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AIMS AND SCOPE

Managing Global Transitions (MGT) is a quarterly, scholarly journal that covers diverse aspects of transitions and welcomes research on change and innovation in increasingly digitalized and networked economic environments, from a societal, organizational, and technological perspective. MGT fosters the exchange of ideas, experience, and knowledge among developed and developing countries with different cultural, organizational, and technological traditions. MGT invites original scientific, research, and review papers advancing the field of transitions in societies, organizations, and technologies.

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Integrating Happiness Research into Endpoint Indicators of Social Life Cycle Analysis

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Endpoint indicators for social life cycle analysis (S-LCA) are still less consolidated than those for environmental LCA. There is a broad consensus that human well-being should be the overarching goal of social sustainability and therefore also of S-LCA. However, to date the two major databases for S-LCA are restricted to a multiplication of working hours with a quality- or risk-adjusted factor. This paper aims to evaluate the congruence between this technical pragmatism and well-established findings of happiness research. The analysis starts with the argument that evidence and consequentiality are necessary criteria for any variables used. It is then shown that some of the variables such as poverty are not consequential, while the unit of working hours lacks any evidence about a relationship with subjective well-being. The analysis concludes that a simple point-based endpoint indicator would be more appropriate for S-LCA than the current hour-based indicator.

Key Words: social sustainability, life cycle analysis, indicators, endpoint
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Introduction

Endpoint indicators in life cycle analysis are appreciated for their simplicity and openness to interpretation, while their subjectivity is sometimes a reason for debate (Cays 2021). Models for the aggregation of environmental parameters like ReCiPe (Goedkoop et al. 2009) have become important tools to compare the environmental footprint between different products (Dekker et al. 2020), different production sites (Turk et al. 2020) and different time periods (Sanyé-Mengual and Sala 2023).

For social life cycle analysis (S-LCA), the situation is more difficult. It is a much younger methodology with a less established body of research (Bachmann et al. 2024). A literature review identified a lack of standards and code of practice (Arcese et al. 2018). Most empirical work is done either based on the Social Hotspot Database (SHD) (e.g. Diaz-Chavez 2015; Pérez-Lopez et al. 2025) or the PSILCA (Product Social Impact Life Cycle Assessment) database (e.g. Di Noi et al. 2020; Tragnone et al. 2023). But how sound are the endpoint indicators used by these sources in the context of the method's ambition?

This is the question that our study aims to answer. It contributes to consolidation of social LCA methods through a critical analysis of current endpoint indicators. To this end, it starts by demonstrating the major gap between necessary prerequisites for a credible endpoint indicator of S-LCA as set out in basic reference documents and the much more modest approaches used in practical tools. It then shows why happiness research is an important source of relevant information in the definition of an endpoint indicator for S-LCA. On this normative base, the most important indicators currently used in S-LCA are evaluated. From these foundations we derive suggestions for useful S-LCA endpoint indicators. This work makes contributions to simplifying current standards.

State of Endpoint Indicators in S-LCA

There is a consensus that an endpoint indicator in S-LCA should not be a general indicator on social welfare but should restrict itself to the sphere of work. S-LCA aims to assess the social footprint of products (Burchi et al. 2013), meaning that only social aspects arising with the work required to produce the products should be considered. The most important reference guide for S-LCA by United Nations Environment Programme (2020) sends clear signals in terms of the S-LCA most suitable endpoint indicator: it suggests that 'midpoint covers the characterization of impact midway through the cause-effect chain and endpoint at the stage of Area of Protection, i.e. the final impact on human well-being' (United Nations Environment Programme 2020, 53). This quote includes two important notions. One is the reference to what is called 'areas of protection' in environmental LCA, which usually describes an analysis's methodological focus such as natural resources or human health. Whatever the concrete area of protection is, it is to be covered in total by endpoint indicators as described by Finnveden et al. (2009). The second notion is that human well-being is the most basic indicator, as will be shown in detail below.

However, the more we move from theory towards practical implementations of S-LCA the more difficulties arise. As the ambition of well-being indicators usually cannot be met on a sufficiently disaggregated level, workarounds are the rule rather than the exception (Weidema 2018). More recently, Weidema (2023) produced promising results using quality- and disability-adjusted life years. However, all the major databases work with endpoint indicators with less clear reference to well-being. Usually, the endpoint indicators are a composite of working hours and some risk- and quality-related variables. The Social Hotspot Database, for example, constructs the Social Hotspots Index that uses information about: (1) wage, (2) poverty, (3) child labour, (4) forced labour and (5) discrimination and equal opportunities to construct the quality of labour. This is then combined with the hours of working time to calculate the social sustainability index (Takeda et al. 2019). Similarly, the PSILCA database uses risk-adjusted working hours as their unit of product comparison (Martínez-Muñoz et al. 2022). In an attempt to broaden the range of social effects that can be included in an S-LCA, the authors of the database recently incorporated an option to carry out what they call a 'direct quantification of indicators' (Maister et al. 2020), but this does not support aggregation and therefore does not lead to an endpoint indicator. Thus, the relationship between the indicators used in the practice of applied S-LCA and the impact of production on human well-being remains unanswered. To approach this question, it is useful to come back to the essence of social sustainability.

Social Sustainability, Utilitarianism and Happiness Research

The strong link between S-LCA and happiness research can be identified in a few dimensions. First and foremost S-LCA refers to the social pillar of sustainability. However, it has often been remarked that this social pillar has the largest uncertainties in its definitions (Janker and Mann 2020; Biswas et al. 2021; Jankovič 2023). Awan et al. (2018, 70), for example, suggest that the aim of social sustainability 'is to have value for the survival of current business system (customers, partners, and society) and its growth for the future generation equitably and prudently'. Golrang (2015, 50) in contrast argues that 'the main focus and aim of social sustainability is normally to see in the inhabitant's needs, life conditions and social justice'. The difference between the two quotes can be explained by the different environments in which the two studies are embedded: the first is a business context, the second concerns a spatial location. Yet, despite such contextual differences it can still be argued that it is easier to identify an ultimate goal of the social than of the environmental pillar of sustainability. It will always be difficult to weigh the objective of clean air against the objective of biodiversity. In contrast, the concept of social sustainability aligns well with basic ethical concepts.

Deontological arguments focus on the realization of human rights and claim that these rights are the backbone of social sustainability. Treviño-Luzano (2022), for example, compares infrastructure projects with respect to the handling of human rights and draws conclusions on their impact on social sustainability. Popovic et al. (2018) go as far as collecting social sustainability endpoint indicators (mainly outside of S-LCA) that can be traced back to human rights. Utilitarians, in turn, consider human well-being the only relevant goal for making ethical decisions, because all other relevant attributes such as trust and justice will ultimately result in higher subjective well-being. Scholars in this tradition point to the link between well-being and social sustainability. While it is widely accepted that individual predispositions and the family environment have a great effect on subjective well-being (Savahl et al. 2020), it is also acknowledged that other social factors have significant impacts (Adler and Seligman 2016). Rogers et al. (2012) suggest monitoring the different social components of well-being such as physical and social security or social relationships to identify progress in social sustainability. Arcagni et al. (2021) point to the complexity of social phenomena that needs to be considered when measuring social sustainability. Moreover, Conigliaro (2021) demonstrates how decent work (embracing universal individual rights, human needs and social justice) links social sustainability to human well-being. Even though a high level of social sustainability will not automatically translate into a high level of subjective well-being, for example because individual subjects take others or past situations as a reference (e.g. Caporale et al. 2009; Schokkaert et al. 2011), there are important utilitarian arguments for aiming at social sustainability.

The one-dimensionality of utilitarianism (Binder 2009) aligns well with the search for an endpoint indicator. Following the basic utilitarian argument, obviously the contribution of a production process to human well-being must be the ultimate normative scale for such an endpoint indicator. In other words: although it may be difficult to identify how a production process contributes to social well-being, it remains the only relevant question for an S-LCA, to which any endpoint indicator should be tailored as well as possible. Thus, if it would be possible to directly measure the impact of a certain production process on well-being in the respective society, this would be the perfect endpoint indicator for S-LCA. These considerations help in justifying the United Nations Environment Programme's (2020) suggestion to use human well-being as an indicator.

However, even when it is easier to agree on human well-being as the ultimate indicator of social sustainability, there remains the problem of its operationalization. It is impossible to monitor subjective well-being in a country such as Kenya without tea farming or in a country such as Japan without car production, which make it difficult to estimate the effect of these sectors on human well-being. And even if it would be possible to show that people in the hotel business are happier than those in the consulting business, it remains unclear whether the difference in work life is the main cause for this difference. This raises the question: is the proxy used as an endpoint indicator in S-LCA, the combination of work hours and work quality, as close a proxy as we can get?

To answer this question, two principles need to be followed which are well established in environmental LCA but often ignored in S-LCA and other social evaluation methods:

1. *An endpoint indicator has to be evidence-based.* Over the course of the last 60 years, happiness research has become a thriving research field with ample empirical evidence about subjective well-being and its main causes (Delsignore et al. 2021). Every major variable with an impact on human subjective well-being should have been discovered by now. This justifies a reduction of the variables used in S-LCA to those factors which have been shown to increase or decrease subjective well-being. Using an indicator like indebtedness, for example as by Williams et al. (2024), is only meaningful if indebtedness has been shown to have a measurable impact on the well-being of farmers or other relevant stakeholders.
2. *An endpoint indicator has to be consequential.* As in environmental LCA, the indicators used in S-LCA should confine themselves to measurable effects of the production and therefore be consequential, as implied in utilitarianism (Miller 2013). Garcia-Sanchez et al. (2023), for example, include access to sanitary services as a variable in their S-LCA analysis. This leads to more favourable assessments in richer countries and leads to a negative evaluation of countries where sanitary facilities are rare. However, access to sanitary services should make life easier, more pleasant and healthier (Zhou et al. 2021); the core question is whether the production process assessed leads to a change in workers' access to sanitary facilities. As in en-

vironmental LCA (Schulz et al. 2020), credible reference scenarios have to be defined describing the likely situation without the respective production process. Only if the production process changes workers' access to sanitary services for the better or for the worse, should such an indicator be included.

An Evaluation of S-LCA Endpoint Indicators

It has been shown above how S-LCA uses indicators in practice which are supposed to correlate with individual well-being. As these indicators usually have a quality component and a work time component, it is useful to have a separate look at each of them.

QUALITY COMPONENTS

People usually spend a major share of their life time at their workplace or at least in a work relationship. Hence, an established finding is that subjective work quality is an important driver of subjective well-being (Dockery 2005). However, subjective work quality is not something that can, and typically would, be included in an S-LCA, as it is aimed at using data for indicators that are as objective as possible. The introduction of subjective indicators in an LCA-based system would open too many possibilities for manipulating results. Considering that 'the study of workplace happiness is one of the most advanced and long-established branches of happiness scholarship' (Thin 2012, 379), a key question is whether there are objective work quality indicators that are used by S-LCA and have an empirically robust relationship to subjective well-being.
We can come up with some answers to this question when we analyse factors used by the Social Hotspot database (Benoit-Norris, Cavan et al. 2012), one of the major data suppliers in the field, and check whether these factors fulfil the conditions of being evidence-based and consequential. It is beyond this paper's scope to cover all 26 quality components. Hence, the five with the greatest possible heterogeneity will be examined in greater depth.

Wage Assessment

As proxy to determine whether wage may be an issue in a country-specific sector, this subcategory assesses whether the country-specific sector average wage is below or above some relevant thresholds: the country minimum wage, the country living wage

> and the country Sweat free wage [Benoit-Norris, Bennema et al. 2018, 29].

The first question to be answered is the connection between income and subjective well-being as the methodological focus of happiness research. Although this correlation is easily overestimated and weakening in higher income classes (Mahadea and Rawat 2008; Sengupta et al. 2012; Chomentauskas and Paulauskaité 2020), it is stable and largely uncontested (Graham 2011). This fact satisfies the condition of empirical validation, but not yet of consequentiality.

The issue of consequentiality comes down to the question: is it better from a happiness perspective that garment production is carried out in a country where the individual income in the sector is higher than the average income across all sectors? This question can be answered affirmatively. It can be that wages in the garment sector are higher than in other sectors because the country is extremely poor and all other sectors are extremely unproductive. In this case, the criterion privileges poorer countries. Due to the 'declining marginal utility of wealth' (Popp 2011, 70), this would increase overall well-being. It could also be that the garment sector in a country generates above-average wages because of its high productivity or its strong unions. In these cases, it is obvious that maintaining jobs for well-paid workers will generate more utility than maintaining jobs for workers with a low income. Therefore, the indicator 'wage assessment' is also consequential in the sense that its consideration will shift production into countries where the sector's productivity is high, which will increase overall utility and hence subjective well-being for wage workers (Laporšek et al. 2021).

> *Poverty*
>
> Poverty is 'unacceptable deprivation in human well-being'. The poverty rate is the ratio of the number of people whose income falls below the poverty line [Benoit Norris, Bennema et al. 2018, 34].

The same simple judgement applies to the empirical validation of poverty as in the case of wage assessment. The effect of income on subjective well-being is strongest in lowest income groups. Therefore, poverty is not only an 'unacceptable deprivation', but also detrimental to human well-being.

The problem of the poverty criterion lies in consequentiality. Poverty as a proxy for subjective well-being in S-LCA discriminates against poor countries and, vice versa, trade-flows shift towards wealthier countries of origin. This, in turn, will aggravate international inequalities, that will overall tend to have a negative instead of a positive impact on human subjective well-being. This is an important difference compared to the wage assessment variable: while the latter focuses on an intersectoral comparison, poverty is taken into account nationwide, losing therefore the direct link to the specific sector and the production conditions. Fair trade coffee, for example, may still be discriminated against with the 'poverty' criterion if it occurs in the 'wrong' country.

The poverty criterion is a good example for the importance of consequentiality. Production in an extremely poor environment does not necessarily support social sustainability. However, poor regions do not have a chance to escape their precarious living conditions if they cannot generate added value through engagement in economic activities such as those subjected to S-LCA. It is dangerous and ultimately absurd if the option of engaging in an economic activity is made impossible due to a bad result of an S-LCA.

> *Child Labour*
>
> UNICEF data regarding the percentage of children aged 5-14 years engaged in child labor is integrated in the SHD besides data from the Understanding Children's Work (UCW) database. The UCW database is compiled by UNICEF, ILO, [International Labour Organisation] and the World Bank and includes data about the percentage of children working by economic sector aiming at producing research to inform policies in the area of labour and youth employment [Benoit Norris, Bennema et al. 2018, 39].

The evidence on whether child labour has a direct and negative impact on human well-being is unclear and blurred. In a meta study, Kinasih (2023) finds both positive effects like a higher self-esteem and also negative impacts like increased stress. Another, more complex line of argumentation leads to a larger and clearer body of empirical evidence: many studies show that child labour has a negative impact on education (Beegle et al. 2009; Buonomo Zabaletta 2011; Abdelfattah 2015). The time during which children have to work is unavailable for school attendance or doing homework. Moreover, it is an established research finding that education is a predictor of subjective well-being: studies by Cuñado and de Gracia (2012), Chen (2012) and Jongbloed (2018), for example, show that all levels of education contribute to higher levels of well-being, directly and through additional mediating variables.

As it is easy to recognize that child labour fulfils the criterion of consequentiality, S-LCA can contribute to avoiding production systems and regions in which children play a significant role. This is likely to contribute to human well-being.

> *Forced Labour*
>
> This subcategory provides an assessment of the risk of forced labour by country and by country-specific sector. The Global Slavery Index (GSI) 2016 provides a quantitative ranking of 167 countries around the world according to the estimated prevalence of slavery, that is, the estimated percentage of enslaved people in the national population at a point in time [Benoit Norris, Bennema et al. 2018, 39].

The social worlds that include forced labour are commonly hidden from the public. It is therefore usually impossible to carry out standardized surveys among labourers being forced into their job, and the empirical evidence about the effects of forced labour on subjective well-being is mostly restricted to single cases in which affected persons say they were or are unhappy with conditions under which they have to work (LaFraniere 2006).

However, there is clear empirical evidence that freedom and subjective well-being are positively correlated (Jackson 2017; Abdur Rahman and Veenhoven 2018), no matter whether these freedoms are political or economic (Animashaun and Ubabukoh 2021). If scientific proof is needed that forced labour is extremely likely to decrease overall wellbeing, this is probably the closest we can get.

The criterion of consequentiality is fulfilled for forced labour. If we know that a product is made by modern slaves, we can contribute to a change to the better if we avoid this product.

> *Discrimination and Equal Opportunities*
>
> The US department of State's Human rights report provides information on whether or not countries have included principles of non-discrimination in their constitution, whether or not these principles have been transposed into national legislation, if the national governments are enforcing the rules. Based on what is included in

> the constitution, the national law/regulatory system and the level of enforcement by the government combined with information on the existence of discrimination, the risk levels are determined for the different countries [Benoit-Norris, Bennema et al. 2018, 62].

It is not only intuition that tells us that discrimination makes persons unhappy, but also empirical research. Padela and Heisler (2011), for example, show how anti-Arab discrimination in the US after the terror attacks in 2001 makes affected people unhappy. Similarly, unmarried mothers in a tribal setting who perceive themselves as being discriminated against are unhappier than other unmarried mothers (Thasleema and Rajan 2022), and transgender women's discrimination translates into unsubjective well-being (Barrientos et al. 2016). Empirically it is sufficiently validated that discrimination has detrimental effects on subjective well-being. Abid et al. (2020) provide a credible model to understand this nexus through emphasizing the mediating roles of fairness perception and civility.

However, it should be noted that, probably because of easier data access, national rather than sectoral data are used. This suggests that taking the discriminatory degree of countries into account is, similar to poverty, not consequential. For example, avoiding coffee from Uganda is unlikely to make Uganda a less discriminating country and therefore will not make anybody happier.

THE COMPONENT OF WORKING HOURS

The indicators used in S-LCA are usually composed of the variables evaluated above (and others) multiplied by the working hours needed to produce one unit of the good assessed. It is therefore essential to evaluate whether the amount of work time also meets the criteria of evidence and consequentiality.

While the general impact of our work life on subjective well-being is considerable, it is now necessary to examine the literature on the impact of the quantitative component – the number of hours worked – on subjective well-being. Here, the evidence is very limited. We know that flexitime makes workers happier (Okulicz-Kozaryn and Golden 2017), but this is not considered in S-LCA. Golden and Wiens-Tuers (2006) found no net effect of required overtime and heterogeneous effects of mandatory overwork on subjective well-being. There are regional differences in the optimum amount that people prefer to work (Okulicz-Kozaryn

2011), but there is no empirical evidence that human labour should be considered as an evil that should be minimized, reflecting a dogma from medieval times (Voutyras 1980).

In contrast, there is a vast body of literature about the effects of unemployment on human well-being. Winkelmann (2014) emphasizes that bringing people back into work does more for their subjective well-being than compensating them financially. He also demonstrates that unemployment even has a lasting negative effect on subjective well-being including the years after taking up work again. The relationship between unemployment and subjective well-being is extremely stable over differences in time and regional cultures (Di Tella et al. 2003; Kuzu et al. 2019; Barros et al. 2023). It is not appropriate to link this fact too tightly to the use of working hours as an indicator for unhappiness. However, in combination with the lack of evidence that additional work hours decrease subjective well-being, it becomes obvious that the 'working hours' variable is not an evident predictor of unhappiness.

Evidently, the consequentiality of the 'working hours' variable is a given. The production processes require time, and this is operationalized through working hours.

SYNTHESIS

Table 1 summarizes the result of evaluating several variables used for the endpoint indicator in the social hotspot database on the two criteria of consequentiality and evidence. Most variables meet the two criteria, but not all. In particular, poverty in a country will not be alleviated by discriminating against this country, but rather to the contrary. The same applies to discrimination, except if accounting for this discrimination in an S-LCA will set up political pressure. But this is an unlikely presumption. In addition, the number of working hours has no measurable relationship to human well-being, so it is misplaced in an S-LCA.

TABLE 1 Summary of the evaluation of social hotspot database variables

	Consequentiality	Evidence
Wage assessment	✓	✓
Poverty	✓	✓
Child labour	✓	✓
Forced labour	✓	✓
Discrimination	✗	✓
Working hours	✓	✗

For both the SHD and PSILCA databases, the endpoint indicator is the mathematical product of two numbers. Our analysis suggests that one of these numbers is unrelated to well-being as the relevant reference. If this claim is justified, it requires a major reform of endpoint indicators. The current multiplication allows for a tangible hours-based number, whereas an abatement of working hours would only allow for some more abstract index.

In addition, the evaluation of consequentiality has indicated that some slimming on the side of such an index through skipping several of the factors currently integrated would also increase the significance of the endpoint indicator. Indicators relating to the national level seem to be less useful than specific sectoral data, for which the difference between 'wage assessment' and 'poverty' is a good case in point. It is socially beneficial to invest in sectors that generate above-average added value in a country, reflected by good wages. However, it makes no sense to prefer rich countries over poor countries if the aim is to eradicate poverty.

Summary and Conclusions

The S-LCA method is relatively young, so it is no surprise that not all indicators used so far support all principles of current S-LCA. This should be taken into account when acknowledging that the endpoint indicators used in S-LCA have grave weaknesses in terms of their consequentiality and their evidence in relation to subjective well-being. These are two criteria identified as crucial for a meaningful S-LCA. The results of our study lead to the suggestion to slim down the analysis to a few core indicators for which this clear-cut connection with subjective well-being exist.

It is the underlying assumption of both the S-LCA method and this paper that production processes are out of reach for buyers and consumers of the product. The conditions of evaluation change if it is possible to renegotiate production conditions within the value chain. If it was possible, for example, to make binding and reliable agreements to eradicate forced labour in the production process, this would do more for well-being than the avoidance of the product.

To do justice to the overarching objective of well-being in S-LCA, this paper suggests a great need for future research. This includes the development of a consolidated list of appropriate indicators and a sound weighing method. In sum, historically, S-LCA has not grown out of its infancy yet.

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Reducing Food Waste and Boosting Profits through Inventory Management: The Case of Small Slovenian Bakeries

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This article explores the role of inventory management in reducing food waste and improving economic performance in selected Slovenian bakeries, contributing to a more efficient, environmentally responsible and sustainable economy. Using semi-structured interviews with key bakery personnel and an in-depth analysis of business documentation, our study applies the Economic Order Quantity (EOQ) model and Newsvendor model to test the following two hypotheses: (H1) improving inventory management at Bakery 1 can reduce total annual procurement costs by more than 15% without causing spoilage or raw material waste, and (H2) minimizing food waste at Bakery 2 may not necessarily align with maximizing profit. The findings confirm that applying these models can enhance production and procurement planning, demonstrating that while cost reductions and waste minimization are achievable, they may not always be fully aligned. The study underscores the importance of strategic inventory management in balancing financial and environmental objectives in small bakeries.

Keywords: EOQ and Newsvendor inventory management models, inventory optimization, food waste minimization, sustainable economy, Slovenia

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Introduction

Food waste is a pressing global issue with profound economic, environmental, and ethical implications. It is estimated that approximately 1.3 billion tons of edible food, or one-third of global food production, is lost or wasted annually (Goossens et al. 2019, 1). Despite growing awareness and various initiatives, food waste remains a major challenge,

contributing significantly to sustainability issues and resource depletion (Riesenegger et al. 2023). In particular, the food supply chain – extending from farmers to final consumers – creates waste at every stage, including raw material acquisition, production, distribution, and retail (Osojnik Črnivec et al. 2021, 8; Seminar 2016, 17; Kennard 2019). Food waste leads to substantial resource losses (Osojnik Črnivec et al. 2021, 42–48; Ministrstvo za kmetijstvo, gozdarstvo in prehrano 2021, 20–21; Šubic 2023; Álvarez-de-los-Mozos, Badurdeen, and Dossou 2020, 1795; Dora et al. 2019, 48–49; Parfitt et al. 2010; Gunders 2012, 10–11; CARE-4CLIMATE 2022).
The growing global population, expected to reach 9.6 billion by 2050, further intensifies the strain on resources like food, water, and energy (Hafyan et al. 2024, 1). In this context, food waste exacerbates environmental degradation and economic losses, as resources invested in producing discarded food are essentially wasted (Lin et al. 2018; Handayati and Widyanata 2024).

Among food categories, bread is one of the most wasted products globally. With annual bread production exceeding 100 million tons, estimates suggest that hundreds of tons are discarded daily (Rejeb et al. 2022, 1). In developed countries, more than half of all bread produced is wasted, primarily due to overproduction and unsold inventory (Rejeb et al. 2022, 1–2; Hafyan et al. 2024, 2). While a significant portion of this waste occurs at the end of the supply chain, bread-making also generates waste throughout the production and distribution process (Hafyan et al. 2024, 2). Despite this, food waste solutions in the industry have largely focused on managing surplus rather than addressing the root cause of overproduction, leaving a critical gap in waste prevention efforts.

The existing literature on food waste solutions largely focuses on managing surplus through initiatives like redistribution systems, dynamic pricing, and food-sharing platforms, while ignoring the foundational issue of production planning (Li 2022; Caldeira et al. 2019, 31; Riesegger et al. 2023, 2). These interventions tend to be reactive, stepping in when waste has already occurred rather than preventing overproduction and inefficient resource use upfront. Moreover, food-sharing platforms, although well-intentioned, may unintentionally incentivize overproduction by creating financial incentives to generate surplus (Almeida Oroski and Silva 2023, 816–827). This reactive, surplus-focused approach does not address inefficiencies in production planning, where waste originates.

To problematize this issue, our study critically examines the unintended consequences of existing food waste interventions and explores alternative solutions. In particular, we focus on small bakeries, where bread waste is prevalent, and where production planning inefficiencies contribute significantly to food waste. The gap in the literature is clear: while there is substantial research on inventory models for perishables, few studies explicitly consider how these models can address food waste in the bakery sector. Our study seeks to close this gap by proposing a proactive approach that focuses on production planning rather than post-production waste management.

To address this gap, we apply two widely used inventory models – the Economic Order Quantity (EOQ) model and the Newsvendor model – to help small bakeries optimize their procurement and production processes. By applying these models, we aim to help small bakeries make more informed production decisions, reducing waste at its source and improving profitability.

The main contribution of our study lies in the tailored application of inventory models to small bakeries, an area that has been underexplored in current research. While large-scale bakeries benefit from advanced forecasting tools, small bakeries often face tight margins and limited resources. Our study demonstrates how simple, yet effective inventory models can address the specific challenges faced by small bakeries, helping them achieve sustainable operations while enhancing financial performance. Furthermore, by focusing on data-driven strategies for demand forecasting and waste reduction, our research provides bakery owners with practical tools for sustainable decision-making that can be easily implemented in their daily operations.

In the following section, we provide a theoretical background and literature review, highlighting key findings and gaps in the existing research. The methodology section outlines the research design, data collection, and analytical techniques employed. The results and analysis section presents the key findings and interprets their significance. Finally, the conclusion and policy implications section summarizes the key insights, discusses the broader implications, and offers recommendations for policymakers and future research.

Theoretical Background and Literature Review

Food waste presents significant environmental, social, and financial concerns, with its impact increasing as it moves further down the supply chain (Al-Obadi et al. 2022). Ocicka and Raźniewska (2018, 549) emphasize that the most costly losses occur in later stages due to higher processing and distribution expenses. Since food processing serves as the link between agricultural production and consumers, enhancing efficiency at this stage is crucial. Raak et al. (2017, 5) argue that identifying and mitigating the factors contributing to food waste during processing is key to developing effective prevention strategies.

Mohamed (2024, 3–4) underscores the importance of inventory management in food waste prevention, as it directly influences efficiency, customer satisfaction, and overall profitability. By strategically balancing total costs, product availability and procurement optimization, businesses can significantly reduce waste. However, Sonko and Akinlabi (2020, 13), and Yavari et al. (2020) point out that managing perishable goods presents unique challenges, as their quality declines over time, making timely inventory control essential.

Vu et al. (2022, 103) and Huang et al. (2021, 4) advocate for a proactive approach to food waste management, aligning with the waste management hierarchy, which ranks prevention as the most effective method. Rather than focusing on redistribution or disposal, businesses should prioritize strategies such as demand forecasting, production planning, and inventory optimization to prevent surplus before it occurs. Riesenegger et al. (2023, 2) reinforce this perspective, referencing the United Nations Environment Programme (UNEP) food waste hierarchy, which emphasizes prevention as the most effective strategy for reducing waste at its source.

Rahal (2024) stresses the importance of optimization models in improving decision-making within perishable supply chains, enabling businesses to minimize losses while maintaining service levels. In the bakery sector, Nansubuga et al. (2024) identify lean inventory systems and strong supplier relationships as key factors in aligning supply with demand to mitigate waste. Given the short shelf life of bakery products, particularly bread, achieving this balance remains a pressing challenge.

Duarte et al. (2021) demonstrate that integrating forecasting methods with inventory planning can significantly reduce waste during the production phase of bakery operations. Gioia et al. (2022) further argue that perishable inventory management requires tailored strategies that account for limited shelf life and fluctuations in demand, ensuring that businesses avoid both overproduction and underproduction. Hofer (2020) highlights the ongoing challenge companies face in balancing inventory size and costs – while businesses strive to maintain sufficient inventory to meet customer demand, the associated financial risks drive them to minimize stock levels.

EOQ MODEL

To address these challenges, inventory models provide structured solutions for managing perishable food stocks. The Economic Order Quantity (EOQ) model is a fundamental tool in inventory management, balancing ordering and holding costs to minimize total inventory-related expenses and maximize profitability (Venilla and Karthikeyan 2024, 3003; Morufu and Olayimika 2016, 95). Despite being introduced over a century ago by Ford W. Harris (Harris 1913), the model remains highly relevant due to its simplicity and effectiveness in optimizing stock levels. Andriolo et al. (2013), Prameswari et al. (2024, 390) and Kurniawan et al. (2024, 29) further highlight the model's relevance for perishable goods, as it prevents excess stock that may lead to obsolescence or waste while ensuring a sufficient supply to meet demand.

The EOQ model has been widely applied in the food and beverage industry, where managing perishable inventory is essential to maintaining product quality (Widiastini et al. 2019; Annisa et al. 2023; Nagib et al. 2016). EOQ can therefore be particularly useful in bakery operations where ingredient procurement must be carefully managed to balance cost efficiency and product freshness. Since the stock cycle for perishable goods must not exceed their shelf life, applying EOQ with constraints specific to perishability ensures better control over waste (Macías-López et al. 2021, 3). To account for perishability constraints, researchers have explored adaptations of the model to address real-world complexities, such as fluctuating demand, bulk discounts, and deteriorating items (Alnahhal et al. 2024, 1; Mehta 2023; Patriarca et al. 2020; Zeng et al. 2019; Toles 2018). These enhancements make EOQ a relevant and adaptable tool for modern inventory challenges.

EOQ was chosen for this study because it provides a structured yet flexible approach to managing ingredient procurement in small bakeries. Unlike more complex inventory models that may require extensive computational resources or real-time data inputs, EOQ offers a practical solution that aligns with the operational scale of small businesses. By determining the optimal order size, bakeries can avoid unnecessary storage costs, reduce spoilage, and improve cost efficiency.

Newsvendor Model

The Newsvendor model is widely used for perishable products with short shelf lives (Riesenegger et al. 2023, 9). This single-period inventory model focuses on determining the optimal stock level for a given period, helping businesses balance the risks of overstocking and understocking.

One of the key challenges in bakery inventory management is forecasting demand accurately (Hall and Kronberg 2023). Seasonal fluctuations and consumer preferences introduce stochastic variations that make demand difficult to predict, increasing the likelihood of stockouts or surplus. Overstocking leads to excessive waste, particularly for perishable items, while unsold products occupy valuable storage space and increase holding costs. Conversely, stockouts can result in lost sales, dissatisfied customers and necessitate more expensive emergency procurement (Khan et al. 2023, 2460; Kurniawan et al. 2024; Sonko and Akinlabi 2020, 13). Riesenegger et al. (2023, 4) highlight how growing consumer preference for fresh products further complicates inventory decisions, as customers often select items with longer expiration dates, leaving older stock unsold. This behaviour underscores the importance of dynamic inventory policies that adapt to changing demand patterns and consumption behaviours.

Anitha et al. (2023) argue that improper inventory management, such as inaccurate demand forecasting and rigid replenishment policies, contributes significantly to food waste.

The Newsvendor model provides a structured approach to mitigating these risks by incorporating demand probability distributions and cost trade-offs between excess inventory and shortages (Solari et al. 2024, 1234). Recognizing that demand distributions are often unknown in practice, Castro Moraes and Yuan (2021) and Liu and Zhang (2023) propose data-driven methods that maximize expected profit by determining inventory and pricing levels based on historical demand and feature data.

Bakeries must find an optimal balance between availability and waste reduction. The Newsvendor model facilitates this by optimizing production levels based on demand probabilities while considering waste minimization strategies such as, according to Riesenegger et al. (2023, 4), discounting near-expiry products. Additionally, the Newsvendor model has been effectively applied in retail business to perishable goods like fresh produce, which share similar inventory challenges with bakery products (Chen et al. 2017; Keskin et al. 2021).

THE RESEARCH GAP

The current literature extensively acknowledges the environmental, financial, and operational impact of food waste in the supply chain, particularly within food processing and bakery operations (Raak et al. 2017; Mohamed 2024; Vu et al. 2022). While various studies emphasize the importance of inventory optimization and the applicability of EOQ and Newsvendor models for perishable goods (Riesenegger et al. 2023; Kurniawan et al. 2024; Prameswari et al. 2024), the engagement often remains at a conceptual or simulation-based level, lacking empirical validation within small-scale, real-world bakery contexts. Furthermore, although researchers have proposed model adaptations for perishability constraints and demand variability, few have critically examined how such models interact with the operational limitations and sustainability goals of micro-enterprises.

This gap becomes especially evident in bakery settings, where balancing cost-efficiency and waste reduction involves daily trade-offs influenced by shelf life, consumer behaviour, and resource constraints. Our study directly addresses this underexplored intersection by applying EOQ and Newsvendor models to two Slovenian bakeries using actual business data and interviews, thereby offering a grounded contribution to the literature. It demonstrates that while these models can indeed optimize procurement and reduce waste, economic and environmental goals may not always align perfectly, highlighting the need for nuanced, context-sensitive inventory strategies in small food enterprises.

Purpose, Objectives, and Hypotheses

The purpose of this research is to investigate, through the case study of two selected Slovenian bakeries, how improved inventory management could enhance economic performance and reduce food waste, thereby contributing to a more efficient, sustainable, and environmentally friendly economy.

To achieve this purpose, we set the following objectives:

- to identify the challenges faced by the selected small Slovenian bakeries in inventory management,
- to determine the demand forecasting methods employed by the selected bakeries,
- to explore how the selected bakeries manage potential excess inventory, and

- using the classical EOQ model (economic order quantity), the EOQ model with quantity discounts, and the Newsvendor model, to define possible solutions for more effective inventory management and production planning to minimize food waste and improve economic results in the selected bakeries.
- In the subsequent research, we tested the validity of the following two research hypotheses:

H1: *By improving inventory management, Bakery 1 could reduce total annual procurement costs by more than 15% without causing spoilage or waste of raw materials.*

H2: *The goal of minimizing food waste at Bakery 2 may not necessarily align with the goal of maximizing profit.*

This research integrates the EOQ model for ingredient purchasing with the Newsvendor model for daily production planning. This dual-model approach ensures better alignment between stock levels and demand fluctuations. Our research extends the application of these models beyond individual case studies, offering a replicable framework for bakeries facing similar inventory challenges. The findings provide practical insights for small and medium-sized bakeries looking to balance cost efficiency, demand variability, and waste reduction – an area where research, according to Vu et al. (2022, 124), remains limited in developed countries. The study aligns with broader sustainability goals while enhancing the financial viability of food businesses.

Methodology

This chapter outlines the methods used to achieve the objectives, as well as the description of the sample, the instrument, and the data processing procedure.

Data Collection Methods and Application of the EOQ and the Newsvendor Model

To achieve the set goals and test the proposed hypotheses, we first reviewed relevant literature related to optimizing food supply chains, the issue of food waste, modelling, and inventory management. In this process, we used the comparison method, through which we compared and evaluated the findings and views of different authors on inventory management. As part of our research, we collected primary data through business documentation from companies and semi-structured interviews with representatives from two selected Slovenian bakeries. These data were analysed using content analysis, while quantitative data were statistically processed. In the case of the first bakery, the data were applied within the framework of the classical EOQ model and the EOQ model with quantity discounts, while in the case of the second bakery, the data were applied within the framework of the Newsvendor model/stochastic demand model for a single period to improve inventory management and optimization.

EOQ model

The EOQ model helps determine the optimal inventory quantity that meets demand while minimizing annual costs and waste (Fernando 2024). The classic EOQ model is based on several assumptions, which simplify the real-world situation to make the model work effectively. Here are the key assumptions of the EOQ model (Muller 2011, 127–128):

- Demand rate is known, continuous, constant, independent and uniform over time. In reality, demand often fluctuates seasonally or daily.
- No stockouts are allowed (the model assumes there are no shortages; demand is always met).
- All costs are precisely known and do not change (there are fixed order costs – each order has a fixed cost, regardless of the order size – and constant holding costs – the cost to hold or store inventory is known and constant per unit per time period).
- Lead time is zero (the time between placing an order and receiving it is fixed and known). In reality, suppliers may have inconsistent lead times.
- Each order is delivered individually.
- Only one product is considered, which means there are no savings from consolidating multiple items into a single order. The EOQ model typically applies to a single product or item.
- Inventory is replenished instantly once the order arrives (no gradual stock build-up).
- The purchase price per unit is constant (i.e. there are no bulk discount incentives)

The inventory cycle involves three variables: (i) the order quantity Q which is the fixed order size always placed; (ii) the cycle time T which is the time between two consecutive orders and depends on the order quantity; and (iii) the demand D which represents the number of units needed in stock during a given period. Only the order quantity is directly under our control. The quantity entering inventory during the cycle is Q while the quantity exiting is D × T. These two quantities must be equal because the inventory level at the beginning and end of the cycle is zero.

The total cycle cost consists of three components. The product of UC (cost per unit) × D (demand) represents the fixed unit cost component.

$$\frac{RC \times D}{Q}$$

represents the vari1able component of the inventory acquisition cost (the number of orders placed during the cycle = 1) while

$$\frac{HC \times Q \times T}{2}$$

represents the variable component of the inventory holding cost (T = holding time; Q/2 = average inventory level). Therefore, the total cost per cycle is:

$$UC \times Q + RC + \frac{HC \times Q \times T}{2}.$$

The total cost per cycle is divided by the cycle length T, resulting in the total cost per unit of time:

$$TC\ (total\ \cos t) = \frac{UC \times Q}{T} + \frac{RC}{T} + \frac{HC \times Q}{2}$$

We know that or . When we substitute this into the equation, we get:

$$TC = (UC\, x\, D) + \frac{RC \times D}{Q} + \frac{HC \times Q}{2}$$

The inventory holding cost component increases linearly while the inventory acquisition cost component decreases with the order quantity. The total cost curve takes the form of an asymmetric 'U' with a distinct minimum that corresponds to the optimal order quantity. For orders smaller than the optimum, total costs increase due to higher inventory acquisition costs while for orders larger than the optimum, costs rise due to higher inventory holding costs. The optimal order quantity is determined by taking the derivative of the total cost function concerning quantity and setting it equal to 0:

$$\frac{d(TC)}{d(Q)} = -\frac{RC \times D}{Q2} + \frac{HC}{2} = 0.$$

We solve for Q to obtain the optimal quantity:

$$EOQ = Qo = \sqrt{\frac{2 \times RC \times D}{HC}}$$

We know that . In the equation, we replace with and solve for the optimal cycle length :

$$To = \frac{Qo}{D} = \sqrt{\frac{2 \times RC}{D \times HC}}$$

The unit cost in the total cost formula is fixed. Therefore, we focus on the part that forms the variable costs:

$$VC\ (variable\ \cos ts) = \frac{RC \times D}{Q} + \frac{HC \times Q}{2}.$$

The optimal variable costs are obtained by substituting Q with Qo in the VC equation. The result is compared with Qo and it is found that VCo = HC × Qo. The optimal cost per unit of time is the sum of the fixed and variable components:

$$TCo = UC\ x\ D + VCo$$

The inventory acquisition costs and inventory holding costs are equal at the economically optimal order quantity: .

$$\sqrt{\frac{RC \times HC \times D}{2}}.$$

$$VC_o = RC \times D \times \sqrt{\frac{HC}{2 \times RC \times D}} + \frac{HC}{2} \times \sqrt{\frac{2\ x\ RC\ x\ D}{HC}}$$

$$= \sqrt{\frac{RC \times HC \times D}{2}} + \sqrt{\frac{RC \times HC \times D}{2}}$$

$$= \sqrt{2 \times RC \times HC \times D}.$$

The EOQ model may suggest a decimal value for goods that can only be purchased in discrete units. Suppliers may not offer standard package sizes, delivery is made with vehicles of fixed capacities, etc. Sometimes, it is necessary to round the order quantity. Variable costs near the optimal order quantity remain quite stable. We compare the minimum variable costs *VCo* at the optimal order quantity *Qo* with the variable costs and get (Waters 2003, 69–73, 77–80):

$$\frac{VC}{VCo} = \frac{RC \times D}{Q \times HC \times Qo} + \frac{HC \times Q}{2 \times HC \times Qo}$$

When we use $Qo = \sqrt{\frac{(2 \ \times RC \times D)}{HC}}$, we get:

$$\frac{VC}{VCo} = \frac{1}{2} \times \left(\frac{Qo}{Q} + \frac{Q}{Qo}\right)$$

The assumption that the lead time is 0 and the goods arrive as soon as the order is placed seldom holds in practice. It is in the interest of all stakeholders to minimize the lead time. If both the lead time and demand are constant, it makes sense to schedule orders so that they arrive before the existing inventory is exhausted. The reorder level is expressed as (Bussom 2014):

$$ROL = lead\ time\ (LT)\ \times\ demand\ per\ unit\ of\ time\ (D).$$

Unlike the classical EOQ model, the EOQ model with quantity discounts assumes that costs change with the volume of purchases. The EOQ model assumes stable conditions where the goal is to minimize costs in the long term.

Newsvendor model

Sometimes, however, models for a shorter period, even for just one period, are necessary. For example, a newspaper seller wants to have enough copies to meet demand on Sunday morning. If he buys too many copies from the wholesaler, he is left with unsold inventory that becomes worthless by the end of the day. If he buys too few copies, there is unmet demand, which could have generated more profit (Hofer 2020). In such cases, the Newsvendor model can be used to determine the optimal quantity.

The Newsvendor model (also called the Single-Period Inventory Model) is used for inventory decisions involving perishable or seasonal items – like newspapers, fashion items, or holiday products – where you only get one chance to order before demand is realized. Assumptions of the Newsvendor model are:

- *Single Selling Period*: the product is sold during a single, finite time period (no replenishment is possible). In our case study this period is one day.
- *Uncertain Demand*: demand is a random variable with a known probability distribution.
- *Single Order Decision*: only one order is placed before the selling season begins; no reordering.
- *Known Costs:* the model assumes known unit cost (c), selling price (p), and salvage value (v) or stockout cost.
- *Overage and Underage Costs:* the model balances overage cost (Co), which is a cost of ordering too much (leftover inventory), and underage cost (Cu), which is a cost of ordering too little (lost sales).
- *Instantaneous Delivery:* the entire order arrives before the selling period starts (no lead time issues).
- *No Holding Beyond the Period:* unsold inventory is either discarded, salvaged at a lower value, or has no value after the period.

Assuming the newspaper seller buys *Q* copies, the following applies:

- If the demand *D* is greater than *Q*, the seller sells all the copies and generates a profit of $Q \times (SP - UC)$ (assumption: no penalty for lost sales).
- If the demand *D* is smaller than *Q*, the seller sells *D* newspapers at full price and receives the value *SV* for each remaining newspaper Q – D. In this case, the profit is $D \times SP + (Q - D) \times SV - Q \times UC$.

The optimal value for *Q* maximizes the expected profit. To simplify the calculation, let us assume that $SV = 0$. In this case, we obtain values for demand, profit, and probability, as shown in Figure 1. The expected profit *EP(Q)* from purchasing *Q* newspapers is the sum of the profits, each multiplied by its respective probability.

$$EP(Q) = \sum(\text{expected profits when } D < Q) + \sum(\text{expected profits when } D \geq Q)$$

$$= \sum_{D=0}^{Q} [D\, x\, SP - Q \times UC] \times Prob(D) + \sum_{D=Q+1}^{\infty} Q\, x\, [SP - UC] \times Prob(D)$$

$$= SP \times \left[\sum_{D=0}^{Q} D \times Prob(D) + Q \times \sum_{D=\ Q+1}^{\infty} Prob(D) \right] - Q \times UC.$$

Demand	Profit	Probability
0	0 × SP − Q × UC	Prob(0)
1	1 × SP − Q × UC	Prob(1)
2	2 × SP − Q × UC	Prob(2)
⋮	⋮	⋮
Q − 1	(Q − 1) × SP − Q × UC	Prob(Q − 1)
Q	Q × (SP − UC)	Prob(Q)
Q + 1	Q × (SP − UC)	Prob(Q + 1)
⋮	⋮	⋮
∞	Q × (SP − UC)	Prob(∞)

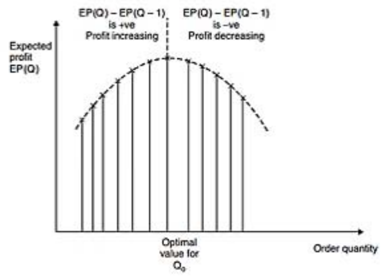

FIGURE 1 Demand, Probability of Sale, and Expected Profit from Purchasing Each Copy

SOURCE Waters (2003)

The expected profit increases with the order quantity until it reaches a maximum, after which it starts to decline.

If $EP(Q) - EP(Q-1)$ is a positive number, the profit from additional copies of the newspaper increases.

If $EP(Q) - EP(Q-1)$ is a negative number, the profit from additional copies decreases.

The optimal order quantity Qo is the point at which the profit starts to decrease if an additional copy is purchased (see Figure 1). We have found $EP(Q)$. If we substitute $(Q-1)$ instead of Q, we get the expected profit if the newspaper seller buys $(Q-1)$ copies of the newspaper (Waters 2003, 156–159; Cachon and Terwiesch 2013, 250–254):

$$EP(Q-1) = SP \times \left[\sum_{D=0}^{Q-1} D \times Prob(D) + (Q-1) \times \sum_{D=Q}^{\infty} Prob(D)\right] - (Q-1) \times UC$$

$$EP(Qo+1) - EP(Qo) = SP \times \left[\sum_{D=Qo+1}^{\infty} Prob(D) - \frac{UC}{SP}\right].$$

We want to find a point where the following holds:

$$EP(Qo) - EP(Qo-1) > 0 > EP(Qo+1) - EP(Qo)$$

or

$$SP \times \left[\sum_{D=Qo}^{\infty} Prob(D) - \frac{UC}{SP}\right] > 0 > SP \times \left[\sum_{D=Qo+1}^{\infty} Prob(D) - \frac{UC}{SP}\right]$$

We get:

$$Prob(D \geq Qo) > \frac{UC}{SP} > Prob(D \geq Qo + 1)$$

Including SV, we obtain the final result:

$$Prob\ (D \geq Qo) > \frac{UC - SV}{SP - SV} > Prob(D \geq Qo + 1).$$

SAMPLE DESCRIPTION

The interviews were conducted with the management of both bakeries, specifically with the proxy of Bakery 1 and the founder of Bakery 2. Both interviewees are men, approximately 30 years old. The first interviewee is an economist by profession and took over the bakery from his father while the second is a chef who, after several years of experience at a renowned Slovenian restaurant, decided to embark on an independent path. Bakery 1 has been in operation since 1987 and has a significantly longer history compared to Bakery 2, which was founded in 2020. Bakery 1 employs around 20 people across its four locations while Bakery 2 has 3 full-time staff members. In addition to its bakery offerings, Bakery 1 also specializes in pastry making while Bakery 2 provides catering services and supports the organization and execution of various events. To facilitate this, Bakery 2 has established contractual partnerships with eight waiters and five chefs.

DESCRIPTION OF THE INSTRUMENT

Primary data was collected through semi-structured interviews. The questions were sent to the interviewees in advance via email. To ensure better understanding, we also provided sub-questions for each main question. Later, due to a tight schedule, we arranged a phone interview with the proxy of Bakery 1 to discuss the questions, while the interview with the owner of Bakery 2 took place at the company's headquarters. This allowed us to clarify each question in more detail. We assume that both interviewees understood the questions correctly and answered honestly and that the quantitative data from the business documents they provided were accurate and precise. The interviews were designed with 10 main open-ended questions prepared in advance, which served as the starting point for the conversations.

Moreover, these interviews were specifically designed to elicit the quantitative data required for inventory optimization models. During each interview, targeted questions were asked to obtain concrete figures on product demand (e.g. number of units sold the previous day), purchase and selling prices, holding and ordering costs, delivery lead times, and spoilage or waste rates. In many cases, participants referred to their records on the spot or provided detailed estimates based on their operational routines. These data points, supplemented by the documentation they shared (e.g. stock reports and sales logs), were used as direct inputs for the quantitative models presented in the analysis.

After receiving responses to these questions, we were able to ask additional questions on various topics, as the conversation naturally unfolded. We were careful not to influence the responses with our questions, aiming to let the interviewees speak as much as possible, with the interviewer speaking as little as possible. The questions in the semi-structured interview addressed the following topics: types of inventory in the bakery, challenges faced by the bakery in inventory management, production planning, management of surplus inventory, inventory valuation methods, and raw material procurement.

DATA PROCESSING DESCRIPTION

The data obtained through the interviews were analysed using content analysis for the part where we were interested in the opinions and perspectives of the interviewees. The numerical data from the business documentation regarding production were statistically processed and used within the framework of the EOQ and Newsvendor models for inventory management. Geographically, the study was limited to the selected bakeries in Slovenia (specifically in the Savinja Valley region). In terms of time, the study was set in 2024 and limited to the period from February 17, 2023, to May 10, 2024. In terms of subject matter, it primarily focused on the operational function of inventory management, which is an important aspect of business economics in the context of food waste issues. Since this is a case study of two selected bakeries, the generalizability of the research findings should be understood in this context.

Results and Analysis

Based on the data obtained from the companies' business documentation and through the interviews, we subsequently analysed inventory management in the selected bakeries. Using two theoretical models, we identified potential solutions for more efficient inventory management and production planning in both bakeries.

BAKERY 1

Bakery 1 is a small artisanal bakery that engages in both retail and wholesale. The bakery primarily holds stock of materials and raw ingredients, such as various types of flour, yeast, salt, sugar, margarine, and butter. They do not have semi-finished products but do carry some retail goods for sale in their stores. The assortment of finished products is stable in 90% of cases and includes bread, pastries, potica (Slovenian cake), cookies, and homemade noodles.

The bakery strives to manage its raw material inventory efficiently to maintain the freshness and quality of its products. According to them, key factors are the availability and price they can negotiate with suppliers. They try to acquire raw materials with shorter shelf lives on a weekly basis or even twice a week. For flour, they have silos with a capacity of 4.8 tonnes, which allows them to store and purchase larger quantities, resulting in a better price for the flour. White and semi-white flour are ordered every month and a half, while the other ingredients are ordered monthly. For wholesale, there is a regular daily ordering system, which allows for a good estimate of the quantity of products the bakery needs to provide. For retail, the estimate is based on past trends.

Products that are not sold are redistributed for animal feed, with 4% of the total daily production being sold for this purpose. The value of these products, based on the original price, is on average 80% lower. White bread is turned into breadcrumbs.

The bakery operates on average 5 days a week, 50 weeks a year. For both retail and wholesale, they produce an average of 120 loaves of white and semi-white bread and an additional 40 loaves of other types of bread daily. Yeast, sugar, and salt are purchased for all bread types together. On average, they use 120 kg of white and semi-white flour, 160 cubes of yeast (0.04 kg each), 2.6 kg of sugar, and 2.2 kg of salt per day. The procurement costs for new stock are €10 for flour, €14.50 for yeast, €8.36 for sugar, and €12.10 for salt. The supplier covers the delivery costs of all ingredients. Storage and insurance costs are 30% per year for flour, 20% per year for yeast, 19% per year for sugar, and 15% per year for salt. The ingredients are ordered in advance and at fixed intervals, regardless of the current demand for bread. Additionally, the demand for bread in both retail and wholesale is relatively stable. We therefore treated the demand for bread ingredients as stable and independent of fluctuations in the demand for white and semi-white bread, which allowed us to analyse the situation using the EOQ model and calculate the optimal order quantity, total annual procurement costs, and total variable costs:

$$EOQ = Qo = \sqrt{\frac{2 \times RC \times D}{HC}}$$

$$TC = (UC\ x\ D) + \frac{RC \times D}{Q} + \frac{(HC \times Q)}{2} \quad VC = \frac{RC \times D}{Q} + \frac{HC \times Q}{2}.$$

Quantity discounts for purchasing larger quantities of flour, as well as the corresponding holding costs (HC), are shown in Table 1.

The annual consumption of white and semi-white flour in the bakery is 30,000 kg. The bakery currently orders 3,600 kg of flour every 6 weeks. With this quantity, the total costs amount to €9,856 per year. This is not the optimal quantity because, at the optimum, the equality $RC = HC$ must hold. We calculated the optimal quantity using the standard procedure for the model with quantity discounts. The discounts result in a stepped, discontinuous total cost curve. The minimum point of each curve is represented by Qoi. We know that:

$$Qoi = \sqrt{\frac{2 \times RC \times D}{I \times UCi}}$$

For each curve, the minimum is either valid or invalid. It is valid if it falls within the order quantity range at a specific cost per unit, and invalid if it falls outside this range (Bolton 2023). The valid total cost curve always increases to the left of the valid minimum. This means that the valid minimum of the total cost curve must be at or to the right of the minimum at the break-even point. We calculated the EOQ at the lowest price

TABLE 1 Purchase Prices for Flour with Quantity Discounts

Unit cost (UC)		Holding costs (HC)
0–24 kg:	€0.52/kg	0.52 × 0.3 = €0.156
25–99 kg:	€0.46/kg	0.46 × 0.3 = €0.138
100–499 kg:	€0.40/kg	0.40 × 0.3 = €0.12
500–1,999 kg:	€0.36/kg	0.36 × 0.3 = €0.108
2,000–4,999 kg:	€0.32/kg	0.32 × 0.3 = €0.096
5,000–7,499 kg:	€0.29/kg	0.29 × 0.3 = €0.087
7,500–9,999 kg:	€0.27/kg	0.27 × 0.3 = €0.081
10,000 kg:	€0.25/kg	0.25 × 0.3 = €0.075

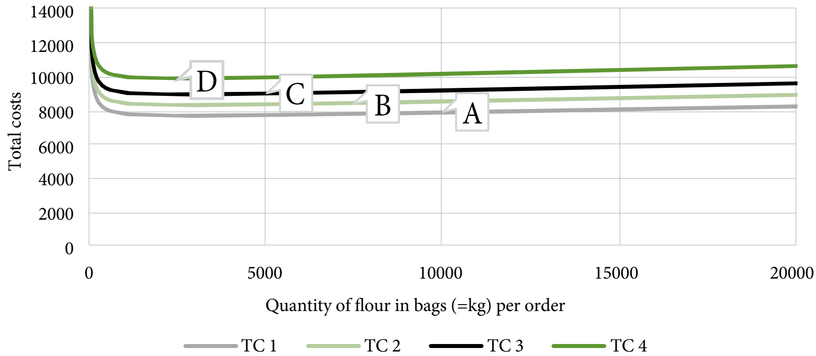

FIGURE 2 Total Cost Curves (in EUR)

per unit, but the calculated quantity was not within the corresponding quantity range. This was an invalid minimum. We then calculated the total annual costs at the break-even point for a quantity of 10,000 kg (point A in Figure 2). Similarly, the minimum of the second (TC 2) and third total cost curve (TC 3) was also invalid. Therefore, we calculated the total costs at the break-even points B and C (see Figure 2). When calculating the EOQ for TC 4, the quantity was within the corresponding quantity range. This was a valid minimum. We then determined the total costs at the valid minimum, obtaining point D (see Figure 2).

In the end, we compared the solutions.

- Point A: Q = 10,000 kg, TC = €7,905 p.a.
- Point B: Q = 7,500 kg, TC = €8,444 p.a.
- Point C: Q = 5,000 kg, TC = €8,978 p.a.
- Point D: Q = 2,500 kg, TC = €9,840 p.a.

While the classic EOQ model assumes a constant unit purchase price, this study introduces all-units quantity discounts for flour. This accurately reflects real supplier pricing and enables cost saving through bulk procurement. To accommodate this, the model evaluates total costs – including ordering, holding and purchasing costs – across discount tiers, selecting the quantity that minimizes overall cost rather than only the EOQ formula output. This increases the model's practical relevance.

The lowest total costs were achieved with an order quantity of 10,000 kg, which is also the optimal order quantity. Therefore, the order would be placed three times a year, which would reduce total annual costs by as much as €1,951. However, such procurement is associated with an expansion of storage capacity for flour, which means higher fixed costs related

TABLE 2 Purchase Prices of Ingredients

Ingredient	Unit cost (EUR)	Holding costs (EUR)
Yeast	1.70 /kg	1.70 x 0.2 = 0.34
Sugar	1.20 /kg	1.20 x 0.19 = 0.228
Salt	0.30 /kg	0.30 x 0.15 = 0.045

to the regular maintenance of silos. While the money would be tied up in stock for a longer period (120 days), this procurement policy would offer the bakery greater bargaining power, a better price per unit, and lower total annual costs. Given that flour has a shelf life of several years when properly stored, and that silos provide controlled storage conditions, such procurement would be suitable because it would not lead to flour waste.

The purchase prices for yeast, sugar, and salt are shown in Table 2.

Yeast is delivered to the bakery once a week, with each delivery being 32 kg. The annual consumption is 1,600 kg. The optimal order quantity is 320 kg. However, yeast is a perishable ingredient with a shelf life of 4 weeks. Purchasing quantities greater than $160 \times 0.04 \times 5 \times 4 = 128$ kg (3,200 yeast cubes) at once would therefore result in significant waste. The further the actual order size is from the optimal one, the higher the variable costs, which means the bakery should strive to place an order as close as possible to 320 kg. In this case, the bakery cannot order more than 128 kg at a time. We compared the variable costs at the optimal order quantity with the variable costs at the 128 kg quantity and found that reducing the order size by 60% increases annual variable costs by €48.96 (or 45%).

$$\frac{VC}{108.8} = \frac{1}{2} \times \left[\frac{320}{128} + \frac{128}{320} \right] = €157.76\ p.a.$$

The annual savings in this case still amount to €527.34.

Currently, the bakery places orders of 46 kg of salt at a time, which costs them €310.69 annually. The annual consumption of salt is 550 kg. Given that the unit cost and, consequently, the holding cost of salt are relatively low, it makes sense to place only one order per year. This would reduce the total annual procurement costs for salt by €128.49. Salt is a long-lasting ingredient. Therefore, from the perspective of quality deterioration or spoilage, this purchasing policy would not pose a problem.

The bakery orders sugar on a monthly basis, which means that they place orders of 55 kg. The annual consumption is 660 kg. This purchasing policy costs the bakery €898.59 annually. The EOQ model suggests an optimal order quantity of 220 kg. This would result in placing orders three times a year, which leads to an annual savings of €56.43.

BAKERY 2

Bakery 2 is a modern artisanal sourdough bakery. Daily, they offer between 20 to 30 bakery products. The biggest challenge in inventory management is determining the optimal stock level for finished products each day. To determine the optimal inventory level, they primarily rely on observing customer purchasing habits. Unsold leftovers, which cannot be sold at a discount the next day, are frozen and reserved for internal use. White and mixed bread are turned into breadcrumbs and used in bread doughs for catering while the rest is used as feed for their chickens. The bread is prepared using a lengthy process that can take up to 24 hours. As they say, making sourdough is a process that does not allow for shortcuts. In the research, we used the Newsvendor model to solve the problem of daily determining the optimal inventory level for finished products, using wholemeal bread as an example. The demand for wholemeal bread is uncertain, and unsold leftovers lose their value after a day. If the bakery prepares too little bread, it results in a loss of sales (opportunity cost). Table 3 shows the predicted and actual daily demand for the ten best-selling products of Bakery 2 on March 13, 2024.

In forecasting demand for the next day, the bakery used the same method for all listed products, i.e. transferring the actual demand data

TABLE 3 A/F Ratio

Product Description	Actual Demand	Forecast	A/F ratio	Rank	Percentile/Rank divided by total number of products (10)
Seasonal bread	4	8	0.50	1	10
Sweetbox	3	5	0.60	2	20
Bread 'Model'	11	16	0.69	3	30
Dark wholemeal bread	42	45	0.93	4	40
Bread Tartin	72	72	1.00	5	50
Baguette	16	15	1.06	6	60
Apple nest	13	12	1.08	7	70
Apricot bun	14	12	1.17	8	80
Cinnamon roll	12	10	1.20	9	90
Bun with chocolate and raspberries	12	9	1.33	10	100

TABLE 4 Discrete Distribution Function for Wholemeal Bread Using Past A/F Ratios.

A/F ratio	Q	F(Q)
0.5	21	0.1
0.6	25	0.2
0.6875	29	0.3
0.9333	39	0.4
1	42	0.5
1.0666	45	0.6
1.0833	46	0.7
1.1666	49	0.8
1.2	50	0.9
1.3333	56	1

from the previous day to the following day. The bakery predicted that the demand for wholemeal bread on March 14, 2024, would be the same as the previous day, i.e. 42 loaves. Upon reviewing past data, we found that the actual demand for several products on March 13, 2024, was either higher or lower than forecast. For all data points, we calculated the *A/F* ratio (*Actual Demand/Forecast*). Using these ratios, we measured the relative forecast errors for all products on March 13, 2024. We assumed that the forecast accuracy for wholemeal bread for the following day would be comparable. Therefore, for each A/F ratio, we could determine the corresponding level of demand (*Actual Demand* = *A/F ratio* × *Forecast*) for wholemeal bread and the probability of such or lower demand occurring (see Table 4).

We obtained a discrete probability distribution, which reflected the bakery's past forecasting accuracy but only predicted a limited number of possible outcomes. As an alternative to this probability distribution, we used a normal distribution. The randomness of actual demand is directly related to the randomness of the A/F ratio, as the forecast itself is not random. Therefore, the following applies:

$$\mu\ (\text{expected actual demand}) = \text{Expected}\ \frac{A}{F}\,\text{ratio}\ \times \text{Forecast}.$$

$$\sigma = \text{std.}\frac{A}{F} \times \text{Forecast}.$$

The standard deviation of our probability distribution was 12, and the mean value was 40.

We also defined the cost of stockouts (*Underage cost/Cu*), which is also the cost of lost opportunity, equal to the profit generated from selling one loaf of wholemeal bread (*selling price -purchase cost*), and the cost of excess inventory (*Overage cost/Co*), which is equal to the loss incurred from selling a loaf of bread at its salvage value (*purchase cost -salvage value*). The following applied to wholemeal bread:

- Selling price = €3.50/loaf.
- Purchase cost = €1.93/loaf.
- Salvage value (-50%) = €1.75/loaf.
- Co = €1.57.
- Cu = €0.18.

The bakery planned to produce *Q* = *42* units of the product. Within the marginal analysis, the question arose whether it should increase the quantity to (*Q* + *1*). The additional unit could potentially bring extra profit if the unit was sold.

$$\begin{aligned} \textit{Expected profit} &= Cu \times P\,(\,demand\ > Q\,) \\ &= Cu \times (1 - P(\,demand \le Q\,) \\ &= Cu\ (\,1 - F(\,Q\,)\,). \end{aligned}$$

$$\begin{aligned} \textit{Expected loss} &= Co\ x\ P(\,demand \le Q\,) \\ &= Co\ x\ F(Q)\,. \end{aligned}$$

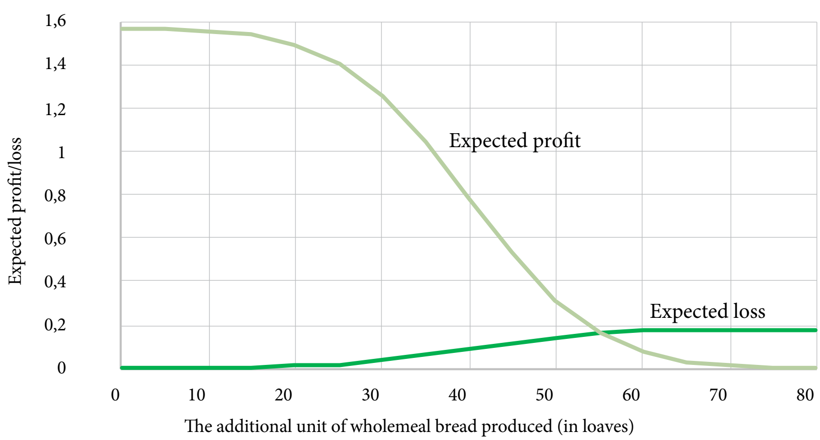

FIGURE 3 Expected Profit and Loss of an Additional Unit of Wholemeal Bread

When the produced quantity of wholemeal bread is very small, the probability of selling the additional unit is very high, $P\,(demand > Q) \cong 1$. Therefore, the expected profit is approximately €1.57. At the same time, the probability of not selling the additional unit approaches 0. As the produced quantity Q increases, the expected profit from the additional unit decreases while the expected loss increases. At a certain quantity, the expected loss exceeds the expected profit, and increasing the quantity Q becomes no longer profitable (see Figure 3).

We wanted to maximize profit at the optimal production quantity where the following holds:

$$Cu\ (1 - F(Q) = Co \times F(Q).$$

$$Cu - CuF(Q) = Co\ F(Q).$$

$$F(Q) = \frac{Cu}{Cu + Co}$$

$$Q = F^{-1}\left(\frac{Cu}{Cu + Co}\right).$$

$$\left(\frac{Cu}{Cu + Co}\right)$$

is called the *critical ratio*. At the optimal quantity Q, the following holds:

$$P\ (demand \leq Q) = \frac{Cu}{Cu + Co}$$

The critical ratio in our case was 0.8971. In the bakery, they would need to produce the quantity Q of wholemeal bread so that the probability that the demand for it is equal to or less than Q is 89.71%. This quantity was obtained using the MS Excel function NORMINV (0.8971,40,12). Alternatively, we could have found the variable z in the table of the standard normal distribution where the probability that the standardized normal variable z is less than or equal to a certain value is equal to the critical ratio. For the calculation, we would use the following formula: $Q = \mu + z\sigma$. We found that the bakery would need to produce $Q = F^{-1}\ (0.8971) = 55.18$ loaves $\cong$ 55 loaves of wholemeal bread on March 14, 2024. Using the loss function, we calculated the lost sales at Q = 55 using the equation *ELS* (*Expected lost sales*)$=\sigma \times L(z)$ where σ is a standard deviation and

$L(z)$ is the loss function. In our case demand was normally distributed, so we used the $L(z)$ table for the calculation. Alternatively, we could also have used the following Excel formula:

$$L(z) = \mathit{Normdist}\,(z,0,1,0) - z \times (1 - \mathit{Normsdist}(z)).$$

The standardized normal variable z, which corresponds to the selected quantity, in our case Q = 55, was calculated using the following formula:

$$z = (Q - \mu)/\sigma = (55.182 - 40)/12 = 1.265$$

$$L(1.265) = \mathit{Normdist}\,(1.265;0;1;0) - 1.265 \times (1 - \mathit{Normsdist}(1.265)) = 0.04902.$$

$$\sigma \times L(z) = 12 \times 0.\,04902 = 0.58824 \cong 1.$$

The expected lost sales were 0.58824, which means that the bakery can expect a loss of 1 unit of demand with the production of 55 loaves. Each unit of demand either results in a sale or represents a lost sale. The expected demand is the mean value of the demand distribution (μ), so the following holds:

$$\mathit{Expected\ sales} = \mu - \mathit{Expected\ lost\ sales}.$$

We estimated the expected sales in the case where the bakery produces 55 loaves of wholemeal bread, and the demand forecast follows a normal distribution. In this case, the expected lost sales amounted to 1 unit, and the expected sales were 40 − 1 = 39 units.

The expected leftover inventory is the average of all the values that the remaining stock can take. Each loaf of bread produced can either be sold or remain at the end of the day. Therefore, the following equation holds:

$$\mathit{Expected\ sales} + \mathit{Expected\ leftover\ inventory} = Q.$$

If the demand forecast is normally distributed and 55 loaves of bread are produced, the expected remaining stock is 55-39=16 units.

For each unit sold, the bakery earns the difference between theselling price and the purchase cost. For each unit that is not sold, it loses the difference between the purchase cost and the salvage value. The expected profit is calculated using the following formula:

$$Expected\ profit = \begin{bmatrix} (Selling\ price - purchase\ cost) \\ \times Expected\ sales \end{bmatrix} - \begin{bmatrix} (Purchase\ cost - Salvage\ value) \\ \times Expected\ leftover\ inventory \end{bmatrix}.$$

If the demand forecast is normally distributed and 55 loaves of wholemeal bread are produced, the expected profit is maximized and amounts to (1.57 × x 39) – (0.18 × 16)=€58.35.

SENSITIVITY ANALYSIS

To evaluate the robustness of inventory decisions, we conducted a sensitivity analysis on both the Economic Order Quantity (EOQ) and Newsvendor models. This analysis helps to understand how variations in key parameters affect overall performance and cost. The EOQ Model was tested under several conditions, including increased demand and higher holding costs. In the base case (yeast demand), the EOQ was 369.42 kg, leading to a total annual cost of 2,845.60€. When demand increased by 10%, the EOQ rose to 387.45 kg, with an associated annual cost of 3,124€. Conversely, when holding costs increased by 15%, the EOQ slightly decreased to 361.3 kg, while the annual cost rose marginally to 2,854.85€. These results (for yeast, salt and sugar) highlight that EOQ is sensitive to both demand and holding costs, though the total cost impact remains moderate, suggesting the model's relative stability in practical applications.

For the Newsvendor model, we evaluated performance across similar demand scenarios. In the base case, with a bake quantity of 45 loaves, expected sales were approximately 36.95 loaves, resulting in 3.05 loaves of lost sales and 8.05 loaves in leftover inventory. This yielded an expected

TABLE 5 EOQ Model Sensitivity Analysis

Scenario	EOQ (kg)	Total Annual Cost (€)
Base case - YEAST	369.42	2,845.60
Demand +10%	387.45	3,124.00
Holding costs +15%	361.29	2,854.85
Base case - SALT	550.00	189.20
Demand +10%	576.84	206.88
Holding costs +15%	537.91	190.98
Base case - SUGAR	220.00	842.16
Demand +10%	230.74	923.80
Holding costs +15%	215.16	845.85

TABLE 6 Sensitivity of Expected Profit to Quantity Baked (Newsvendor model)

Quantity baked (in loaves)	Exp. sales	Exp. lost sales	Exp. leftover inv.	Exp. profit (EUR)
45	36.95	3.05	8.05	56.56
55	39.41	0.59	15.59	59.07
60	39.76	0.24	20.24	58.78

TABLE 7 Effect of Demand Mean Variation on Optimal Production (Newsvendor model)

Scenario	Mean	Std. dev.	Optimal Q
Base case	40	12	55
Higher demand	45	12	60
Lower demand	35	12	50

TABLE 8 Impact of Demand Variability on Inventory Decisions (Newsvendor model)

Scenario	Mean	Std. dev.	Optimal Q
Base case	40	12	55
Higher demand	40	15	59
Lower demand	40	10	53

profit of €56.56. Increasing demand to an optimal 55 loaves improved sales to 39.41 and profit to €59.07, with slightly more leftovers. A further increase in baked quantity to 60 loaves maintained high sales (39.76) but also increased leftovers (20.24), slightly reducing profit to €58.78 (see Table 6). Similarly, increasing demand variability while keeping the standard deviation constant (see Table 7), or increasing the standard deviation while holding the demand mean constant (see Table 8), both led to higher production quantities – in the first case due to increased demand, and in the second due to greater uncertainty.

Overall, the sensitivity analysis confirms that both models react predictably to parameter changes, reinforcing their usefulness for inventory planning.

Conclusion and Policy Implications

Below are the key findings based on the analysis of relevant literature and the conducted research.

In connection with the first goal, we find that Bakery 1 primarily faces the issue of managing the stock turnover of raw materials while Bakery 2 struggles with determining the optimal stock quantities of finished products daily.

In connection with the second goal of the research, we find that Bakery 1 prepares the demand forecast based on past trends. Similarly, Bakery 2 places a strong emphasis on observing consumer purchasing habits when forecasting demand. In both bakeries, we highlight the lack of systematic recording of actual daily demand, demand forecasts, and forecast errors, which serve to estimate the standard deviation of demand. Bakery management should not forget that, due to a lack of stock, actual demand may exceed actual sales. In cases where it is not possible to monitor actual demand after stock shortages occur, it is necessary to estimate actual demand reasonably. In the case of Bakery 2, we found that the data on actual demand for an item should not simply be transferred and used as a forecast for the following day. We also need a forecast of how demand will vary around the forecast. The uncertainty is captured by the standard deviation of demand. While it is impossible to align supply and demand fully, since the quantity of bread to be offered must be decided well before the start of sales and demand is uncertain, it is possible to make a decision that balances the cost of overproduction and the cost of insufficient production. Uncertainty should not lead to ad hoc decision-making.

In connection with the third goal, we find that surpluses occur daily. The products that Bakery 1 cannot sell are redistributed for animal feed while Bakery 2 freezes them for internal use, and the surplus is used as feed for domestic chickens. White bread in both bakeries is ground into breadcrumbs, and Bakery 2 also uses white and mixed bread for breadcrumbs which are included in catering and thus add value to the bread.

In connection with the final goal, we highlighted the usefulness of the EOQ and Newsvendor models in solving the problems identified by the bakeries during the interview. In Bakery 1, perishable ingredients are purchased 1–2 times a week, and white and whole-wheat flour every month and a half, while other ingredients are purchased monthly. Based on our research and the application of the EOQ model, we would recommend to the bakery management to order dry ingredients – flour, salt, and sugar – less frequently but in larger quantities than they currently do, because this is much more cost-effective for the bakery, and due to the long shelf life of the ingredients, it does not result in waste. The bakery would, thus, place flour orders of 10,000 kg, which is associated with expanding storage capacity, salt orders of 550 kg, and sugar orders of 220 kg. The situation is different for yeast, where the EOQ model predicts a larger purchase quantity than they currently order. However, this would lead to significant waste due to the shorter shelf life of yeast. To avoid waste and minimize annual procurement costs, it makes sense to purchase exactly 128 kg (no more and no less) of yeast at a time. By implementing optimal procurement of white and whole-wheat flour for bread, the bakery would save as much as €1,951 (18.35% compared to the previous state), and by purchasing yeast, sugar, and salt for all types of bread, they would save €712.26 (about 15% compared to the previous state) annually. Based on the results of our research, *we can confirm H1* that Bakery 1 could reduce total annual procurement costs by more than 15% through more efficient inventory management without causing spoilage or waste of raw materials.

These outcomes align closely with findings in prior studies. For example, Wardana et al. (2025), in a case study of Chopfee Coffee Shop, reported a 71.7% inventory cost reduction following the implementation of EOQ for coffee beans and sugar. While the magnitude of cost savings in our study is smaller, the application is similarly effective, particularly considering the more modest scale and input variability of the bakery studied here. Similarly, Mulyana and Zuliana (2019) applied EOQ in a small-medium enterprise Ananda Bakery and observed improved inventory control and reduced stockouts. As in that study, our EOQ approach includes a focus on raw material ordering consistency and annual cost reduction, although safety stock was not incorporated due to relatively stable demand in Bakery 1.

In the case of Bakery 2, we found that the quantity produced, which maximizes profit, is usually not equal to the expected demand. If the cost of stockouts is greater than the cost of excess inventory, as is the case with wholemeal bread, the quantity that maximizes profit is greater than the expected demand. The critical ratio is, in fact, greater than 0.5. A loaf that remains costs the bakery much less than not having a loaf available if there is demand for it. Although the goal of our research was to minimize the mismatch between supply and demand in the case of wholemeal bread and thus minimize bread waste, the model suggests that explicit costs should not outweigh opportunity costs if the bakery wants to maximize profit. The remaining inventory at the end of the day is actual, while lost sales are an opportunity cost of the mismatch between supply and demand. Focusing on minimizing explicit costs in Bakery 2 results in producing less wholemeal bread than they should to maximize profit. To maximize profit, they should have produced 55 loaves of wholemeal bread on the selected day, March 14th, which is 13 more loaves than they actually produced that day.

This insight closely mirrors the findings of de Muinck Keizer et al. (2024), where a stochastic Newsvendor model was used to optimize stocking strategy for cakes in small bakeries under demand uncertainty. Their model extended the classic Newsvendor framework by accounting for customer substitution behaviour and demand forecasting. While our approach did not include substitution effects, it reinforced the importance of accounting for lost sales and missed profit opportunities due to conservative production estimates. If the bakery aims to achieve the goal of maximizing profit while also minimizing waste, it must effectively manage the expected remaining bread stock, which in this case is relatively high due to the reasons mentioned before. For products that are intended for animal feed, where the salvage value is much lower (80–90% lower than the selling price) and the inequality Co > Cu holds, the Newsvendor model suggests producing a smaller quantity of the product than the expected demand, which leads to a smaller expected remaining stock and waste. We *can also confirm H2* that the goal of minimizing food waste in Bakery 2 is not necessarily compatible with the goal of maximizing profit.

Understanding and applying the EOQ and Newsvendor models, together with practices that create added value (e.g. circular economy), could enable the management of these and other similar companies to better plan production and procurement, both in terms of cost management and subsequent profit maximization, as well as minimizing waste. Although the study was conducted in only two small Slovenian bakeries, the findings can be applied to other bakeries in several meaningful ways. The core inventory management challenges – such as unpredictable demand, limited storage, and the perishability of products – are common to many bakeries, regardless of size. The models used in this research (EOQ and Newsvendor) are flexible and can be adapted to any bakery that has access to basic operational data like daily demand, production costs, and spoilage rates. Other bakeries can apply the same methodology by collecting similar input data and using the models to optimize their ordering and production decisions. While exact figures may differ depending on bakery size, product range, or supplier relationships, the approach provides a practical decision-making framework that improves efficiency and reduces waste. In this way, the results may serve as a guide for other bakeries aiming to improve inventory practices, especially those with similar characteristics to the case bakeries.

In practice the application of the Newsvendor model and EOQ model can be time-consuming and challenging for small bakery owners, especially due to the need for accurate demand forecasting and probabilistic analysis. Without access to advanced tools or technical expertise, manually calculating optimal order quantities may be impractical. However, user-friendly software or mobile apps tailored for small businesses could simplify this process. By integrating sales history, local demand patterns, and built-in statistical tools, such applications can automate the Newsvendor and EOQ logic and provide real-time information on either the optimal order quantity of raw materials or the optimal quantity of the final product to be produced – helping bakery owners make smarter daily production decisions with minimal effort.

Based on our study, the following actionable recommendations are proposed for practitioners and policymakers. Data-driven inventory planning should be implemented through the use of historical sales data to estimate demand. EOQ should be applied for stable inputs, while the Newsvendor model should be used for perishable goods with uncertain demand. Production should be adjusted dynamically based on demand trends through monitoring demand shifts and use of updated demand estimates to recalculate Newsvendor quantities weekly or even daily. Quantity discounts should be applied strategically. When purchasing large quantities to benefit from price reductions, they should evaluate holding costs carefully to avoid unnecessary waste. Digital tools for forecasting might also be introduced. Practitioners might adopt simple forecasting software integrated with sales data to make EOQ and Newsvendor decisions semi-automated and user-friendly for non-specialists.

In addition to operational improvements at the bakery level, broader support from policymakers and local authorities is essential to scale the benefits of inventory optimization and food waste reduction across the sector. They can support training programmes on inventory optimization, offer tax benefits or grants to bakeries that adopt quantifiable food waste reduction strategies, or encourage bakeries to track and share food waste metrics, creating benchmarks and best practices within the local food ecosystem.

Besides optimal inventory management, further studies on how bakeries can reduce waste might focus also on other potential waste reduction strategies like circular economy principles integration such as repurposing unsold products into new offerings or partnering with local farms for composting organic waste. Dynamic pricing models could be implemented to discount items nearing the end of their freshness window, encouraging timely sales. Donation programmes to local shelters or food banks can help reduce surplus without loss. Additionally, using real-time sales tracking to adjust production dynamically, and adopting smaller batch baking practices throughout the day (just-in-time baking), can help minimize overproduction. Finally, investing in employee training on portion control, storage techniques, and efficient ingredient usage can also significantly cut down on internal waste.

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Opportunities for Indian Women in Gig Jobs without Using Digital Platforms: The Importance of Vocational Training

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Flexible working hours can provide a better option for Indian women entering the workforce. This can be accomplished by engaging in gig jobs without depending on a digital platform, as many individuals have limited access to technology. Casual labourers and self-employed workers are considered gig workers who can perform their jobs without utilising digital platforms. The Probit model identifies the factors that can enhance the likelihood of such gig jobs occurring without the use of a digital platform for Indian women. By employing a Bivariate Probit regression model based on Periodic Labour Force Survey data for 2022–23 and addressing endogeneity, the paper demonstrates that both formal and informal vocational training positively influence women's participation in gig jobs without relying on any digital platform. However, the impact of informal training is more pronounced.

Keywords: gig job, own-account worker, casual wage labourer, unpaid household job, formal vocational training, bivariate probit regression
JEL *Classifications:* C51, C87, J44, J78, R20

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Introduction

The participation rate of the female labour force is low compared to that of their male counterparts. Globally, the labour force participation rate for men is 72%, while for women it is only 47% (International Labour Organization 2022). India is no exception in this regard. The Periodic Labour Force Survey (PLFS) of 2022–23 (National Sample Survey Office 2023) has revealed that the overall male labour force participation rate in India stands at 78.5%. In contrast, it is merely 22% for females (aged 15 and above). The reasons behind this low female labour force participation rate in India include the dilemma between fulfilling household duties and contributing to family income (Kapsos et al. 2014), maternity and childcare (Sudarshan and Bhattacharya 2009), migration due to marriage (Premi 1980), lack of high-level skills, and various cultural and socio-economic factors. These constitute supply-side factors, whereas demand-side factors involve several institutional norms for women, labour market regulations, and gender-specific jobs for male candidates, among others. Occasionally, the jobs preferred by educated women are in shorter supply compared to those sought by educated male job seekers. Consequently, many women withdraw from the labour force (Klasen and Pieters 2015).

The fifth goal of the 17 Sustainable Development Goals within the 2030 Agenda is to achieve 'gender equality'. Women's empowerment is a crucial aspect of this (UN Women 2018). However, women's economic empowerment is not confined to their participation in the labour market; it also encompasses their role in the household economy. Traditionally, it has been believed that only women are responsible for the unpaid household task of nurturing the family. This also encompasses domestic chores and all forms of care work, including caring for elderly individuals, children, and sick household members (Sengupta 2016). Household work, being unpaid, is not recognised as an economic activity. Consequently, such work is not reflected in national statistics. In contrast, domestic duties performed by a domestic worker in exchange for cash or in-kind benefits are considered economic activities, and an appropriate activity status code has been assigned to them (National Sample Survey Office 2014). Setting aside those supply and demand factors, women in India are 'time-poor' due to the burden of unpaid household and care work. 'Time Poverty is the shortage of time available to devote to purely personal requirements, including leisure and relational activities' (Ghosh 2016, 1). It is challenging for working women to balance their professional and household responsibilities. Therefore, a gig job can be more suitable for them due to its flexible work arrangements. Gig workers can establish their schedules and flexible working hours to supplement their income for themselves and their families (DoorDash 2021).

The primary motivation for this study is grounded in the facts presented by the report *India's Booming Gig and Platform Economy* (National Institution for Transforming India, NITI Ayog, 2022). The report indicates that gig jobs will represent approximately 4.1% of the Indian workforce by 2030. 'Gig job' is generally defined as 'on-demand labour services and precarious jobs', where a job is an actual task that needs to be done. According to the International Labour Organisation (International Labour Organization 2011), a 'precarious job is defined by uncertainty regarding the tenure of employment, an ambiguous employer-employee relationship, a lack of access to social security benefits, low pay, and legal and practical obstacles to joining a union and bargaining collectively.' The report further explains that gig jobs are performed on a short-term, task-based (specific assignment or duty) basis, often (though not always) facilitated by a digital platform, where workers are not traditional employees but independent contractors or service providers.

The Government of India introduced the Social Security Code in 2020, which recognised the gig job for the first time in the Indian labour market. This law defines a gig job holder as an individual engaged in income-generating activities outside the traditional employer-employee relationship (Ministry of Law and Justice, 2020, 8, Section 1(35). However, this law does not specify whether a gig job will always be digital platform-based, and provides a separate definition of platform workers who use an online platform (Ministry of Law and Justice 2020, 10, Section 1(60 and 61)). Furthermore, gig job holders frequently participate in both offline and online modes. For instance, a platform taxi driver may sometimes also provide rides offline when there is low online demand or when the platform assigns fewer tasks (Arya 2023).

Examining the composition of the Indian labour force in 2019–20 reveals that 86% of urban informal workers were deprived of social security benefits, while the remaining 14% were formal jobholders (Roy and Kundu 2023). The Periodic Labour Force Survey (2021–22) data show that about 35% of the informal labour force are own-account workers, and 23% are casual workers. In both types of jobs, there is no traditional employer-employee relationship. In the National Institution for Transforming India (2022), these workers are categorised as non-platform gig workers as they do not require any online platform for their work. Thus, these two types of workers can be identified as gig workers, but they are not termed as platform workers (Gupta 2023, 20–21). On the other hand, online platforms generally offer hyperlocal jobs related to driving and delivery. Consequently, these roles require access to the internet and smartphones, which many women find challenging in a male-dominated society like India. According to the Mobile Gender Gap Report (Global System for Mobile Communications Association 2024), only 37% of women in India are mobile internet users, resulting in a gender gap of approximately 30% in mobile internet adoption. Many women lack access to two-wheeler vehicles, which are typically advantageous for delivery purposes. The most pressing concern is the safety of women platform workers. They often fear for their security, especially in the evening when the demand for work or assignments is high. In many instances, they are also denied social security benefits from the platforms to which they are connected. Most surveys on gig job holders in India indicate a minimal presence of female workers in platform-based gig jobs. In a study on food delivery platform work conducted by the National Council of Applied Economic Research (National Council of Applied Economic Research 2023), 99% of the 924 respondents are male workers across 28 major cities in India. Most women engage in female-centric jobs, even on these platforms, such as cleaning and caretaking (Hunt and Samman 2019). They are also involved in beauty and wellness but are marginalised in the delivery and ride-hailing sectors of the gig economy (Chaudhary 2021). However, jobs in the beauty industry accounted for only 1.17% of the total jobs created in 2019 (BetterPlace 2019). Furthermore, according to the TeamLease EdTech (n.d.) study, female delivery partners earn 8–10% less per month than their male counterparts in India, highlighting the presence of the gender wage gap. Considering these factors, it can be concluded that a gig job that does not utilise online platforms could be a suitable job opportunity for Indian women.

Setting those matters aside, a question arises concerning the role of skill acquisition in women's participation in the job market. In today's world, skill acquisition is crucial for securing employment. In this context, the classic theoretical model by Galor and Zeira (1993) discusses the investment in human capital and an individual's decisions regarding skill formation. However, skills can be developed in various ways. One significant method is through vocational training. Vocational training can take both formal and informal forms. Workers in India with formal vocational training earn higher wages than those without such training (Bahl et al. 2021). Informal vocational training has been academically overlooked and is chosen by those who are educationally disadvantaged and lack economic capital (Bazaz and Akram 2022). Despite this, informal training equips a large segment of the workforce in the informal sector with valuable skills. Budget 2024–25 (Ministry of Finance 2024) considers 'Employment and Skilling' one of the priorities for Viksit Bharat (Developed India – a visionary initiative by the Government of India), with over 2 million youth set to be skilled over five years under the Skilling Programme.

Against this backdrop, the paper aims to investigate the possible factors that lead a woman (18–45 years) to choose a gig job as a livelihood without using any digital platform. The investigation will utilise PLFS data for 2022–23 (National Sample Survey Office 2023). In addition to other demographic and socio-economic factors, the paper will also examine whether vocational (both formal and informal) training plays a significant role in enhancing the participation of women in gig jobs that do not rely on digital platforms for operation.

The study is organised as follows: the next section summarises the literature review on female labour force participation, gig jobs, and the importance of vocational training. This is followed by a description of the data and the methodology used. The results section discusses the significance of formal and informal vocational training concerning women's participation in gig jobs without using online platforms. Finally, concluding remarks, along with policy recommendations, are presented.

A Brief Review of the Literature

It has already been mentioned that female labour force participation in India is markedly lower than that of males. Most women in India are compelled to undertake unpaid domestic jobs due to patriarchal societal norms, which dictate that women are solely responsible for household chores (Kabeer 2012). The burden of unpaid domestic work is significantly higher in the Eastern and Northern states compared to the Southern states (Mukherjee and Majumder 2015). The findings further suggest that faster economic growth, higher market wages, and improved education can reduce the proportion of unpaid work. Less educated women and those from society's lower wealth quintile tend to engage in unpaid domestic labour (Singh and Pattanaik 2020). However, the relationship between the female labour force participation rate (FLFPR) and monthly per capita consumption expenditure (MPCE) deciles is not U-shaped; instead, it is negative. Even women who are primarily graduates and belong to the higher-income class exhibit lower LFPR, illustrating the dominance of the income effect over education (Chattopadhyay and Chowdhury 2022). Both men and women are more likely to exit the labour market if they come from households with better economic conditions over the past decade, with this effect being more pronounced for women (Chattopadhyay et al. 2023). Women in India are 12 to 23 percentage points less likely to take up a suitable job if they face a one-hour commute. They predominantly seek part-time, flexible roles close to home (Chatterjee and Sircar 2021). Conversely, Rey et al. (2021) have confirmed an inverted U-shaped relationship between the duration of maternity leave and female labour force participation, with a maternity leave threshold of around 30 weeks, beyond which female participation declines. Nonetheless, an increase in maternity leave results in higher female participation below this threshold. In contrast, according to National Institution for Transforming India (2022), women are more inclined to engage in gig jobs after their education and marriage. This is indeed a positive finding, as the macroeconomic trend indicates that married Indian women withdraw from the labour force due to caregiving responsibilities and to facilitate the family's upward social mobility.

In this context, some existing literature on female gig workers will be discussed. Kasliwal (2020) addresses the flexibility provided by gig platforms. The paper also offers suggestions to ensure social security benefits, as well as digital and physical safety for female gig workers. Similarly, women with young children prefer platform jobs due to their flexibility and attractive earning potential. However, it can be difficult for digitally illiterate women to participate in platform work (Institute for Financial Management and Research 2020). Female teachers (especially in the age group of 30-35 years) had fewer working hours than men across all age categories at Skyneg, the largest online English language learning school in Eastern Europe (Dokuka et al. 2022). The findings also indicate that women work less in the evenings within the gig economy. Signes (2017) examines whether those engaged in the gig economy are considered employees or self-employed and provides suggestions for new special labour regulations. Companies that connect customers directly with individual service providers conduct their business through workers they refer to as self-employed. Moreover, female employment has increased across all job categories: self-employed (34%), casual labourer (38%), salaried temporary job (39%), and permanent salaried job (26%) in urban areas during the unlock period of the pandemic. Additionally, the rise in casual labour for women is significantly higher in rural areas (Bansal and Mahajan 2023).

The paper by Hyland et al. (2020) has shown the global picture of gender discrimination by the law. Using the World Bank data, they find positive correlations between more equal laws concerning women in the workforce and more equal labour outcomes. Occupational gender segregation exists in Slovenia, and females are in a better position concerning occupational segregation (Kovac et al. 2009). Field et al. (2021) explore how increasing control over earnings incentivises a woman to work in rural India. Women with paid, inflexible job have significantly better mental health than those who do unpaid household job only (Wang and Lu 2023).

Some studies examine whether vocational training enhances female labour force participation. Women at all education levels who have vocational training are more likely to be part of the workforce than those without such training (Fletcher et al. 2017). Kumar et al. (2019) reveal that formal vocational training is associated with higher wages, with the most substantial effect observed in the primary sector. Access to formal vocational training among youth is concentrated in the higher expenditure quintile and among those with advanced education levels. Unfortunately, young people from underprivileged backgrounds struggle to access formal vocational training. Although males dominate informal training uptake, women are more likely to pursue formal training. Therefore, to serve as a policy instrument for skilling women, their access to formal training needs to be expanded (Endow and Dhote 2024).

Moreover, the COVID-19 pandemic has accelerated the trend of shifting from full-time employment to gig work. Boston Consulting Group (2020) estimated that the number of gig economy jobs is about 8 million in India. This could increase to about 90 million jobs in the non-farm sector in the next 8 to 10 years. Therefore, it can be said that the gig job is the future. On the other hand, the Indian government also adopted the Skilling India Initiative to skill the workforce through vocational training courses. The scheme highlights the provisions for female workers, such as building new institutes specially for women, increasing female trainers, flexible training hours, etc.

From the existing literature, it is evident that none of the literature focuses on the relevance of gig jobs for women who are not using any digital platform as a possible opportunity for job creation. However, the paper considers this, acknowledging the challenges of platform jobs faced by Indian women. The present study also explores whether one possible way to increase the participation of women in gig jobs without using platforms is through enhancing their skills, which can be achieved with the help of vocational training. Most of the literature treats formal vocational training as an exogenous covariate. The present paper treats it as an endogenous variable because women's participation in such training depends on their household's monthly consumer expenditures, which is used as a proxy for household income.

Against this backdrop, there are some research questions:

(1) *What factors might influence Indian women to choose gig jobs without relying on a digital platform, rather than solely engaging in unpaid domestic duties? Does the educational qualification of women play any significant role in opting for such a gig job?*

(2) *It is also necessary to investigate whether females require skills to engage in such gig jobs. In this regard, does vocational training (both formal and informal) play any role in the involvement of women in gig jobs in India, particularly for those who lack access to any digital platform?*

Data and Methodology

DATA

To address the aforementioned research objective, this investigation utilised unit-level data from the Periodic Labour Force Survey (PLFS) report for 2022–23 (National Sample Survey Office 2023). The primary aim of the PLFS is to provide detailed insights into employment and unemployment indicators in India, as well as information on various demographic and socioeconomic factors affecting individuals. The PLFS data encompasses four quarters, spanning from July 2022 to June 2023. In urban areas, a rotational panel sampling design has been implemented, while a cross-sectional survey is used in rural areas. Workers from both rural and urban regions have been included. Data from visit 1 of all four quarters of the PLFS, 2022–23, have been extracted to prevent the repetition of the same households in the sample. The Usual Principal Activity Status is employed here to estimate individuals' employment and unemployment status.

The PLFS data categorises workers' employment status in India into three broad categories: (i) self-employed workers, (ii) casual wage labourers, and (iii) regular wage/salaried employees. However, self-employed workers are further divided into three subcategories: (a) own-account workers, (b) employers, and (c) unpaid helpers in household enterprises.

Therefore, to address the research objectives, it is crucial to know the definition of the following workers:

- *Own-account workers* manage their enterprises independently or with one or a few partners, without hiring labour during the entire reference period. They may have unpaid helpers to assist them. They have autonomy and economic independence in their job. Being the sole owner of their enterprises, they do not make avail of social security benefits like provident funds, gratuity, etc., and do not have a traditional employment relationship with another person or entity.[1] They may enter into contracts with their customers, but not typical employment contracts on a personal basis. They do not receive any fixed salary from an employer but earn income based on the services they render or the products they sell. Some other examples of own-account workers are plumbers, electricians, beauticians, tailors, etc.
- *Casual Wage Labourers* are workers engaged in others' farm or non-farm enterprises (both household and non-household) and receive in return wages according to the terms of a daily or periodic job contract. They are generally employed daily for specific tasks in an establishment. Even so, they do not have a regular employer-employee relationship with the establishment concerned and have no job security. Though they enjoy some benefits, such as health care, casual labourers in the informal sector are deprived of drawing social security benefits like the provident fund. For example: construction workers, farm labourers, factory workers, etc.

Here, *Unpaid female household caregivers* are considered the reference category in this paper.[2] According to the *Female Labour Utilisation in India Report* (Ministry of Labour and Employment 2023), about 44.5% of women in India are not included in the labour force because of 'child care/personal commitments in homemaking', 3.4% because of social reasons, and 33.6% of women want to pursue their studies.

In this investigation, informal female gig workers who do not use online platforms have been captured. Therefore, individuals who receive social security benefits, like provident funds and gratuity, are excluded from the dataset. The literature suggests that most gig workers belong to the age group of 18–45 years.[3] Hence, the sample has been restricted to only that working age group of women for this analysis. Following the definition of gig workers who do not use platforms, the data on individuals who belong to the status codes[4] of own-account workers (PLFS code-11), casual labourers in 'public works'[5] other than MGNREGA (code-41) and casual labourers in 'other types of works' (code-51) have been extracted from the existing dataset. Moreover, to represent the unpaid female domestic caregivers, the data on individuals who are engaged in 'domestic duties only' (code-92) and 'attended domestic duties along with a free collection of goods (vegetables, roots, firewood, cattle feed, etc.), sewing, tailoring, weaving, etc. for household use' (code-93) have also been extracted.

The unpaid helpers in household enterprises and employers in the self-employed category are not considered here because they do not receive regular wages in return for the work performed. They do not run their household enterprise but assist the related person living in the same household in running the household enterprise. However, the employers work on their own by hiring labour. So, there is a possibility of having an employer-employee relationship in that case, which does not satisfy the definition of a gig job. The rest of the status codes are excluded from the analysis because individuals assigned with these codes are either unemployed or not included in the labour force, other than women engaged in domestic duties. So, the extracted dataset is ready to serve the research objective.

DESCRIPTION OF THE SAMPLE AND ITS DESCRIPTIVE STATISTICS

This section focuses on the description of the sample and information regarding the participation of women in gig jobs without using any digital platform based on their educational qualifications and vocational training, with the help of descriptive statistics. The paper considers a sample of 109,122 individuals, constituting 82.79% of the females who perform domestic duties, and 17.21% who are gig workers (who do not use an online platform for work) in the traditional informal sector. About 64.7% of females reside in urban areas, and 35.3% are from rural areas. Nearly 26.67% of rural females have entered the workforce as gig workers, whereas this figure is only 12.04% for urban females. For young females aged 18–25 years, only 8.92% engage in a gig job without using a digital platform, whereas the number is about 18.91% for females aged 26–45 years. The sample consists of about 72.08% of females who belong to the Hindu community, and 18.38%, and 9.54% of the individuals who belong to the Muslim and other communities, respectively. However, only 17.41% and 9.81% of Hindu and Muslim females, respectively, engage in such gig jobs, and the remaining women manage their unpaid domestic duties, i.e. they are not in the labour force. Moreover, it is evident from the data that females from SC (Scheduled Castes) and ST (Scheduled Tribes) (combined 40.25%) and OBC (Other Backward Classes) (40.5%) communities are more interested in gig jobs. In contrast, only 19.25 % of females from the 'General' category are willing to pick up such jobs, and most prefer to engage in unpaid domestic responsibilities.

Education is one of the key determinants of employment; therefore, we shall examine whether in India, there exists any association between various levels of education and the participation of women in gig jobs which do not require an online platform to function. From Figure 1, it is quite surprising that at lower levels of education, the participation of women in such a gig job is much higher. Specifically, most females who have completed their graduation and post-graduation studies prefer to remain at home instead of joining the labour force. This may occur due to a lack of suitable employment opportunities or income and substitution effects.

Moreover, as women's education increases, the possibility of being employed also increases for salaried jobs, whereas an increase in education results in a decrease in women's labour force participation rate in the case of casual wage labour and jobs on family farms and in businesses.

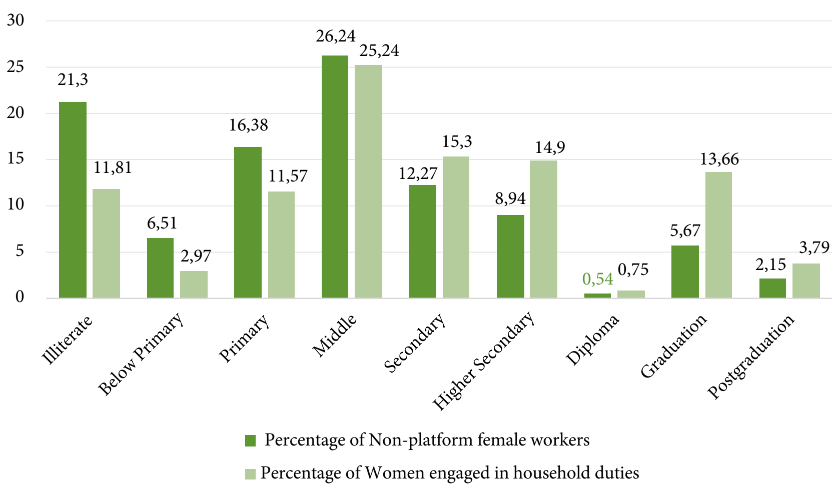

FIGURE 1 Educational Qualifications of Female Workers Working without Using Any Digital Platform and Women Engaged in Household Duties (15-45 years) (in %)

SOURCE Estimated by the authors using PLFS 2022–23 data

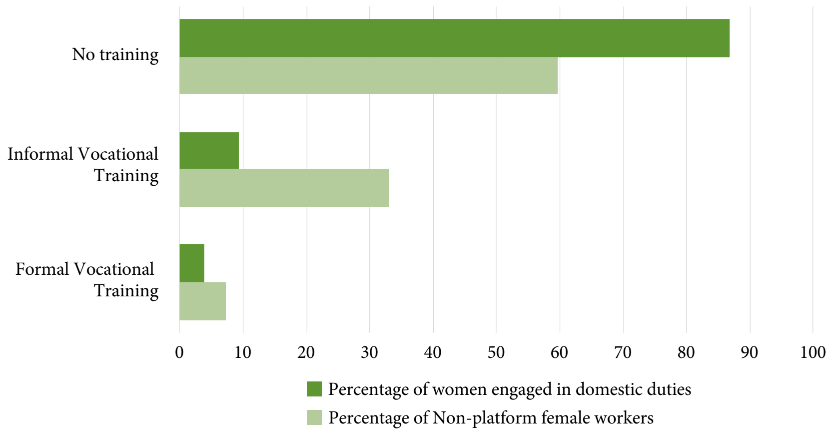

FIGURE 2 Formal and Informal Vocational Training Among Female Workers Working without Using Any Digital Platform and Women Who Engage in Domestic Duties

SOURCE Authors' Estimation using PLFS (2022–23) data.

Women do not engage in manual labour if they receive moderate levels of education (Chatterjee et al. 2018).

Next, we shall explore the relationship between women's participation in gig jobs without using a digital platform and their formal and informal vocational training statuses. In this context, Figure 2 clearly shows that women who have participated in formal and informal vocational training have a much higher participation rate in such gig jobs than those who do not have any vocational training.

The paper will discuss whether females, as the head of their families, take up the job of gig workers to run their families, or engage in such a job as spouses of the head of their families, to augment family income (shown in Table 1).

TABLE 1 Percentage of Female Workers (working without using any digital platform) Based on Their Relation to the Head of the Family

Relation to Head	Percentage of female non-platform workers	Percentage of females who engage in domestic duties
Self (if the concerned woman is the head of the family)	13.39	2.56
Spouse of the head	62.09	58.10
Others	24.52	39.34
Total	100	100

SOURCE Authors' calculation using PLFS (2022–23)

It is observed from Table 1 that 13.39% of female workers who engage in gig jobs are the head of their families, and 62.09% of them are the spouses of their families' heads. However, females who engage in household duties are more likely to be the spouses of the head or other household members. A minimal percentage (2.56%) of females prefer unpaid household duties over participation in the job market, being the head of the family.

METHODOLOGY

According to India's legal system, the terms 'employee' and 'worker' have different legal meanings. The former refers to the organised sector, while the latter pertains to the unorganised sector. Gig workers are a subset of unorganised workers (Gupta 2023). According to PLFS data for 2022–23, 30.7% of working women are own-account workers, and 36.7% serve as unpaid helpers in family businesses in India. Furthermore, 16.7% of women engage in casual labour, whereas only 15.9% hold regular salaried jobs. The female labour force participation rate is higher in rural areas compared to urban ones in India; however, most women in rural regions are involved in low-paying, unpaid family and own-account jobs, whereas urban areas predominantly offer higher-paying, regular salaried roles (Fernandez and Puri 2023). It is important to note that most formal, regular salaried jobs require skilled and specialised workers, yet the majority of Indian women are low-skilled (Kumar 2022). However, individuals aged 18–40 working in precarious jobs in Slovenia report low satisfaction, including increased incidences of depression, anxiety, and emotional exhaustion symptoms (Umicevic et al. 2021).

Given the nature of gig jobs, this paper discusses the importance of vocational training for Indian women, particularly those aged 18 to 45, as they consider gig jobs that do not require digital platforms instead of remaining unpaid household caregivers. This shift allows them to contribute to their family's income while fulfilling their household responsibilities. A simple probit model (Section 4) has been employed to identify the factors that encourage women to participate in gig work, focusing on the role of education as the first research objective. Additionally, a bivariate probit model (Section 5) has been utilised to examine the influence of formal and informal vocational training on women's engagement in gig jobs.

TABLE 2 Description of the Variables Used in Various Regression Equations

Sector

- The variable Sector indicates the residing area of the ith woman, i.e. whether she is from an urban or a rural area. The rationale behind selecting this variable is to identify from which sector women are more inclined to gig job without using an online platform.
- Sector=1 if the ith woman resides in an urban area and 0 otherwise
- (Ref: Rural area).

Household size (hh_size)

- The variable represents the household size of the ith woman, i.e. the number of individuals residing in her family. The paper explores whether a woman is more willing to take up gig work when her household size increases. If the coefficient is positive, it indicates that a woman will take up gig jobs when her household size increases. This may happen because of the high dependency ratio in her family.

Religion

- Hindu=1 if the ith woman belongs to the Hindu religion and 0 otherwise (Ref: she belongs to the non-Hindu religion).
- Muslim=1 if the ith woman belongs to the Muslim religion and 0 otherwise (Ref: she belongs to the non-Muslim religion).
- In this analysis, mainly two religions have been focused on because in India, about 79.8% of the total population is Hindu, 14.23% are Muslims, and the remaining 5.97% constitutes religions such as Buddhism, Jainism, Christianity, etc. (Ministry of Home Affairs 2011). The paper seeks to identify which religion's women are more interested in the gig economy.

Social Group: SC-ST category, OBC category

- SC-ST = 1 if the ith woman belongs to the SC-ST (Scheduled Castes and Scheduled Tribes) category,
  = 0 if she belongs to other social groups.
- OBC = 1 if she belongs to the OBC (Other Backward Classes) category,
  = 0, otherwise.
- SC and SC communities are combinedly treated as the dummy variable, SC-ST. A social group is also considered an important variable to explore whether women from any backward classes of society are more willing to participate in a gig job than those from other groups. In India, SC communities are disadvantaged groups and have faced severe discrimination in the past; STs are tribal communities, and OBCs are socially and educationally backward communities, but they do not fall under SC and ST categories.

Relation to Head: Self, Spouse of the Head

- Self =1 if the ith woman is the head of the family and 0 otherwise.
- Spouse of Head = 1 if the ith woman is the spouse of the head of the family and 0 otherwise.
- The main objective behind selecting this variable is to find whether a female head of a family finds a gig job, a means of earning to sustain her family. When she is the spouse of the family's head, she is interested in a gig job to supplement her family's income.

Age (18–45 years)

- This variable represents the age of the ith woman. It indicates whether the tendency to engage in a gig job increases (decreases) with the increase (decrease) in the age of a woman or vice versa.

Agesq

- This is the square of the age variable. This is used to examine the fact that as age increases, the probability of joining as a gig worker (without using a platform) increases (decreases) at a decreasing (increasing) rate or not.

TABLE 2 *Continued*

General education
- This is a categorical variable that represents the general education level of the ith woman.

Education Level: Below the primary
- Education Level: Below primary =1 if she has received education below the primary level.

Education Level: Primary
- Education Level: Primary=1 if completed primary school education.

Education Level: Middle
- Education Level: Middle=1 if completed middle school education.

Education Level: Secondary
- Education Level: Secondary=1 if completed secondary education.

Education Level: Higher Secondary (HS)

Education Level: Higher Secondary=1 if completed higher secondary education.

Education Level: Diploma
- Education Level: Diploma=1 if holding a diploma.

Education Level: Graduate
- Education Level: Graduate=1 if completed graduation degree.

Education Level: Post-graduate
- Education Level: Post Graduate=1 if completed post-graduation degree.
- (Ref: If the ith woman is illiterate=0.)
- This variable indicates whether women with low educational levels prefer a gig job or whether the tendency to engage in a gig job is more prevalent among women with higher education levels.

Informal Vocational Training*
- Informal Vocational Training=1 if she has any informal vocational training. It is considered a Dummy variable.
- (Ref: Does not have any informal vocational training.)

Formal Vocational Training*
- Formal Vocational Training=1 if a woman has formal vocational training, and it is 0 if she does not have any formal vocational training (Reference category).

Household's Usual Monthly Consumer Expenditure# (hh_consumer_exp): It is here used as an Instrumental Variable of Formal Vocational Training
- includes monthly usual consumer expenditure on the purchase of goods and services for households (excluding footwear and clothing), the imputed value of usual consumption in a month from homegrown stock like rice, milk, firewood, etc. and also from wages in kind, free collection gifts, etc.; annual expenses on clothing, footwear and household durables like furniture, vehicles, TV, mobile, etc. (annual expenses should be divided by 12).

NOTES * Both informal and formal vocational training lead to skill enhancement. Therefore, these two are important indicators of the participation of women in the job market. The detailed description is given in Section 5.
The rationale behind choosing this variable as an instrument is discussed in detail in Section 5.

SOURCE Prepared by authors using PLFS data for 2022–23.

Factors Influencing Women's Participation in Gig Jobs without Using Online Platforms

SIMPLE BINARY PROBIT MODEL

Initially, a simple probit model is employed to explore the impact of various explanatory variables (narrated in Table 2) on the participation of female job seekers in gig jobs that do not require online platforms. In this case, explanatory variables comprise several demographic and socioeconomic variables and different general education levels.

A probit model is derived from a binary response model:

$$FPNPG_i^* = X_i^{'}\beta + \varepsilon_i, \tag{1}$$

where $FPNPG_i^*$ is the latent dependent variable; X_i represents the vector of independent variables, and ε is the random error term. Here, $FPNPG_i^*$ is unobservable because the net benefit received from joining a gig job or the ability of a worker to take up a gig job is unobserved. However, the outcome can be observed easily. Hence, it is denoted by a binary dependent variable, $FPNPG_i$.

$FPNPG_i$ =1 when there is participation of the i[th] female worker in gig jobs without using online platforms, and it takes the value of '0' for unpaid female caregivers who devote their entire time to household duties. The binary probit model is as follows, where both formal and informal vocational training of the respondent is excluded:

$$\begin{aligned} FPNPG_i = {} & \alpha_0 + \beta_1\ sector_i + \beta_2\ hh\_size_i + \beta_3\ hindu_i \\ & + \beta_4\ muslim_i + \beta_5\ SC\_ST_i + \beta_6\ OBC_i \\ & + \beta_7\ hh\_consumer\_\exp_i + \beta_8\ self_i + \beta_9\ spouse\ of\ head_i \\ & + \beta_{10}\ age_i + \beta_{11}\ age_i^2 + \beta_{12} below\_primary_i + \beta_{13} primary_i \\ & + \beta_{14} middle_i + \beta_{15} secondary_i + \beta_{16}\ HS_i + \beta_{17}\ graduate_i \\ & + \beta_{18}\ post\_graduate_i + u_i. \end{aligned} \tag{2}$$

The potential decision-making factors that may influence the dependent variable are outlined in Equation (2). Equation (2) is estimated using the Simple Probit Model, and its result is presented in Table 3.

REGRESSION RESULT OF SIMPLE PROBIT MODEL

From Table 3, it is evident that women from urban areas are less likely to take up the job of gig workers who do not use online platforms to sus-

TABLE 3 Determinants of the Likelihood of Participation of Females in Gig Jobs (without using online platforms) in India

Simple Probit Model		
Dependent Variable: Participation of women in non-platform gig jobs		
Variables	Value of Coefficients	Marginal Coefficients
Sector	-0.54552*** (0.01051)	-0.11842*** (0.00223)
Household size	-0.02907*** (0.00328)	-0.00631*** (0.00071)
Household's usual consumer expenditure in a month	5.88e-07 (8.21e-07)	1.28e-07 (1.78e-07)
Religion		
Hindu	-0.3296*** (0.01601)	-0.07155*** (0.00346)
Muslim	-0.58438*** (0.02122)	-0.12686*** (0.00457)
Social group		
SC-ST	0.26429*** (0.01428)	0.05737*** (0.00309)
OBC	0.16482*** (0.012605)	0.03578*** (0.00273)
Relation to head		
Self	0.69706*** (0.02446)	0.15131*** (0.00526)
Spouse of the Head	0.230025*** (0.01483)	0.04993*** (0.00321)
Age (18–45 years)	0.1926*** (0.0067)	0.04181*** (0.00145)
Age2	-0.00244*** (0.000099)	-0.00053*** (0.000022)
General Education		
Below Primary	0.13907*** (0.02518)	0.03689*** (0.00685)
Primary	-0.052*** (0.01755)	-0.0129*** (0.00435)
Middle	-0.16639*** (0.01584)	-0.03946*** (0.00385)
Secondary	-0.19814*** (0.01844)	-0.04638*** (0.00433)
HS	-0.30643*** (0.01992)	-0.06861*** (0.00444)
Graduate	-0.46122*** (0.022617)	-0.09656*** (0.00458)
PG	-0.29729*** (0.03295)	-0.06682*** (0.00686)
Constant	-3.17596*** (0.10868)	Number of Observations-109122
LR χ^2 (17)	14849.12***	
Pseudo R^2	0.1482	

NOTES The standard errors are provided in the parentheses. *** denotes significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

SOURCE Estimated by authors using PLFS data for 2022–23.

tain their livelihood than those from rural areas. As observed, women in rural areas are more likely to pick up gig jobs like own-account workers or casual wage labourers. They are less interested in regular-salaried jobs (Bairagya et al. 2019). About 67% of the urban population uses the internet, whereas this figure is just 31% for the rural areas (Oxfam India 2022). Therefore, a gig job without an online platform is more convenient for rural females compared to a platform job. When household size increases, women aged between 18 and 45 years are less inclined towards gig jobs. This may occur because there may be more children and elderly persons in the family. Therefore, a woman is compelled to look after her family members. It creates a hindrance for her in joining the job market. On the other hand, when there are more male-earning members in the family, the income effect pushes the female out of the workforce and forces her to engage in unpaid household chores. Similarly, women who belong to Hindu and Islamic religions are less likely to take up non-platform-based gig jobs relative to other religions, and this tendency is more dominant among Muslim women.

However, women from backwards castes like SC - ST, and OBC communities are more interested in participating in gig jobs to earn their livelihood (0.26429). Women from the ST community work the most. The highest unemployment rate is among the upper caste (National Sample Survey Office 2023). When a woman is the head of the family or the spouse of the family head, she is more inclined towards gig jobs, where a digital platform is not required to get a job. Then she has acquired the power to make decisions regarding participation in the job market. Women aged 18 to 45 are more interested in performing gig jobs without using any digital platform. However, this tendency is concave as it is increasing at a decreasing rate considering job seekers' age. This supports the National Institution for Transforming India, NITI Ayog (2022) report, where it was mentioned that gig workers generally belong to the younger section of the workforce.

It is observed that education is one of the main determinants of female participation in the labour market. However, Table 3 depicts that the coefficients of different levels of education are negative and statistically significant, except for the 'Below Primary' level. It is evident from the result that as the education level rises, women prefer not to engage in informal gig jobs. This tendency is more dominant if the woman has a graduation degree. The research by Herrmann et al. (2023) indicates that signalling higher levels of educational attainment does not have a statistically significant impact on the income levels of gig job seekers. The regression result has also established that 'hh_consumer_exp' has no significant impact on women's participation in non-platform-based gig jobs.

Next, the paper will further investigate whether this variable has any indirect effect on a woman's participation in a gig job or not. In this context, a second research objective is considered. Here, the model incorporates both formal and informal vocational training. It is suspected that women's participation in formal vocational training is endogenous. If that is true, a bivariate / seemingly unrelated bivariate Probit regression model is the most suitable technique to address the endogeneity issue. Otherwise, it will produce a biased estimate of the impact of formal vocational training on women's participation in informal gig jobs. The details will be discussed in the following section.

Importance of Formal and Informal Vocational Training behind Women's Participation in Gig Jobs without Using Online Platforms

Vocational training represents a significant option for Indian women seeking job opportunities, as it equips them with practical skills and promotes economic independence. This training can facilitate their entry into the job market as own-account workers or casual workers, without reliance on digital platforms. The formal vocational training is acquired through institutions/organisations and is recognised by national certifying bodies, leading to diplomas/ certificates and qualifications. For example: ITI (Industrial Training Institute) training, beautician courses, tailoring, tourism, handicrafts, electrical power and electronics, etc. (National Sample Survey Office 2023). Diploma holders and individuals taking vocational training are not identical. A person acquires informal vocational training through 'self-learning' (acquires expertise in a vocation through their effort, without any formal training), 'learning on the job' (acquires expertise while in their current or past job, either through informal training by the employer or through the exposure of their job), through 'hereditary' sources (acquiring marketable expertise by an individual, which enables them to carry out the occupation of their ancestors over generations) and so on. To accomplish the second research objective, the application of the bivariate probit model is necessary (discussed in following section).

A Bivariate Probit Model

The paper intends to examine the causal effect of vocational training on women's participation in gig jobs (which do not require online platforms for jobs). As per PLFS data, vocational training can be classified into formal and informal vocational training. A binary response model is specified to investigate the causal relationship. The model is given as follows:

$$FPNPG_i^* = \alpha_0 + \alpha_1 FV_i + \beta' X_i + u_i \tag{3}$$

$FPNPG_i$ is a binary variable that represents the participation of the i^{th} female worker in gig jobs without using any platform, and it depends on formal vocational training (FV_i) and the vector of covariates, including informal vocational training and other socio-economic explanatory variables (mentioned in Table 2). Here, $FPNPG_i^*$ is a latent variable,

$$FPNPG_i = \begin{cases} 1 \ \textit{if } FPNPG_i^* > 0 \ \textit{i.e. if the } i^{th} \textit{ woman participates} \\ \qquad\qquad \textit{in gig job without using any platforn} \\ 0 \ \textit{if } FPNPG_i^* \leq 0 \ \textit{ i.e. if the } i^{th} \textit{ woman is engaged} \\ \qquad\qquad \textit{in unpaid domestic duties.} \end{cases}$$

Most studies consider vocational training as an exogenous covariate. However, in this analysis, Equation (3) is suspected to suffer from an endogeneity problem. In this context, the paper by Bairagya et al. (2021) showed that vocational training promotes female labour force participation, considering both formal and informal vocational training as endogenous covariates. For the participation in formal vocational training, they have used the 'number of registered skill providers within the district' as an instrument, and 'the proportion of informal vocational training holders within the district' (to represent a larger informal vocational training network in that district) has been used as an instrument for participation in informal vocational training.[6] They have employed the Trivariate Probit model to address the concerned endogeneity. In this analysis, the participation of females in formal vocational training is treated as an endogenous covariate, as it may be influenced by several economic conditions of the household to which she belongs. An individual has to incur a cost to pursue formal vocational training. However, participation in informal training is treated here as an exogenous variable. An individual does not bear any monetary cost while receiving informal vocational training.

Generally, a two-stage least squares-based instrumental variable technique (IV 2SLS) is employed to solve the endogeneity problem when there is a continuous dependent variable concerning continuous endogenous covariates (Wooldridge 2002). When the endogeneity problem arises in a binary dependent variable with continuous endogenous covariates, the problem can be tackled by using an Instrumental Variable Estimation in the Probit Model (IV Probit) (Kundu 2015; Zaghdoudi 2014).

In this investigation, the most important thing is that the dependent variable ($FPNPG_i$) here is binary, and the potential endogenous covariate (i.e. participation in formal vocational training) is also binary. The existing literature suggests a 'bivariate probit model / seemingly unrelated bivariate probit model' to estimate the impact of the binary endogenous covariate on the binary response model (Arendt and Holm 2006; Torres et al. 2016). In this study, a binary response model with one endogenous covariate has been designed to resolve the endogeneity problem. Therefore, the equation that determines the 'participation of women in formal vocational training' (*FVi*) is shown by Equation (4).

$$FV_i^* = \varnothing_0 + \varnothing_1 hh\_consumer\_\exp_i + \varnothing_2^{'} X_i + v_{1i} \tag{4}$$

where FV_i^* is a latent variable. Equation (4) is also a binary choice model:

$$FV_i = \begin{cases} 1 \text{ } if\, FV_i^* > 0 \quad i.e.\ if\ i^{th}\ woman\ participates \\ \quad in\ formal\ vocational\ training \\ \\ 0 \text{ } if\, FV_i^* \leq 0 \quad i.e.\ if\ i^{th}\ woman\ does\ not\ participate \\ \quad in\ formal\ vocational\ training. \end{cases}$$

Generally, formal vocational training is achieved through formal institutions. Therefore, an individual may incur a certain amount of expenditure to carry out her formal training. The data on the expenditure for formal vocational training are not available in PLFS. However, there is a possibility that a woman's participation in formal vocational training depends on her household's monthly income. Due to the unavailability of data on households' income in PLFS, household's usual monthly consumer expenditure ($hh\_consumer\_exp_i$) is used as a proxy for the average monthly income of the representative household. In this context, Equation (4) shows that the participation of women in formal vocational training is regressed on its instrument, a household's usual monthly consumer expenditure ($hh\_consumer\_exp_i$), along with other exogenous independent variables (X_i). However, a bivariate probit model is applied to obtain consistent and efficient estimators.

REGRESSION RESULTS OF BIVARIATE PROBIT MODEL

A bivariate Probit regression model has two equations: one to determine formal vocational training, and the other to determine the participation of women in gig jobs without using online platforms. These two equations are estimated simultaneously in a bivariate Probit model, and the results will be presented in Table 4. From Table 3, it is already evident that more educated women are reluctant to participate in a gig job which does not use online platforms. Therefore, different levels of education are not considered as an explanatory variable in the bivariate Probit regression model.

Participation in formal vocational training depends on many factors. Here, a household's usual monthly consumer expenditure is considered one of the key determinants of female participation in formal training. Besides that, many socioeconomic factors such as an individual's residential region, caste, religion, marital status, age and so on, influence an individual's decision to receive formal vocational training. Hence, Table 4 depicts the result of the Bivariate Probit model (mainly focusing on determinants of women's participation in gig jobs without using any platform), considering the endogeneity issue between formal vocational training and women's participation in gig jobs.

Table 4 shows that participation in formal vocational training (endogenous covariate) has a positive impact on females' participation in a gig job that does not need online platforms. The correlation coefficient between the error terms of Equations (3) and (4) (Athr ρ) is positive and statistically significant, which exhibits a strong piece of evidence that formal vocational training is endogenous in this analysis. The Wald statistic is also statistically significant and indicates that the model is fitted correctly. The impact of some explanatory variables, such as the individual's residential region, religion, caste, total number of family members, age and her relation to the head of the family, is discussed in the case of Table 3.

It is observed that a woman who receives informal vocational training through self-learning, on-the-job experience, and hereditary sourc-

TABLE 4 Determinants of the Participation of Women in Gig Jobs (considering formal vocational training as endogenous covariate)[a] without Using Any Digital Platform

Variables	Dependent Variable: Participation of Women in Informal Non-platform-based Gig Jobs
	Value of Coefficients
Sector	-0.57192*** (0.01232)
Household size	-0.01498*** (0.00346)
Religion	
Hindu	-0.32633*** (0.01603)
Muslim	-0.61286*** (0.02141)
Social group	
SC_ST	0.35872*** (0.01463)
OBC	0.20675*** (0.01307)
Relation to head	
Self	0.78645*** (0.02628)
Spouse of the Head	0.31309*** (0.01595)
Age (18–45 years)	0.17951*** (0.00721)
Agesq	-0.00217*** (0.00011)
Formal Vocational Training	0.37817** (0.15494)
Informal Vocational Training	0.93593*** (0.01266)
Constant	-3.567*** (0.11196)
No. of observations	109122
Wald (11)	18181.68***
Arth ρ	0.18349** (0.07527)
P	0.18146** (0.07279)

SOURCE Estimated by authors using PLFS data for 2022-23 (using STATA software).

NOTES The standard errors are provided in the parentheses. *** denotes significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.
[a] As a bivariate probit regression model is estimated by capturing two equations together.

es (PLFS 2022-23) has a higher probability of joining the workforce as a non-platform-based gig worker. In this context, the paper by Das and Kundu (2023) discusses hidden forms of child labour among poor households. One such form involves children participating in agricultural activities and family enterprises, receiving informal training primarily from elderly family members. The study further suggests that hidden child labour allows families to earn higher incomes than those without hidden child labour. Although such work is unpaid, it serves as a vital source of informal training that women, particularly in poorer segments of society, have gained through experiential learning since childhood. Consequently, informal vocational training can be a significant factor in women's participation in gig work without relying on any platforms in their adulthood.

The coefficient of the instrument (household monthly income used as a proxy for household-level consumer expenditure) is positive and statistically significant, although the impact is marginal (0.0000235***). Therefore, a woman is more likely to participate in formal vocational training when her household's monthly income improves. Moreover, formal vocational training increases the likelihood of Indian women taking up non-platform-based gig jobs. However, our results suggest that the impact of informal vocational training (0.93593) is considerably stronger than that of formal training, which is only 0.37817 for entering gig jobs without using any platform. It is noteworthy that a woman with formal vocational training has a greater chance of participating in informal gig jobs without using a platform. To address the skills gap, it is crucial to enhance skills among female job seekers to generate quality employment and foster their independence in a country like India. Target 4.3 of the Sustainable Development Goals advocates for equal access to affordable technical, vocational, and higher education by 2030. Nevertheless, in 1977, the Vocational Training Programme for women was launched to engage women in economic activities (Ministry of Skill Development and Entrepreneurship 2015a). According to the ASER (Pratham UK, 2024) report, in countries such as Germany and Italy, young populations are approximately ten times more likely to be enrolled in vocational courses. Therefore, India needs to elevate this proportion to reap the benefits of its demographic dividend. Furthermore, the Indian Government has introduced several skill-enhancement programmes, such as the National Policy for Skill Development and Entrepreneurship (Ministry of Skill Development and Entrepreneurship 2015a), aimed at empowering individuals through extensive skilling and fostering sustainable livelihoods for all citizens via a culture of innovation-based entrepreneurship. Additionally, the Pradhan Mantri Kaushal Vikas Yojana (Ministry of Skill Development and Entrepreneurship 2015b) provides free short-term skill training to youth. The Union Budget (2024-25) has allocated over Rs 3 trillion for schemes that benefit women and girls, aimed at eradicating the low participation of women in the workforce.

Concluding Remarks with Policy Recommendations

The paper identifies possible reasons for women's participation in gig jobs that do not require online platforms. In this patriarchal society, women are 'time-poor'. They invest a significant amount of their time in unpaid domestic duties and do not have sufficient time to engage in the labour market to contribute to their family's income. In this context, gig jobs, with their flexible hours and absence of traditional employer-employee relationships, present a suitable option for women, encouraging them to participate in the workforce. Although gig jobs are a viable option, these positions do not entitle workers to any social security benefits, raising concerns about quality, job security, and social protection. Despite these limitations, the paper primarily focuses on the positive aspects of non-platform gig jobs. It observes that socioeconomic factors such as religion, caste, and an individual's general education significantly influence women's participation in non-platform gig jobs. Highly educated women are less likely to engage in such roles. Both formal and informal vocational training increase the likelihood of a woman participating in gig jobs without using any digital platform. However, the effectiveness of informal vocational training is much greater than that of formal training, illustrating that informal vocational training has a substantial influence on female labour force participation. Participation in formal vocational training is endogenous in this context. The paper demonstrates that a household's monthly consumer expenditure positively impacts participation in formal vocational training. It also shows that formal vocational training among women can enhance their chances of joining gig jobs without using any digital platform. Therefore, the Government should undertake essential initiatives to encourage women to engage in formal vocational training programmes, thereby increasing their participation in gig jobs, which are renowned for their flexibility and autonomy. The Indian Government has launched the Skill India Mission to enhance the employment conditions of female job seekers through skill development and vocational training. Furthermore, the National Education Policy from 2020 aims to promote gender equity and ensure equitable access to quality education for all students. The Government should organise more formal vocational training programmes free of charge or at minimal cost for Indian women. Based on the study, it can be concluded that women with formal vocational training can participate in the Indian labour force through self-employment.

In India, we lack separate data on gig workers as defined by the International Labour Organisation's definition of a gig job. Therefore, we rely on the Periodic Labour Force Survey data to continue our analysis of gig job participants who do not require digital platforms for their work.

The present paper examines the relevance of gig jobs without a platform for Indian women. However, it is possible to conduct a comparative study on working conditions between platform-based female gig workers and female gig workers who receive job assignments without using any platform.

Notes

1 Suppose a woman is engaged in making pappad at home. She does not work under any employer or on the premises of the employer but markets the homemade products by herself or through other members of her household to earn a profit; she is considered an own-account worker (NSSO 2023).

2 They are involved in producing goods and services that are potentially marketable and hence are economic. When they are outsourced for payment by any household, they are embraced in both estimates of national income and employment (Ghosh 2016).

3 The NITI Aayog (2022) Report suggests that gig workers mainly belong to the 18–45 age group.

4 In this analysis, we have considered the broad status of employment instead of National Occupation Classification (NOC) codes, as the focus is given to gig workers who do not use online platforms rather than platform workers following the definition of gig workers under the Code on Social Security (Ministry of Labour and Employment 2020). As per the DP-WEE Report, an unorganised work is 'a home-based job, self-employed job, or casual wage job in the unorganised sector' (S.2 (m); Ministry of Labour and Employment 2008). Even a platform and gig worker belonging to the organised sector with more than ten workers would still be an unorganised worker as none of the Acts like protection of the Workmen's Compensation Act, 1923; the Industrial Disputes

Act, 1947; the Employees' State Insurance Act, 1948; the Employees' Provident Funds and Miscellaneous Provisions Act, 1952; the Maternity Benefit Act or the Payment of Gratuity Act, 1972; (Schedule II; Ministry of Labour and Employment 2008) covers her. The Niti Aayog (2022) Report has selected some occupations that have gig workers from the NOC 2004. Some data on occupation codes are missing in NSSO (2023).

5 Here, public jobs refer to those activities which are sponsored by the government or local bodies to generate wage employment under a poverty alleviation programme. It covers work like the construction of roads, dams, digging of ponds under schemes like Sampoorna Grameen Rozgar Yojana and so on. Here, the casual labourers in MGNREGA jobs (code-42) are excluded because this activity code is applicable only in the Current Weekly Status, but here, Usual Principal Activity status is considered (NSSO 2023).

6 The data for the instrument of formal vocational training are collected from National Career Service, 2020 though they have used PLFS data for 2017–2018 to conduct the entire analysis.

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Is the Environmental Kuznets Curve Still Relevant in the Modern Context? – Insights From Air Pollutants in Chinese Cities

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This study investigated the presence of EKC-like relationships between various socioeconomic variables and air pollution indicators across 151 Chinese cities, analysed by quadratic regression models and geographic weighted regression (GWR) analysis. The results present critical insights into the applicability and limitations of the EKC. Only Air Quality Index, Nitrogen Dioxide (NO_2), and Fine Particulate Matter ($PM_{2.5}$) show statistically significant correlations with one socioeconomic variable, respectively, in an EKC-like pattern which is meaningful in reality. GWR coefficients serve as a diagnostic tool to identify those burdened cities where stricter emissions standards, greener industrial practices, or economic restructuring should be prioritized. The spatial dependencies challenge the EKC's assumption of isolated environmental-economic dynamics. Stricter environmental regulations in developed areas often lead to the displacement of polluting activities to regions with laxer standards. Policy efforts in tackling air pollution should focus on directly reducing emissions through localized, technology-based interventions rather than relying on economic growth to eventually improve air quality. Spatially targeted policies informed by city-specific patterns are essential, as pollution outcomes are shaped by regional industrial structures, population density, and cross-boundary spillover effects.

Key Words: air pollution, city development, geographic weighted regression, sustainable development, ecological development
JEL *Classification:* Q56

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Introduction

Over the course of past industrial revolutions, human activities have had a growing impact on the environment. Thus, since the 1960s, the importance of environmental protection that mitigates negative effects from development, such as pollution, has gradually emerged into the spotlight.

Within this context, the Environmental Kuznets Curve (EKC) has been utilized to estimate the relationship between industrial development and the environment (Dinda 2004). First introduced by Grossman and Krueger (1991) as an application of the Kuznets Curve concept (Kuznets 1955), the EKC hypothesizes that as the economy grows, environmental damage increases at first but then eventually declines. This relationship can be used to assess the current status and estimate future pollution levels.

However, whether the Kuznets curve can explain the modern context has been debated by scholars from the early 2000s (Stern 2004; Guo and Shahbaz 2024). Stern (2004) discovered that developing countries began addressing environmental issues and adhering to the developed countries' standards before achieving high levels of per capita income. Additionally, many emerging technologies offer changes in pollutant types and pollution intensities (Wang et al. 2022; Wang et al. 2024), further complicating this discussion. Historically, research on the Kuznets Curve was mainly based on the context of industrialized countries in the West (Dasgupta et al. 2002). Therefore, there is a need to revisit this classic model considering the contemporary context.

China offers a valuable case for this analysis. It has developed a massive industrial system in a relatively short time, and the environmental impact brought by this rapid growth is clearly shown even over a limited time span (Luo et al. 2025; Song et al. 2012). China has not yet shown a significant tendency to move its industries abroad, indicating ongoing efforts to balance growth and environmental progress. The manufacturing industry accounted for 37.8% of China's GDP (National Bureau of Statistics of China 2016).

This research investigates the relationship between socioeconomic development and environmental pollution using Chinese cities as the study area. Our analyses focus on various air pollution indicators, such as Air Quality Index, Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Particulate Matter ≤ 10 micrometers in diameter (PM_{10}), Particulate Matter ≤ 2.5 micrometers in diameter ($PM_{2.5}$), and Sulfur Dioxide (SO_2), and socioeconomic variables. Using global quadratic equations, we first explore whether the inverted U-shape is present in Chinese cities. We then further examine Geographically Weighted Regression results that consider spatial heterogeneity in relationships between the development indicators and air pollution intensities. We fill in the gap in the literature by providing granular city-level analysis to reveal hidden patterns that existing country-level panel EKC studies cannot do. Currently, city-level EKC analysis that considers spatial aspects is limited. Our study contributes to this discussion by comparing the global regression models and models with city-specific coefficients and providing insights on shaping future mitigation policies. There are large development disparities between different regions within China. Eastern, central, and western regions of China differ greatly in terms of per capita income, education level, and industry typologies, making China a good case for examining this literature gap (Long and Zhang 2011). The result will benefit policymakers in identifying the regions with high correlations between specific pollution components and the characteristics of the region, which helps prioritize mitigation strategies.

In the following sections, we discuss arguments in the literature and then introduce our data and methods. Next, we present our findings and interpret the results in the discussion section. Finally, we end by summarizing the main findings and room for future research.

Literature Review

This section is divided into three parts. The first section discusses the three phases of EKC theory, and the second introduces applications of worldwide and China-specific EKC analyses. In the third section, we will address how our study contributes to the existing EKC studies.

INTERPRETATION OF EKC THEORY

The Environmental Kuznets Curve is an inverted U-shape that represents three phases of economic development. The first phase is the pre-industrial economy with low income and lower levels of industry sector. In this first one-third of the whole phase, developments are driven by using natural resources with highly pollutant methods. Due to low awareness of the impacts of human activities on the environment, the pollution level rises (Kaika and Zervas 2013). The second phase is the industrial economy, with the mid-income level status of a region. In this phase, the use of natural resources starts to run out and waste accumulates. The last phase is when the region reaches high income through growth with less intensity in industrialization through information and technology-driven sectors. This pivot is mainly due to regulations to protect the environment. On the EKC curve, this phase is defined after the turning point of environmental degradation is achieved (Leal and Marques 2022).

STUDIES TESTING THE VALIDITY OF THE EKC HYPOTHESIS

Existing Studies Challenging Validity

Many scholars have tested the validity of the EKC hypothesis, with studies showing mixed findings depending on the country and statistical model used. The most frequent indicator that was used as the dependent variable was CO_2 emissions for exploring the inverted U-shape relationship. Measures such as GDP, fossil fuel energy consumption, population density, and urbanization were frequently discussed together as development indicators (Işik et al. 2019; Wang et al. 2023). The references of each variable are presented in the Appendix.

Using panel data from eight OECD countries, Işik et al. (2021) found that Turkey, Australia, Canada, and France support the hypothesis in their undecomposed model, which uses regular GDP. However, when they decomposed the per capita GDP to only isolate the *increasing* section of GDP within their time-series data to more accurately test the true intended EKC relationship, none of the countries exhibited an inverted U-shape curve for the relationship between GDP and CO_2 emissions. This indicates that there are heterogeneous patterns across countries and more importantly, highlights the need for disaggregated analysis to complement longitudinal approaches and uncover hidden patterns.

A similar study was conducted to examine variations within the US by the same research team. Işik et al. (2019) analysed the EKC hypothesis across all 50 US States based on their CO_2 levels using two types of models, common correlated effects (CCE) and the augmented mean group (AMG). While the CCE approach did not find a significant EKC relationship on average, the AMG model that estimates each state individually supported the hypothesis in 14 states. Their results indicate that revealing heterogeneous effects across units enables more targeted and region-specific policy implications.

Many authors mentioned that since there are mixed findings regarding the validity of the hypothesis, more empirical studies are required to fully understand these relationships and guide future policymaking for sustainable development. Studies that validate the relationship argue that countries validating the EKC curve have been eager to shift to adopting cleaner energy sources and governments may enforce regulations to encourage a more environmentally sustainable development strategy upon reaching a certain threshold (Apergis and Ozturk 2015; Bibi and Jamil 2021). Studies arguing the weakness of the hypothesis indicate that there may be conditions where the intensity of economic activities due to economic growth exceeds the pollution reduction enabled by innovative technologies, leading to an increase in pollution overall (Shafik and Bandyopadhyay 1992; Azomahou et al. 2006). He and Richard (2010) point to changes in industrial structure, participation in international trade, and environmental indices.

Findings From EKC Studies Based in China

China has contributed the most to the existing EKC literature (Bashir et al. 2021). Since China is experiencing a rapid growth rate and has an urgency to mitigate pollution levels, researchers have examined the relationship between economic growth and subsequent environmental degradation using various pollution indices. Like EKC studies based on other countries, while some studies validate the EKC hypothesis in China, some argue otherwise, and some reveal mixed findings due to the use of different statistical techniques and examination of diverse pollutants.

China is geographically large, and the scope of analysis varies by study. As seen in the US study above, the existence of the EKC hypothesis is likely to emerge when more disaggregated specifications with localized pollution proxies are used (Mahmoodi Nesheli et al. 2021). There are a few studies that have been conducted at the city level in China. Xie et al. (2019) corroborated the EKC hypothesis between economic growth and $PM_{2.5}$ using spatial autoregressive models with 2015 data from 249 Chinese cities. Using both national and city-level data, He et al. (2021) found EKC heterogeneity between the western, central, and eastern regions. Their study also observed variations between cities with varying environmental regulations. Similar conclusions are drawn in Jiang and Zheng's (2017) work that explored pollution concerning income as a development index.

CONTRIBUTION OF THIS STUDY

At present, many studies around the world rely on country-level data. Since China is a large country with varying levels of socioeconomic status across regions, a more granular investigation is warranted and our data enables this scrutiny. National panel studies have emphasized the need for spatial and temporal disaggregation, and our paper contributes to the literature by analysing the relationship between economic growth and environmental outcomes spatially at the city level through geographic weighted regressions. Estimating incorporating spatial aspects is challenging since it requires the completeness of granular data to catch their spatial effects. Currently, there are few studies incorporating spatial heterogeneity in city-level analysis within China (Gui et al. 2019; Zhao et al. 2021), but the number of studies is limited. Our study also contributes to the literature by providing an EKC validity discussion using comprehensive economic growth indicators, such as GDP and population and air pollutant measurements, including Air Quality Index, CO, and NO_2 for 151 Chinese cities. This enables understanding of characteristics of pollutants by region and informs policymakers in understanding how certain pollutants are tied to the region-specific development strategies.

Data and Methodology

DATA COLLECTION

In this study, 302 cities in mainland China were selected as the initial sample group. A total of 151 cities are included in the statistical analysis after removing cases with missing values in certain variables, mainly those related to the infrastructure-related variables. The Air Quality Index (AQI), CO, NO_2, O_3, SO_2, PM_{10}, and $PM_{2.5}$ are used as air pollution indicators. These indicators are frequently utilized in air pollution-relevant studies (Cheng et al. 2016). The Appendix (Table A.1) presents existing studies that utilize the variables included in this study. The air pollution data are acquired from the Qingyue Data service, which is free upon request for academic research purposes (Qingyue Data 2024). The original dataset is organized by air quality detection stations, with a unique code that can be used to aggregate the data by city. All air pollution indicator data are summarized by year. The data preparation is as shown in equations (1) and (2).

$$\overline{P}_{ik} = \frac{1}{n_i}\sum_{j=1}^{n_i} P_{ijk} \tag{1}$$

$$\log P_{ik} = \ln(\overline{P}_{ik}), \tag{2}$$

where P_{ijk} is the value of air pollution indicator k at station j in city i, n_i

is the number of stations in city *i*, and $logP_{ijk}$ is the log-transformed average value of air pollution indicator *k* in city *i*.

A series of socioeconomic variables are chosen based on the purpose of the study and the availability of the data. All socioeconomic data is collected by the first author from the Provincial Yearbook of Chinese Provinces in PDF versions. The yearbooks can be acquired from the local census bureau of each province.

One problem with the data used in this study is that both the air pollution data and socioeconomic data are from 2015. This is a compromise approach, given the socioeconomic data's availability and the nature of this study's objectives. This choice was necessitated by the limited availability of free air pollution data for the years 2015 and 2016, and the insufficient socioeconomic development data for major cities in 2016. The primary objective of this study is to examine the relationship between the socioeconomic development of cities and their air pollution levels, and then to assess the adequacy of the EKC in representing or explaining their relationship. The considerable variation among Chinese cities in terms of development levels, even within a single year, justifies our cross-sectional approach. Employing 2015 data does not compromise the study's validity (He et al. 2021). The absence of digitally formatted socioeconomic data for many cities in China adds to the difficulties of collecting enough valid samples.

Socioeconomic development variables include the ones representing economic scale (GDP/Capita), urbanization level (urbanization rate), industry structure (percentages of GDP generated by agriculture, manufacturing industry, and service industry), and employment structure (percent of labour in agriculture). The infrastructure established is represented by road length, electricity consumption, energy intensity, and roadway density.

One of the socioeconomic variables, the urbanization rate, is an official measurement in China based on the Hukou system (Qin and Zhang 2014). It classifies residents as either agricultural or non-agricultural based on Hukou. The urbanization rate of a city is calculated by:

$$\frac{\text{The number of residents with Non - agricultural Hukou}}{\text{Total number of residents}}. \tag{3}$$

The rates are presented in the census yearbooks. The summary of all data used is presented in Table 1.

TABLE 1 Summary of Socioeconomic Variables and Air Pollution Indicators

Category	Variable	Mean
Economic Scale	Population (*10,000)	434.13
	GDP/Capita (RMB)	51398.39
Urbanization Level	Urbanization Rate (%)	54.71
Industry Structure	% Agriculture in GDP	12.68
	% Service Industry in GDP	41.01
	% Manufacturing Industry in GDP	46.31
Employment Structure	% of labourers in Agriculture	36.54
Infrastructure	Road Length (km)	2009.63
	Electricity Consumption (10,000*kwh)	2199025.70
	Energy Intensity (kBtu/m^2)	61.73
	Roadway Density (km/km^2)	2.86
Air Pollution Indicators	Air Quality Index (AQI)	80.04
	Carbon Monoxide (CO)	1.06
	Nitrogen Dioxide (NO_2)	30.49
	Ozone (O_3)	59.13
	Particulate Matter ≤ 10 μm in diameter (PM_{10})	87.59
	Particulate Matter ≤ 2.5 μm in diameter ($PM_{2.5}$)	49.37
	Sulfur Dioxide (SO_2)	22.68

STATISTICAL AND SPATIAL ANALYSIS METHODS

For the statistical analysis, we designed a two-step Quadratic Regression + Spatial analysis approach.

Quadratic regression analysis

We first employed a quadratic regression model with no spatial information involved. This enables us to understand the statistical correlations between the socioeconomic variables and different air pollutants. Quadratic regression is a statistical method used to model the relationship between a dependent variable and an independent variable by fitting a quadratic equation to the data. The equation takes the form of:

$$\textit{Air Pollution Indicator} = \beta_0 + \beta_1 X + \beta_2 X^2 + \varepsilon, \tag{4}$$

where X is the socioeconomic variable (e.g. GDP/Capita), $\beta 1$ is the linear coefficient, $\beta 2$ is the quadratic coefficient, and ε is the error term.

One advantage of quadratic regression is its ability to capture non-linear relationships that appear to be U-shaped or inverted U-shaped, resembling the EKC curve. When exploring the relationship between a city's socioeconomic status and air pollution, quadratic regression allows for the examination of potential nonlinearity in the relationship. It also enables the identification of 'turning points' or thresholds in the relationship. The turning point in the EKC refers to the socioeconomic development level at which environmental degradation peaks and then starts to decline as socioeconomic development continues. The turning point is crucial for policy because, hypothetically, before the turning point, the region may focus on cleaner industrialization and proactive regulation, while after the turning point, it may accelerate environmental investment and sustainability transitions.

Mathematically, the turning point is the value of the independent variable at which the predicted air pollution indicator is at a maximum (inverted U-shape) or minimum (U-shape), depending on the sign of the quadratic term. The turning point $X*$ (value of X where pollution peaks) is calculated by:

$$X^{*} \frac{-\beta_1}{2\beta_2}. \tag{5}$$

If $\beta 2 < 0$: the curve is an inverted U (EKC-like shape). $X*$ is where pollution peaks and starts declining. If $\beta 2 > 0$: the curve is a U-shape. The turning point is a minimum, not consistent with the EKC.

The turning point helps determine the socioeconomic level at which the dynamic with air pollution changes. Most importantly, quadratic regression allows quantitative measures of the relationship's direction and statistical significance, providing a more comprehensive understanding of their correlations.

Geographic Weighted Regression analysis

Following the identification of statistically significant and practically interpretable EKC-like relationships through global quadratic regression, this study employs Geographically Weighted Regression (GWR) to examine the spatial heterogeneity of these relationships. While the global model reveals overall associations across the entire dataset, it assumes spatial stationarity in the influence of socioeconomic variables on air pollution indicators. That assumption is problematic in the context of Chinese cities, where variations in industrial structure, enforcement capacity, urban form, and topography contribute to location-specific pollution dynamics. Also, the very low explanatory power of EKC shown by quadratic regression analysis indicates the existence of uncaptured factors, which we assume are spatial factors.

GWR is selected as the spatial analysis model to account for such heterogeneity. It estimates a local regression equation at each city, weighing nearby observations more heavily than those farther away. Unlike global regression, where coefficients are fixed across space, GWR allows the regression coefficients to vary by location. This framework is particularly suited for this study, as all independent variables, such as population size, GDP, and sectoral economic shares, are continuous and numerically scaled, enabling local parameter estimates to reflect their spatial variation in explanatory power.

Technically, the GWR model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \tag{6}$$

where is the air pollution indicator in city i, x_{ik} is the value of the k-th independent variable (in this study it is the socioeconomic variables), and $\beta_k(u_i, v_i)$ are location-specific coefficients estimated at spatial coordinates (u_i, v_i).

The estimation is done using weighted least squares:

$$\hat{\beta}(u_i, v_i) = (X^{\top} W_i X)^{-1} X^{\top} W_i y, \tag{7}$$

where is a diagonal matrix of spatial weights determined by a kernel function. This study uses a Gaussian kernel:

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{b^2}\right), \tag{8}$$

where d_{ij} is the distance between city i and city j, and b is the bandwidth controlling the spatial extent of the local neighbourhood.

The use of GWR in this study is not intended to replace global inference but to complement it by identifying the spatial structure of variation in air pollution indicator–socioeconomic variable relationships. Doing so enables a more precise understanding of how the pairs of air pollution indicators and socioeconomic variables correlate with the spatial information considered. This approach enhances the explanatory depth of the analysis and provides a foundation for place-sensitive environmental policy recommendations.

Quadratic Regression Analysis and Discussion

VARIABLE CHOICE

The variables are chosen based on the Pearson correlation coefficients between the natural-logged dependent variables (air pollution indicators) and the independent variables. The chosen variables are then tested with a heuristic nonlinear correlation model. We use an adaptive local linear correlation computation by segmenting the data points and applying regression tests to each segment adaptively, identifying multiple local regions of linear correlations to estimate the overall nonlinear correlation (Ranjan and Najari 2019). The correlation estimate lies between 0 and 1. The higher the value, the stronger the nonlinear correlation. Negative values are not valid here. Due to multiple local correlation computations, the net p-value of the correlation estimate is adjusted to avoid false positives. The variables that present a nonlinear relationship with the air pollutants are then used for quadratic regression analysis.

NONLINEAR ANALYSIS AND DISCUSSION

The chosen socioeconomic variables are shown in Table 2. The table demonstrates that though some of the variables might be statistically correlated with the air pollution indicators, they do not appear to have a nonlinear correlation. Socioeconomic variables are chosen for the quadratic regression test if:

1. adjusted p-value ≤ 0.01 (statistically significant correlation at the 90% confidence level),
2. nonlinear correlation estimate > 0.2 (nonlinear correlation exists).

The variables must satisfy both requirements to be eligible for quadratic regression analysis. For example, in the case of CO, the adjusted p-value supports at > 90% confidence level that population is correlated with CO, but the nonlinear correlation estimate (< 0.2) suggests that there is no nonlinear correlation between CO and population. Thus, the population is not selected for quadratic regression analysis.

O_3 is eliminated at this step because no socioeconomic variable is statistically significantly correlated with it.

Based on the results presented in Table 2, NO_2 is the pollutant that is correlated the most with the socioeconomic variables. PM_{10} has a poten-

TABLE 2 Nonlinear Correlation Test for Statistically Significant Variables

Air Pollution Indicators	Chosen Socioeconomic Variable	Correlation Estimate (>0.2)	Adjusted p-value <0.01
AQI	GDP	0.107	0.05
	Population	0.208	0.01
	% Manufacturing Industry	0.109	0.06
	Energy Intensity	0.216	0.06
CO	GDP	0.246	0.81
	Population	0.095	0.1
	% Manufacturing Industry	0.181	0.01
	Road Density	0.185	0.11
NO_2	GDP	0.455	0.002
	GDP/Capita	0.349	0.01
	Population	0.437	0.005
	Urbanization Rate	0.294	0.02
	% Manufacturing Industry	0.195	0.01
	% Service Industry	0.231	0.005
PM_{10}	GDP	0.252	0.41
	Population	0.129	0.03
	% Manufacturing Industry	0.036	0.53
	% Employment in Agriculture	0.133	0.02
	Energy Intensity	0.201	0.08
$PM_{2.5}$	GDP	0.165	0.005
	Population	0.309	0.002
	% Manufacturing Industry	0.168	0.003
	Energy Intensity	0.266	0.02
SO_2	GDP	0.249	0.101
	Population	0.028	0.63
	% Manufacturing Industry	0.167	0.002
	Road Length	0.125	0.29

tial quadratic relationship with certain variables, though none of them is statistically significant at the 90% level. Among all the socioeconomic variables, population and the percentage of manufacturing industry in GDP are correlated with the most air pollution indicators. These two variables are the ones closely related to economic and industrial activities.

Figures 1, 2, 3, 4, and 5 visualize the quadratic regression results involving the chosen socioeconomic variables and their corresponding air

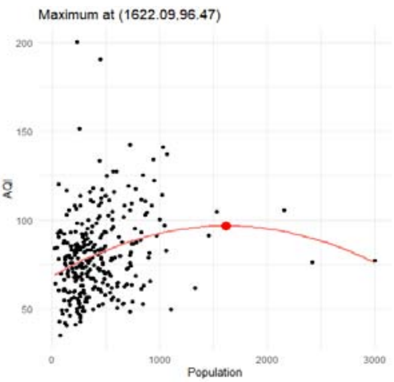


FIGURE 1 Quadratic Regression Curve for Population – AQI

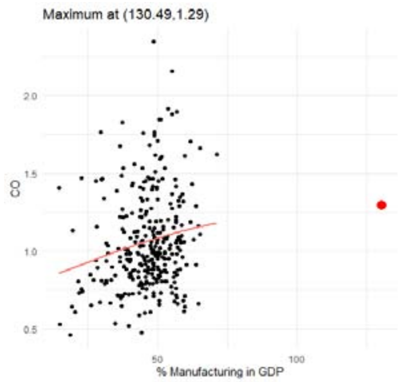


FIGURE 2 Quadratic Regression Curve for % Manufacturing Industry in GDP – CO

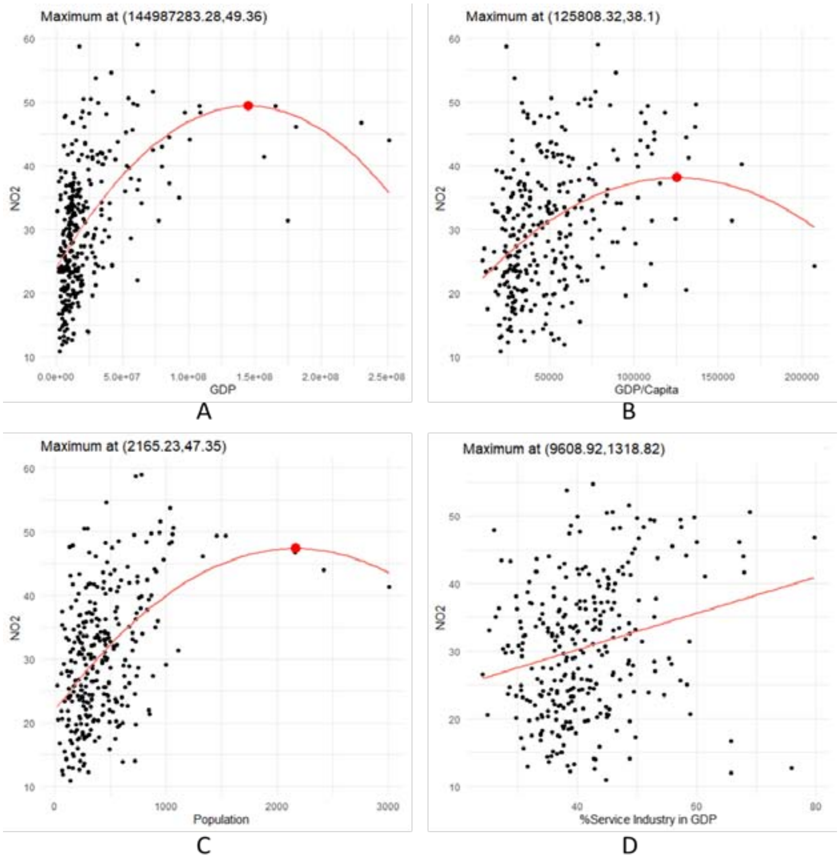


FIGURE 3 Quadratic Regression Curve for All Chosen Independent Variables – NO_2

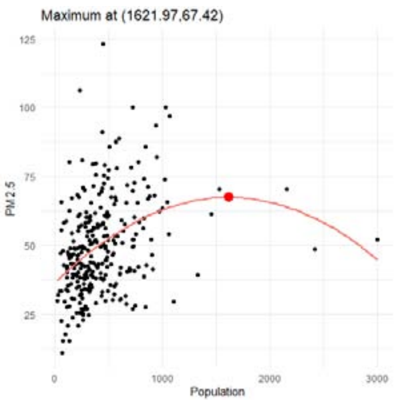


FIGURE 4 Quadratic Regression Curve for Population*10,000 – $PM_{2.5}$

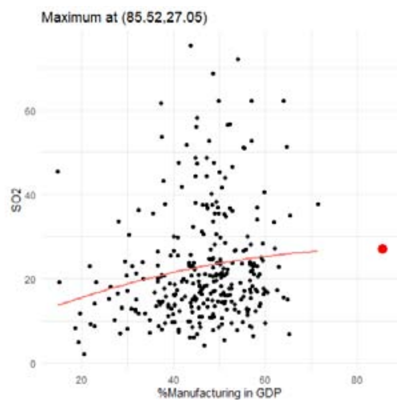


FIGURE 5 Quadratic Regression Curve for % Manufacturing Industry in GDP – SO_2

pollution indicators. Figure 3 shows that NO_2 is correlated with most socioeconomic variables that are statistically significant, showing an EKC-like pattern. The turning point occurs at 83.68% urbanization and 34.91 NO_2 concentration. This suggests that NO_2 pollution increases with urbanization but peaks around 84%. Given that some cities reach this level of urbanization, the turning point is theoretically and practically interpretable, supporting an EKC-like relationship between urbanization and NO_2. The maximum point appears at \$125,808 GDP/capita and 38.1 NO_2. While the EKC is statistically evident, this GDP level is extremely high and exceeds that of most cities in the dataset. This limits the practical relevance of the curve's peak.

We notice from Figures 1 and 4 that the turning points on the curves regarding the relationships between population versus AQI and $PM_{2.5}$ are very similar. This could suggest a phenomenon that, once a city reaches a more advanced economic stage with a large population, it starts to tackle air pollution issues, as the EKC hypothesis suggests.

Figure 2 shows that the maximum point of the curve representing the relationship between the percent of manufacturing in GDP and CO is (130.49, 1.29), which is meaningless in practice given the unachievable value of 130.49%. A similar pattern also appears in Figure 5, which demonstrates the correlation between the percentage of manufacturing industry in GDP and SO_2. Figure 5 shows that the turning point on the curve is 85.52%. None of the cities have a manufacturing industry that takes over 80% of the GDP. The turning point is at 9608.92% for the per-

TABLE 3 Quadratic regression model results

Model	Intercept	Linear coeff	Quadratic coeff	Turning Point X	R^2	Adj R^2	Practicality	P value quad
Population_AQI	68.091	0.71	-0.0042	1622.09	0.07	0.06	Yes	0.034
%Manufacture _CO	0.733	2.95e-4	-1.17E-09	130.487	0.03	0.03	No	0.0015
GDP_NO2	23.96	3.5e-7	-1.21E-15	144987283.3	0.29	0.29	Yes	8.18e-9
GDPpC_NO2	19.526	0.0086	-3.30E-05	125808.32	0.15	0.15	Yes	0.79
Population_NO2	21.925	0.45	-0.00267	2165.23	0.22	0.22	Yes	0.62
%Service_NO2	19.422	0.27	-1.41E-05	9608.92	0.053	0.05	No	0.99
Population_PM2.5	36.252	0.03	-1.08E-05	1621.97	0.15	0.14	Yes	0.0056
%Manufacture _SO2	7.492	0.02	-5.42E-06	85.52	0.03	0.02	No	4.71e-4

cent of service industry in GDP in relation to NO_2, which is not only practically meaningless but also statistically insignificant. All these observations with practically impossible or statistically insignificant turning point values reflect a poor model fit, making the EKC concept inapplicable.

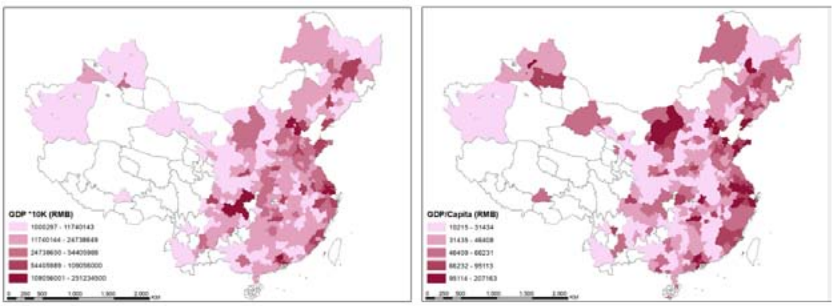
In all, among the air pollutants examined in this study, NO_2 is the most closely correlated with socioeconomic variables with an EKC-like pattern, demonstrating signs that air quality may improve as the region reaches higher stages of economic development. The quadratic regression demonstrates that the relationships of Population vs. AQI, GDP vs. NO_2, and Population vs. $PM_{2.5}$ have statistically significant EKC-like relationships. The other air pollution indicators cannot be fully described by statistically significant socioeconomic variables in an EKC-like relationship. Table 3 presents a summary of quadratic regression results. The last column, named 'P value quad', is the p-value for the quadratic terms, showing whether the EKC-like relationship is statistically significant. The values in bold are statistically significant at the 90% confidence level, which will make the pairs the candidates for GWR analysis for the following step. The column named 'practicality' shows how practical the turning point is in reality as discussed previously.

Geographic Weighted Regression Analysis and Discussion

The original EKC hypothesis did not include consideration of spatial factors. Yet air pollutants transport and diffuse spatially. In addition, the quadratic regression analysis results indicate the presence of spatial factors of the air pollution indicators, given the very low explaining power of the EKC hypothesis. Therefore, we disclose the spatial correlation of socioeconomic variables and air pollution indicators by GWR models by using the pairs of variables found with statistically significant EKC-like relationships in quadratic regression models. Socioeconomic variables are mapped to disclose spatial distribution in section 5.1. A Moran's I analysis result, which shows statistically significant spatial clustering patterns of air pollution indicators, is presented in Appendix Table A.2 with captions.

MAPPING THE SOCIOECONOMIC VARIABLES

China has distinctive economic subdivisions (He et al. 2002), which can be discovered in the following maps of socioeconomic variables. Figures 6 to 9 demonstrate the various development measures of 151 cities in China of GDP, urbanization rate, employment structure, and economic structure.



A. GDP of Major Cities (2015)

B. Per Capita GDP in Major Cities (2015)

FIGURE 6 Total GDP and Per Capital GDP of 151 Cities

FIGURE 7 Urbanization Rate of 151 Cities

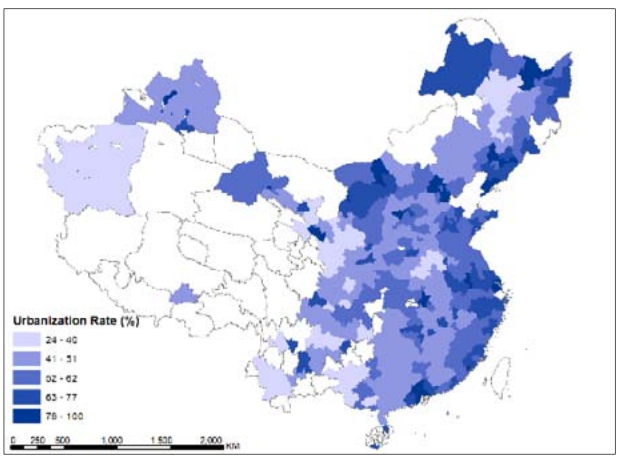


FIGURE 8
Employment Structure (% Employment in Agriculture)

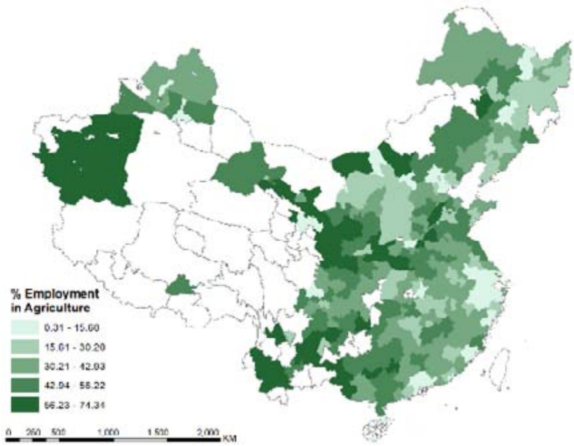


FIGURE 9
Economy Structure (% GDP in Service Industry)

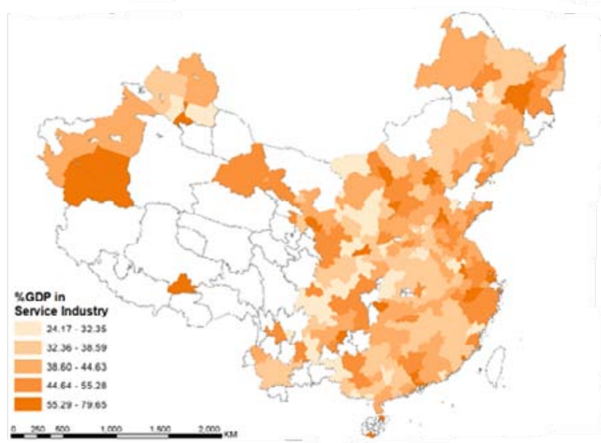


Figure 6 demonstrates that the East coastal area is the area with the highest GDP, especially the southeastern coast. This area encompases several top metropolitan areas, including Shanghai, Guangzhou, Shenzhen, etc. The northwest and north-central areas are less developed compared to the eastern coastal areas.

Regarding urbanization rates, the northeast and east coast regions have the highest levels (Figure 7). Several central cities have high urbanization rates. This trend aligns with the spatial distribution of GDP. The employment structure (Figure 8) is represented by the percentage of employment in agriculture; the higher the ratio, the less developed the area is. The western and central areas have higher agriculture employment compared to the coastal areas and the region surrounding Beijing.

The economic structure (Figure 9) is represented by the percentage of GDP produced by the service industry. The higher this share, the lower the share of GDP produced by manufacturing and agriculture, indicating a developed city. This follows the distribution patterns of GDP and employment structure with a few exceptions, such as Hetian, a major tourist city with large ore production industries.

GEOGRAPHIC WEIGHTED REGRESSION

The first pair for GWR analysis is AQI – Population. The global linear regression model showed only a weak association, with an R^2 of 0.05 (Figure 10.C). However, residual diagnostics confirmed that model assumptions were reasonably met: the standardized residuals approximated a normal distribution with a mean near zero, and no severe heteroscedasticity was observed in the residual-versus-predicted plot.

The spatial distribution of the local GWR coefficients (Figure 10.A) reveals considerable variation in the AQI – Population relationship across cities. In eastern and central provinces (areas such as the Yangtze River Delta, Shandong Peninsula, and parts of the Beijing-Tianjin-Hebei region), GWR coefficients are strongly positive. This indicates that population concentration is associated with elevated AQI levels, likely due to compounded traffic density, construction activity, and industrial operations in these areas. In contrast, several cities in the west and far north display weak or even slightly negative coefficients, suggesting decoupling between population size and pollution levels, or just because of the lower density. The spatial variation in explanatory power is further supported by the local R^2 map (Figure 10.B). High local R^2 values (>0.6) are concentrated in the populous eastern coastal corridor and parts of the Northeast. This pattern suggests that in these regions, population size is a strong predictor of AQI variation.

Figure 11 demonstrates the GWR results of pair CO – % Manufacturing Industry of GDP. Although the global regression (Figure 11.C) suggests a limited role of manufacturing in explaining CO concentrations, the spatial analysis reveals clear clusters where the relationship is substantial. The GWR coefficient map (Figure 11.A) reveals considerable heterogeneity in how manufacturing share in GDP correlates with CO levels. Cities in the central plains (lower Yangtze River corridor), and certain inland provinces in Southwest China show positive coefficients, where higher proportions of manufacturing in GDP are associated with increased CO pollution.

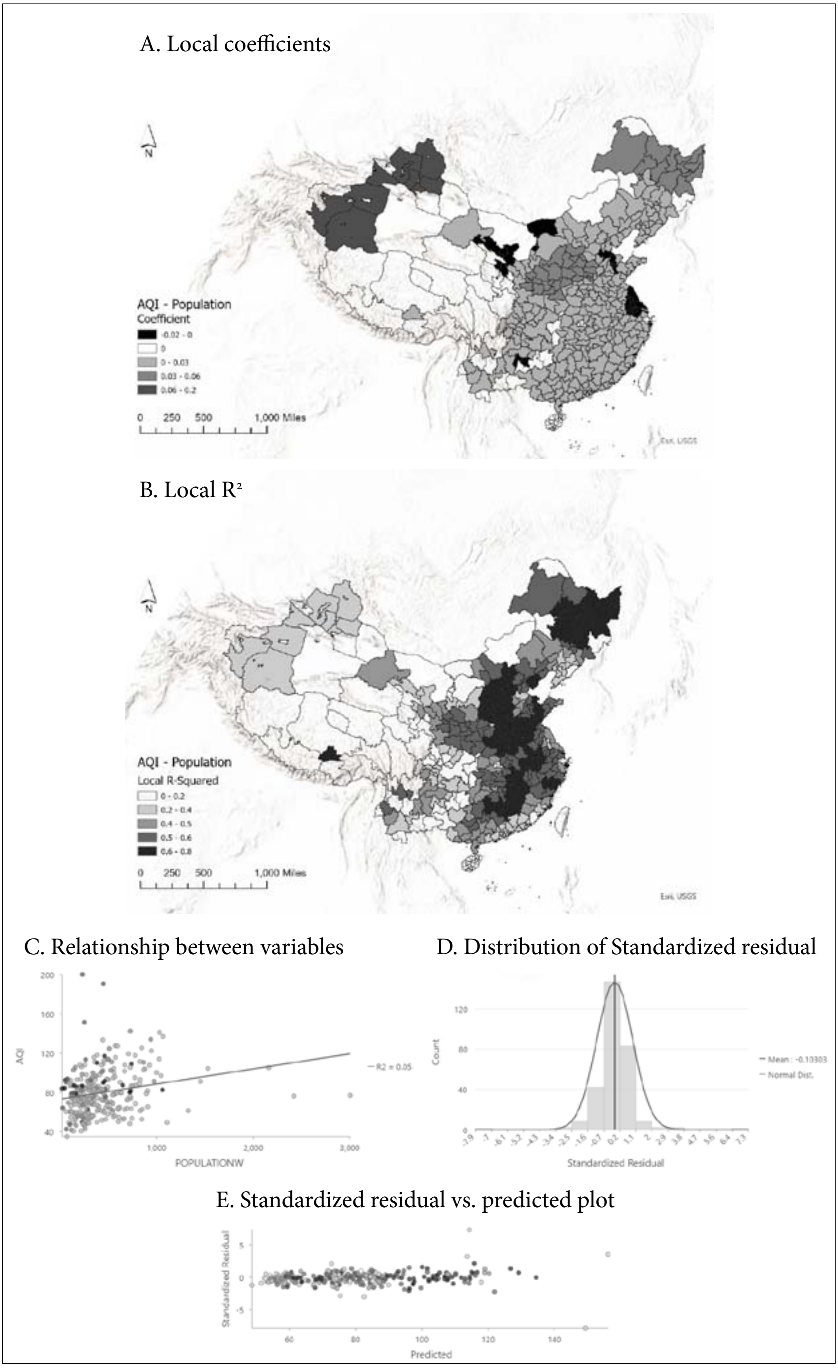


FIGURE 10 GWR results for AQI – Population

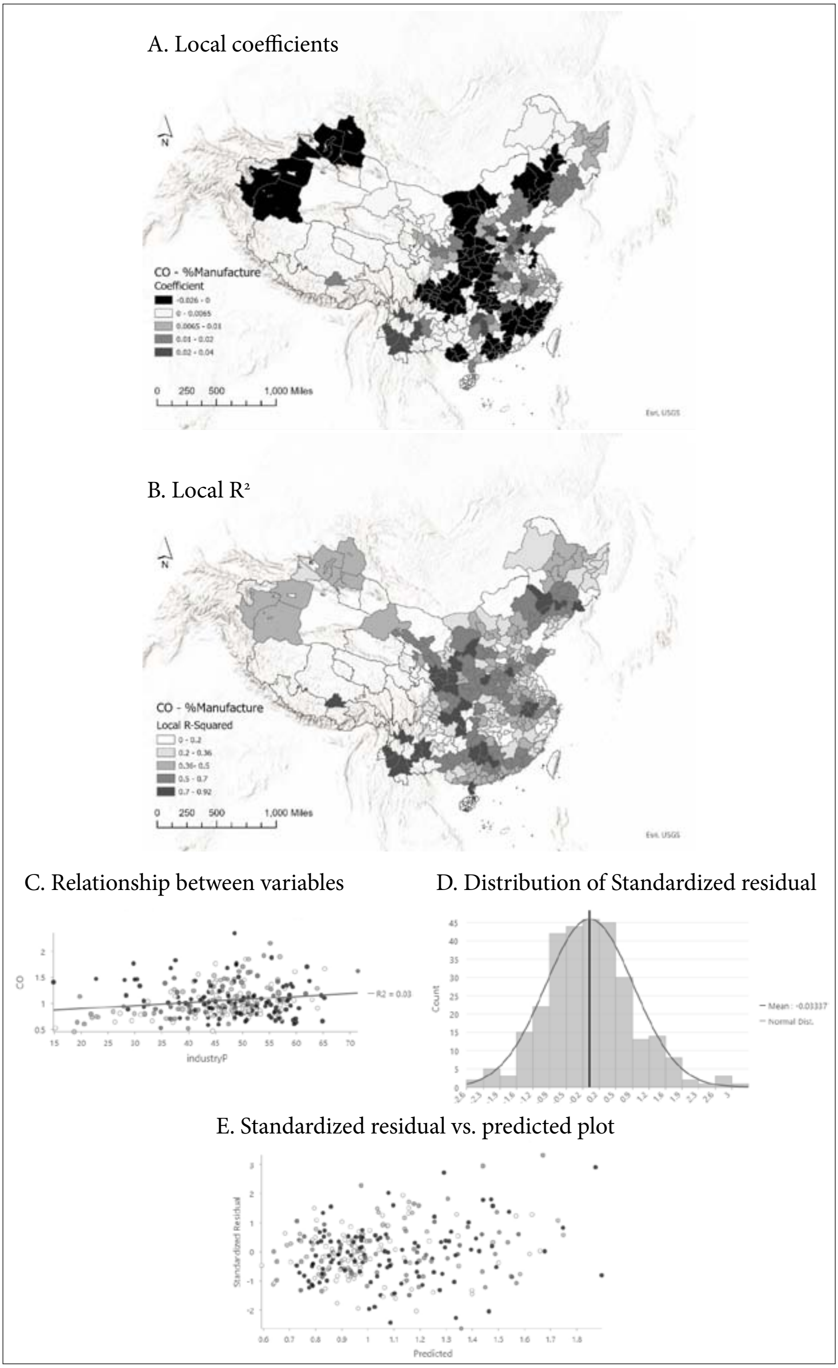


FIGURE 11 GWR results for CO – % Manufacturing Industry in GDP

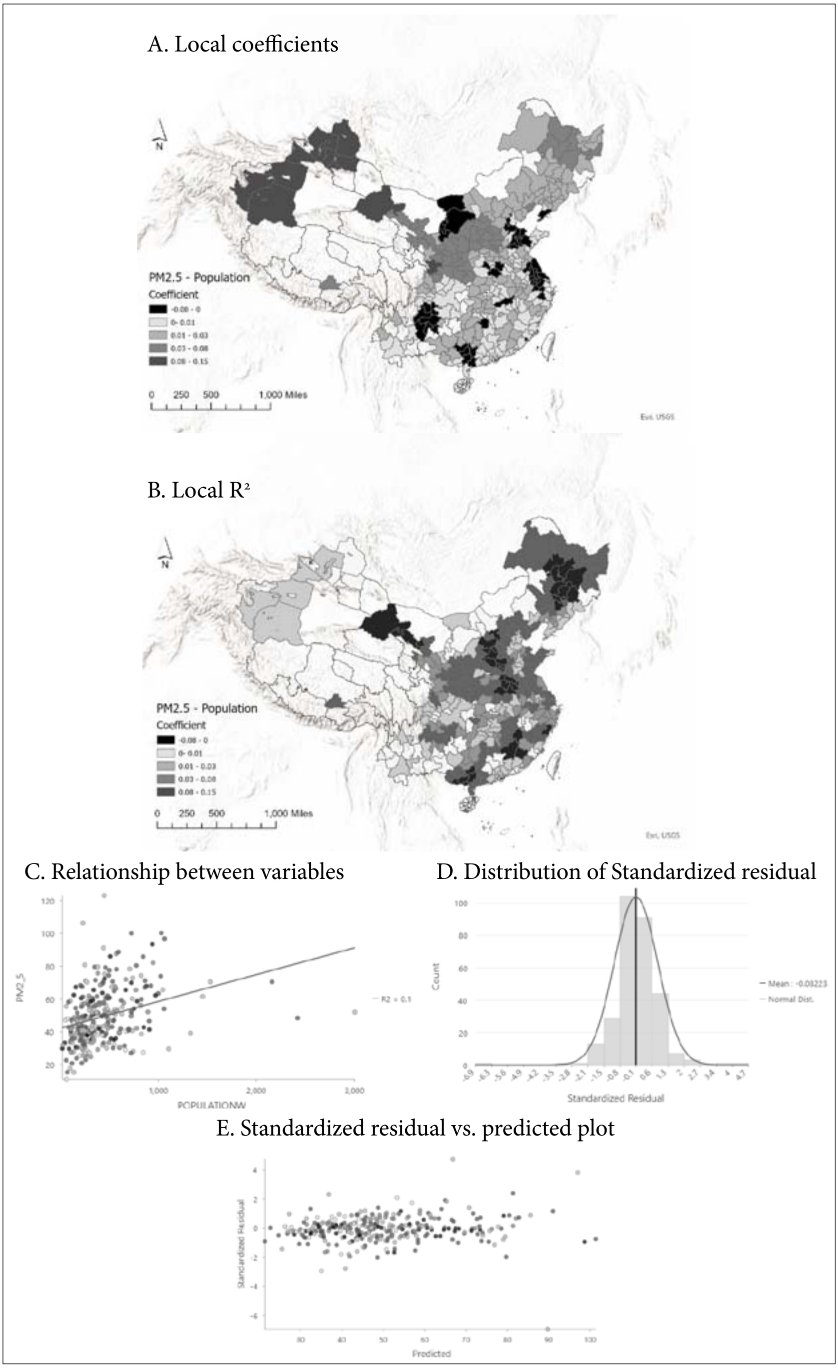


FIGURE 12 GWR results for $PM_{2.5}$ – Population

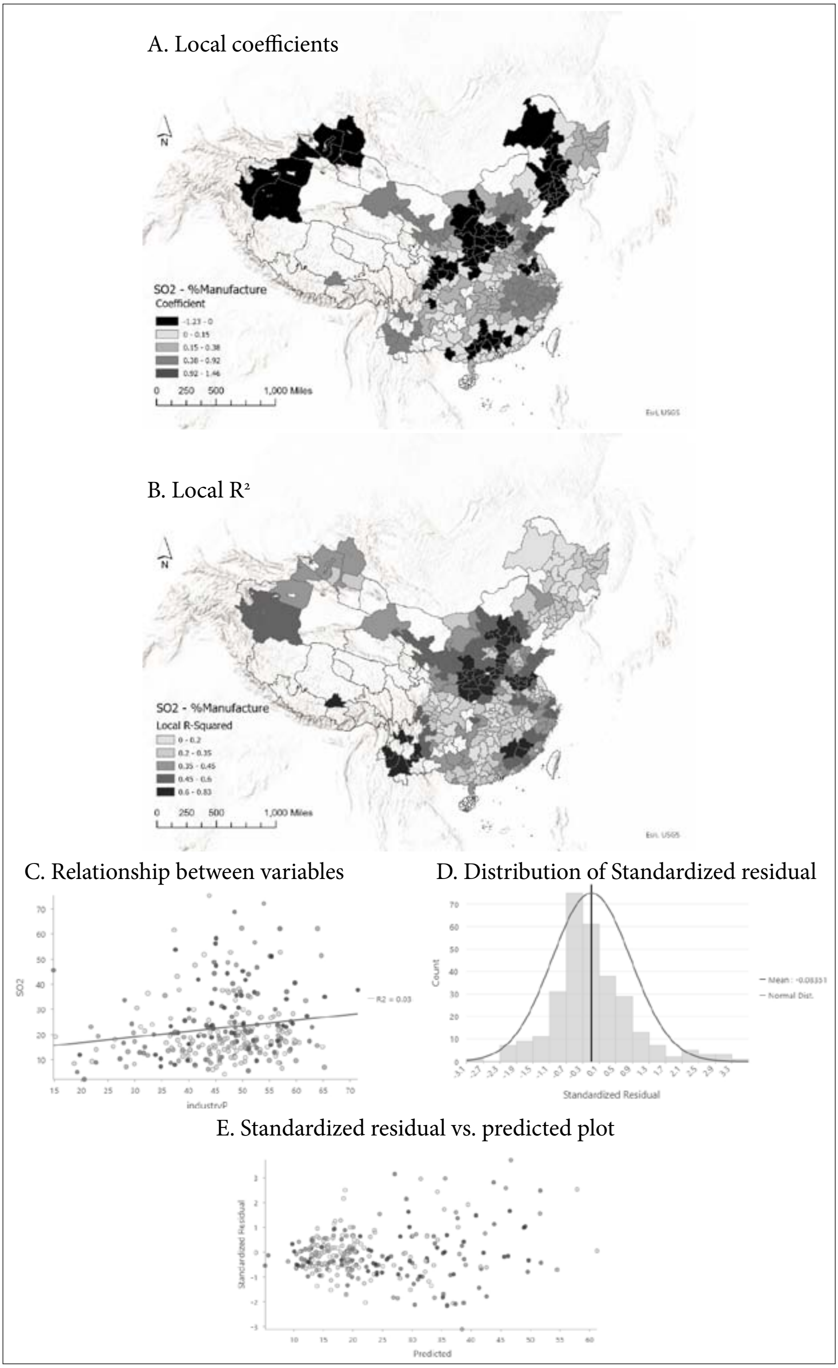


FIGURE 13 GWR results for SO_2 - %Manufacturing Industry in GDP

These areas correspond to older industrial zones and secondary cities where environmental regulation is often weaker and industrial facilities remain coal- or fuel-intensive. Conversely, in western and far northern regions including parts of Xinjiang, Inner Mongolia, and Gansu, the GWR coefficients are near zero or even negative. This may be attributed to lower population densities or non-manufacturing-dominated economies. The spatial distribution of the local R^2 values (Figure 11.B) further underscores the non-uniformity of this relationship. High explanatory power ($R^2>0.5$) is concentrated in the central provinces such as Henan, Hunan, and Sichuan. In these regions, the contribution of the manufacturing industry to local CO pollution is more consistent and likely reflects outdated industrial processes or higher emission intensity.

Figure 12 presents the GWR results of the pair of $PM_{2.5}$ – Population. The global linear regression results in a modest R^2 of 0.10, suggesting a limited explanatory power when assuming a constant relationship across space. Diagnostic plots indicate that model assumptions are generally satisfied. The GWR (Figure 12.A) coefficient map illustrates a strong spatial divergence in the relationship between city-level population and $PM_{2.5}$ concentrations. In the eastern coastal regions (Jiangsu, Zhejiang, and Shandong, parts of Hunan, Hubei, and Anhui), coefficients are consistently positive and exceed 0.08. These areas are highly urbanized, with dense population cores, active construction, and transportation networks. In contrast, in less industrialized or lower-density regions such as western Gansu, Xinjiang, and Inner Mongolia, GWR coefficients are negative or near zero. Cities with local R^2 values (Figure 12.B) above 0.4 cluster in the mid-Yangtze River basin and along the southeast coastal belt, where population density is most influential in predicting $PM_{2.5}$ levels. These results confirm that the relationship between population and $PM_{2.5}$ is highly spatially contingent and cannot be generalized using a single national model.

Figure 13 discloses the relationship between SO_2 concentrations and the percentage of manufacturing in GDP. The coefficient map (Figure 13.A) demonstrates that in cities across Hunan, Jiangxi, Shandong, and parts of Henan and Hebei, there is a consistently positive relationship between the proportion of manufacturing and SO_2 concentrations. These regions represent historically industrialized zones with ongoing use of sulfur-heavy energy sources, such as coal-fired power plants and outdated production processes. In these areas, manufacturing remains a major contributor to SO_2 levels. The local R^2 map (Figure 13.B) reinforces these patterns. Stronger explanatory power clusters in the central and southern regions of China, with local $R^2 > 0.45$ in many cities. Much of the northwestern and western regions exhibit weak model fits, with local $R^2 < 0.2$, underscoring the limited relevance of this relationship in those contexts.

The spatially explicit results derived from the GWR analysis reveal meaningful heterogeneity in how socioeconomic variables correlate with air pollution indicators across Chinese cities. By moving beyond global regression models, the GWR results challenge the assumption of uniformity embedded in the traditional EKC hypothesis.

In the case of the population's influence on pollutants such as AQI and $PM_{2.5}$, the findings demonstrate phenomena traditional EKC cannot fully explain. Eastern and central coastal regions show a stronger positive relationship, even though these areas have higher socioeconomic development levels. These are likely driven by urban concentration, vehicular emissions, and energy demand, whereas less developed interior cities experience either weaker or negative correlations. Targeted interventions, such as building energy-efficient infrastructure and improving urban ventilation, must be concentrated in rapidly densifying cities where population correlates with higher pollutant levels.

Regarding industrial composition, CO and SO_2 show highly uneven associations with the manufacturing share of GDP. In industrial heartlands, particularly in parts of Northeastern Plain, manufacturing remains a substantial driver of pollutant concentrations. Yet, in cities with declining or restructured industrial sectors, the link is considerably weaker or even reversed. This reveals a critical insight for environmental governance, that decarbonization and pollution mitigation should not solely be oriented around sectoral averages, but rather spatially informed strategies that recognize which cities bear the environmental costs of national industrial output.

The localized explanatory power captured through maps of local R^2 indicates that pollution control strategies must reflect regional variations in explanatory strength. In some cases, socioeconomic factors may explain a considerable portion of pollution variance, while in others, alternative drivers, such as meteorological conditions, inter-regional spillovers, or regulatory effectiveness, may be more important. This spatial variability in model fit also exposes the limitations of EKC-inspired thinking that presumes a universal pathway from pollution to development.

Conclusion and Reflections

This study provides evidence that challenges the simplistic reliance on the EKC as a framework for environmental planning in developing regions. The quadratic regression results indicate that while certain socioeconomic indicators, such as population and GDP, show statistically significant EKC-like relationships with air pollution levels, the practicality of their turning points varies widely, suggesting that passive development alone will not lead to environmental improvement.

The GWR analysis further reinforces the limitations of a one-size-fits-all strategy. It highlights spatial heterogeneity in the strength and direction of relationships between socioeconomic factors and air pollution indicators across Chinese cities. In particular, the relationship between urban population and $PM_{2.5}$ or AQI varies geographically, with stronger correlations found in highly urbanized regions such as the Yangtze River Delta and parts of the North China Plain. These areas require urgent, place-based strategies focusing on transit electrification, congestion pricing, and building retrofits to mitigate air quality impacts from dense urbanization.

Several limitations of this study must be acknowledged. The analysis ultimately includes 151 Chinese cities, constrained by data availability. The absence of a comprehensive digital data infrastructure at the local government level hindered access to longitudinal and standardized datasets. Our analysis is cross-sectional, relying on data from the year 2015. While this limits our ability to assess temporal dynamics, the substantial developmental heterogeneity across Chinese cities within the same year justifies a cross-sectional approach. The study eventually fulfills its central aim, to evaluate the extent to which the EKC framework can explain the relationship between urban socioeconomic development and air pollution. The findings highlight the need for caution in extrapolating EKC results and the importance of context-specific factors, including geography, data scale, and policy environments, in shaping pollution-development trajectories (He et al. 2021). Another limitation of this study lies in its omission of key confounding factors related to climate conditions, natural conditions, and the built environment in the global quadratic regression analysis. While the regression models were designed to isolate the relationship between individual socioeconomic indicators and air pollution levels, the exclusion of variables such as wind patterns, elevation, and temperature inversions may affect the robustness of the results. However, the primary objective of the quadratic regression was to detect overarching EKC relations between economic environmental variables, not to construct fully specified atmospheric models. Their absence was therefore a necessary tradeoff to maintain model interpretability and comparability across regions. Nevertheless, their influence is not dismissed. Spatial heterogeneity captured in the GWR analysis partially accounts for such local environmental effects, reinforcing the value of a two-step approach that begins with a simplified global estimation and follows with a spatially adaptive local model. Future studies incorporating climate and physical geography layers could enhance the explanatory power and realism of pollution modelling in urban settings.

When planning future strategies for air pollution mitigation, policymakers in developing countries should be cautious in relying on the EKC as a guiding framework. The air pollution policy should be geographically and economically sensitive. In industrial regions where manufacturing remains strongly linked to CO and SO_2 emissions, as evidenced by elevated local coefficients and R^2 values, regulatory attention must be directed toward industrial upgrading. This includes retrofitting facilities with low-emission technologies, enforcing stricter emissions caps, and incentivizing the relocation or transformation of high-polluting industries into greener sectors. However, unlike historical patterns in developed countries, simply shifting pollution-intensive industries to less developed regions is no longer a viable or ethical strategy. The focus must shift toward real mitigation rather than spatial displacement. And recent studies even suggest that including renewable energy variables may improve the explanatory power of EKC models in the Chinese context (Chen et al. 2019; Dong et al. 2019).

Uneven GWR explanatory power suggests the presence of alternative drivers of pollution, such as atmospheric transport, externalities from neighbouring cities, or uneven enforcement of environmental policy. These cases point to the need for improved regional coordination and air quality management at broader spatial scales. Inter-jurisdictional mechanisms such as regional emissions trading schemes, shared air monitoring networks, and cross-boundary pollution control agreements may be necessary to address these systemic spillover effects.

Furthermore, the limitation of this study reveals the importance of integrated data systems for supporting differentiated policy design. Many of the limitations in this study, particularly the inability to conduct longitudinal analyses, stem from the lack of consistent city-scale data at the national level. Building transparent, interoperable, and regularly updated data infrastructures will not only improve future research but also strengthen cities' capacity to design policies responsive to their unique environmental challenges.

In all, policymakers should abandon overreliance on theoretical EKC trajectories and instead adopt differentiated strategies grounded in empirical relationships observed at the city level. Pollution control interventions must be locally tailored, technologically adaptive, and regionally coordinated to reflect the spatial complexity of socioeconomic-environmental interactions in contemporary urban China. Efforts to reduce pollution must be deliberate, not deferred. Policy should focus on reducing emissions at the source rather than displacing pollution geographically or temporally. Relying on passive structural shifts, such as sectoral changes or deindustrialization, is unlikely to yield equitable or sustainable outcomes without targeted environmental regulation, investment in clean technologies, and regional coordination.

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Appendix

TABLE A.1 References for variables used in this study

Type	Variable	References
Socioeconomic variables	GDP/Capita	Işik, Ongan, and Özdemir (2019); Nasrollahi et al. (2020)
	Urbanization rate	Bashir et al. (2021)
	Population	Işik, Ongan, and Özdemir (2019); Nasrollahi et al. (2020)
	Road length	Wang and Zha (2024)
	Energy intensity	Bashir et al. (2021); Nasrollahi et al. (2020)
	% Service Industry(S) in GDP	Li et al. (2019); Nasrollahi et al. (2020)
	% Manufacturing Industry in GDP	Li et al. (2019); Nasrollahi et al. (2020)
	% Labourers in Agriculture	Li et al. (2019)

TABLE 2 *Continued*

Type	Variable	References
Air pollution variables	Air Quality Index	Wu et al. (2018)
	CO	Dasgupta et al. (2002); Nasrollahi et al. (2020)
	NO_2	Dasgupta et al. (2002)
	PM_{10}	Dasgupta et al. (2002); Krzyzanowski et al. (2014)
	$PM_{2.5}$	Dasgupta et al. (2002); Krzyzanowski et al. (2014)
	SO_2	Dasgupta et al. (2002)

TABLE A.2 Morans' I analysis results of air pollution indicators

Air Pollution Indicator	Moran's I Index	Z-score
AQI	0.2249	44.8032
CO	0.1552	31.0061
NO_2	0.1682	33.4775
$PM_{2.5}$	0.2122	42.1551
PM_{10}	0.1702	34.6849
SO_2	0.2045	40.7122
O_3	0.0735	15.1473

Overall, Moran's I results show that all air pollution indicators tend to spatially cluster. Table A.2 shows the Moran's I analysis results. While Moran's I index is not very high, all values are close to each other, suggesting that the difference between clusters is not very large. Also, the Index shows that AQI, $PM_{2.5}$, and SO_2 have the most evident clustering pattern. Moran's I values range from 0.0735 (for O_3 - Ozone) to 0.2249 (for AQI), with Z-scores well above the conventional threshold for statistical significance (e.g., $Z > 2.58$ at $\alpha = 0.01$). These results suggest that, while the spatial patterns of air pollution are not random, the degree of spatial dependence is generally weak to moderate across the study area.

Moran's I results show that there is a clear tendency for cities adjacent to exhibit similar air quality. The results suggest that the EKC, when applied without accounting for spatial interactions, risks misrepresenting the true dynamics of pollution change. Spillover effects disrupt the closed-system logic of the EKC, calling for more spatially informed models and multi-scalar policy responses that reflect the interconnected nature of urban environmental systems. Further, this indicates that the smaller cities could potentially suffer from the air pollution produced by neighbouring metro areas and thus must bear the environmental cost caused by the large cities' activities. Therefore, based on the findings, especially for the air pollution indicators that show strong clustering patterns, such as AQI, $PM_{2.5}$, and

SO_2, the EKC curve may not be directly applicable for measuring the relationship between economic development and air quality.

The relatively low Moran's I values can be attributed to several practical and methodological factors. First, air pollution tends to originate from highly localized sources, such as traffic corridors, industrial zones, and specific land uses, which do not always align with broader regional spatial trends. Second, the heterogeneity among urban systems in terms of industrial structure, population density, topography, and infrastructure introduces considerable spatial noise, further weakening the degree of measurable spatial autocorrelation.

Despite the low magnitude of the Moran's I indices, their associated Z-scores indicate a high degree of statistical significance. This implies that the observed spatial clustering, though limited in strength, is not a product of random spatial arrangement. These findings emphasize the importance of localized environmental management strategies. Furthermore, the results support the validity of employing non-spatial regression models in this study, complemented by spatial diagnostics, rather than fully spatial econometric models that assume strong spatial dependence in the dependent variable.

Moran's I results offer critical insight into the limitations of the EKC, particularly in its assumption that the relationship between economic development and environmental degradation is spatially self-contained. While the EKC hypothesis assumes that pollution levels will rise and eventually fall as a region develops economically, it implicitly assumes that environmental outcomes are primarily determined by internal economic dynamics, rather than by interactions with neighbouring regions.

Abstracts in Slovene

Vključevanje raziskav o sreči v končne kazalnike družbene analize življenjskega cikla

Stefan Mann in Melf-Hinrich Ehlers

Končni kazalniki za analizo družbenega življenjskega cikla (S-LCA) so še vedno manj konsolidirani kot tisti za okoljsko LCA. Obstaja široko soglasje, da bi moralo biti človekovo blagostanje osrednji cilj družbene trajnosti in s tem tudi S-LCA. Kljub temu sta trenutno dve glavni podatkovni zbirki za S-LCA omejeni na množenje delovnih ur s kakovostnim ali tveganjsko prilagojenim faktorjem. Namen tega prispevka je oceniti skladnost med to tehnično pragmatičnostjo in dobro uveljavljenimi ugotovitvami raziskav o sreči. Analiza se začne z argumentom, da sta dokazljivost in posledičnost nujna kriterija za vsako uporabljeno spremenljivko. Nato je prikazano, da nekatere spremenljivke, kot je revščina, niso posledične, medtem ko enota delovnih ur ne izkazuje nobenih dokazov o povezavi s subjektivnim blagostanjem. Analiza zaključi, da bi bil preprost točkovni končni kazalnik primernejši za S-LCA kot trenutni kazalnik, ki temelji na urah.

Ključne besede: družbena trajnost, analiza življenjskega cikla, kazalniki, končni kazalnik
Klasifikacija JEL: P11
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Optimizacija zalog kot orodje za zmanjšanje živilskih izgub in povečanje dobičkonosnosti: Študija primera malih pekarn v Sloveniji

Špela Lipnik in Žiga Čepar

Ta članek raziskuje vlogo upravljanja zalog pri zmanjševanju zavržkov hrane in izboljšanju gospodarske uspešnosti v izbranih slovenskih pekarnah ter tako prispeva k učinkovitejšemu, okoljsko odgovornemu in trajnostnemu gospodarstvu. Z uporabo polstrukturiranih intervjujev s ključnim osebjem pekarn ter poglobljeno analizo poslovne dokumentacije študija uporablja model ekonomske količine naročila (EOQ) in model Newsvendor za preverjanje naslednjih dveh hipotez: (H1) izboljšanje upravljanja zalog v Pekarni 1 lahko zmanjša skupne letne stroške nabave za več kot 15 % brez povzročanja kvarjenja ali zavržkov surovin, in (H2) zmanjševanje zavržkov hrane v Pekarni 2 ni nujno usklajeno z maksimiranjem dobička. Ugotovitve potrjujejo, da uporaba teh modelov lahko izboljša načrtovanje proizvodnje in nabave ter pokažejo, da

sta tako zniževanje stroškov kot zmanjševanje zavržkov dosegljiva, vendar nista vedno popolnoma usklajena. Študija poudarja pomen strateškega upravljanja zalog za uravnoteženje finančnih in okoljskih ciljev v malih pekarnah.

Ključne besede: modeli upravljanja zalog EOQ in Newsvendor, optimizacija zalog, zmanjševanje zavržkov hrane, trajnostno gospodarstvo, Slovenija
Klasifikacija JEL: Q010, Q530
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Priložnosti za indijske ženske pri priložnostnih delih brez uporabe digitalnih platform: Pomen poklicnega usposabljanja

Sayantani Santra in Amit Kundu

Fleksibilni delovni čas lahko ponudi boljšo možnost za indijske ženske, ki vstopajo na trg dela. To je mogoče doseči z opravljanjem priložnostnih del brez odvisnosti od digitalnih platform, saj ima veliko posameznikov omejen dostop do tehnologije. Priložnostni delavci in samozaposleni so obravnavani kot delavci na podlagi priložnostnih pogodb (gig workers), ki lahko svoje delo opravljajo brez uporabe digitalnih platform. Probit model identificira dejavnike, ki lahko povečajo verjetnost opravljanja takšnih priložnostnih del brez uporabe digitalne platforme za indijske ženske. Z uporabo bivariantnega Probit regresijskega modela, ki temelji na podatkih Periodične ankete o delovni sili za leto 2022–23, in ob upoštevanju endogenosti članek pokaže, da tako formalno kot neformalno poklicno usposabljanje pozitivno vplivata na udeležbo žensk pri opravljanju priložnostnih del brez uporabe digitalnih platform. Vendar pa je vpliv neformalnega usposabljanja izrazitejši.

Ključne besede: priložnostno delo (gig job), samozaposleni delavec, priložnostni nadomestni delavec, neplačano gospodinjsko delo, formalno poklicno usposabljanje, bivariantna Probit regresija
Klasifikacija JEL: C51, C87, J44, J78, R20
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Je okoljska Kuznetsova krivulja še aktualna v današnjem času? – Analiza onesnaženosti zraka v kitajskih mestih

Jun Wang, Shinah Park in Gulsah Akar

Ta študija je raziskovala prisotnost odnosov, podobnih okoljski Kuznetsovi krivulji (EKC), med različnimi socioekonomskimi spremenljivkami in kazalniki onesnaženosti zraka v 151 kitajskih mestih, analiziranih z uporabo kvadratnih regresijskih modelov in geografsko utežene regresije (GWR). Rezultati ponujajo ključne vpoglede v uporabnost in omejitve EKC. Le indeks kakovosti zraka, dušikov dioksid (NO_2) in drobni delci ($PM_{2.5}$) kažejo statistično pomembne korelacije z eno socioekonomsko spremenljivko, vsaka v vzorcu, podobnem EKC, ki je smiselna v realnosti. Koeficienti GWR služijo kot diagnostično orodje za prepoznavanje mest z večjimi obremenitvami, kjer bi bilo treba prednostno uvesti strožje emisijske standarde, okolju prijaznejše industrijske prakse ali gospodarsko prestrukturiranje. Prostorske odvisnosti postavljajo pod vprašaj predpostavko EKC o izolirani dinamiki med okoljem in gospodarstvom. Strožji okoljski predpisi v razvitih območjih pogosto vodijo k premiku onesnažujočih dejavnosti v regije z milejšimi standardi. Politike za boj proti onesnaženosti zraka bi se morale osredotočiti na neposredno zmanjšanje emisij z lokaliziranimi, tehnološko podprtimi ukrepi, namesto da bi se zanašale na gospodarsko rast kot sredstvo za izboljšanje kakovosti zraka. Prostorsko ciljno usmerjene politike, ki temeljijo na vzorcih posameznih mest, so bistvene, saj so rezultati onesnaženosti oblikovani z regionalnimi industrijskimi strukturami, gostoto prebivalstva in čezmejnimi učinki razlitja.

Ključne besede: onesnaženost zraka, razvoj mest, geografsko utežena regresija, trajnostni razvoj, ekološki razvoj
Klasifikacija JEL*:* Q56
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