Non-response in the Italian Building Permits Survey: a comparative analysis of imputation methods

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Abstract

Non-response bias is a relevant issue in survey data. When information is missing, inferences drawn exclusively from observed data may fail to accurately reflect the entire population structure, leading to potentially invalid conclusions. Depending on the nature of the underlying selection mechanism, traditional estimators may be biased. As a result, alternative methods robust to selection bias arising from incomplete data should be considered. This paper discusses various approaches to handling missing data in the Italian Building Permits Survey. The results of this study are part of a broader project, launched in 2020, aimed at harmonising imputation methods for both the structural and the short-term versions of the survey, which was implemented in June 2021.

Keywords: Unit non-response, cross-sectional imputation, longitudinal imputation

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1. Introduction

One of the main drawbacks of survey data is missing data. Depending on the nature of the selection mechanism underlying the missing data, statistical units with complete data may fail to accurately reflect the population structure, leading to violations of the properties of traditional estimators. The way missing data are handled depends on several factors, in particular, the nature of the underlying mechanism for missing data. If the mechanism is ignorable with respect to the parameters being estimated, traditional methods will yield consistent estimates. However, if this is not the case, adjustments must be made to account for the incomplete data.

In longitudinal surveys, non-response is particularly problematic because the same units are repeatedly observed over time. As a result, the non-response rate may increase with each subsequent wave of data collection. This study analyses non-response in the context of the Italian Building Permits Survey. This census survey is longitudinal and collects monthly data on new residential and non-residential buildings, as well as any enlargements of pre-existing buildings, based on building permits issued by municipalities. The survey aims to produce both annual structural building statistics and a smaller set of quarterly short-term indicators for transmission to Eurostat.

Historically, non-response in this survey has been addressed using different imputation methodologies, depending on the frequency of the statistics and the characteristics of the municipalities, particularly their population size. For structural statistics, a mixed approach combining longitudinal and donor techniques has been applied to Self-Representative (SR) municipalities, i.e., those with 50,000 or more inhabitants. For short-term statistics, a mixed approach was used for SR municipalities, while regression-based methods were employed for Non-Self-Representative (NSR) municipalities, i.e., those with fewer than 50,000 inhabitants. The decision to apply a mixed approach was based on differences in response propensities between SR and NSR municipalities, as well as on differences in response rates for structural and short-term statistics.

In recent years, following the introduction of stricter penalties for non-responding municipalities and a new data collection system by the Italian national Institute of Statistics (Istat), response rates have improved significantly, suggesting the potential for a new approach to addressing missing data.

This paper presents experimental results from a comparative analysis of the short-term version of the Istat Building Permits Survey, assessing the performance of various imputation methods. These results form part of a broader project to introduce a new methodological framework for imputing missing data in the survey. The aim is to identify improved procedures from both statistical and practical perspectives and to develop a harmonised methodological approach across the survey's structural and short-term versions. The new methodological framework took effect in June 2021, with the dissemination of the short-term statistics for the first quarter of 2021 and the structural statistics for the year 2020.

The paper is organised into five Sections. The first Section introduces the analysis. The second Section discusses theoretical aspects of non-response treatment. The third Section outlines the main features of the survey, including the data, the imputation methods under comparison, the simulation framework, and the statistical measures used to assess the results. The fourth Section presents the main results of the simulation, both at the aggregate and disaggregated levels, together with a sensitivity analysis examining the impact of shocks on response rates. The final Section provides concluding remarks and further considerations.

2. Theoretical aspects of non-response treatment

The literature on missing data traditionally distinguishes between two types of non-response: item non-response and unit non-response, based on whether the information available for each unit is partially or entirely missing. In the context of the Istat Building Permits Surveys, item non-response is largely negligible, as respondents are typically contacted for follow-up when a questionnaire is partially completed. Conversely, unit non-response, which refers to total non-response within the reference period, is of greater importance, particularly when it exhibits systematic non-response (attrition).

The choice of the most appropriate imputation method depends on several factors, in particular the nature of the underlying missing-data mechanism. As this mechanism is usually unknown, valid inferences about the assumed model parameters for the data require certain assumptions.

Most imputation procedures are based on the Missing at Random (MAR) assumption, which states that, conditional on the observed data, the probability of non-response is independent of the missing values (Little and Rubin 2002). When the non-response mechanism is independent of both the missing and the observed values, the missingness is said to be Missing Completely at Random (MCAR).

The literature on missing data presents a variety of approaches to data imputation.

The present study evaluates the predictive performance of several methods from both the cross-sectional (Chen and Shao 2000; Manzari 2004) and longitudinal imputation (Eurostat 2014) classes.

2.1 Cross-sectional and Longitudinal Imputation Methods

Among methods for cross-sectional data, a straightforward approach to missing data is to exclude units with incomplete information from the analysis (complete-case analysis). However, there are two potential problems with complete-case analysis. First, if units with missing values systematically differ from fully observed units, they do not constitute a random sample of the entire data set (i.e., under an MCAR non-response mechanism); this strategy may lead to biased estimates. Second, even under the MCAR assumption, analysing only complete-case respondents may yield less accurate estimates. In addition, depending on the extent of missing data, there may be too few complete cases to make valid inferences.

An alternative approach to handling missing data is to use all available information from both respondent and non-respondent units by constructing homogeneous imputation classes. These classes are subsets of units, both respondent and non-respondent, identified using fully observable variables. Within each class, the imputed values are homogeneous and consistent with those of the responding units. This strategy has been shown to help reduce both the bias introduced by non-response and the variability associated with imputation (Kalton and Kasprzyk 1986; Kovar and Whitridge 1995).

Within the class of cross-sectional data methods, another technique for predicting missing values is conditional imputation based on auxiliary variables. This approach introduces a notion of similarity between units, obtained by estimating an appropriate distance function that depends only on fully observable auxiliary variables (nearest neighbours). For each imputed unit, the donor is selected from units that minimise the distance function (Chen and Shao 2000).

Another approach to handling missing data uses regression techniques, either directly or indirectly (Bethlehem 1988). In this method, the values of the missing variable are predicted using a parametric model, represented by a regression equation that depends only on fully observable variables (regression imputation). The predicted values can then be used directly to replace the missing data, or indirectly through homogeneous adjustment cells of units (Brick and Montaquila 2009; Kalton and Flores-Cervantes 2003; Little 1986).

A second class of imputation methods applies to longitudinal data, in which respondents provide responses over time in a systematic way. For each unit i, with $i = 1, ..., n$, data vectors are collected over t periods, with $t = 1, ..., T$. For period t, a vector of cross-sectional data (observed units) is available, whereas for unit i, a vector of longitudinal data, which is likely to be highly correlated, is collected (Greene 2002; Wooldridge 2001). In this setting, non-response becomes a more important issue than in the traditional context, as it affects both the cross-sectional and longitudinal dimensions of the data. From a theoretical perspective, dealing with non-response in panel data is more complex than in the classical case, as it involves managing the two dimensions of data: cross-sectional and longitudinal (Rubin 1987).

In panel data, longitudinal information offers at least two advantages. First, longitudinal data for a given statistical unit are typically reliable predictors of missing values, leading to more accurate imputations. Second, having both backward and forward information for imputation is particularly useful for variables that change over time, such as short-term statistics (Eurostat, 2014). However, even in a longitudinal context, cross-sectional imputation methods may be necessary in certain cases, such as for units responding for the first time in the panel or for completely non-compliant units. In such cases, alternative strategies may be employed, such as constructing prediction models for missing values based exclusively on information from responding units. The choice of imputation method depends on the characteristics of the observed variable. For instance, in a longitudinal context, the seasonal pattern of a variable may reveal important features that could influence the imputation process.

3. Application of a case study: the Istat Building Permits Survey

The Istat Building Permits Survey is a census-based survey that collects monthly data on new construction projects or the enlargement of pre-existing structures, both residential and non-residential, authorised by certified building permits (including building permits, the Start-of-Work Certified Report (SCIA), or Public Construction Work). Changes of use and renovations to pre-existing buildings that do not increase the buildings' volume are not included in the survey's scope. The observed population comprises municipalities applying for single-building works, either a completely new building (even if demolished and rebuilt) or an enlargement of a pre-existing building. Two or more building works carried out under the same building permit constitute two or more units of analysis, for which similar forms are completed.

The survey is part of the Italian National Statistical Programme and produces two types of statistics. Structural indicators are produced annually (Structural Statistics), and since 2003, quarterly economic indicators (Short-Term Statistics) have been transmitted to Eurostat within 90 days of the end of the reference quarter, in accordance with EU Regulation[2]. Until June 2021, the treatment of non-response in the short-term version of the survey followed different methodologies depending on: 1) the size of the municipality in terms of population (SR and NSR municipalities); 2) the nature of the non-response within a three-month period (total or partial non-response). Total non-response in SR municipalities was treated using Minimum-Distance Donor (MDD) techniques, while partial non-response was addressed using longitudinal information from the same municipality. Regression-based imputation techniques based on propensity scores were applied to both total and partial non-response in NSR municipalities (Bacchini et al. 2006). In addition, because of lower non-response rates in SR municipalities, census-type imputation techniques were used, whereas sampling techniques were applied in NSR municipalities (Garozzo and Rallo 2008).

Rising response rates in recent years, particularly among NSR municipalities, have prompted a reconsideration of the imputation framework (Leo and Tuzi 2023). With high response rates, sampling-

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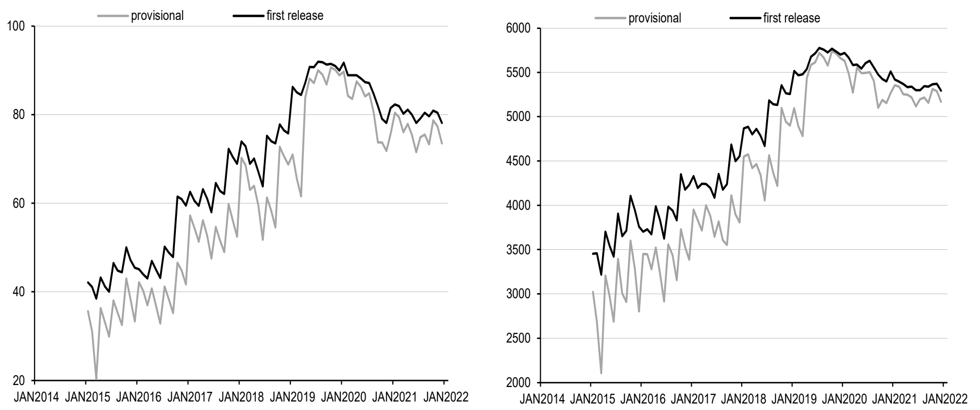
based imputation methods are no longer mandatory and may even be inconsistent with the structural version of the statistics. Moreover, in the context of panel data, longitudinal information could improve the quality of the imputed data.

3.1 The Data

The participation of responding units has increased significantly over the years, both in the proportion of the population and in the absolute number of municipalities. The most significant increases occurred in 2018 and 2019, particularly from the second quarter of 2018 onwards, when the provisional data line moved closer to the first revision, reflecting higher response rates in the first data release (Figure 3.1).

The annual average of weighted response rates at the provisional release (Table 3.1) rose from 56% in 2016 to over 90% in 2019, with the 2019 weighted rate reaching 93%. While the weighted and absolute rates were similar until 2018, the discrepancy became more pronounced in 2019, likely due to higher response rates in less populous municipalities.

Figure 3.1 - Fraction of respondents relative to total units (left side) and related population (right side). Provisional and first revision releases. Years 2014-2022 (a)



Source: Istat, Building Permits Survey
(a) On the right side, the population is divided by 10,000.

Due to the historically low response propensity of NSR municipalities, the short-term survey has generally restricted the use of longitudinal data to imputing missing values in SR municipalities. However, with the recent improvement in response rates, one purpose of the experimental analysis was to assess whether extending longitudinal imputation procedures to include less-populated municipalities could improve the quality of the estimates.

Table 3.1 - Response rates by different data releases. Years 2016-2019 (absolute and weighted annual averages)

YEARS	Absolute rates		Weighted rates	
	Provisional	1st Revision	Provisional	1st Revision
2016	39.60	48.75	56.27	64.70
2017	52.64	63.46	62.67	71.36
2018	63.58	72.43	75.18	83.05
2019	82.72	89.31	90.25	93.52

Source: Istat, Building Permits Survey

Table 3.2 presents the weighted and absolute response rates for SR and NSR municipalities in 2019, by the number of months of collaboration and the geographical area to which the municipality belongs. The weighted response rate for municipalities that participated for at least 11 months is 78.6% in the provisional release, increasing by approximately 10 percentage points in the first revision. The proportion of non-respondents, defined as those who did not provide data, was 2.4% in the provisional data, compared with 2.3% in the first revision, reflecting a persistent non-response component.

Regarding the nature of the units, 87.2% of SR municipalities with at least 11 months of collaboration are included in the provisional data, compared with 73.7% of NSR municipalities. Overall, the proportion of municipalities with the highest number of months of participation is substantial. Among respondents in the 1-10 months category, the average number of months of collaboration is relatively high, with NSR municipalities averaging 7.8 months and SR municipalities averaging 8.4 months.

Response rates for SR municipalities in the 11-12 months category are very high across all Italian regions, even at the provisional release. However, significant differences are observed among NSR municipalities. The weighted response rate in the Northern regions is approximately 80% at the provisional release and exceeds 90% at the first revision.

In contrast, the response rate for the Central regions and Islands reaches 70% at the provisional release and rises to 80.0% at the first revision. The

Southern regions show lower response rates, at 61.5% at the provisional release and 73.0% at the first revision.

Table 3.2 - Weighted response rates by number of collaboration months, type of municipality, and Italian geographical area. Year 2019 (percentage values)

GEOGRAPHICAL AREAS	0 months		1-10 months		11-12 months	
	Provisional	1st Revision	Provisional	1st Revision	Provisional	1st Revision
NSR Municipalities						
North-West	0.9	0.9	16.8	8.2	82.3	90.9
North-East	0.9	0.9	20.0	7.0	79.0	92.1
Centre	3.7	3.5	22.8	11.7	73.5	84.8
South	7.8	7.6	30.6	19.4	61.5	73.0
Islands	4.4	4.1	26.1	15.3	69.5	80.6
Total	**3.4**	**3.2**	**23.0**	**11.8**	**73.7**	**84.9**
Mean (Median)			7.8 (9.0)	7.5 (8.0)	11.8 (12.0)	11.9 (12.0)
SR Municipalities						
North-West	0.0	0.0	8.1	0.0	91.9	100.0
North-East	0.0	0.0	4.2	2.7	95.8	97.3
Centre	0.0	0.0	14.7	10.4	85.3	89.6
South	1.2	1.2	21.3	13.1	77.5	85.7
Islands	4.1	4.1	9.2	4.8	86.6	91.1
Total	**0.8**	**0.8**	**12.0**	**6.9**	**87.2**	**92.4**
Mean (Median)			8.4 (9.0)	8.5 (9.0)	11.9 (12.0)	11.9 (12.0)
Total	**2.4**	**2.3**	**19.0**	**10.0**	**78.6**	**87.6**
Mean (Median)			7.8 (9.0)	7.5 (8.0)	11.8 (12.0)	11.9 (12.0)

Source: Istat, Building Permits Survey

The evidence from the analysis suggests that extending longitudinal imputation procedures to include less populous municipalities is a reasonable approach. Furthermore, the geographical dimension should not be neglected when planning new procedures.

3.2 Alternative methodologies for missing data imputation

Due to higher non-response rates and greater variability in the estimates, the analysis was carried out on the subpopulation of NSR municipalities. Among the cross-sectional methods, three imputation procedures were tested, based on: (a) a similarity criterion between statistical units, (b) homogeneous imputation groups, and (c) the prediction of missing data using regression models. For purely theoretical purposes, a method based solely on the available data was also included.

Within the class of methods based on the criterion of similarity between units, two versions of the Minimum-Distance Donor (MDD) technique were tested: the simple version (Quis) and the normalised version ($\text{Quis}_{\text{norm}}$). The latter accounts for the municipality's population size. Missing data are replaced with the value of the minimum-distance donor, estimated using a set of auxiliary variables identified within homogeneous strata defined by geographical and social characteristics. These auxiliary variables, known for all units in the NSR subpopulation, include geographical area and the municipality's population. The strata for the simulation were obtained by combining five population classes (0-3,000; 3,001-7,000; 7,001-13,000; 13,001-25,000; 25,001-50,000) with five Italian geographical areas (North-West, North-East, Centre, South, Islands).

Let $(x_1, \ldots, x_q)$ denote the vector of q auxiliary variables, and $D(i, k)$ the distance function between the missing unit i and the potential donor k. The minimum-distance donor k for the non-respondent unit i is selected by minimising the following distance function with respect to the auxiliary variable x:

$$D(i,k) = \sum_{j=1}^{q} |x_{ji} - x_{jk}| \tag{1}$$

A second useful approach within the class of cross-sectional methods approximates missing values using statistical measures, such as the mean (MSTR, MSTRnorm) and the median (MED_{STR}), estimated within homogeneous strata of responding units. The missing value is replaced by the average or median of the observed values within the stratum to which the non-responding unit belongs. The strata are those described in the previous section.

Let n^r_h denote the number of respondents in the h stratum to which the non-respondent municipality i belongs. The imputed value for the non-respondent unit i is then given by:

$$y_h^i = \frac{1}{n_h^r} \sum_{j=1}^{n_h^r} y_j \tag{2}$$

In addition to the simple average, a normalised version is estimated using the same weighting structure as described for the MDD technique. Furthermore, to account for potential outliers, median-based estimators were also tested.

The last class of cross-sectional methods comprises adjustment-cell models, which are based on the definition of groups of sample units (cells) with approximately equal response probabilities for a specific item (Eltinge and Yansaneh 1977; Bethlehem 2002). Adjustment cells are formed by grouping sample units according to their estimated response probabilities, derived either directly or indirectly via regression equations. The resulting adjustment estimator for a population average or total will have non-response bias close to zero, provided that the within-cell covariances between survey items and response probabilities are approximately zero (Falorsi et al. 2005). In addition to the Fabi estimator (used until 2021), which imputes missing data by identifying homogeneous non-responding cells, a classical regression imputation technique (Regr) was also tested, in which the estimated probabilities are used directly in the imputation procedure. The Fabi estimator, employed for imputing non-response in NSR municipalities, is an adjustment-cell estimator:

$$\tilde{Y}_t = \sum_{k \in r_t} y_{t,k} w_{t,k} = y_{t,k} \frac{1}{\pi_{t,k|at}\varphi_{k|s_t} + (1 - \pi_{t,k|at})\varphi_{k|\bar{s}_t}} \tag{3}$$

where $y_{t,k}$ is the variable of interest for the k-th unit at time t, $w_{t,k}$ is the corresponding weight for the k-th unit, derived from the estimated parameters of the logistic regression; $\pi_{t,k|at}$ and $(1 - \pi_{t,k|at})$ represent the inclusion and non-inclusion probabilities, respectively, while $\varphi_{k|s^t}$ and $\varphi_{k|\bar{s}^t}$ denote the conditional probabilities of response for the two subsamples. The last two terms are approximated by the proportions of responding units in each subsample relative to the corresponding totals.

The use of repeated time-series data for the same unit is particularly suitable for imputing missing data in a longitudinal context. This study proposes a set of procedures that combine longitudinal information in different ways. The first version employs short-term information, namely the three months preceding the missing data, aggregated using a simple average (LT). The second version uses longer-term information, namely the twelve months preceding the missing data, which are aggregated in several ways: simple average (LA), simple average excluding the extreme values of the distribution (LA_{minmax}), and the median (LA_{median}). Let $_{yi,t}$ be the observed value of the *y* variable for the generic *i*-th unit at time *t*, and let $r_{i,t}$ be the dichotomous variable indicating response and non-response for the *i*-th unit at the same time *t*, such that:

$$r_{i,t} = \begin{cases} 0 & \text{se } y_{i,t} = 0 \\ 1 & \text{se } y_{i,t} \geq 1 \end{cases} \tag{4}$$

If $y_{i,t}$ is missing but longitudinal information is available, its value will be replaced with the average observed in the previous period. Let the reference period be defined by the extremes *t−m* and *t−1*. The imputed value will then be derived from the following expression:

$$\tilde{y}_{it} = \frac{\sum_{k=t-m}^{t-1} r_{i,k} y_{i,k}}{\sum_{k=t-m}^{t-1} r_{i,k}} \tag{5}$$

The imputed value is approximated by the average of the observed $y_{i,k}$ values from *t−m* to *t−1*, weighted by the dichotomous variable $r_{i,k}$. As noted in the literature, a drawback of these methods is that they are not applicable to units that are either completely non-respondents or have limited longitudinal information. In such cases, the procedure is not applicable, and the MDD imputation method must be used.

For purely theoretical purposes, an estimator based on complete information (AvCs) is proposed. A total of twelve estimators were tested: two based on donor imputation (Quis and $Quis_{norm}$); three based on simple and normalised averages (MSTR, $MSTR_{norm}$) and the stratum-wise median (MED_{STR}); two based on regression imputation (Fabi, Regr); one based on available cases only (AvCs); and two based on longitudinal imputation methods (LA, LT). Within the longitudinal methods, three versions of data aggregation were empirically tested: first, the simple mean (LA_{mean}); second, the median (LA_{median}); and finally, the simple mean pre-treated to exclude outliers (LA_{minmax}).

3.3 The simulation design

The aim of the analysis was to evaluate the performance of different imputation methods in estimating key variables from the short-term version of the survey, specifically the number of residential dwellings and the non-residential surface area. The simulation was carried out using monthly data from the first quarter of 2018 to the last quarter of 2019. The quality of each imputation method was assessed using the provisional version of the data, which was characterised by lower response rates. SR municipalities were excluded from the simulations, both because of their high response rates and because longitudinal methods were already in use for them. The simulation was carried out on the fully responding municipalities within each of the 24 months. For each month, 100 random samples of units were generated, consistent with the geographical distribution of response and non-response in the reference month. Missing units were selected from each sample according to the observed proportions in the true distribution, while preserving the original geographical structure. The samples were drawn within strata defined by the five Italian geographical areas: North-West (NW), North-East (NE), Centre (C), South (S) and Islands (I). It should be noted that the number of sample units may vary from month to month, depending on the number of respondents and the territorial distribution of responses and non-responses. However, it remains consistent across samples within the same month.

In 2019, for instance, 5,469 of 7,750 NSR municipalities responded in January, 5,050 in February, and 6,881 in December (Table 3.3). The 100 samples for January were drawn from the respondent subpopulations (5,469 for January, 5,050 for February, and 6,881 for December). Each sample was simulated to reflect the territorial distribution of the entire population (respondents and non-respondents) for that month. The proportion of non-respondent units sampled within each geographical area matched the true distribution. For instance, in January 2019, 25.7% of residents in the NE were classified as non-respondents, while the remaining 74.3% were respondents. A similar distribution was observed in the NW, where 16.8% of residents were non-respondents, and the remaining 83.2% were respondents.

The different imputation methods used require further explanation. Regarding the longitudinal methods, samples were drawn from the subpopulation of respondents likely to have a higher propensity to respond in earlier periods. To minimise potential bias in the estimates due to self-selection in the samples, the true backward information has been replaced with a simulated version based on the reference population's distributions. In the case of the LT method, it covers the three months prior to the missing data.

Table 3.3 - Distribution of simulated municipalities by Italian geographical area and month. Year 2019 (absolute and percentage values) (a)

MONTHS	North-West		North-East		Centre		South		Islands		Total
	n	Sampling fraction	n	Sampling fraction	n	Sampling fraction	n	Sampling fraction	n	Sampling fraction	
January	1,147	16.8	2,203	25.7	610	34.8	999	42.4	510	30.9	5,469
February	1,094	20.6	2,027	31.6	559	40.3	908	47.6	462	37.4	5,050
March	1,051	23.7	1,929	34.9	511	45.4	821	52.7	413	44.0	4,725
April	1,238	10.2	2,696	9.0	745	20.4	1,234	28.8	571	22.6	6,484
May	1,290	6.4	2,797	5.6	796	15.0	1,324	23.6	611	17.2	6,818
June	1,266	8.1	2,768	6.6	792	15.4	1,299	25.1	610	17.3	6,735
July	1,300	5.7	2,824	4.7	821	12.3	1,393	19.7	628	14.9	6,966
August	1,280	7.1	2,802	5.5	806	13.9	1,380	20.4	620	16.0	6,888
September	1,250	9.3	2,759	6.9	789	15.7	1,319	23.9	593	19.6	6,710
October	1,300	5.7	2,832	4.5	822	12.2	1,428	17.6	633	14.2	7,015
November	1,297	5.9	2,825	4.7	814	13.0	1,416	18.3	622	15.7	6,974
December	1,279	7.2	2,790	5.9	797	14.9	1,391	19.8	624	15.4	6,881
TOTAL	**1,378**		**2,964**		**936**		**1,734**		**738**		**7,750**

Source: Istat, Building Permits Survey
(a) *n* = Sample size of always respondents.

Regarding the MDD procedure, the possibility of encountering empty donor cells was a primary concern. This arose from using multiple strata, resulting from integrating a five-dimensional population variable with a five-dimensional geographic variable. However, given the high response rates observed in recent years, this is considered unlikely.

The Fabi estimator was simulated by partitioning the municipalities into sampled and non-sampled units in line with the original population distribution. Stratification was carried out by constructing 25 strata based on combinations of demographic and geographic variables. For the longitudinal information used to estimate the logistic models, the response/non-response vectors at times $t-1$ and $t-2$ were simulated using the actual distributions from the previous two years. This approach reduces the risk of self-selection that could arise when sampling only from the initial subpopulation of respondents. The way the samples were selected ensures that, because the process is random, the two backward vectors for the same municipality may differ across replications. However, the overall distribution structure remains consistent with respect to the response/non-response pattern.

3.4 Statistical measures of accuracy

The performance of each imputation method was assessed by comparing the distributions of the simulated and true data. Several statistical measures were used: bias and variability of estimates, and the sensitivity of the methods to exogenous shocks. With the exception of the regression-based methods, where the discrepancy between the two distributions can be assessed only at the aggregate level (the sum of the variables), all other methods were compared at the highest level of disaggregation of the data.

Simple and absolute distance measures were used to estimate the deviations between simulated and true values for the donor technique, methods based on homogeneous grouping of units, and methods using longitudinal information. Simple means and Standard Deviations (SDs) were then calculated for these measures. These statistics are intended to provide insight into the bias of the estimates, its direction, and the variability introduced by the different imputation procedures. The similarity between the distributions of the original data, $Y = (Y_1, Y_2, \ldots, Y_n)$, and those of the imputed data, $\tilde{Y} = (\tilde{Y}_1, \tilde{Y}_2, \ldots, \tilde{Y}_n)$, was assessed using various distance measures. The first measure was the simple distance, which approximates the difference between the original and the imputed data by estimating the simple average:

$$d_1(\tilde{Y}, Y) = \frac{1}{n} \sum_{i=1}^{n} (\tilde{Y}_i - Y_i) \tag{6}$$

A second measure approximates the difference between the imputed and true values in absolute terms:

$$d_2(\tilde{Y}, Y) = \frac{1}{n} \sum_{i=1}^{n} \left| \tilde{Y}_i - Y_i \right| \tag{7}$$

To assess the degree of similarity between the simulated and true distributions, the Kolmogorov-Smirnov (K-S) distance was also calculated. This statistical measure quantifies the degree of similarity between the simulated and theoretical distributions by the maximum distance between their respective cumulative distribution functions[3]. Denoting $F_{\tilde{Y}}$ and F_{Y_n} as the cumulative distribution functions of the simulated and true data, respectively, the K-S distance is given by the following formula:

$$d_{KS}(F_{\tilde{Y}_n}, F_{Y_n}) = \max_t(|F_{\tilde{Y}_n}(t) - F_{Y_n}(t)|) \tag{8}$$

In addition to the methods described above, the simulated and true totals were compared across all imputation procedures using the Mean Absolute Percentage Error (MAPE). This is a widely used indicator in the field of Short-Term Statistics. The MAPE measures the relative discrepancy between the true and simulated totals, expressed as a percentage. Let $\tilde{Y}$ and Y represent the distributions of the simulated and true data, respectively, and let $n = (n_1, n_2)$ be the data vector, where n_1 is the subset of units with complete information and n_2 is the subset of units with missing data.

The approximate measure of the distance between the observed and simulated totals is:

$$d_3(\tilde{Y}, Y) = 100 \cdot \frac{|\sum_{i=1}^{n} Y_i - \sum_{i=1}^{n} \tilde{Y}_i|}{\sum_{i=1}^{n} \tilde{Y}_i} \tag{9}$$

Finally, to evaluate the robustness of the imputation methods described in Section 3.2, a sensitivity analysis was conducted with respect to exogenous shocks to response rates in a single month. The analysis assessed the effects of these shocks on various statistical indicators at the monthly, quarterly, and annual levels.

3 The Kolmogorov-Smirnov test does not rely on any assumptions regarding the underlying distribution. It has the advantage that the distribution of the test statistic is independent of the cumulative distribution function being tested.

4. Results

This Section focuses on estimating key variables in the residential and non-residential sectors, using 2,400 simulated samples. The findings from the cross-sectional and longitudinal methods were assessed at both the disaggregated and aggregated levels.

By contrast, estimates derived from weighting techniques were evaluated only at the aggregated level.

4.1 Micro-level analysis

Statistical measures were computed for each year, month, and sample using a pair of 12x100-element matrices, which were then synthesised through successive aggregations. Deviations between the imputed and true values were estimated at the highest level of data disaggregation (the municipality). Averages over the 12 months were then computed for each sample, and an overall average was derived. For each group defined by month, sample, and field of interest (residential and non-residential), both simple and absolute distances between imputed and true values were estimated. The statistical measures described in the previous section were applied to both the full sample of respondent and non-respondent units and to the subsample of imputed units only. The statistical indicators based on absolute distance are intended to highlight inconsistencies between the distributions, while the simple version of the distance reveals the presence of bias and its direction.

All imputation techniques produced better results in 2019 than in 2018, primarily due to higher response rates in 2019. In line with Istat's recent policy to increase municipal participation in surveys, future trends are more likely to resemble those observed in 2019 than in 2018 (Tables 4.1 and 4.2). Focusing on 2019, the results show very small differences between methods, particularly for the total sample. Across imputation methods, the mean and standard deviation of the absolute distance measures exhibit a trade-off: methods that perform better on the mean-deviation metric tend to show greater variability, and vice versa. This relationship is particularly evident in the residential context.

Table 4.1 - Absolute deviations between imputed and true values by imputation method. Years 2018 and 2019 (mean and standard deviation (SD) of average values) (a) (b)

IMPUTATION METHODS	2018				2019			
	Full sample		Imputed values		Full sample		Imputed values	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
RESIDENTIAL CONTEXT								
Quis	0.304	2.154	0.851	3.568	0.135	1.264	0.784	3.118
$Quis_{norm}$	0.304	2.158	0.852	3.575	0.135	1.265	0.784	3.121
MSTR	0.267	1.553	0.749	2.549	0.119	0.898	0.686	2.169
$MSTR_{norm}$	0.266	1.550	0.744	2.545	0.118	0.895	0.682	2.163
MED_{STR}	0.176	1.612	0.493	2.693	0.079	0.945	0.454	2.338
AvCs	0.177	1.625	-	-	0.079	0.952	-	-
LA	0.235	1.555	0.663	2.571	0.108	0.894	0.619	2.166
LA_{mean}	0.178	1.574	0.498	2.627	0.079	0.906	0.454	2.236
LA_{minmax}	0.272	1.652	0.768	2.724	0.126	0.987	0.737	2.388
LT	0.258	1.752	0.723	2.905	0.115	1.005	0.663	2.437
NON-RESIDENTIAL CONTEXT								
Quis	0.808	10.658	2.259	17.610	0.360	5.986	1.956	14.236
$Quis_{norm}$	0.809	10.658	2.260	17.611	0.360	5.987	1.957	14.237
MSTR	0.726	6.766	2.024	11.111	0.336	4.087	1.821	9.577
$MSTR_{norm}$	0.723	6.779	2.019	11.134	0.335	4.089	1.816	9.582
MED_{STR}	0.415	6.651	1.160	11.053	0.194	4.111	1.050	9.749
AvCs	0.415	6.651	-	-	0.194	4.111	-	-
LA	0.667	7.137	1.868	11.812	0.312	4.551	1.735	10.751
LA_{mean}	0.420	6.631	1.175	11.018	0.197	4.096	1.065	9.709
LA_{minmax}	0.681	7.371	1.912	12.202	0.310	4.374	1.735	10.289
LT	0.725	8.617	2.031	14.398	0.327	5.365	1.828	12.625

Source: Istat, Building Permits Survey
(a) Deviations estimated at the municipality level.
(b) Non-residential values in hundreds.

Table 4.2 - Simple distance between imputed and true values by imputation method. Years 2018 and 2019 (mean and standard deviation (SD) of average values) (a) (b)

IMPUTATION METHODS	2018				2019			
	Full sample		Imputed values		Full sample		Imputed values	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
RESIDENTIAL CONTEXT								
Quis	-0.003	2.176	-0.008	3.670	-0.001	1.272	-0.009	3.215
$Quis_{norm}$	-0.003	2.180	-0.007	3.677	-0.001	1.273	-0.009	3.217
MSTR	-0.001	1.577	-0.003	2.662	-0.001	0.907	-0.003	2.278
$MSTR_{norm}$	-0.001	1.574	-0.002	2.657	-0.001	0.904	-0.002	2.270
MED_{STR}	-0.170	1.613	-0.476	2.696	-0.076	0.945	-0.440	2.341
AvCs	-0.177	1.625	-	-	-0.079	0.952	-	-
LA	-0.025	1.573	-0.067	2.657	-0.006	0.902	-0.033	2.253
LA_{mean}	-0.141	1.578	-0.394	2.646	-0.062	0.908	-0.355	2.254
LA_{minmax}	0.030	1.675	0.093	2.831	0.020	0.996	0.138	2.495
LT	-0.008	1.771	-0.023	2.996	-0.004	1.012	-0.008	2.525

Source: Istat, Building Permits Survey
(a) Distance estimated at the municipality level.
(b) Non-residential values in hundreds.

Table 4.2 cont. - **Simple distance between imputed and true values by imputation method. Years 2018 and 2019** (mean and standard deviation (SD) of average values) (a) (b)

IMPUTATION METHODS	2018				2019			
	Full sample		Imputed values		Full sample		Imputed values	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
NON-RESIDENTIAL CONTEXT								
Quis	0.026	10.693	0.071	17.777	-0.006	5.999	-0.030	14.378
$Quis_{norm}$	0.027	10.693	0.072	17.779	-0.006	5.999	-0.029	14.379
MSTR	0.010	6.812	0.022	11.333	-0.002	4.105	-0.009	9.779
$MSTR_{norm}$	0.011	6.826	0.025	11.354	-0.002	4.107	-0.007	9.783
MED_{STR}	-0.414	6.651	-1.159	11.053	-0.194	4.111	-1.050	9.749
AvCs	-0.415	6.651	-	-	-0.194	4.111	-	-
LA	-0.035	7.173	-0.095	11.982	-0.020	4.563	-0.048	10.902
LA_{mean}	-0.389	6.633	-1.088	11.030	-0.182	4.097	-0.984	9.719
LA_{minmax}	-0.021	7.407	-0.052	12.374	-0.025	4.387	-0.055	10.449
LT	0.006	8.652	0.018	14.559	-0.015	5.375	-0.002	12.766

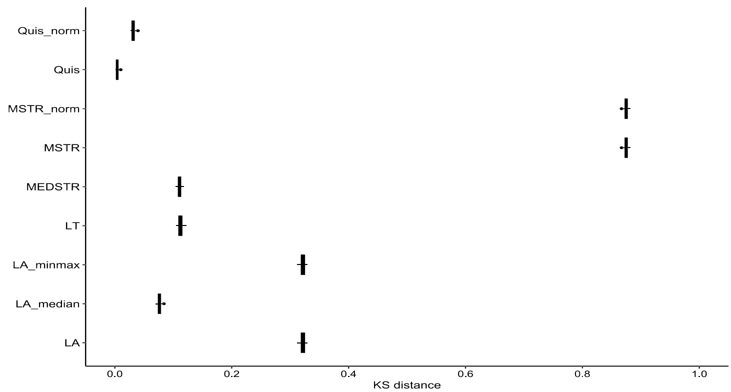
Source: Istat, Building Permits Survey
(a) Distance estimated at the municipality level.
(b) Non-residential values in hundreds.

Across both the residential and non-residential sectors, the best results, in terms of average absolute distances, are those based on the median approximation, whether in a cross-sectional form (MED_{STR}) or in a longitudinal context (LA_{median}). In addition, the most convenient standard deviations for both fields are those obtained using simple and normalised means by stratum (MSTR and $MSTR_{norm}$). Very similar results were obtained for the residential domain with the LA estimator and for the non-residential domain with the LA_{median} estimator. Overall, in terms of absolute distance measures, the traditional annual longitudinal technique (LA) achieves the highest performance in the residential case, whereas the annual longitudinal technique with aggregation via the median (LA_{median}) yields the best results in the non-residential case.

Simple deviation means are generally underestimated by all methods except the annual longitudinal technique (LA_{minmax}), which excludes extreme values. This technique slightly overestimates in the residential context. Smaller biases are observed for donor techniques (Quis), for those based on stratum means (MSTR), and for longitudinal techniques based on quarterly information (LT) or on monthly information aggregated by means (LA). Using the median to impute missing values, whether by cross-sectional (MEDST) or longitudinal (LA_{median}) methods, results in greater bias in the estimates. Furthermore, MDD techniques show increased instability, as evidenced by the standard deviations of the simple distance measures. The results suggest that methods based on stratum means are superior in both contexts, and that the traditional annual longitudinal (LA) technique is also superior in the residential domain.

The Kolmogorov-Smirnov distance measures for both the residential and non-residential sectors perform optimally when the MDD method is used. In contrast, the stratified means (MSTR) preserve the characteristics of the observed data (Figure 4.1) to a lesser extent than alternative techniques. This result is closely related to the zero-inflated nature of the observed data distribution, which is better approximated by the donor technique. As with previous indicators, longitudinal imputation yields intermediate results.

Figure 4.1 - Box Plot of the Kolmogorov-Smirnov (K-S) distance. Year 2019



Source: Authors' processing

4.2 Macro-level Analysis

Mean Absolute Percentage Error (MAPE) indicators were estimated for each sample, month and imputation method. Aggregate measures for each imputation technique were obtained by first averaging the sample-level MAPEs for each month, then calculating the overall average at the global level. The twelve indicators were then compared across time frequencies: annual, quarterly and monthly (Table 4.3)[4].

4 For simplicity, the results of the normalised versions have been omitted, as they showed very similar results to the non-standardised versions.

Across all imputation techniques, the annual MAPE for 2019 was lower than for 2018, indicating improved response rates over time. Median-based imputation techniques (MED_{STR} and LA_{median}) produced less accurate results in both residential and non-residential domains. By contrast, the most efficient technique, indicated by the lowest MAPE, was imputation by stratum mean (MSTR).

In the residential domain, imputation methods based on regression techniques (Fabi, Regr), those based on average values stratified by stratum (MSTR), and those using annual longitudinal data (LA) yield small, very similar MAPE values. By contrast, the donor technique (Quis) and the quarterly longitudinal approximation (LT) are slightly less effective. All other methods are considered less suitable for this context. In the non-residential field, the imputation method based on average values differentiated by stratum (MSTR) performs best, followed by regression-based estimators and the annual longitudinal method (LA) or its variant that excludes extreme values (LA_{minmax}). Conversely, the donor techniques (Quis) and those based on quarterly longitudinal data (LT) perform comparatively less well.

Table 4.3 - Mean Absolute Percentage Errors (MAPEs) by imputation method and domain. Years 2018 and 2019

	RESIDENTIAL CONTEXT								NON-RESIDENTIAL CONTEXT								Non-resp. Rate
	Quis	MSTR	MED_{STR}	LA	LA_{median}	LA_{minmax}	LT	Fabi	Quis	MSTR	MED_{STR}	LA	LA_{median}	LA_{minmax}	LT	Fabi	
YEAR																	
2018	6.3	4.9	32.9	6.1	27.1	9.1	5.8	4.7	11.2	8.3	30.9	8.1	28.9	9.5	9.4	8.5	24.8
2019	3.1	2.3	15.6	2.6	12.5	5.1	3.0	2.4	5.3	4.0	14.2	5.1	13.3	5.1	5.6	4.5	9.7
QUARTER																	
2018-I	6.9	5.9	28.8	5.4	24.3	4.8	5.0	5.5	11.0	7.3	26.8	8.8	25.4	9.6	7.9	7.4	25.3
2018-II	6.8	5.0	38.2	10.9	33.0	5.3	7.6	5.0	9.6	7.6	37.6	6.6	35.4	7.3	10.3	7.6	29.0
2018-III	6.8	5.3	38.0	4.9	30.2	13.0	7.6	5.0	18.4	14.3	34.8	11.3	32.4	12.2	12.6	14.5	27.4
2018-IV	4.4	3.4	26.7	3.3	21.0	13.4	3.2	3.3	5.7	4.2	24.4	5.7	22.7	8.7	6.8	4.3	17.6
2019-I	5.1	4.0	30.3	4.6	24.2	6.9	5.2	4.1	9.3	7.2	29.0	9.9	27.0	9.8	11.4	8.6	18.6
2019-II	2.4	1.8	12.5	2.1	10.1	3.7	1.9	1.8	4.5	3.3	10.7	3.2	10.1	3.2	3.9	3.6	8.3
2019-III	2.4	1.7	10.4	2.2	8.3	5.5	2.9	1.8	3.7	2.7	9.3	3.8	8.6	3.7	4.3	2.9	6.5
2019-IV	2.5	1.7	9.3	1.7	7.3	4.1	1.9	1.8	3.8	2.7	7.8	3.4	7.3	3.7	3.0	2.9	5.6

Source: Istat, Building Permits Survey

Table 4.3 cont. **- Mean Absolute Percentage Errors (MAPEs) by imputation method and domain. Years 2018 and 2019**

	RESIDENTIAL CONTEXT								NON-RESIDENTIAL CONTEXT								Non-resp. Rate
	Quis	MSTR	MED_{STR}	LA	LA_{median}	LA_{minmax}	LT	Fabi	Quis	MSTR	MED_{STR}	LA	LA_{median}	LA_{minmax}	LT	Fabi	
2019																	
Jan.	3.8	3.1	25.8	2.4	19.9	9.5	3.1	3.2	12.3	11.3	24.1	9.7	23.0	9.8	11.0	11.4	15.7
Feb.	5.7	4.0	30.4	2.9	23.5	8.0	3.4	4.4	6.4	4.6	30.3	10.1	27.3	7.6	12.4	5.0	19.1
Mar.	5.9	4.9	34.7	8.4	29.2	3.1	9.1	4.8	9.3	5.8	32.7	9.9	30.7	11.9	10.8	9.5	20.9
Apr.	2.7	1.7	14.6	1.6	11.6	6.4	2.2	1.8	6.8	4.4	13.2	4.7	12.6	4.8	4.6	4.3	10.1
May	1.9	1.7	10.9	2.6	9.3	1.7	1.9	1.6	3.3	2.9	8.2	2.6	7.7	2.5	3.6	3.9	7.6
June	2.5	2.0	11.8	1.9	9.4	3.1	1.6	2.0	3.4	2.5	10.8	2.4	10.1	2.4	3.4	2.6	7.2
July	2.4	1.8	9.4	2.4	8.4	2.0	1.7	1.8	3.6	2.7	8.5	2.5	8.1	2.6	2.6	2.6	5.4
Aug.	2.4	1.7	9.7	3.0	7.0	8.4	5.3	1.7	3.1	2.5	8.9	5.7	8.1	5.3	6.9	2.7	6.2
Sep.	2.3	1.7	12.0	1.4	9.6	6.0	1.7	1.7	4.5	2.9	10.4	3.2	9.8	3.3	3.2	3.4	7.7
Oct.	1.9	1.6	8.1	1.9	7.0	2.1	2.0	1.7	4.1	2.7	6.9	2.6	6.5	2.7	2.5	3.2	5.1
Nov.	3.0	1.7	9.5	1.4	7.3	4.5	1.6	1.7	2.5	2.2	7.9	4.4	7.3	5.1	3.2	2.3	5.5
Dec.	2.5	1.9	10.2	1.7	7.7	5.8	2.0	1.9	4.8	3.2	8.7	3.2	8.2	3.5	3.1	3.3	6.4

Source: Istat, Building Permits Survey

The greater accuracy of the MSTR imputation method in both the residential and non-residential contexts is confirmed at the quarterly frequency. This is followed by the longitudinal method approximated by the annual average (LA). A similar analysis at the monthly frequency yields comparable results in the non-residential context. However, in the residential context, as evidenced by the greater prevalence of months with the lowest MAPE throughout the year, the annual longitudinal (LA) method generally yields better results than the other methods. In the residential domain, the lack of convergence between results at the annual and quarterly frequencies and those at the monthly frequency is likely influenced by the March 2019 period, which was characterised by an exceptionally high non-response rate.

The MAPE results suggest that the imputation method based on stratified means (MSTR) is preferable when the aim is greater stability at the aggregate level, even in the presence of high non-response rates. Conversely, the longitudinal method (LA_{minmax}), despite its lower precision under low response rates, generally yields better results in terms of the number of months for which the MAPE is minimised.

4.3 Sensitivity analysis

To assess the robustness of the different imputation techniques, a sensitivity analysis was conducted with respect to changes in the response rates for a specific month, reducing them to 70%. The impact of this perturbation was assessed at monthly, quarterly, and annual frequencies, based on estimates of the indicators presented in Section 3.4[5].

Table 4.4 presents the estimated means and standard deviations of the absolute values of the distance measures and the MAPEs across different data frequencies.

Table 4.4 - Mean and standard deviations of absolute distances, and MAPE by imputation method. Perturbation in response rates. Year 2019

IMPUTATION METHODS	YEAR			QUARTER			MONTH		
	Mean	SD	MAPE	Mean	SD	MAPE	Mean	SD	MAPE
				RESIDENTIAL CONTEXT					
Quis	0.172	1.397	3.7	0.227	1.642	4.8	0.523	2.708	10.1
MSTR	0.152	1.009	2.9	0.202	1.197	3.9	0.465	2.031	8.4
MED_{STR}	0.101	1.067	20.6	0.131	1.252	29.4	0.302	2.123	69.9
LA	0.139	1.002	2.8	0.182	1.159	2.4	0.424	1.970	3.5
LA_{median}	0.101	1.018	16.6	0.128	1.192	23.8	0.294	2.028	56.7
LA_{minmax}	0.166	1.112	8.1	0.232	1.313	16.2	0.544	2.259	40.9
LT	0.148	1.126	3.1	0.192	1.291	2.5	0.448	2.198	3.6
Fabi	-	-	2.9	-	-	4.2	-	-	8.8
				NON-RESIDENTIAL CONTEXT					
Quis	0.440	6.443	6.4	0.482	5.603	8.2	1.076	7.510	15.7
MSTR	0.408	4.406	4.8	0.435	3.545	5.8	0.976	5.376	11.7
MED_{STR}	0.236	4.432	19.5	0.250	3.560	29.1	0.567	5.408	71.8
LA	0.401	4.932	7.9	0.502	4.096	14.8	1.190	6.512	38.7
LA_{median}	0.239	4.414	16.6	0.252	3.535	23.8	0.569	5.354	56.7
LA_{minmax}	0.400	4.742	8.3	0.517	3.965	16.6	1.218	6.259	43.7
LT	0.412	5.908	7.3	0.486	5.091	9.8	1.146	8.811	23.9
Fabi	-	-	5.3	-	-	6.0	-	-	11.5

Source: Istat, Building Permits Survey

For both the residential and non-residential sectors, the most significant effects of the disturbance are observed at the monthly and quarterly levels in the month and quarter in which the shock occurs, whereas the effects at the annual level are minimal. The methods with the lowest absolute averages are those based on the median (LA_{median} or MED_{STR}), as well as the annual

5 For the analysis, only the most relevant results are presented in this document, although all indicators have been calculated.

longitudinal technique (LA) for the residential domain, which also exhibits the lowest variability. In the residential domain, the least effective techniques, in terms of both the mean and the standard deviation of absolute distances, are those based on the donor method (Quis) or on longitudinal data without outliers (LA_{minmax}). A similar pattern of results can be observed at the annual level in the non-residential area.

In the non-residential domain, there is less convergence towards a single method, as shown by the results at the quarterly and monthly levels. The largest deviations are observed for the annual longitudinal method (LA) and its outlier-free variant (LA_{minmax}), whereas the donor technique (Quis) and the method based on short-term longitudinal data (LT) show greater variability.

For the macro-level indicators, the results are consistent across data frequencies and both domains. In the residential domain, the lowest MAPEs are achieved by longitudinal methods using annual or quarterly averages (LA, LT). In the non-residential domain, the most accurate results are obtained using methods based on stratum-level averages (MSTR) and regression estimators (Fabi). Methods based on the median value (MED_{STR}, LA_{median}) and on longitudinal data without extreme values (LA_{minmax}) are not recommended. However, results vary by data frequency: the MAPE of the LA_{minmax} estimator at the annual level is significantly lower than that of its quarterly and monthly versions.

The results of the sensitivity analysis to response-rate shocks provide useful insights into both the statistical superiority of certain techniques over others and the possibility of excluding some low-performing methods. In general, the first category includes the LA technique (for dwellings) and the MSTR method (for both dwellings and non-dwellings). Although the latter does not produce the best results in absolute terms, it offers an intermediate solution across the indicators used. Methods based on MDD techniques belong to the second group. Moreover, the choice of the most appropriate imputation method is closely related to data frequency, especially in the non-residential context. It is therefore crucial to take into account the time domain underlying the statistics when making this decision.

5. Concluding remarks

The increase in response rates observed in recent years in the Building Permits Survey has prompted a re-examination of the methodological framework for imputing missing data. The use of different imputation methods has become less effective as response rates have increased, even in smaller municipalities. In addition, the existing literature suggests that, in panel surveys, longitudinal information has strong predictive power for imputing missing data.

This study evaluated several imputation methods, both cross-sectional and longitudinal, for the NSR subset of municipalities. The results showed that, compared with the procedures used before the innovations introduced in June 2021, better results can be achieved not only through alternative cross-sectional methods but also by using longitudinal information for the same unit.

In both application fields, the outcomes of the micro, macro, and sensitivity analyses do not converge to an optimal imputation technique in absolute terms. Significant differences occur at the domain level, with lower convergence in the non-residential field due to its greater variability.

Regarding estimate quality, there are significant differences between the two application areas. In the residential context, there is near-complete convergence towards the annual longitudinal technique and the stratified mean. The Kolmogorov-Smirnov distance measure is the only technical limitation in this respect. However, strict distributional similarity is not a crucial factor in selecting the most efficient procedure, since building permit statistics are produced in aggregate form. In the non-residential domain, greater dispersion in the results is observed. The mean by stratum is identified as the most appropriate technique, followed by longitudinal methods based on the median or those excluding extreme values from the distribution. In contrast, donor techniques generally yield suboptimal results.

The experimental analysis confirms the predictive power of longitudinal information for imputing missing data in the Building Permits Survey. The findings also suggest that different approaches should be applied depending on the field of interest, residential and non-residential. In addition, the sensitivity analysis provides useful insights into the limitations of certain methods relative to others and highlights the importance of the time frequency of the statistics in choosing the most appropriate method.

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