Projecting the Past: Micro-Based Backcasting Methods in Business Statistics through Micro Decomposition Analysis

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Abstract

Backcasting is a key component for ensuring data consistency and reliability in historical data using modernised classifications and emerging methodological supplements to meet contemporary realities within the business economy. This methodological note explores pragmatic backcasting techniques, emphasising the adequacy of micro-based approaches in business statistics. By focusing on the role and inherent obligation of National Statistics Institutes (NSIs) to provide the public with adequate research tools, the paper highlights the importance of these applications in enhancing relevance, usability, and transparency in statistical practices. Introducing the re-labelling and exploring the pattern re-calibration approaches, the paper demonstrates their practical applications through hypothetical examples. These proposed methods are particularly aimed at, but not limited to, statistical population frames that are not necessarily balanced panels across reference years. These methods are exemplified in the context of Structural Business Statistics (SBS) and related statistical domains, which seek to offer detailed and accurate profiles of economic activities and trends. The paper advocates for the adoption of such techniques by NSIs to supplement statistical outputs across different classifications, thereby building user confidence, and calls for further application of these methods to expand the inventory of backcasting series through effective practices.

Keywords: Backcasting, NACE Rev. 2.1, Business statistics, National Statistics Institutes (NSIs).

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1. Introduction

In the rapidly evolving landscape of business economics, maintaining the integrity, relevance, and consistency of historical data is more pivotal than ever. As businesses and policymakers strive to adapt to contemporary realities, the classifications and methodologies used to interpret statistical measurements must evolve accordingly. As the global statistical community adopts new classification standards, historical data may seem in jeopardy under new classifications and methods. Backcasting emerges as a perennial solution for aligning historical data with modernised classifications and methodologies, thereby preserving data consistency over time. This technique is particularly important for National Statistics Institutes (NSIs) aiming to provide a seamless historical perspective despite changes in classification systems.

By focusing on micro-based approaches, this paper highlights the importance of retaining the relevance of past measurements in statistical practices It proposes and elaborates on methods that enable NSIs to achieve these goals, centring on the ability to compare like-with-like across multiple time periods. Without the implementation of backcasting, users may resort to generating their own solutions to fill any significant gaps in data, potentially leading to an inaccurate view of economic history and its related analysis and interpretation. It is therefore necessary that national official statistics compilers undertake this work, as they possess specific knowledge and detailed access to the data and its quality, placing them in a unique position to ensure the accuracy and integrity of backcasted data.

This paper does not treat the re-coding process as an intrinsic methodological step of backcasting, such as transitioning each business or statistical unit from NACE Rev. 2 to NACE Rev. 2.1. Rather, re-coding is being recognised as a foundational and preparatory process; a critical stage from which each statistical domain must borrow strength from. This preliminary work is essential and is assumed to have been completed prior to undertaking the backcasting process.

2. Literature Review

Backcasting as a technique has its roots in the 1970s and has continued to evolve over the years. Originally documented by Robinson (1982) as a policy analysis tool for energy planning, backcasting often involves working backwards from a desired future outcome, to determine the necessary steps to achieve that outcome, making it a valuable tool for long-term planning and strategy development (Robinson, 1982; Quist & Vergragt, 2006). Over time, backcasting has been applied across various domains, including environmental planning, energy consumption, urban development, and economic contribution.

The concept of backcasting has not remained static; it has evolved and been adapted across various disciplines, including within statistical institutes. Recent advancements have seen the integration of sophisticated computational techniques aimed at improving both the accuracy and efficiency of backcasting processes. Liu et al. (2020) highlight the use of advanced statistical methods, including machine learning, to refine macroeconomic policy analysis, which can similarly be applied to automate re-coding processes in backcasting. Tan (2020) further contributes to this discussion by highlighting the use of model-assisted inference with regularised estimation techniques, which aligns well with the goals of modern backcasting practices. In general, the re-coding stage serves as the initial step, facilitating the subsequent stage of actual backcasting.

Micro-based approaches involve detailed re-coding and decomposition of individual data points. These approaches have gained prominence due to their high accuracy levels, by using a so-called 'bottom-up' process that begins with the micro-level observations and builds up to aggregate results. These methods are generally resource-intensive but optimal for business statistical domains that delve into significant detail, often up to NACE Class levels. Macro-based approaches, in contrast, use aggregated data to estimate historical values and are generally simpler and faster but may lack detail and accuracy at finer levels (UNSD, 2018; Eurostat, 2010).

As micro-based approaches to backcasting have developed, methods that deconstruct complex data sets into their constituent parts have emerged, allowing for greater precision. These techniques are especially useful in areas such as policy management, where a granular understanding of the impact of decisions over time is essential (McDowall & Eames, 2006; Bibri, 2020).

Hybrid approaches that combine micro and macro methods have also emerged, leveraging the strengths of both to provide a balance between accuracy and resource efficiency (UNSD, 2018; Eurostat, 2010). The application of robust statistical methods has further enhanced the reliability of backcasting techniques, making them less sensitive to outliers and model assumptions (Bibri, 2020; Fan et al., 2020). These developments have made backcasting a versatile and indispensable practice in various statistical domains, including business statistics.

The UNSD Handbook on Backcasting (2018) and Eurostat's Backcasting Handbook (2010) provide comprehensive guidelines on backcasting methodologies. These handbooks emphasise the importance of ensuring data consistency over time, for reliable trend analysis and forecasting. Transparent methodologies not only enhance the credibility of the data provided by NSIs but also ensure the reliability of statistical outputs, which are important for informed decision-making.

Accurate backcasting is essential for aligning historical data with different classifications, preserving the integrity and usability of the data across time periods. This alignment is particularly significant for policymakers, researchers, and businesses, as it prevents flawed analyses and misinterpretations of economic history (Liu et al., 2020; Hokimoto, 2017; Fan et al., 2020).

3. Methodological Framework

A variety of techniques designed to maintain data consistency and relevance across different classification systems and time periods can be applied in business statistics. For the purpose of this article, the potential use of backcasting methods that hinge on a macro approach is being ruled out in favour of micro-based approaches. The nature of business statistics involves not only the detailed dissection of industries (often at the NACE Class level) but also a data collection mechanism that leverages the strengths of micro-level data analysis. This emphasis often leads business statistics to engage in projects involving Micro Data Linking (MDL) and a firm-level perspective to analyse the competitiveness and productivity among domestic firms. Conversely, macro-based approaches may be more suitable for broader economic contexts, such as aggregates of Gross Domestic Product (GDP), due to their focus on long time series and lesser attention to fine details. For instance, the UNSD Handbook on Backcasting (2018) advocates for revisions in National Accounts that are designed to be reasonable for long time series, structured into a taxonomy with methodological soundness, with the primary goal of preserving the key attributes of economic history. This objective differs from the aims of business statistics, which focus on backcasting shorter time series with a higher level of detail.

In principle, micro-based approaches focus on the detailed re-coding of individual data points (e.g., individual records or observations), offering a highly granular level of detail. These methods often involve a "bottom-up" process, starting from the most detailed level and aggregating upwards. They are particularly beneficial for domains requiring a high degree of accuracy and detail, such as business statistics, where data may need to be classified up to specific industry codes like NACE Class levels.

From the outset, a key point to consider is that various statistical agencies employ a wide spectrum of methodologies in business statistics, ranging from sampling frame selection to the stratification levels and grossing-up methodologies. These diverse components must be considered when designing a multi-faceted backcasting approach that can potentially be applied across various circumstances beyond a single methodological process. The design of such a backcasting methodology must ensure that the results align backwards with the original population and that the results obtained using legacy classifications align with no or minimal divergence to the original aggregates.

For example, one traditional grossing-up approach used in business statistics involves assigning a sampling weight or expansion factor to each unit in the sample, reflecting the number of business units each observation represents in the total population. This is generally considered a traditional grossing-up technique, often referred to as inverse probability weighting, which avoids complexities and is easy to implement.

$$X = \sum_{h=1}^{H} \left(\sum_{i=1}^{n_h} \left(x_{hi} \times \frac{N_h}{n_h} \right) \right) \qquad [1]$$

where x_{hi} is a sample value, and $\frac{N_h}{n_h}$ is the weight assigned to the observation for a single stratum. X is the total estimate across all strata and h denotes each stratum (from 1 to H, the total number of strata). N_h are the total population counts in stratum h and n_h is the number of sampled units in stratum h. This method is straightforward and has its own advantages and disadvantages, but it may not fully capture the complexity of performance and variations in business sizes within the same cluster.

Another grossing-up method, distinct from the previous one, is the ratio-estimator approach, which uses performance ratios to scale sample data to the target population parameters. This technique derives key variables, such as Gross Value Added (GVA), from functions of input variables like Turnover. In this method, the business units featured in the unsampled portion of known key variables such as ‘Turnover’ within a business statistical population of a specific stratum is estimated by applying ratios derived from the sampled observations. This method ensures that the grossing-up process aligns with key proxies, such as the 'Turnover' value of the statistical population, rather than merely the number of business units. It reflects the observed performance patterns in proportion to the population pillar values of the unsampled portion. This method is not based solely on multiplying observations; instead, it replicates the performance patterns observed in the sample, scaled appropriately to account for the relative size of the unsampled business units. In simple terms, this can be exemplified as follows:

$$Y = \left(\sum_{i=1}^{n} Y_i\right) + \left(\frac{\sum_{i=1}^{n} \frac{Y_i}{X_i}}{n} \times \ (X - X_s)\right) \qquad [2]$$

Where Y_i and X_i represent the observed values of the target and auxiliary variables for the i-th sample unit, n is the number of sampled observations, X is the total auxiliary variable for the population within a single stratum, and X_s is the sum of the auxiliary variable for the sampled observations. Y represent the total target variable estimate of a single stratum.

These two examples are presented to illustrate the diversity in grossing-up methods, each fundamentally different from the other. The key takeaway is that both approaches, along with various other methods, can be adapted and unified under a common framework for backcasting, as proposed in this methodological note. It is important for a backcasting method to exhibit flexibility and applicability, offering a practical solution for NSIs regardless of the specific grossing-up method employed.

4. Proposed Method for Backcasting

When discussing micro-based approaches in backcasting, the literature often gravitates towards applications involving fully available and collected data, typically at the level of survey observations. Guidelines, such as those outlined in the Eurostat handbook (2010), suggest that while individual data points or figures remain unaltered during the backcasting process, both the sample observations and the broader statistical population must be re-coded according to the updated classification system. It also adds that micro-based methodology necessitates that each data series undergoes re-processing and fresh grossing-up to re-aggregate industries under the new nomenclature. In this context, this section explores two specific backcasting methods: the re-labelling approach and the pattern re-calibration approach. Both methods necessitate that the business register supporting business surveys is double coded for the two classifications.

The handbook on backcasting (Eurostat, 2010) clarifies that in sample surveys (as opposed to full censuses), the micro-approach does not provide significant advantages over the macro-approach in terms of data preservation. This is because the re-grossing up process can introduce variances, leading to differing results when applying grossing-up factors to business entities of varying sizes, which are reclassified under the new system. This leads to the first type of backcasting, which typically involves retaining the primary data unchanged except for the nomenclature reclassification of the statistical population. This methodology, referred to in this paper as the 'pattern re-calibration approach,' involves creating new clusters or 'families' of observations and re-grossing the sample data based on these newly derived categories, particularly when the nomenclature serves as a stratification factor, which is commonly the case.

The intricacies and complexities of adopting a micro-based approach emerge when implementing such new classifications and integrating them against the backdrop of deployed sampling and grossing-up methodologies. In scenarios where a census survey is conducted, complexities related to sampling are eliminated since the entire statistical population is covered. In such cases, the process merely requires reclassifying each business unit under the new nomenclature. As every unit is observed, the new groupings can be seamlessly re-aggregated, ensuring that the census totals (variable aggregates) remain consistent.

However, backcasting approaches may encounter complications when applied to sample surveys, as they can result in a loss of original data fidelity and variations in total economy variables. The pertinent question then becomes: How can a sampled approach be effectively transformed to harness the benefits of a census approach, thereby mitigating these issues?

This transformation can be realised through Micro Decomposition Analysis (MDA), a technique which must be applied in a manner analogous to the grossing-up method initially used to extrapolate sample survey results to population-level figures. The objective is to trace backwards, not merely to the level of sample observations, but further into the granular details of the statistical population. This involves deconstructing the grossing-up results by reversing the grossing-up factor, breaking down the aggregate results into finer components that correspond to each business unit's contribution within the target population.

By drawing on the two grossing-up methodological examples outlined in section 3, this method involves either replicating values from a donor group or emulating similar patterns within clusters of companies in the same stratum. The idea behind this motive is akin to peeling back the layers of an onion. Initially, only the outer layer (the aggregate) is visible, but as each layer is carefully removed, more is revealed underneath. This approach metaphorically 'peels back' the layers of the sample data, allowing for a detailed examination of each component, much like uncovering the many layers of an onion to reveal its core.

When applying this method, the sum of the constituent components (business units in the statistical population), derived and distributed from the aggregate, must match the aggregate totals for every variable without exception. Once this key process is completed, the aggregates of all variables, fragmented by each business unit, will sum up to the original aggregate totals. This method is being referred to as the 're-labelling approach,' where the initial MDA process allows for each component (business unit) of the statistical population to be re-labelled under a different classification regime (such as a new nomenclature). The aggregate totals are broken down and spread into fine components based on individual contributions, ensuring that while the classification changes, the overall aggregates are preserved. This approach ensures that each business unit in the target population is accurately represented, faithfully reflecting its original contribution according to the respective original grossing-up methodology, while the new labels are recombined to form new industry categories.

By applying this methodology to the two hypothetical examples discussed in Section 3 of this paper, the micro decomposition analysis can be illustrated as follows:

For the inverse probability weighting approach:

$$x_{uh} = \frac{\sum_{i=1}^{n_h} \left(x_{ih} \times \frac{N_h}{n_h} \right)}{\sum_{i=1}^{n_h} \left(\frac{N_h}{n_h} \right)} \quad [3]$$

where, x_{uh} represents the estimate for the unsampled unit in stratum h. x_{ih} is the observed value for the i-th sampled unit in stratum h and $\frac{N_h}{n_h}$ is the expansion factor (weight) applied to the sampled units to represent the entire stratum h.

This formula essentially calculates the decomposed weighted average of the sampled data within stratum h and applies it to estimate the value for an unsampled individual business unit in that stratum. It uses the same grossing up method, in reverse, to arrive to the level of the unsampled population units.

For the ratio estimator approach:

Starting from formula [2], to reverse the process and derive the values at the statistical population unit level, the observed values Y_i are retained and unchanged as sampled observations. For the unsampled portion, the estimation process retraces the procedure by calculating the individual contributions that were initially aggregated.

The individual contributions from the unsampled portion can be estimated as:

$$y_j = \left(\frac{\sum_{i=1}^{n} \frac{Y_i}{X_i}}{n} \right) \times x_j \qquad [4]$$

where y_j represents the estimated value of the target variable for the j-th unit in the unsampled population, and x_j is the auxiliary variable value for the same unit.

The total can then be retrieved as:

$$Y = \left(\sum_{i=1}^{n} Y_i \right) + \left(\sum_{j=1}^{m} y_j \right) \qquad [5]$$

where m is the number of units in the unsampled portion. Here, y_j for each unit j in the unsampled population can be derived using the average ratio $\left(\frac{\sum_{i=1}^{n} \frac{Y_i}{X_i}}{n} \right)$ and the individual value x_j.

In the process of applying the above notation to deconstruct the aggregates into the form of the statistical population, the sample observations would be represented by the actual observed values. As indicated, the notation above for deriving the individual contributions would only be applicable to the business units in the statistical population that were not included as sample observations. This would mean that the actual data collected from the sampled units remain intact, while the estimation techniques are used to specifically account for the unsampled portion of the population.

The two examples above are not intended to specifically illustrate how a particular business survey, such as the SBS, should apply micro decomposition analysis. The appropriate application depends on the specific grossing-up methodology employed by the NSI. These examples are presented to demonstrate the general applicability of decomposition in backcasting through two grossing-up techniques that may be commonly used in statistical offices. They illustrate how this technique can be adapted to each grossing-up method for use in the MDA process. The aim is to show that this method can potentially be applied across a variety of grossing-up methodologies.

The process is essentially akin to reverse engineering each grossing-up method. An important aspect of this process is not just scaling back the grossing-up to the sample observation level but extending it to the population level. This involves deconstructing the grossing-up of individual population data points to align them with new classifications in a micro-based backcasting context. Once the total economy, represented in its spread-out form, is re-labelled with the new nomenclature, the aggregates can be recombined to form new aggregates, as demonstrated in, for instance, equation [5].

6. Discussion

In considering the efficacy of micro-based approaches to backcasting, as explained in section 3, the ability to thoroughly reclassify an entire statistical population into a new classification system is central to its ability to be implemented. This process necessitates double coding, where each business unit is assigned to both the legacy and new classifications. This dual classification is a prerequisite when classifications and measurement criteria evolve to meet contemporary realities.

The two backcasting methods discussed—the pattern re-calibration approach and the re-labelling approach—each offer clear advantages as well as challenges. The pattern re-calibration approach aligns closely with traditional methods, adjusting weights and grossing-up techniques to reflect new classification patterns. This method is particularly attractive when there is a concern that new groupings from introduced classifications could significantly alter the economic profile or offer a heterogeneous pattern of performance in the newly formed clusters. Such concerns typically arise when groups that were previously classified under a certain category are reclassified or merged into a significantly different category with prominent new attributes. These changes can markedly alter the economic profile, as well as the perceived uniformity within the clusters. By implementing this method, it allows for a refreshed set of patterns that more accurately reflects the contemporary realities and distinct characteristics of the data. When reworking the process, this approach attempts to mirror the updated distribution of industries within the economy under the new classification system.

However, there is a trade-off: while this method can enhance accuracy at the stratification level of the new classification, it may introduce aspects such as increased sampling issues, as typically in backcasting exercises, adding additional observations is ruled out to maintain the consistency of the exercise. This is particularly likely when new categories (e.g., industries) emerge and are allocated very few observations. Similarly, existing industries may see a reduction in sample size as many observations may shift to represent other categories. This situation could result in an insufficient number of observations to accurately represent a particular stratum, especially in cases of deeply stratified samples. There may also be issues on another level; with observations grouped together in a newly designed category not being as homogeneous as expected, leading also to new sets of unforeseen outliers. Both issues can potentially lead to an increase in sampling error, as the grouped observations in a new category may have different technological and productivity levels. These concerns, while noteworthy, should not be overstated.

In contrast, the re-labelling approach embodies the core principles of MDA. This method involves a comprehensive deconstruction of every single variable, systematically reclassifying individual data points across the entire population, including both sampled and unsampled units, under a new nomenclature. The primary benefit of this approach is its ability to maintain the total economy aggregates without altering the historical economic data. This stability is particularly valuable in contexts where preserving the integrity of historical data is of utmost importance, as it ensures that past data remains reconcilable with new classifications without the need to appear as an exercise involving revisions.

The re-labelling approach's methodology provides a smooth framework for pure backcasting, as opposed to retropolation, which often involves estimating past aggregates which in principle did not exist. At its core, this method assumes that the business units, when originally grossed up, were accurately represented within their respective strata, reflecting their accurate performance pattern, regardless of the classification changes. This method carefully conserves the historical totals by reclassifying the statistical population under new categories while maintaining the original economic aggregates for all variables. The process ensures that each business unit is accurately represented, reflecting its original contribution, thereby preserving the economic history. This stability could also be extended to related statistical domains such as the IFATS, where the aggregates by country of Ultimate Controlling Institution (UCI) remain unchanged, ensuring consistency in the exposure of the economy to residents of other countries.

In summary, the notable challenge in the pattern re-calibration approach is its potential to alter the overall economic profile. This method, while offering a dynamic and flexible response to new classifications, can sometimes lead to discrepancies. For example, newly defined industries may not have sufficient data representation, or existing industries might be aggregated in a way that overlooks significant differences in productivity or technology levels.

The re-labelling approach, however, mitigates these risks by adhering closely to the existing data structure. It avoids the pitfalls of sampling errors and maintains the stability of the aggregate totals. This approach is particularly attractive in scenarios where the goal is to provide a seamless transition to a new classification system without introducing any minor revision that could alter the perceived economic history over time. The method's focus on maintaining the original data's integrity ensures that the historical data series remain consistent, providing a reliable foundation for analysis.

In conclusion, while both methods offer valuable tools for backcasting, the choice between them hinges on the specific objectives and constraints of the NSIs. The pattern re-calibration approach offers flexibility and a potential for increased accuracy in reflecting new classifications. In contrast, the re-labelling approach provides stability and continuity, preserving the historical data and economic aggregates. This approach, synonymous with true backcasting, avoids the complexities and potential inaccuracies associated with retropolation, offering a clear, stable, and faithful representation of the economy's past under a new classification system.

By some interpretations, the re-labelling approach could be considered a hybrid methodology. While it begins and ends with the same original aggregates, it systematically deconstructs them down to the level of individual business units, effectively linking macro and micro approaches. This method attempts to integrate elements from both the macro and micro approaches, yet it leans more toward the micro analysis ideology due to its focus on reconnecting every single entity at micro level within the population dataset.

In practice, a hybrid approach could potentially be applied by first implementing the pattern re-calibration approach as the backcasting method, followed by a decomposition exercise to harness the strengths of MDA. For example, the pattern re-calibration approach could initially be used to align SBS data with new classifications, followed by the application of MDA to break down the new results into tiny fragments and ensure full consistency when using SBS to compile IFATS and other related domains. This integrated approach would allow for a nuanced understanding of the data, ensuring that all aspects of the economy are accurately represented and understood in light of new classifications.

Ultimately, the choice of method will depend on the severity of the changes introduced by the new classification and the respective NSI's priorities, whether they lie in strictly retaining the original results or in embracing new classification systems to reflect precise sampling at the level of grossing up. The re-labelling approach stands out as a preferred method for pure backcasting, ensuring that the transition to new classifications does not disrupt the continuity of economic history documented in the past, thereby providing a stable and reliable basis for economic analysis and policy-making.

The concept of the Statistical Unit ‘Enterprise’

Business statistics, by virtue of council regulation (EEC) No 696/93 on statistical units, must illustrate their respective results by following the ‘Enterprise’ statistical unit for most annual statistical domains. This requirement can present some intricacies during a backcasting exercise, particularly in cases where the initial data collection and sampling methodologies are conducted at the level of registered legal organisations rather than at the Enterprise level, before being converted to the statistical unit ‘Enterprise’. Such complexities may become quite glaring when a pattern re-calibration approach is employed at a very crude stage of grossing up, especially if it necessitates reconfiguring the profiling structure of individual Enterprises. This issue is particularly pronounced when the data collection level does not align with the Enterprise-level reporting requirements, as alterations in the Enterprise profiling structures may arise unless the observation units and the grossing-up technique are both based at the Enterprise level.

The application of the re-labelling approach through MDA may circumvent these challenges, offering a practical solution. By decomposing sample aggregates down to the level of Enterprises, rather than to the data collection level of registered legal organisations, the re-labelling approach enables the reclassification of each enterprise simply through the relabelling of the ‘delegate’ business unit (main economic activity of the Enterprise). This method ensures that the Enterprise structure remains unchanged from the original profiling process, preventing potential revisions that might otherwise occur due to changes in the potential re-profiling of Enterprise Groups.

In essence, for cases involving complex Enterprise methodologies and data collection mechanisms at the level of registered legal organisations, the re-labelling approach offers a more stable and straightforward alternative. It facilitates the preservation of Enterprise structures while simplifying the adaptation process to new classifications.

7. Conclusion

This paper has evaluated two primary backcasting methods, with a particular focus on introducing the re-labelling approach through MDA, while emphasising the importance of micro-based approaches in business statistics. These methods were explored by examining their specific characteristics, highlighting their respective advantages and limitations, and demonstrating their application using two distinct grossing-up methods. The primary emphasis was on demonstrating the practical application of MDA through the re-labelling approach, which is particularly effective in preserving the historical economic narrative while adapting to new classification systems.

While concepts such as backcasting, micro-based data handling, and reclassification have been explored in various contexts, this paper provides a synthesis for novel backcasting methodology. Although there may be overlaps with existing techniques, the integration and application of this method in the contexts described, represent an original contribution which may be straightforward to apply when having access to micro-level data. The backcasting exercise is presented as an essential tool for maintaining relevance and accuracy in official economic and business statistics. It particularly involves working backwards to understand and utilise past economic conditions and observations.

The preservation of official economic history is fundamental, as it serves as a significant knowledge asset. Balancing methodological rigour with practical application is also key for the successful implementation of backcasting methods. Such transparency builds user confidence and supports informed decision-making, ensuring that data remains accurate and reliable.

The potential for expanding the use of these methods extends beyond the immediate scope of this paper. The method's application was primarily illustrated within the context of SBS, serving as the prime example and demonstrating how the techniques discussed can maintain consistency across various elements, such as Turnover or GVA, ensuring stability of aggregates during backcasting. Furthermore, this paper explained that the methodology could be extended to other domains, such as IFATS, to preserve consistency in aggregates by the country of UCI. Additionally, the same method could be adapted for backcasting in other statistical domains. For instance, it could be used to project existing results backcasted to align with updated national industry classifications. It could also be applied for backcasting SBS data (for the same NACE transition) by region or institutional sector, ensuring that total aggregates by region and institutional sector remain consistent without requiring any adjustments.

Future research could focus on refining these methods and exploring their potential applications further. It is key for NSIs to continue prioritising methodological rigour and transparency to uphold the credibility and reliability of their statistical outputs. By doing so, they can better serve the needs of data users and maintain the integrity of official statistics.

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