Research Article

Testing Baumol's Cost Disease in Tourism: Productivity, Prices, and Labour Costs in Selected EU Countries Post-COVID

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This paper investigates the impact of the transition from manufacturing to tourism on sectoral inflation and labor costs. Using panel data econometric models for 15 selected EU countries from 2011 to 2023, the study confirms key dynamics predicted by Baumol's Cost Disease (BCD) hypothesis. The findings reveal that higher productivity is positively associated with both implied prices and hourly labor costs across sectors, supporting the wage equalization mechanism central to BCD. However, the relationship between productivity and wages or prices is weaker in labor-intensive sectors like tourism, underscoring their structural vulnerability to wage-driven cost pressures. Additionally, the COVID-19 pandemic significantly increased implied prices but had no statistically significant impact on labor costs, highlighting the differential effects of external shocks on wages versus prices. These results emphasize the challenges faced by low-productivity, labor-intensive sectors in managing cost dynamics, offering insights for policymakers addressing sectoral imbalances in the context of BCD.

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1. Introduction

Baumol's Cost Disease (BCD), introduced by Baumol and Bowen[1], explains why labor-intensive sectors like healthcare, education, and tourism experience rising real costs due to stagnant productivity. It highlights why the costs of labor-intensive services rise faster than those of goods-

 doi.org/10.32388/1JHL0U

producing industries with higher productivity gains. This theory is particularly relevant to service sectors such as healthcare, education, tourism, and the arts, where productivity improvements are inherently constrained by the need for human interaction and attention. In these sectors, the value of the service is often tied to the quality and duration of the provider's attention, making the adoption of productivity-enhancing technologies more challenging without sacrificing service quality. As a result, labor costs in these industries tend to increase faster than productivity, ultimately leading to rising prices and slower economic growth. This phenomenon is especially pronounced in developed economies, where services dominate the economic structure and contribute more significantly to GDP.

In most developed economies of the European Union, the service sector dominates economic activity, accounting for 60–80% of GDP (TheGlobalEconomy.com 2023). For instance, the United Kingdom (73%), Germany (64%), France (70%), and Luxembourg (81%) exemplify this trend, reflecting the sector's critical role in driving economic growth and employment. Key subsectors within the service economy include financial services (e.g., banking and insurance), professional services (e.g., legal, consulting, and IT), healthcare and education, and tourism and hospitality.

Tourism, as a prime example of an attention-driven service sector, faces unique challenges within the framework of BCD. Tourism services, such as waitering, tour guiding, and concierge activities, rely heavily on human attention to deliver personalized, high-quality experiences to customers. These roles are labor-intensive and difficult to automate without compromising service standards. For instance, a waiter in a restaurant must dedicate their full attention to ensuring customer satisfaction, while a tour guide must engage with travelers, answer questions, and provide an interactive experience. The necessity of human interaction in these roles underscores the "attention economy" embedded in tourism, where the service provider's time and focus are central to the value delivered . This reliance on attention not only limits productivity growth but also exacerbates the impact of rising labor costs, as argued by Vollrath (2020). We would particularly stress this dynamic in the post-COVID era, when many tourism-dependent economies are striving for recovery.

Furthermore, the interplay between labor costs, productivity, and prices in tourism versus manufacturing sector has not been comprehensively analyzed within the framework of Baumol's cost disease. The objective of this study is to address these gaps by testing Baumol's cost disease in the tourism sector of selected EU countries in the post-COVID period.

This paper contributes to the literature by addressing a critical gap in understanding the relationship between productivity, labor costs, and prices in the tourism sector, offering insights into the structural challenges it poses for economic growth in the selected areas of the EU. Specifically, it examines the implications of relying on tourism as a central development strategy while neglecting the challenges of de-industrialization, which may have long-term consequences for balanced and sustainable economic growth. Today, we are witnessing transformative shifts in political arenas across the global stage, driven by globalization's impact on developed economies—particularly their transition from manufacturing to knowledge-based sectors such as IT, R&D, and consulting, as emphasized by Sawatani and Fujigaki[2]. Additionally, there is a growing reliance on tourism, even as production increasingly shifts to lower-cost regions.

This paper is structured as follows. After the introductory part, the next section provides a detailed literature review, highlighting the key studies and gaps related to BCD in the tourism sector, especially in the post-COVID context. This is followed by the Theoretical Framework of Baumol's Cost Disease Hypothesis (BCDH), which outlines the conceptual underpinnings of BCDH and its application to tourism. After this, the paper describes the data sources and datasets used, ensuring transparency in how the empirical evidence is derived. The subsequent section, Empirical Specification, presents the methodological approach, including the baseline technique and robustness strategy employed in the analysis. The empirical part of the paper then follows, where the findings are presented and interpreted. The discussion and conclusion section synthesizes the results, draws policy implications, and suggests avenues for future research. Finally, the paper concludes with a reference list, and in the Appendix, it includes the Mathematical Framework of BCDH and a complete list of the tables, which are based on the empirical evidence generated through the analyses conducted in this study.

2. Literature Review

Despite the relevance of BCD to tourism, there remains a significant gap in the literature regarding its application to this sector, particularly in the context of the post-COVID economic landscape. Existing research has largely focused on other service industries, such as healthcare and education, while tourism has received comparatively little attention. Nevertheless, BCD as a topic linked to tourism issues has persisted for some time. For example, Smeral[3] highlights that this theory has been widely applied to tourism, where productivity growth is constrained by the nature of service delivery. The emotional labor involved in co-created tourism experiences adds further complexity to productivity challenges in tourism, as BCD theory argues that these tasks cannot be easily automated or substituted with technology[4]. This makes tourism a prominent example of a sector where the quality of service relies heavily on human attention, further amplifying the effects of BCD.

Recent studies confirm that BCD remains a persistent issue, exacerbated by the inability to substitute labor with technology in labor-intensive sectors such as tourism. For instance, Doerksen[5] emphasizes this challenge, while Ek et al.[6] identify the tourism sector as particularly vulnerable due to its reliance on services like hospitality and customer support. Empirical evidence from China's performing arts sector, using data from the Ministry of Culture and Tourism, demonstrates that while digital technologies can mitigate some effects of BCD, they do not eliminate them entirely[7]. Similarly, Tang[8] found that the digital economy drives tourism development in the UK but faces structural limitations in non-OECD countries, where BCD effects remain pronounced.

The tourism-led growth hypothesis has also been a focal point of recent research. For example, Balado-Naves et al.[9] developed a multisector growth model to test this hypothesis, finding that tourism specialization yields positive growth rates only if the tourism sector is more productive than other sectors. However, this finding contrasts with the central insight from the BCD conjecture, which argues the opposite—that tourism's labor-intensive nature inherently limits productivity growth. Supporting this view, the "Beach Disease" hypothesis, introduced by Tubadji and Nijkamp[10], suggests that over-reliance on tourism can lead to economic imbalances, particularly in developing economies. This highlights the structural vulnerabilities associated with tourism-dependent growth strategies, particularly in light of BCD.

Technological advancements offer potential solutions to mitigate BCD's impact on tourism. Mithas et al.[11] emphasize the role of information technology in addressing BCD in healthcare, suggesting that similar approaches could enhance productivity in tourism. Digital tools and automation, such as online booking systems or artificial intelligence-driven customer support (AI-DCS), offer opportunities to increase efficiency and reduce labor costs, though their effectiveness varies across sectors[12]. However, the human-centric nature of tourism services—such as personalized customer care and experiential services—limits the extent to which these tools can replace labor without compromising quality.

The COVID-19 pandemic exacerbated the challenges posed by BCD in tourism. The sector's reliance on labor-intensive services made it particularly vulnerable to rising costs and reduced productivity during the crisis[13]. Post-pandemic recovery efforts have underscored the need to address these structural issues, balancing the pursuit of productivity improvements with the preservation of employment in tourism. Another dimension of this structural transformation is its environmental implications. Dezfuli et al.[14] found that the shift from goods-based to service-based economies, often driven by BCD, is associated with reduced CO_2 emissions. This suggests that while BCD poses economic challenges, it may also contribute to environmental sustainability by reducing reliance on resource-intensive industries. However, the environmental benefits of this transformation must be weighed against the economic costs of rising service prices, particularly in tourism-dependent economies.

Cross-country perspectives reveal that the impact of BCD varies significantly across national contexts, influenced by factors such as cultural proximity and international tourism dynamics. Tubadji and Nijkamp[10] argue that tourism plays a crucial role in economic equilibration, particularly in countries with cultural proximity. However, the sector's susceptibility to BCD poses challenges for long-term growth, especially in developing economies that rely heavily on tourism as a driver of GDP.

Policy implications and public support are critical for addressing the economic challenges posed by BCD in tourism. The public goods aspects of sectors affected by BCD, such as prestige-related tourism and education, justify government intervention to mitigate its effects[15][16]. Public support, including subsidies or targeted investments, often becomes necessary to address rising costs in labor-intensive tourism services where productivity improvements are inherently limited[17].

3. Theoretical Framework of BCDH

BCDH builts on intuition that goods-producing sectors tend to experience higher productivity growth over time, whereas service-producing sectors face slower productivity growth due to their labor-intensive nature. This disparity leads to rising relative prices for services, even when productivity in those sectors remains stagnant. As incomes rise, demand for services increases because services are income-elastic. Consequently, more labor shifts into the service sector despite its slower productivity growth. The result is an increase in the relative cost of services compared to goods over time.

Baumol's theory emphasizes that productivity in services is constrained by the inherent need for human time and attention—factors that are difficult to replace or augment with technology. This constraint fundamentally differentiates services from goods in terms of productivity growth potential.

doi.org/10.32388/1JHL0U

To outline BCDH and its implications for inflation dynamics, labor costs, and productivity growth in a two-sector economy (goods and services), we draw on key insights derived from the Mathematical Framework of BCDH section (included in the Appendix for detailed inspection). These insights are summarized as follows: - Faster productivity growth in the goods sector ($g_G > g_S$) drives inflation dynamics. The inflation differential $\Delta\pi(t) = g_G - g_S$ explains why service sectors experience higher inflation. Rising wages and stagnant productivity in services lead to higher labor costs and prices.

While Baumol's framework offers a robust explanation of sectoral cost dynamics, external shocks such as the COVID-19 pandemic can disrupt these theoretical predictions. The pandemic has introduced significant uncertainty by altering labor market structures, demand for services, and productivity patterns in ways that are difficult to predict. These disruptions make it harder to apply the theoretical framework to current and future economic conditions with certainty. However, we will assess these issues in the econometrics section of the paper. For now, we leave this as part of the theoretical discussion.

4. Empirical Specification

4.1. Panel Difference-in-Differences (PDiD) as a Baseline Regression

The concept of Panel Difference-in-Differences (PDiD) builds upon the traditional Difference-in-Differences (DiD) methodology, which is widely attributed to Ashenfelter and Card[18]. This method is particularly effective for causal inference when evaluating the effect of an intervention or treatment across groups and over time. To evaluate the relationships proposed by BCDH and to examine the average post-COVID effect, we estimate the following baseline PDiD regression model:

$$Y_{it} = \beta_0 + \beta_1 \cdot \mathrm{log\_Productivity}_{it} + \beta_2 \cdot \mathrm{NACE\_R2I}_i + \beta_3 \cdot \mathrm{treatment\_post}_t + \\ \beta_4 \cdot (\mathrm{log\_Productivity} \times \mathrm{NACE\_R2I})_{it} + \epsilon_{it}$$

This specification leverages the DiD framework by comparing the effects of productivity growth (log_Productivity) on the dependent variable (Y_{it}, e.g., Log_Implied_Price or log_Labour_Cost_per_Hour) for country i in period t across sectors (tourism vs. manufacturing) and over time (pre- vs. post-COVID).

In this model, Y_{it} represents the dependent variable for country i in period t. The term $\mathrm{log\_Productivity}_{it}$ is the natural logarithm of productivity, measured as output per worker or a similar metric. $\mathrm{NACE\_R2I}_i$ is a dummy variable equal to 1 for the tourism sector and 0 for manufacturing.

 doi.org/10.32388/1JHL0U

Similarly, $\mathrm{treatment\_post}$ is a dummy variable that equals 1 for the post-COVID years (2020–2023) and 0 for the pre-COVID baseline period (2011–2019). Lastly, the interaction term $(\mathrm{log\_Productivity} \times \mathrm{NACE\_R2I})_{it}$ captures sectoral asymmetry, highlighting how the productivity effects in tourism differ from those in manufacturing.

We expect $\beta_1 > 0$ because BCDH posits that higher productivity growth in manufacturing (the "progressive" sector) should dampen output price inflation and labor cost growth. However, a positive $\beta_1 > 0$ would imply that productivity gains are associated with higher output prices or rising labor costs, potentially reflecting market power, wage bargaining, or input cost rigidities. The coefficient β_2 is also expected to be positive, as tourism, which inherently faces structural rigidities (e.g., labor-intensive operations), should have baseline output prices and labor costs that are higher than those in manufacturing.

The coefficient β_3, associated with the treatment_post variable, is hypothesized to be positive ($\beta_3 > 0$). This reflects the expectation that post-COVID disruptions, such as supply-chain shocks and labor shortages, have increased output prices and labor costs on average across both sectors. Finally, the interaction term coefficient β_4 is expected to be negative ($\beta_4 < 0$). This is a critical aspect of BCDH, as it implies that productivity improvements in tourism, a "stagnant" sector, are less effective at curbing price or cost growth compared to manufacturing. A negative β_4 would indicate that productivity gains in tourism have weaker mitigation effects on costs and prices than in the progressive manufacturing sector. That interaction term is critical for identifying the sector-specific difference-in-differences effects of productivity on prices or costs, particularly in tourism versus manufacturing. This is why β_4 plays a pivotal role in testing the BCDH and sectoral asymmetry hypotheses.

The plan is to implement a PDiD approach as the baseline econometric technique to analyze the relationships in the dataset. This methodology will undergo a series of diagnostic tests to address potential econometric challenges, ensuring that the chosen specification is robust and well-suited to the complexities of the data. The focus will be on refining the model to account for issues such as heteroskedasticity, cross-sectional dependence, and serial correlation. If serial correlation issues arise, we may need to reconsider our initial assumptions that random effects (RE) or fixed effects (FE) models suffice, as highlighted by Bertrand, Duflo, and Mullainathan[19] and Wooldridge[20], ensuring that our empirical analysis remains reliable and valid.

doi.org/10.32388/1JHL0U

4.2. Testing Robustness of the Baseline Method

The robustness of the baseline PDiD method will be tested using the following econometric techniques:

- Robust and Clustered Standard Errors: To address heteroskedasticity and within-cluster correlation, we will apply robust and clustered standard errors at the country-sector level, following Bertrand, Duflo, and Mullainathan[19].
- Heteroskedasticity-Robust Standard Errors: These will be used to ensure the validity of results under non-constant variance across observations, as suggested by White[21].
- Clustered Standard Errors: To refine fixed-effects estimates while accounting for group-level dependencies, we will implement clustering, as discussed by Cameron and Miller[22].
- Random Slopes Models: Mixed-effects models with random slopes will test the sensitivity of results to within- and between-cluster variation, following Wooldridge[20].

This multi-step approach addresses potential issues such as heteroskedasticity, cross-sectional dependence, and serial correlation. If serial correlation proves problematic, we will follow Bertrand, Duflo, and Mullainathan[19] by adjusting standard errors or applying block bootstrap methods. Together, these techniques ensure that the baseline method's findings are rigorously validated against econometric challenges, enhancing the reliability of the analysis and mitigating risks of bias from statistical artifacts.

4.3. Data and source

The dataset comprises data from 15 EU countries: Austria, Belgium, Czechia, Estonia, Greece, Finland, France, Italy, Lithuania, Luxembourg, Latvia, the Netherlands, Sweden, Slovenia, and Slovakia, covering the period from 2011 to 2023. The selection of these countries was constrained by data availability, as significant gaps in other EU countries rendered their inclusion unfeasible. For the selected countries, smaller data gaps were addressed using imputations performed with the mice package[23], ensuring a complete and reliable dataset for analysis. The data used in this study underwent transformations to compute key indicators such as Implicit Price, Labour Costs per Hour, and Labour Productivity, specifically tailored for the manufacturing sector (C = Total Manufacturing) and the tourism sector (I = Accommodation and Food Service Activities). These transformations relied on growth accounting principles and sector-specific data from authoritative sources, including the wiiw-GDP Release 2024, produced by the Vienna Institute for International Economic Studies[24]. This dataset provides valuable insights into economic performance, offering data on value-added, growth accounting components, and capital deepening measures, which are critical for analyzing sectoral trends and labor income shares.

To enhance interpretability, logged transformations were applied to continuous variables, focusing on percentage changes and growth rates, while dummy variables were used to capture sector- and time-specific effects, such as the tourism sector (NACE_R2I) and the post-COVID period (treatment_post). Growth accounting and capital deepening serve as foundational inputs for deriving these key indicators, ensuring sector-specific nuances are adequately addressed.

These transformations enable a detailed decomposition of sectoral performance, facilitating comparisons between manufacturing and tourism, where tourism is proxied by the values inherited from Accommodation and Food Service Activities. For example, labor productivity is computed as the ratio of real value-added to total hours worked, providing insights into sectoral efficiency as reflected in wages. Similarly, the implicit price index (a proxy for sectoral inflation) and labor cost per hour offer critical perspectives on pricing and cost dynamics. The use of logged continuous variables highlights relative changes, while dummy variables capture key treatment effects, enabling robust and reliable analysis in the context of BCD. This approach assumes that tourism, as proxied by Accommodation and Food Service Activities, provides a suitable framework for analyzing sectoral dynamics in the post-COVID era.

Table 1 below summarizes the variables, their formulas, data sources, and transformations used in the study.

Variables	Dana	Transformation
Implicit Price	TFP2__VA	Logged
Labour Cost	Shares__LabourIncome , TFP2__VA	Logged
Labour Cost per Hour	Computed from previous formula, TFP2__LPH	Logged
Labour Productivity	TFP2__VA, TFP2__LPH	Logged
Sector Indicator	NACE__R2I	Dummy (Tourism = 1)
Post-COVID Indicator	Treatment__Post	Dummy (Post-COVID = 1)

Table 1. Summary of Data Transformations

Source: Authors' calculation.

5. Evidence of BCDH's Analysis

The results analysis is structured in two parts. First, it involves the selection and application of a suitable panel data Difference-in-Differences (DiD) technique to evaluate the primary outcomes. Second, it entails the reassessment of these primary results using the baseline regression method selected through rigorous econometric testing. This two-step approach ensures the robustness and reliability of the findings, addressing both methodological and data-specific challenges.

5.1. Econometric Technique Selection: Justification for Panel-Corrected Standard Errors (PCSE)

The choice of PCSE as the baseline method was guided by extensive diagnostic testing to address key econometric challenges in the panel dataset.

5.1.1. Model Diagnostics

These diagnostics (presented in Table 2) were conducted during the initial evaluation phase—primarily using fixed effects (FE) and/or random effects (RE) models—to address econometric challenges, ultimately leading to the selection of PCSE as the more appropriate method.

Test	Statistic	Degrees of Freedom (df)	p-Value	Conclusion
Heteroskedasticity	Chi-sq = 10.336	df = 4	p = 0.035	Heteroskedasticity detected.
Cross-Sectional Dependence	z = 4.91	–	p = 0.000	Significant cross-sectional dependence.
Serial Correlation	Chi-sq = 58.308	df = 26	p = 0.000	Serial correlation detected.
F-Test for Individual Effects	F = 2.287	df1 = 14, df2 = 371	p = 0.005	Significant individual effects id

Table 2. Model Diagnostics Supporting the Use of Panel-Corrected Standard Errors (PCSE)

Source: Authors' calculation.

Evidence of heteroskedasticity suggested non-constant error variances across observations, risking inefficient estimates in traditional models. Additionally, significant cross-sectional dependence was identified, likely due to economic interdependence among countries, which standard FE and RE models cannot manage effectively. Serial correlation within panel units further complicated the analysis, necessitating a method that accounts for autocorrelated disturbances.

While FE and RE models can handle individual effects, they fall short in simultaneously addressing heteroskedasticity, serial correlation, and cross-sectional dependence. PCSE stands out in this context by correcting for non-constant variances, modeling contemporaneous error covariance, and accommodating autocorrelation. Therefore, based on these diagnostic findings, the PCSE results presented in Table 3 were determined to be the most robust and appropriate econometric technique for this analysis.

Variable/Dependent variable	Log Implied Price	Log Labour Cost per Hour
	Model 1	Model 2
(Intercept)	-3.022 (-27.07* **)	-2.771 (-3.75* **)
log_Productivity	0.073 (*2.56 **)	0.504 (3.47* **)
NACE_R2I	0.387 (*2.34 **)	0.323 (0.64)
treatment_post	0.634 (3.60* **)	-0.048 (-0.04)
log_Productivity:NACE_R2I	-0.137 (-2.91 **)	-0.494 (**-2.00* **)

Table 3. Panel-Corrected Standard Errors (PCSE) results

Source: Authors' calculation. Note: Significance Levels: ***p < 0.01, **p < 0.05, *p < 0.1.

5.1.2. Interpretation of Model 1 Results: Log Implied Price as the Dependent Variable

In Model 1, the dependent variable is log_Implied_Price, and the results reveal several patterns consistent with the dynamics predicted by BCDH. The coefficient for log_Productivity is positive and statistically significant (0.073, p = 0.011), indicating that higher productivity levels are associated with higher implied prices. This finding aligns with Baumol's theory, which suggests that as productivity increases, wages also rise, driving up prices even in sectors where productivity gains are slower. However, it is important to note that the real impact of productivity on labor costs (or wages) is assumed but not explicitly extracted in this model, as labor cost is not directly included as a dependent variable in Model 1. The observed relationship between productivity and implied prices reflects the cost-pass-through mechanism, where higher wages—driven by productivity gains—translate into higher prices, but the direct link between productivity and wages remains implicit in the interpretation.

The variable NACE_R2I, identifying the tourism sector (accommodation and food services) relative to manufacturing, has a positive and significant coefficient (0.387, p = 0.020). This result suggests that implied prices in the tourism sector are generally higher than in manufacturing. This can be attributed to structural differences between the two sectors: tourism is notably labor-intensive and experiences slower productivity growth, making it more vulnerable to rising labor costs under wage equalization.

doi.org/10.32388/1JHL0U

While the model does not directly capture labor costs, the higher implied prices observed in tourism suggest that rising wages in this sector—driven by spillover effects from higher-productivity industries—contribute to the cost-disease phenomenon.

The interaction term log_Productivity:NACE_R2I has a significant negative coefficient (-0.137, $p = 0.003$), indicating that the relationship between productivity and implied prices is weaker in the tourism sector compared to manufacturing. This finding underscores the challenges faced by low-productivity sectors like tourism, where modest productivity improvements do little to offset price pressures driven by rising wages. Again, while the model does not explicitly measure wages, the weaker link between productivity and prices in tourism highlights how labor-intensive sectors struggle to manage wage-driven cost pressures, a central feature of BCDH.

The coefficient for treatment_post, which captures the effect of the COVID-19 period (2020–2023), is positive and highly significant (0.634, $p < 0.001$). This result indicates that the pandemic significantly increased implied prices across both sectors. This surge in prices can be attributed to pandemic-induced disruptions, such as supply chain breakdowns, increased operational costs (e.g., health protocols and labor shortages), and shifts in consumer demand. The finding suggests that external shocks like COVID-19 exacerbate cost-disease dynamics by creating additional upward pressure on prices, particularly in sectors already vulnerable to wage-cost inflation.

In summary, the results provide strong evidence that implied prices increase with productivity, but the strength of this relationship varies by sector. While productivity gains in manufacturing are more closely tied to price stability, slower productivity growth coupled with rising wages in the tourism sector leads to significant price increases. It is critical to emphasize that, although the model assumes a link between productivity and wages in driving these price changes, it does not directly measure labor costs or wages. The observed dynamics are inferred based on Baumol's framework, where rising wages—assumed to follow productivity growth—are implicitly passed through to prices. The COVID-19 pandemic amplified these dynamics, further driving up prices across both sectors and highlighting the vulnerability of labor-intensive industries to external shocks.

5.1.3. Interpretation of Model 2 Results: Log Labour Cost per Hour as the Dependent Variable

In Model 2, where the dependent variable is log_Labour_Cost_per_Hour, the results provide valuable insights into the relationship between productivity, sectoral characteristics, and labor costs.

doi.org/10.32388/1JHL0U

The analysis reveals a clear positive relationship between productivity and hourly labor costs, as indicated by the statistically significant coefficient for log_Productivity (0.504, $p < 0.001$). This suggests that higher productivity is strongly associated with higher wages per hour across sectors. This finding aligns with BCDH, where productivity growth drives wage increases. It also highlights wage equalization mechanisms, implying that productivity gains in one sector can influence wage levels across sectors, even those with slower productivity growth.

The coefficient for NACE_R2I, which distinguishes the tourism sector (accommodation and food services) from manufacturing, is positive (0.323) but statistically insignificant. This indicates that baseline hourly labor costs in tourism are not significantly different from those in manufacturing. However, the interaction term log_Productivity:NACE_R2I, which captures how the relationship between productivity and wages differs between sectors, is negative and statistically significant (-0.494, $p = 0.046$). This result suggests that the positive impact of productivity on hourly labor costs is smaller in the tourism sector than in manufacturing. In other words, while productivity gains in manufacturing are strongly associated with wage increases, the same gains in tourism have a weaker effect. This finding reflects the structural differences between the two sectors: tourism, being more labor-intensive and often characterized by lower-skill activities, struggles to translate productivity improvements into proportional wage increases. This limitation is a critical feature of Baumol's hypothesis, where labor-intensive sectors face inherent constraints in achieving wage growth comparable to that of high-productivity sectors.

The coefficient for treatment_post, representing the COVID-19 period (2020–2023), is negative (-0.048) and statistically insignificant, indicating no meaningful change in hourly labor costs during this time. This result suggests that the pandemic did not directly affect wage dynamics in a statistically significant way. This could be due to wage stability policies, labor protections, or other factors that mitigated the immediate impact of the pandemic on wages, particularly in sectors like tourism, which were heavily disrupted. It is worth noting that the lack of a significant treatment effect contrasts with the findings in other models, such as Model 1, where implied prices were significantly affected during the pandemic. This distinction underscores that changes in prices during the pandemic do not necessarily reflect parallel changes in wages.

Overall, Model 2 demonstrates that productivity is a key driver of hourly labor costs, consistent with BCDH. However, the weaker relationship between productivity and wages in the tourism sector highlights the structural challenges faced by labor-intensive industries. These sectors are less able to

 doi.org/10.32388/1JHL0U

translate productivity gains into wage increases, leaving them more vulnerable to wage pressures driven by spillover effects from high-productivity industries. While the COVID-19 period did not significantly alter hourly labor costs, the results emphasize the importance of sectoral dynamics and structural constraints in shaping wage outcomes, particularly in the context of productivity growth. These findings reinforce the broader narrative of Baumol's hypothesis, with tourism exemplifying the challenges faced by labor-intensive sectors in managing wage growth amidst slower productivity gains.

5.2. Robusness

In this section, we evaluate the robustness of the results presented in earlier models, particularly focusing on the dynamics predicted by BCDH. To ensure the consistency and reliability of our findings, we compare results across multiple estimation techniques, including OLS with robust and clustered standard errors, PCSE, and linear models estimated using FE and with random slopes. These results are presented in Tables 4 to 7 in the Appendix.

Each approach offers unique insights into the relationships between productivity, sectoral characteristics, wages, and prices, while addressing potential econometric concerns. Below, we confirm and enhance the earlier baseline evidence from PCSE results.

5.2.1. Log Implied Price as the Dependent Variable (Model 1)

The robustness of the relationship between log_Productivity and log Implied Price is evident across all models. In the baseline PCSE results, the coefficient for log_Productivity is positive and significant (0.073, $p < 0.05$), indicating that higher productivity levels are associated with higher implied prices. This finding remains consistent when examining results from OLS with robust and clustered standard errors (Table 1: 0.073, significant under heteroskedasticity-robust standard errors; significant but weaker under clustered standard errors) and when using FE-OLS (Table 3: 0.068, marginally significant). Additionally, the mixed-effects model (lmer) confirms this relationship (Table 4: 0.069, $p < 0.1$). These consistent results across estimation techniques reinforce the conclusion that productivity gains are associated with higher implied prices, in line with Baumol's hypothesis.

Similarly, the baseline PCSE results show that NACE_R2I, identifying the tourism sector, has a positive and significant coefficient (0.387, $p < 0.05$), indicating that implied prices in tourism are generally higher than in manufacturing. This pattern is confirmed across other models, particularly in

doi.org/10.32388/1JHL0U

the FE-OLS estimation (Table 3: 0.389, $p < 0.1$) and the mixed-effects model (Table 4: 0.384, $p < 0.05$). These findings underscore the structural differences between the tourism and manufacturing sectors, with tourism being more vulnerable to wage-driven cost pressures due to its labor-intensive nature.

The interaction term log_Productivity:NACE_R2I, which captures how the relationship between productivity and implied prices varies by sector, is consistently negative and significant across all models. In the PCSE results, the coefficient is -0.137 ($p < 0.01$), indicating that the relationship between productivity and prices is weaker in the tourism sector. This finding is corroborated in OLS (Table 1: -0.137, significant under robust and clustered standard errors), feols (Table 3: -0.144, $p < 0.1$), and the mixed-effects model (Table 4: -0.138, $p < 0.05$). These consistent results highlight the structural challenges faced by labor-intensive sectors like tourism in managing wage-driven cost pressures.

Finally, the treatment variable treatment_post, capturing the effect of the COVID-19 period, is positive and highly significant in all models. In the PCSE results, the coefficient is 0.634 ($p < 0.01$), indicating a substantial pandemic-induced increase in implied prices. This finding is confirmed in OLS (Table 1: 0.634, significant under both robust and clustered standard errors), feols (Table 3: 0.628, significant), and the mixed-effects model (Table 4: 0.635, $p < 0.01$). The consistent significance of this variable across estimation techniques emphasizes the pandemic's role as an external shock that exacerbated cost-disease dynamics.

Variable/Dependent variable	**Log Implied Price**	**Log Labour Cost per Hour**
	Model 1	Model 2
(Intercept)	-3.022 (***-25.54 / ***-15.79)	-2.771 (***-5.99 / ***-4.60)
log_Productivity	0.073 (**2.82 / *2.19)	0.504 (**3.03 / **3.24)
NACE_R2I	0.387 (**2.81 / *2.18)	0.323 (0.62 / 0.68)
treatment_post	0.634 (***6.13 / *4.01)	-0.048 (-0.10 / -0.11)
log_Productivity:NACE_R2I	-0.137 (**-3.44 / *-2.55)	-0.494 (*-2.15 / -1.67)

Table 4. Linear Models with Robust and Clustered Standard Errors

doi.org/10.32388/1JHL0U

Source: Authors' calculation

Notes:

- ***t-Values**: The **first t-value** corresponds to heteroskedasticity-robust standard errors; the **second t-value** corresponds to clustered standard errors.*
- ***Interpretation**: The inclusion of both t-values allows for comparison of the robustness of results across different error structures.*

5.5.2. Log Labour Cost per Hour as the Dependent Variable (Model 2)

When examining log Labour Cost per Hour as the dependent variable, the robustness of the relationship between log_Productivity and hourly labor costs is similarly confirmed. In the PCSE results, the coefficient for log_Productivity is 0.504 ($p < 0.01$), indicating that higher productivity is strongly associated with higher wages per hour. This finding holds across OLS (Table 1: 0.504, significant under both robust and clustered standard errors), feols (Table 3: 0.406, $p < 0.1$), and the mixed-effects model (Table 4: 0.431, $p < 0.01$). These results consistently align with Baumol's hypothesis, where productivity growth drives wage increases.

The coefficient for NACE_R2I is positive but statistically insignificant in the PCSE results (0.323, $p > 0.1$), suggesting no meaningful difference in baseline labor costs between the tourism and manufacturing sectors. This insignificance is also observed in OLS (Table 1: 0.323, insignificant) and FE-OLS (Table 3: 0.088, insignificant). However, the interaction term log_Productivity:NACE_R2I is negative and significant in the PCSE results (-0.494, $p < 0.05$), indicating that the impact of productivity on wages is weaker in the tourism sector. This finding is similarly observed in OLS (Table 1: -0.494, marginally significant) and the mixed-effects model (Table 4: -0.413, $p < 0.05$), reinforcing the structural challenges faced by labor-intensive sectors in achieving proportional wage growth from productivity gains.

Interestingly, the treatment variable treatment_post is negative and insignificant in the PCSE results (-0.048, $p > 0.1$), suggesting no meaningful change in hourly labor costs during the COVID-19 period. This finding is consistent across other models, including OLS (Table 1: -0.048, insignificant) and FE-OLS (Table 3: -0.060, insignificant). The lack of a significant treatment effect contrasts with the results for implied prices, indicating that the pandemic's impact on wages was likely mitigated by labor protections or wage stability policies.

5.2.3. Enhancing Earlier Results

The robustness checks provide strong support for the baseline PCSE evidence while enhancing the interpretation of sectoral dynamics and external shocks.

The key relationships between productivity, sectoral characteristics, and implied prices or labor costs are consistent across estimation techniques, confirming the validity of the baseline results.

The weaker link between productivity and wages or prices in tourism, as captured by the interaction term log_Productivity:NACE_R2I, underscores the structural vulnerabilities of labor-intensive sectors in managing wage-driven cost pressures.

Additionally, the significant impact of the COVID-19 period on implied prices, but not on labor costs, highlights the differential effects of external shocks on prices versus wages. Overall, the robustness checks confirm and strengthen the earlier findings, providing a comprehensive and reliable picture of the dynamics underpinning BCDH.

6. Discussion

Our analysis provides strong empirical support for BCDH, demonstrating how productivity growth and sectoral characteristics shape price and wage dynamics in tourism. Both models confirm that productivity gains lead to higher prices and wages overall, consistent with Baumol's original thesis. However, the tourism sector—characterized by its reliance on human interaction and labor-intensive services—struggles to translate productivity improvements into proportional wage growth or price stability. This asymmetry echoes Smeral's[3] findings on tourism's stagnating productivity and aligns with Tubadji and Nijkamp's[10] warnings about the economic risks of overreliance on tourism-led growth, encapsulated in their "Beach Disease" hypothesis, which highlights tourism's structural vulnerabilities. Furthermore, the weaker productivity-price interaction observed in tourism reflects the structural constraints outlined by Frey[4], where labor-intensive services face challenges in mitigating wage-driven inflation.

The COVID-19 pandemic amplified these dynamics in several significant ways. First, the pandemic caused substantial price surges across the tourism sector, which were not matched by corresponding wage increases. This price-wage divergence highlights the sector's vulnerability to external shocks, as noted by Ek et al.[6]. Second, despite the economic disruptions caused by the pandemic, wage levels in tourism remained largely stable. This stability can be attributed to institutional safeguards, consistent with Helland and Tabarrok's[13] findings on wage rigidity during crises. These opposing dynamics—price inflation without wage growth—underline the structural fragility of the tourism sector and its limited ability to absorb external shocks effectively.

Robustness checks across multiple statistical methods further validate these patterns, addressing concerns raised by Ma and Liu[7] about measurement biases in cost-disease studies. The COVID-19 period's distinctive effects—substantial price surges but stagnant wages—serve as a stark example of the sector's structural challenges. Overall, the pandemic revealed the acute susceptibility of the tourism sector to cost-disease dynamics, reinforcing the need for targeted policy interventions.

Our results show that productivity broadly raises wages, consistent with Baumol's thesis. Yet, tourism's muted response underscores its inability to leverage productivity gains for wage growth, mirroring Bernini and Galli's[25] findings of innovation-productivity decoupling in Italian accommodation firms. For instance, the consistent negative interaction term across methods underscores tourism's structural lag, while the pandemic's price effect persists universally. These results challenge Balado-Naves et al.[9], who posited tourism-led growth via productivity, and instead support Nordhaus[26] and Triplett and Bosworth[27], who emphasized manufacturing's superior productivity-wage alignment.

By quantifying tourism's BCD-driven price-wage spirals and resilience gaps, our work bridges Baumol's[1] foundational theory with contemporary empirics, offering policymakers a roadmap to mitigate sectoral imbalances through hybrid models, such as tech-enhanced tourism, and targeted EU cohesion funds. Our findings are in line with the argument by Brandano and Crociata[28] that the tourism sector has played a strategic role in shaping such policies in recent years. These findings also align with a more recent study, which argued that the COVID-19 pandemic has significantly influenced the adoption of artificial intelligence (AI) tools in the tourism and hospitality sector. This shift has further sparked a growing interest in advanced computerized approaches—including AI, robots, and the Internet of Things (IoT)—that are increasingly gaining acceptance and traction[29].

Future research should explore the role of automation and digital technologies in mitigating BCD in tourism, particularly in the post-COVID context. Additionally, cross-country studies could provide valuable insights into how cultural, economic, and structural differences influence the severity and outcomes of BCD in tourism. Finally, there is a need to further investigate the environmental implications of structural transformations driven by BCD, particularly in terms of balancing sustainability with economic growth in tourism-dependent regions.

7. Conclusion

This study provides robust empirical evidence supporting BCDH in the context of tourism, with important implications for understanding sectoral dynamics, wage-price relationships, and the impact of external shocks like the COVID-19 pandemic. By examining productivity, prices, and labor costs across 15 selected EU countries from 2011 to 2023, the analysis reveals that productivity gains broadly drive wage increases and price inflation, consistent with BCD. However, the weaker link between productivity and wages or prices in labor-intensive sectors like tourism highlights the structural vulnerabilities of these industries in managing wage-driven cost pressures.

The tourism sector's reliance on human interaction and labor-intensive services constrains its ability to translate productivity improvements into proportional wage growth or price stability. This structural lag is further exacerbated by external shocks, as evidenced during the COVID-19 pandemic, which caused significant price surges in the tourism sector without corresponding wage increases. These findings underscore the inherent fragility of the sector, where price inflation and stagnant wages create challenges for sustainable recovery and long-term growth.

Robustness checks confirm the validity of these findings, enhancing the reliability of the results. The study also highlights the pandemic's role in accelerating the adoption of digital technologies and AI tools in tourism, offering a potential pathway for addressing the structural limitations of labor-intensive sectors. Policymakers are urged to leverage these insights to mitigate sectoral imbalances through hybrid models, such as tech-enhanced tourism, and targeted EU cohesion funds aimed at fostering innovation and resilience in tourism-dependent economies.

Finally, the study underscores the need for future research to explore the role of automation and digital technologies in mitigating BCD in tourism, particularly in the post-COVID context. Cross-country comparisons and analyses of environmental sustainability should also be prioritized to ensure balanced and sustainable economic growth in tourism-dependent regions. By addressing these challenges, policymakers and stakeholders can better navigate the structural constraints of tourism and foster a more resilient and equitable economic framework.

In light of the evidence we have gathered on BCD, our findings confirm the substantial and enduring impact of manufacturing on productivity and growth. While tourism may emerge as a counterbalance to the decline or outsourcing of manufacturing industries, it does so at the cost of stagnant productivity, significantly higher labor costs, reduced competitiveness, and ultimately less robust economic growth.

Appendix

Mathematical Framework of BCDH

- **Productivity, Costs, and Prices**

The production functions for the **goods** and service sectors are defined as:

$$(1) \quad Y_G(t) = A_G(t) \cdot L_G(t)$$

$$(2) \quad Y_S(t) = A_S(t) \cdot L_S(t)$$

Where: - $Y_G(t), Y_S(t)$: Output in the goods and service sectors at time t. - $A_G(t), A_S(t)$: Productivity in the goods and service sectors at time t. - $L_G(t), L_S(t)$: Labor employed in the goods and service sectors at time t.

The **labor cost per unit of output** in each sector is:

$$(3) \quad C_G(t) = \frac{W(t)}{A_G(t)}$$

$$(4) \quad C_S(t) = \frac{W(t)}{A_S(t)}$$

Where $W(t)$ is the wage rate at time t, assumed equal across sectors due to intersectoral labor competition.

- **Inflation Dynamics and Price Trajectories**

Let $P_G(t)$ and $P_S(t)$ denote the price levels in the goods and service sectors, respectively. Prices are driven by unit labor costs and markups:

$$(5) \quad P_G(t) = (1 + \mu_G) \cdot C_G(t)$$

$$(6) \quad P_S(t) = (1 + \mu_S) \cdot C_S(t)$$

Where: - μ_G, μ_S : Markup factors in the goods and service sectors.

The Log Implied Price (sectoral inflation proxy) is defined as:

$$(7) \quad \text{log\_Implied\_Price}_i(t) = lnP_i(t) \quad \text{for} \quad i \in \{G, S\}$$

- **Inflation Differentials Between Sectors**

The **inflation differential** between the service and goods sectors is given by:

$$(8) \quad \Delta\pi(t) = \pi_S(t) - \pi_G(t)$$

Where $\pi_i(t) = lnP_i(t) - lnP_i(t-1)$ is the sectoral inflation rate.

Substituting (5) and (6) into (8):

$$(9) \quad \Delta\pi(t) = ln\left(\frac{P_S(t)}{P_S(t-1)}\right) - ln\left(\frac{P_G(t)}{P_G(t-1)}\right)$$

$$(10) \quad \Delta\pi(t) = ln\left(\frac{C_S(t)}{C_S(t-1)}\right) - ln\left(\frac{C_G(t)}{C_G(t-1)}\right)$$

Using (3) and (4):

$$(11) \quad \Delta\pi(t) = ln\left(\frac{W(t)/A_S(t)}{W(t-1)/A_S(t-1)}\right) - ln\left(\frac{W(t)/A_G(t)}{W(t-1)/A_G(t-1)}\right)$$

$$(12) \quad \Delta\pi(t) = ln\left(\frac{W(t)}{W(t-1)}\right) - ln\left(\frac{A_S(t)}{A_S(t-1)}\right) - \left[\ln\left(\frac{W(t)}{W(t-1)}\right) - ln\left(\frac{A_G(t)}{A_G(t-1)}\right)\right]$$

$$(13) \quad \Delta\pi(t) = ln\left(\frac{A_G(t)}{A_G(t-1)}\right) - ln\left(\frac{A_S(t)}{A_S(t-1)}\right)$$

Let $g_G = ln\left(\frac{A_G(t)}{A_G(t-1)}\right)$ and $g_S = ln\left(\frac{A_S(t)}{A_S(t-1)}\right)$ denote the productivity growth rates in the goods and service sectors. Then:

$$(14) \quad \Delta\pi(t) = g_G - g_S$$

Since $g_G > g_S$ (productivity grows faster in goods than in services), the inflation differential $\Delta\pi(t)$ is positive, indicating higher inflation in the service sector.

- **Labor Cost Variables**

The labor cost variables (e.g., Log Labor Cost, Log Labor Cost per Hour) are modeled as:

$$(15) \quad \text{log\_Labor\_Cost}_i(t) = ln\left(W(t) \cdot L_i(t)\right)$$

doi.org/10.32388/1JHL0U

$$(16) \quad \text{log\_Labor\_Cost\_per\_Hour}_i(t) = ln\left(\frac{W(t)}{H_i(t)}\right)$$

Where $H_i(t)$ is the total hours worked in sector i.

- **Cobb-Douglas Production Function and Related Equations in Data Extraction**

The Cobb-Douglas production function serves as the theoretical foundation for modeling productivity and output in both goods and services sectors. It is defined as:

$$Y_i(t) = A_i(t) \cdot K_i(t)^{\alpha} \cdot L_i(t)^{1-\alpha}$$

Where: - $Y_i(t)$: Output in sector i (goods or services) at time t.

- $A_i(t)$: Total factor productivity (TFP) in sector i at time t.
- $K_i(t)$: Capital input in sector i at time t.
- $L_i(t)$: Labor input in sector i at time t.
- α: Output elasticity of capital (typically $0 < \alpha < 1$).

- **Labor Productivity**

Labor productivity is derived from the Cobb-Douglas function by dividing output by labor input:

$$\text{Labor Productivity}_i(t) = \frac{Y_i(t)}{L_i(t)} = A_i(t) \cdot \left(\frac{K_i(t)}{L_i(t)}\right)^{\alpha}$$

Taking the natural logarithm, we get:

$$\ln(\text{Labor Productivity}_i(t)) = lnA_i(t) + \alpha \ln\left(\frac{K_i(t)}{L_i(t)}\right)$$

- **Implicit Price**

The implicit price level is derived from the ratio of nominal value added ($\text{VA}_{\text{nominal}}$) to real value added ($\text{VA}_{\text{real}}$):

$$\text{Implicit Price}_i(t) = \frac{\text{VA}_{\text{nominal},i}(t)}{\text{VA}_{\text{real},i}(t)} \times 100$$

Taking the natural logarithm, we get:

$$\ln(\text{Implicit Price}_i(t)) = ln\left(\text{VA}_{\text{nominal},i}(t)\right) - ln\left(\text{VA}_{\text{real},i}(t)\right)$$

- **Labor Cost**

Labor cost is derived from the labor income share (LI_{share}) multiplied by nominal value added:

doi.org/10.32388/1JHL0U

$$\text{Labor Cost}_i(t) = \text{LI}_{\text{share},i}(t) \times \text{VA}_{\text{nominal},i}(t)$$

Taking the natural logarithm, we get:

$$\ln(\text{Labor Cost}_i(t)) = ln\,(\text{LI}_{\text{share},i}(t)) + ln\,(\text{VA}_{\text{nominal},i}(t))$$

- **Labor Cost per Hour**

Labor cost per hour is derived by dividing labor cost by total hours worked (H_{total}):

$$\text{Labor Cost per Hour}_i(t) = \frac{\text{Labor Cost}_i(t)}{H_{\text{total},i}(t)}$$

Taking the natural logarithm, we get:

$\text{Labor Cost per Hour}_i(t)$= ln (Labor Cost*i(t))* – *ln (* $H_{\text{total},i}(t)$)

Additional Tables

Variable/Dependent variable	Log Implied Price	Log Labour Cost per Hour
	Model 1	Model 2
log_Productivity	0.068 (2.525*)	0.406 (2.428*)
NACE_R2I	0.389 (2.829**)	0.088 (0.178)
treatment_post	0.628 (6.039***)	-0.060 (-0.130)
log_Productivity:NACE_R2I	-0.144 (-3.328***)	-0.382 (-2.402*)

Table 5. Heteroskedasticity-Robust Standard Errors

Source: Authors' calculation Notes: Ibidem.

doi.org/10.32388/1JHL0U

Variable/Dependent variable	Log Implied Price	Log Labour Cost per Hour
	Model 1	Model 2
(Intercept)	-3.013 (-26.117***)	-2.588 (-4.368***)
log_Productivity	0.069 (2.468*)	0.431 (3.333**)
NACE_R2I	0.384 (3.284**)	0.135 (0.249)
treatment_post	0.635 (6.358***)	-0.060 (-0.130)
log_Productivity:NACE_R2I	-0.138 (-3.139**)	-0.413 (-2.030*)

Table 6. Results from Linear Mixed-Effects Model with Random Slopes

Source: Authors' calculation Notes: Ibidem.

Variable/Dependent variable	Log Implied Price	Log Labour Cost per Hour
	Model 1	Model 2
log_Productivity	0.068 (2.011)	0.406 (2.507*)
NACE_R2I	0.389 (2.198*)	0.088 (0.182)
treatment_post	0.628 (3.969**)	-0.060 (-0.141)
log_Productivity:NACE_R2I	-0.144 (-2.623*)	-0.382 (-1.296)

Table 7. Robustness Check with Clustered Standard Errors Using FE-OLS

Source: Authors' calculation Notes: Ibidem.

Acknowledgements

This paper is a result of the scientific project Tourism Crises - stakeholders' Roles and RecoveryStrategies (2023-2026) supported by the Faculty of Economics and Tourism "Dr. Mijo Mirković", Juraj Dobrila University of Pula, Croatia.

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Declarations

Funding: The scientific project "Tourism Crises - stakeholders' Roles and RecoveryStrategies (2023-2026)" supported by the Faculty of Economics and Tourism "Dr. Mijo Mirković", Juraj Dobrila University of Pula, Croatia.

Potential competing interests: No potential competing interests to declare.