadings become even smaller. In this way, factors are simplified by selecting groups of variables that load strongly on a factor, thus increasing interpretability and uniqueness of PCs.

In an iterative process, variables were excluded that were deemed unsuitable for further calculation according to the Kaiser–Meyer–Olkin (KMO) indicator measure of sampling adequacy (MSA). The test evaluates the differences between correlations and partial correlations among variables (displayed in an anti-image matrix), as PCA requires the partial correlations to be relatively low compared with the overall correlations. Results are displayed as MSAs. Additionally, those variables that loaded simultaneously on multiple components were excluded to increase the discriminability of the components. To test for the overall feasibility of the data set, Bartlett's test of sphericity was used to ensure that correlations across variables were high enough to perform a PCA. A screen plot analysis of the eigenvalues per factor was used to visually determine the number of appropriate components. Eigenvalues describe the sum of the squared loadings of a component over all variables, ranking components along their explanatory power. Screen plot analysis attempts to determine the optimal number of components in which as much of the variance of all variables is explained by as few factors as possible.

This results in a data set with overall well-correlated variables condensed in distinct, uncorrelated PCs. Like in the previous correlation analyses, the annual factor values of the obtained components were plotted as a time series and correlated with the dependent variables to check for correlations with stock dynamics.

3. EMPIRICAL RESULTS

3.1 SPATIAL CLUSTERS OF CONSTRUCTION DYNAMICS

The best results were obtained with a differentiation of eight clusters. This number of clusters allowed the algorithm to distinguish clearly differentiable clusters for both the use classes of warehouse buildings and industrial buildings, differentiating multiple clusters of varying dynamics for all use classes. A higher number of clusters would lead to higher complexity within use classes, while a lower number of clusters would mix districts of medium warehouse dynamics with districts of medium industry dynamics, eliminating data sets for the subsequent analysis.

Cluster distinction can be observed by looking at cluster centroids (arithmetic averages of all variables per cluster and use class) (Table 2). This analysis distinguished between three office clusters (clusters with low, medium and high office dynamic) as well as two industrial clusters and two warehouse clusters (respectively, one cluster of medium dynamics and one cluster of high dynamics).

Since many districts in Germany do not have significant dynamics in any of the three use classes, the cluster analysis shows a collective category of all districts with low dynamics (cluster 1). A total of 181 districts shows low construction dynamics in all three use classes. The difference in cluster width is striking, a result of the Ward procedure and the preference for external cluster heterogeneity. The number of cases per cluster decreases with increasing average dynamics. The low office dynamics cluster (cluster 2) consists of 38 districts, while the medium dynamics office cluster (cluster 3) only comprises 12 districts. With Frankfurt and the district of Munich, only two cases were matched within the highest office dynamics cluster (cluster 4). This classification is consistent with the observable dynamics in the cluster analysis data set, which is highest in both districts relative to the population. Frankfurt as a banking centre and Munich as a service hub formed the most important office markets in Germany during the period under review. Office clusters consistently show below-average dynamics in industrial and warehouse construction, indicating a clear spatial differentiation between these use classes.

CLUSTER NO.	CLUSTER TYPE	CASES	Σ AVERAGE DYNAMICS	AVERAGE OFFICE BUILDING DYNAMIC	AVERAGE INDUSTRIAL BUILDING DYNAMIC	AVERAGE WAREHOUSE BUILDING DYNAMIC
1	Lowest, no focus	181	**–1.4**	–0.4	–0.6	–0.4
2	Low, office	38	–0.3	**0.9**	–0.5	–0.7
3	Medium, office	12	2.0	**3.0**	–0.6	–0.4
4	High, office	2	7.8	**8.8**	–0.2	–0.8
5	Medium, industrial	95	0.4	–0.3	**0.6**	0.0
6	High, industrial	28	3.1	0.1	**2.4**	0.6
7	Medium, warehouse	37	1.4	0.0	–0.1	**1.5**
8	High, warehouse	8	5.3	–0.1	1.1	**4.3**

Table 2: Average yearly normalised cluster dynamics per inhabitant

Note: Years 2001–15, only considering construction completions > 2500 m^2, in m^2/inhabitants and m^2/year; values are dimensionless due to *z*-standardisation with an average of 0 and a standard deviation of 1; the highest values per cluster are highlighted in bold.

Figure 2 displays a distribution of all 401 districts along their average annual stock dynamics of office, industrial and warehouse buildings as well as their respective clusters within a three-dimensional feature space. Clearly visible is the large number of districts without significant dynamics in one of the three use classes (marked in grey). A few districts show very high average dynamics in certain use classes. The range between districts with no dynamics whatsoever and highly dynamic districts is particularly wide for office buildings (red). In contrast, dynamics of industrial (blue) and warehouse buildings (turquoise) seem to go hand in hand in some districts, making a clear distinction of both use classes more challenging. The fringes of cluster 5 (medium industry dynamics) seem to overlap in part with the medium warehouse dynamics cluster (cluster 7).

The result of the cluster analysis is supported by the linear discriminant analysis, showing very high predictive accuracy of the classification, with 95.8% correctly attributed districts (n = 384). Of the remaining 17 districts, nine were originally attributed to cluster 5 (medium industry dynamics), with the discriminant analysis indicating that five of those districts belong to cluster 7 (medium warehouse dynamics) (for a detailed attribution by district, see the supplemental data online). The reason for this high degree of commonality lies with the strong economic interdependence, as warehouses store and subsequently distribute goods produced in industrial complexes. Around one-fifth of all warehouse buildings in Germany are industrial warehouses (Veres-Homm *et al.* 2015: 37). Districts with higher construction dynamics show a much clearer specialisation in warehouse or industrial function (clusters 6 and 8).

Mapping those clusters allows for the identification of spatial distribution patterns (Figure 3). Office clusters are concentrated in metropolitan areas and urban centres. Despite this obvious spatial correlation, different underlying causes of the high office dynamics can be assumed. In addition to service centres such as Frankfurt, Düsseldorf or Munich, office clusters are also made up of urban districts with important national and regional administrative functions such as Bonn, educational hubs (Darmstadt, Nuremberg) as well as cities with a large share of industrial manufacturing and associated office activity (Wolfsburg, Stuttgart, Ulm). The traditional differentiation of the German office property market into seven top locations (the Big Seven) is only partially supported by the results (JLL 2022). It is striking that for cities such as Hamburg or Berlin, per capita office construction activity is only slightly above average, and Cologne, Germany's fourth-largest city, has a significantly below-average office dynamic—contrary to the general belief of market players (indicating further research).

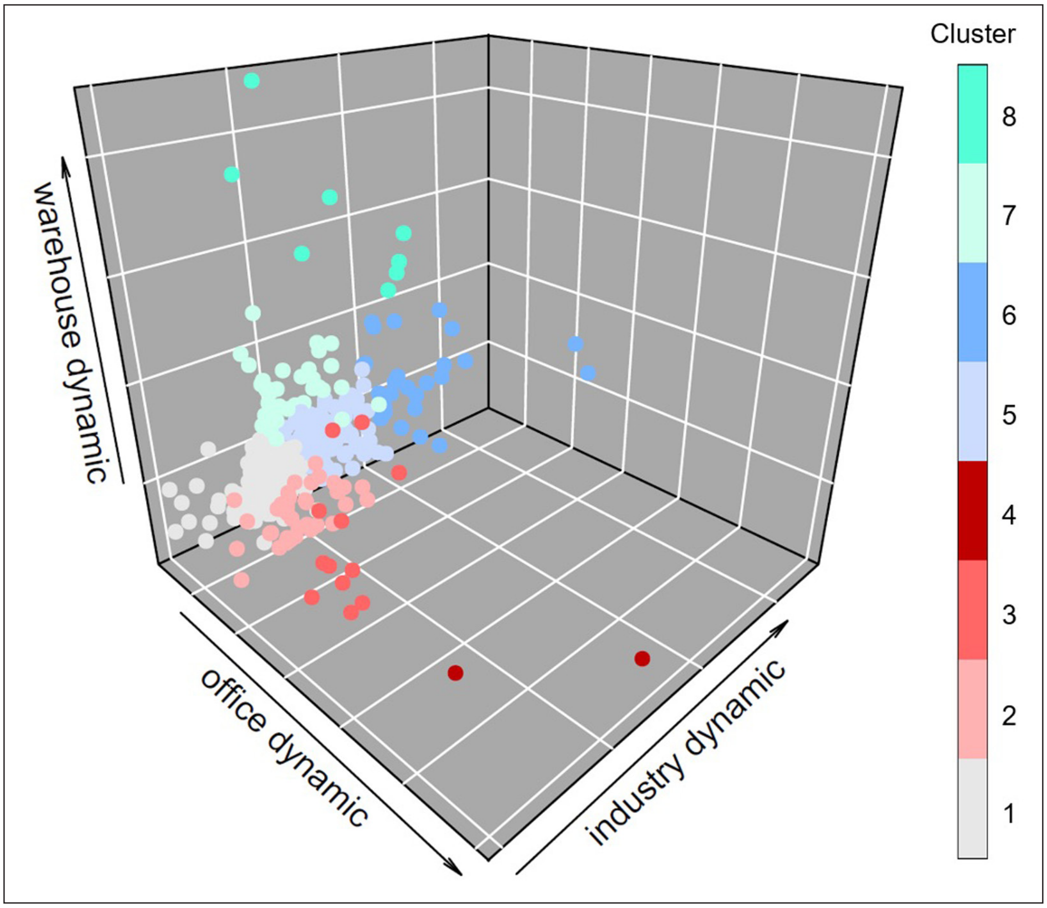

Figure 2: Three-dimensional feature space of 401 German districts classified in office, industry and warehouse dynamics by *k*-means cluster classification.

Source: Statistics of Building Completions 2000–2015, https://www.forschungsdatenzentrum.de/de/bauen-und-wohnen/baufertigstellungen (21 December 2020).

Districts with high and medium warehouse dynamics consistently have highway access. They are usually concentrated in the second row around large urban and economic centres, *e.g.* around Hamburg as the most important freight hub of international trade, around Berlin, Munich or in the Ruhr area. In addition, the analysis identified regional distribution hubs between these large agglomerations, *e.g.* in Erfurt, Koblenz or Bad Hersfeld, home of the largest Amazon hub in the country.

Overall, warehousing clusters appear to be evenly distributed across the country, with a slight emphasis on freight logistics distribution centres of international sea trade routes in the north-west. Those results are consistent with reports by Veres-Homm *et al.* (2015) who identified a similar distribution of key logistics locations in Germany using self-collected market and purchasing data (Veres-Homm *et al.* 2015: 81).

The spatial distribution of districts with high and medium dynamics of industrial buildings is concentrated in southern and eastern Germany. For southern Germany, this effect is due to decades of traditional strength of small and medium-sized enterprises within a highly specialised and globalised manufacturing sector (automobile manufacturers, chemicals and pharmaceuticals, mechanical industry). In eastern Germany, catch-up effects can be assumed. After reunification, the NDB stock grew rapidly in East Germany, partly due to the construction of modern industrial complexes by West German manufacturing companies (Schug *et al.* 2022: 12). As the analysis in this paper starts in the early 2000s, the echoes of this development can be observed, which continued well into the middle of the next decade.

In summary, the analysis confirmed the hypothesis of spatio–functional clusters of NDB similar to previous studies of the DB sector (Wiersma *et al.* 2021).

DOI: 10.5334/bc.357

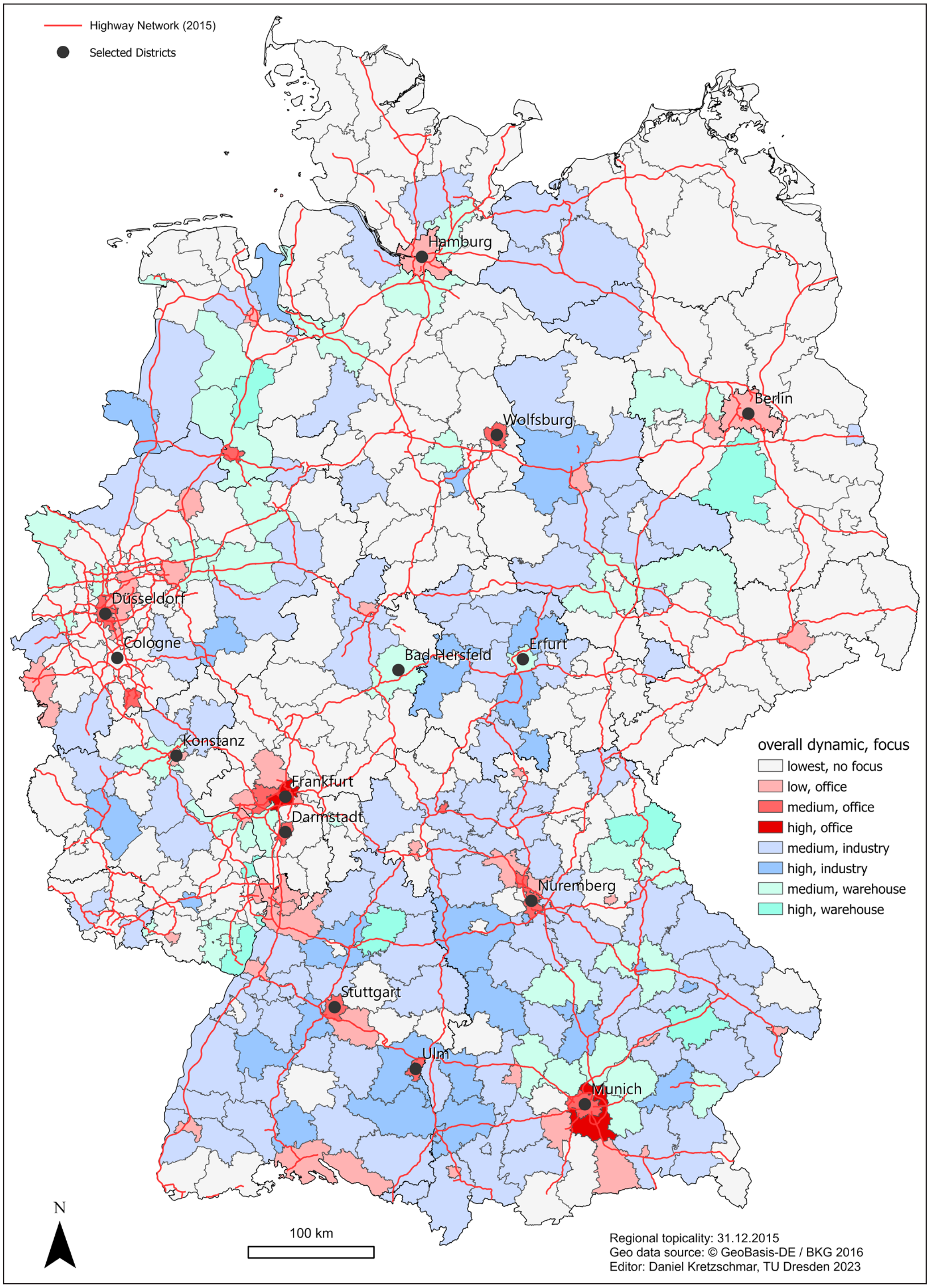

Figure 3: Resulting non-domestic cluster of office, industry and warehouse dynamics at the district level.

Note: Yearly averages from 2001 to 2015; *k*-means approach based on Ward clustering.

Source: Statistics of Building Completions 2000–2015, https://www.forschungsdatenzentrum.de/de/bauen-und-wohnen/baufertigstellungen (21 December 2020).

3.2 SPATIO-TEMPORALLY DIFFERENTIATED CORRELATIONS

Table 3 displays correlation coefficients and the associated significance of the relationship between dependent variables (office dynamics, industrial building dynamics as well as warehouse dynamics) and selected independent variables. Highlighted are correlations with high significance ($p < 0.01$). Figure 4 provides visual interpretation of these calculations for one selected independent variable in each of the three use classes. Values were calculated by cumulating all observations within a selected cluster group (with individual values of all office clusters being taken to determine the correlation with office dynamics, *etc.*).

The analysis revealed a significant relationship with sectoral employment variables as well as with individual economic variables, wages and the price of land ready for construction. There is clear evidence of the nature of the relationships between NDB dynamics and related variables, with dependencies either occurring simultaneously within an annual period (*t*) or lagging dynamics (*t* – 1). With the exception of one variable, no significant positive influence of the analysed variables was found for one-year leading dynamics (*t* + 1). This indicates that the changes in dynamics were triggered by the variables considered here, and not vice versa, changed dynamics influenced the variables. Those findings are in line with observations derived from urban land-use and transport models, confirming several a priori-assumed relationships, including the importance of employment variables, of general economic conditions and of the effects of industrial growth on employment in tertiary sectors (Spiekermann & Wegener 2018).

Regarding office dynamics, the high influence of employment variables is evident. Of note is the correlation with the number of *office employees*, which is not observed for the other two use classes, indicating use class-specific influence. Changes in office employment seem to precede changes in the dynamics of the office building stock, suggesting that these employees were already employed in offices before changes in the office stock dynamics occurred. The same relationship seems to be evident regarding changes in the *price of land ready for construction*, anticipating changes in office building dynamics. In contrast, changes in *hourly wages per employee* occur, on average, simultaneously with changes in office dynamics (Figure 4). It can be assumed that the wage is a more elastic variable than the choice of employment, which is often accompanied by changes in living conditions and other more severe (spatial) circumstances.

Changes in the dynamics of industrial construction appear to be significantly influenced by employment variables as well as economic variables. While economic variables such as gross domestic product (GDP) or gross value added (GVA) precede changes in dynamics, changes in employment occur on average simultaneously with changes in dynamics. It can be assumed that construction activity for industrial buildings—in contrast to office buildings—responds stronger to changes in economic conditions. This response is then accompanied by a change in employment dynamics, with the identified correlations with individual subsectors of tertiary employment pointing to an underlying macroeconomic relationship between the (global) economy and the labour market.

Interestingly, changes in the dynamics of industrial building construction appear to cause changes in employment within the tertiary subsector three (public service employment, education, health). In highly industrialised districts, the authors assume that public sector employment is strongly linked to the dynamics of industrial building construction (and its underlying economic development). This industrial production generates the tax surpluses that can fund an expanding number of public employees. In contrast, employment in service sector 2 (financial, insurance and business services) seems to run ahead of the dynamics in industrial construction. This seems plausible, as this sector provides services upstream in the value chain for companies in the secondary sector and is therefore affected earlier by changing economic conditions.

Warehouse dynamics change in line with economic variables and employment variables, with warehouse dynamics dipping or rising concurrently with these variables to a greater extent than in industrial construction. Of note is the correlation with *logistics employees* (Figure 4), which—like the correlation of *office employees* in office-dynamic districts and to *manufacturing employees* in industrial-dynamic districts—points to use-class-specific influences. Although industrial building dynamics see no correlation with changes in the total *number of manufacturing companies*, a strong correlation is identified to warehouse building dynamics. This variable indirectly reflects the historical effects of construction. For industrial buildings, the existing, long-established companies make a significant contribution to the dynamics through expansions at old locations. Here, the correlation with the number of companies is overlaid by the larger stock effect. However, when looking at the dynamics of warehousing, the correlation becomes evident, as industrial companies usually require large logistics depots for the temporary storage of finished products, which then have to be newly built for newly established companies. Overall, warehouse dynamics appear to be associated with both production-related variables, such as secondary sector employees, as well as services-related variables, such as employees in the tertiary sector one, which includes employees in trade, transport and storage, hotels and restaurants, information and communications.

Table 3: Correlation coefficients of selected influencing variables

Note: *Correlation significant at the 0.05 level (two-tailed); **correlation significant at the 0.01 level (two-tailed).

SPEARMAN RHO	***OFFICE_DYNAMICS***			***INDUSTRY_DYNAMICS***			***WAREHOUSE_DYNAMICS***		
	OFFICE DISTRICTS *T* – 1	**OFFICE DISTRICTS *T***	**OFFICE DISTRICTS *T* + 1**	**INDUSTRIAL DISTRICTS *T* – 1**	**INDUSTRIAL DISTRICTS *T***	**INDUSTRIAL DISTRICTS *T* + 1**	**WAREHOUSE DISTRICTS *T* – 1**	**WAREHOUSE DISTRICTS *T***	**WAREHOUSE DISTRICTS *T* + 1**
Office_employees	0.830**	0.495	–0.082	0.231	0.552*	0.467	0.082	0.468	0.418
Logistics_employees	–0.055	–0.257	–0.06	0.626*	0.081	–0.352	0.753**	0.363	–0.555*
Manufacturing_employees	0.681*	–0.077	–0.363	0.852**	0.534*	–0.181	0.352	0.657*	0.016
Manufacturing_workers	0.791**	0.134	–0.363	0.599*	0.820**	0.148	0.077	0.679**	0.456
Employees_secondary	0.841**	0.147	–0.363	0.593*	0.824**	0.17	0.071	0.692**	0.423
Employees_tertiary_1	0.654*	–0.007	–0.418	0.527	0.793**	0.121	0.297	0.692**	–0.115
Employees_tertiary_2	0.055	–0.582*	–0.637*	0.714**	0.112	–0.505	0.599*	0.363	–0.379
Employees_tertiary_3	0.286	0.407	0.176	–0.511	0.178	0.885**	–0.077	0.108	0.341
GDP	0.451	–0.235	–0.132	0.808**	0.314	–0.352	0.648*	0.635*	–0.341
Gross_value_added_sec	0.165	–0.547*	–0.198	0.819**	0.196	–0.368	0.786**	0.446	–0.522
Gross_value_added_ter_2	0.429	–0.002	–0.055	0.632*	0.464	–0.121	0.297	0.723**	–0.159
Manufacturing_companies	0.5	–0.002	–0.071	0.181	0.376	–0.005	–0.044	0.697**	0.28
Wages/employee/hour	0.560*	0.732**	0.137	–0.385	–0.042	0.231	–0.341	0.046	0.511
Land_price	0.764**	0.116	–0.209	–0.758**	–0.125	0.407	–0.341	–0.262	0.187
n	13	14	13	13	14	13	13	14	13

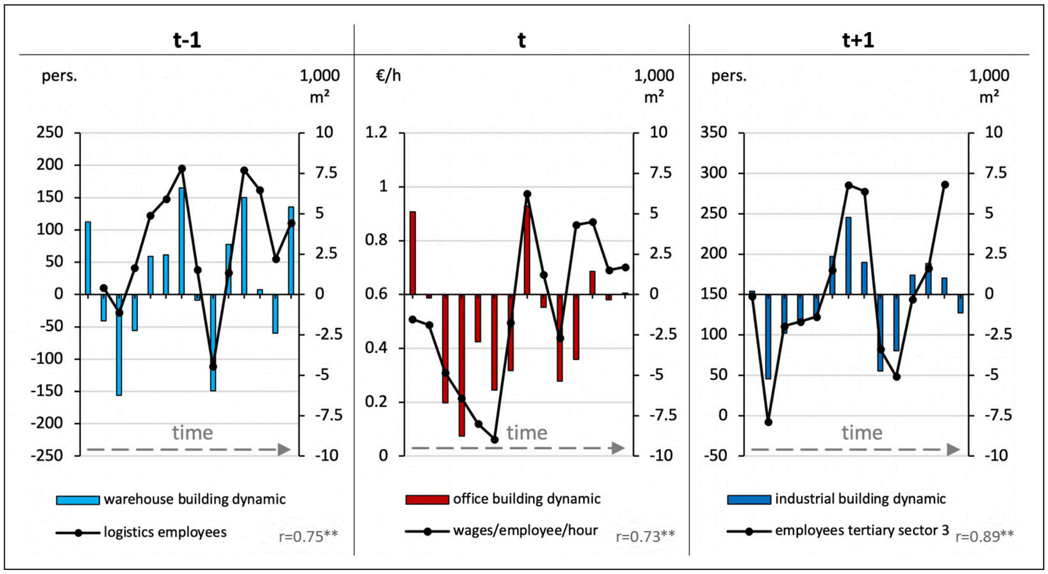

Figure 4: Selected time series of independent variables on non-domestic building (NDB) dynamics.

Note: Differences to previous years, two-year moving average, *t* – 1 displays a one-year time lag (dynamics lagging independent variable); *r* = correlation coefficient: **Correlation significant at the 0.01 level (two-tailed).

For the first time, the hypothesised effect of influencing variables on NDB dynamics could be identified statistically significant by a correlation analysis for office, industrial and warehouse buildings. At the same time, some influencing variables show an effect on more than one NDB use class.

To confirm the assumption of use-class-specific influences, a PCA was conducted to uncover the underlying driver, or components, of the relationship between NDB dynamics and influencing variables and to rule out co-correlations of these components with one another. The next section considers the extent to which the factor values of the identified components reflect the construction activity in the individual use classes and whether they have a higher explanatory power than individual variables.

3.3 USE-CLASS-SPECIFIC DRIVERS OF CONSTRUCTION DYNAMICS

Using a systematic PCA, hypothetical influencing variables were analysed to identify the underlying drivers of the dynamics in non-domestic construction and to check the plausibility of the identified correlations. This was based on a data set of all variables from 2001 to 2015 in 220 districts of high dynamics (n = 3300). Here, independent variables were excluded that had an MSA < 0.6 (see Section 2.3), as well as those variables that did not clearly load to any specific component or had no factor loading > 0.4. The KMO MSA was 0.822, indicating a sound factor extraction, while Bartlett's test of sphericity was significant ($p < 0.001$), suggesting that correlations between variables were sufficiently large to perform a PCA (see the supplemental data online). Only components with an eigenvalue ≥ 1 were considered. As a result, 15 of the previously 35 variables could be considered in the PCA (Table 4).

When matched with office, industrial and warehouse building dynamics over time, three of those four PCs show significant correlation with exactly one of those three use classes (Figure 5). PC1 seems highly correlated with office dynamics when considering a one-year lag (r = 0.75). The component consists of economic, demographic and employment variables strongly associated with office development, such as net migration rates of people aged 18–30, GVA in the public sector, as well as office employment and overall change in GDP. In a similar fashion, the PCAs differentiate PC2 as a component highly correlated with industrial building dynamics (r = 0.74). The component consists of employment variables in the manufacturing sector.

Only a single variable is loading onto PC3, mainly being described by logistics employment as the dominant variable. As such, the component is positively correlated with warehouse building dynamics (r = 0.57). Lastly, a fourth component encompasses variables related to DB dynamics such as employees in the construction sector, GVA of the construction sector, migration of young families and their children, and other population-related variables. These variables, in their composition of construction activity measures and demographic characteristics, point to a DB dynamics driver. In summary, the PCA confirms the hypothesis of independent drivers of non-domestic construction dynamics.

Table 4: Principal components of selected influencing variables with their respective factor loadings

Note: Varimax rotation applied, Kaiser–Meyer–Olkin (KMO) = 0.82, Barlett test for significance < 0.001, total variance explained = 74.7%; only factor loadings > 0.4 are displayed.

ROTATED COMPONENT MATRIX				
VARIABLE	PRINCIPAL COMPONENT			
	1 DRIVER OF OFFICE DYNAMICS	2 DRIVER OF INDUSTRY DYNAMICS	3 DRIVER OF WAREHOUSE DYNAMICS	4 DRIVER OF DOMESTIC BUILDING DYNAMICS
office employees	0.76			
empoyees_tertiary_3	0.75			
GDP	0.66			
Gross_value_added_ter_3	0.90			
net_migration_18_25	0.90			
net_migration_25_30	0.91			
manufacturing_employees		0.85		
manufacturing_workers		0.93		
employees_secondary		0.92		
logistics_employees			0.90	
employees_constr				0.73
Gross_value_added_constr				0.67
population_50_65				0.76
net_migration_0_18				0.72
net_migration_50_65	–0.69			0.44

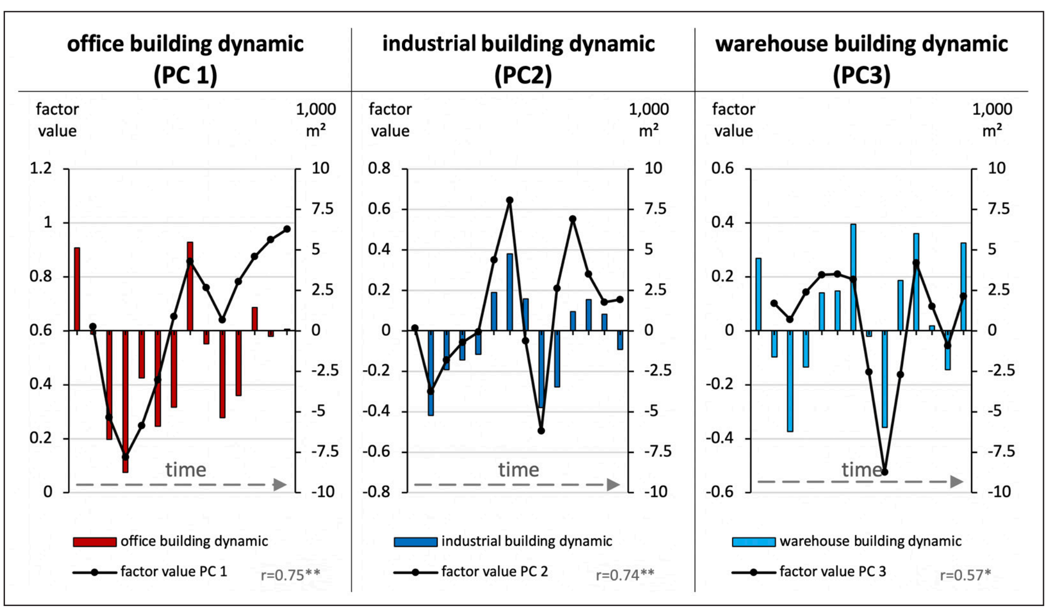

Figure 5: Time-series analysis of factor values of PC1, PC2 and PC3 with non-domestic building (NDB) dynamics of three use classes.

Note: Differences to previous years, two-year moving average; *r* = correlation coefficient: **correlation significant at the 0.01 level (two-tailed); *correlation significant at the 0.05 level (two-tailed).

DOI: 10.5334/bc.357

4. DISCUSSION

4.1 GENERAL OBSERVATIONS

Overall, office dynamics seems to be the dependent variable that is most difficult to represent by the variables considered, where only a few variables show a significant correlation over time. Notable, for example, is the complete lack of correlation with any of the migration variables, population variables, births as well as variables of cyclicality in the construction industry and domestic construction dynamics. Office dynamics appear to be rather erratic, which could be related to the nature of this use class as a financial asset subject to speculation and euphoric exuberance, leading to high vacancy rates within the considered time frame, strongly dampening the correlation. Due to a lack of comprehensive data, vacancies could not be considered.

This could be one of the main reasons for the apparent decoupling between the office driver and office dynamic (Figure 5), as certain variables show a decreasing explanatory power over time, but more suitable variables are not available. For example, it can be assumed that the effects of office suburbanisation cannot yet be adequately represented by the data set. In this case, the way in which employees are recorded is crucial, as it would be necessary to record them not only at their place of residence but also at their place of work. Additional information on commuter flows would further help improving the results.

Individually, the relationship with economic, demographic and affluence-related variables is difficult to detect. The authors were unable to demonstrate a relationship at the regional level for purely demographic variables such as age-class-related in-migration. Workforce-related variables appear to have the highest explanatory power regarding changing dynamics in non-domestic construction. Employment variables already incorporate demographic variables such as population change, economic variables such as changes in productivity or economic output in connection with variables describing the wealth of the workforce. As such, the unification of these individual aspects within the factor of employment allows for a valid approximation of the dynamics in non-domestic construction. Additionally, those employment variables are not necessarily correlated with each other, as suggested by the PCA distinguishing all three use classes according to their respective employment variables. Regarding warehouse dynamics, our results show that logistics employment is the only measurable driver of warehouse dynamics available—with the manifest variable showing even higher correlations with dynamics than the latent factor value of PC3—indicating gaps in data availability.

4.2 RESTRICTIONS DUE TO LIMITED DATA AVAILABILITY

The correlation with employment variables is particularly visible in dynamic regions where demolition and new construction activity relative to the population—at least for a certain use class—is above average. In contrast, the dynamics of non-domestic construction appear more erratic in regions with a lower per capita change in construction activity. It is possible that there is only the appearance of erratic construction activity, and that in reality the dynamics of construction activity in these regions are influenced by entirely different drivers that are far less tangible that the ones found. Experts frequently mentioned the political framework, demolition subsidies or the image of a region as variables that could determine construction activity. However, a deeper quantitative analysis of those factors was not possible due to data restrictions. Even more tangible variables, such as the change in the highway network within a region or the number of e-commerce-induced parcel shipments, could not be considered in this paper because medium-to-small-scale information below the national level was not available. Therefore, especially regarding the warehouse buildings, further model improvements can be expected in future in case of a better data situation. One example is the improved coverage of the national transport industry. Due to the high social interest in quickly available indicators during the Corona pandemic, the Federal Statistical Office started reporting a truck toll mileage index that could be used as a proxy of online trade. Complementary transport indices of air and shipping traffic have been available since then, although they are similarly lacking in small-scale differentiation (Bolz *et al.* 2022).

4.3 TIME FRAME

To evaluate the results, the time frame is critical. The period from 2001 to 2015 is essentially characterised by two, in some respects contrasting, overarching features: (1) a phase of sustained shrinkage, unemployment, the retreat of large parts of the German population into suburban areas, and the associated demolition and reconstruction of parts of the built environment—especially in eastern Germany. This phase is largely characterised by the megatrend of globalisation and its side-effects, such as outsourcing large parts of the workforce, neoliberal flexibilisation of the labour market and a general wage restraint. It culminated in the financial crisis of 2008. This period was followed by (2) a phase of urbanisation, declining unemployment, general prosperity, and brisk construction activity in domestic and non-domestic construction, which was primarily characterised by digitisation and related innovations (Industry 4.0). In the end, a holistic approach was preferred to a separate analysis of the two phases to avoid splitting the important trend break between 2007 and 2008. A particularly long period was deliberately chosen to improve the degree of transferability. Nevertheless, this deliberate decision has an impact on the results of both the cluster analysis and the PCA. For example, it can be assumed that the influence of land prices has increased in the period after 2015, while employment factors may have become less important due to a general saturation of the labour market and the ongoing substitution of labour through mechanisation and digitalisation. During this digitalisation, new types of NDB, such as data centres, network hubs and digital distribution nodes, which have received little attention to date, could gain more importance. Other important use classes with a high proportionate dynamic are retail buildings and agricultural buildings (Kretzschmar *et al.* 2019).

4.4 METHODOLOGICAL LIMITATIONS

Regarding the methodology, it should be noted that even small changes in the typological sorting of NDB, the sequence of methodological steps, and the selection of variables and clusters can lead to different results. Although the recent research confirms a high degree of stability of clusters and components through tests with alternative calculation methods and different input parameters, it is in the nature of such an analysis that different results are to be expected with a different understanding of building dynamics as well as varying independent variables. The difficulty of these analyses lies in the a priori assumption of a fixed number of clusters and components, which can only be validated afterwards by quality criteria of the analysis as well as significance values and other methods of cross-checking. The solution identified here is therefore to be understood as a heuristic solution. Alternative solutions, which show variables with a higher explanatory degree, cannot be ruled out. However, the correlations found in this study are consistent with the experts' statements. This can be understood as an indication of the plausibility of the underlying typology.

4.5 TYPOLOGICAL INTERDEPENDENCIES

The consideration of industrial and warehouse buildings in this paper illustrates the difficulties in attempting to assign different influencing variables to economically interdependent subclasses of non-domestic construction. The cluster analysis shows a parallel dynamic of both use classes in many districts, which was mitigated by a high number of considered clusters. The interdependency continues in the subsequent correlation analysis, showing high correlations between the dynamics of industrial and warehouse buildings. Both use classes can be described by changing employment figures of subsectors of the secondary and tertiary sectors and both use classes seem to prefer similar spatial contexts (rural areas close to larger agglomerations). In this respect, the distinction of two independent drivers for both use classes is an important contribution of this paper. Those results suggest that—in the case of a better data situation and a more functionally differentiated socio-economic data collection—the underlying drivers of other non-domestic-use classes could also be investigated. In that regard, correlation analysis between agricultural buildings and employees in the primary sector would be conceivable.

4.6 INFLUENCE OF OWNERSHIP

The data set considered here also includes the ownership of newly constructed or demolished buildings. In addition to spatio-temporal aspects of the dynamics of the built environment, influences of a sectoral shift of building ownership could also be analysed, which were not pursued further for reasons of generalisability. Kretzschmar *et al.* (2021b) were able to demonstrate this shift in the case of German warehouse buildings. Further analysis could identify the share of public sector ownership in relation to the dynamics in office construction as well as spatio-temporal aspects of the dynamics of warehouse construction in relation to industrial building construction. It can be assumed that warehouses owned by companies attributed to the secondary sector (industrial warehouses) are often constructed close to secondary sector industrial buildings, while tertiary sector warehouse buildings (retail warehouses) are expected to be located at highway intersections and close to larger agglomerations. Depending on the ownership status, the dynamics as well as the underlying influencing variables could be different. Further analysis is needed to better understand these relationships and to quantify the impact of a presumed shift in ownership on non-domestic construction dynamics.

5. CONCLUSIONS

For the first time, the use class-specific drivers of the dynamics in non-domestic construction are identified on a subnational level. The analysis in this paper demonstrates that different functional subsectors of non-domestic buildings (NDB) are influenced by different influencing variables, and that these variables recur to different overarching drivers. These variables are distinct from those that determine domestic construction. The dependency is evident over time and could be further validated by means of a regression analysis.

To explain the dynamics of the built environment and to further unlock its socio-environmental impacts, an analysis of cause–effect relationships is essential. In the past, insufficient non-domestic construction data have been a major persistent factor hindering a broader understanding of the metabolism of the built environment. The method presented in this paper is a first step towards a more comprehensively informed view of the metabolism of man-made constructions. For that reason, it is of importance to be able to distinguish between some important types of buildings (office, industrial, warehouse).

Nevertheless, in-depth analyses in small-scale contexts are necessary to obtain a comprehensive picture of the interactions and to fully grasp the stock dynamics. For this, for example, case studies would be appropriate that capture long-term stock change using digital methods such as building information modelling. With that information, the general dependencies analysed in this paper could be further enriched with local and regional observations, allowing for small-area estimations within random or fixed effect models.

Based on the analysis presented here, it would be advisable to take more account of specific types of use, spatial contexts and the associated influencing drivers. Since this study only examines correlations and not causalities, a regression analysis of the variables identified here would be advisable in a next step to further strengthen the indications of effect relationships. Further research could focus on comparisons of the temporal and spatial dynamics of NDB across different cities and investigate additional use classes such as agricultural or retail buildings. As a result, this work can contribute to a more informed discussion of the future development of the non-residential building stock and the resulting environmental impact due to land use, energy and material consumption or CO_2 emissions.

NOTES

1 In England and Wales, where detailed building stock information is available, office, industrial and warehouse buildings have the largest share of total floor space of all non-domestic-use classes, with industrial buildings accounting for 22% of the total

non-domestic stock, followed by warehouse buildings (18%) and office buildings (15%) (DBEIS 2016). According to the RDC data set, these are at the same time the use classes with the highest overall stock dynamics in Germany. They are followed by retail buildings in fourth place. Since they made clustering difficult due to their uniform spatial distribution, they were not considered further in this paper.

2 According to German construction activity statistics, NDB are predominantly used for non-domestic purposes (more than half of the floor space for non-domestic use). Since the typology does not account for mixed use within buildings, only the predominant use class within a building (in terms of m^2 of floor space) is attributed.

3 In Germany, a district is a small regional subdivision above the municipal level corresponding to the level-3 administrative unit in the Nomenclature of Territorial Units for Statistics (NUTS-3). They comprise 294 rural districts and 107 urban districts (cities which constitute a district in their own right).

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COMPETING INTERESTS

The authors have no competing interests to declare.

DATA AVAILABILITY

The data set of stock dynamics of NDB was obtained from the German Research Data Centre (Statistics of Construction Completions). Data for office employees were provided by empirica ag, Berlin. The data source for the variable of logistics employees was obtained via the provision of data sets on employees subject to social security contributions via the German Federal Employment Agency. Data sources for all remaining variables were obtained from open access via federal and state statistical offices and via statistics on national accounts of the federal government and the states.

ETHICAL APPROVAL

The research complied with the requirements of the data protection officer and the ombudsperson for good scientific practice of the Leibniz Institute for Ecological and Regional Development. Informed consent was obtained from all participants before the interviews.

FUNDING

The Article Processing Charge (APC) was funded by the joint publication funds of the TU Dresden, including the Carl Gustav Carus Faculty of Medicine, and the SLUB Dresden as well as the Open Access Publication Funding of the DFG.

SUPPLEMENTAL DATA

Two files containing supplemental data for this article can be accessed at: https://doi.org/10.5334/bc.357.s1. Statistical data and analysis are provided in a combined xlsx file containing information on cluster attribution (see ***Table S1*** in the supplemental data online), results of correlation analysis (see ***Table S2*** online), principal component analysis (PCA) input variables (see ***Table S3*** online), PCA anti-image matrices (see ***Table S4*** online), results of Kaiser–Meyer–Olkin indicator (KMO) and Barletts test (see ***Table S5*** online), screenplot with eigenvalues (see ***Table S6*** online), rotated component matrix (see ***Table S7*** online), total variance explained (see ***Table S8*** online), factor values (see ***Table S9*** online) and the overview over conducted expert surveys (see ***Table S10*** online). A second docx file 'Statistical Methods' describes the multivariate statistical methods used and their corresponding formulae.

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TO CITE THIS ARTICLE:
Kretzschmar, D., & Schiller, G. (2023). Non-domestic building stock: linking dynamics and spatial distributions. *Buildings and Cities*, 4(1), pp. 727–748. DOI: https://doi.org/10.5334/bc.357

Submitted: 02 June 2023
Accepted: 22 August 2023
Published: 18 September 2023