Furniture Manufacturing Employment and Ambient $PM_{2.5}$ in North Carolina: Evidence from Satellite Data and County-Level Panel Models

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Abstract

This paper examines whether employment in North Carolina's furniture and wood-products manufacturing sector predicts ambient fine particulate concentrations measured by satellite. Using a balanced panel of nine manufacturing-intensive counties from 2014 through 2023, the analysis links quarterly county-level $PM_{2.5}$ to employment and weather in a fixed-effects framework. Model A estimates the elasticity of $PM_{2.5}$ with respect to furniture employment, and Model B augments this specification with an interaction between employment and a linear time trend to test whether the employment to pollution relationship has changed over time. Precipitation enters as an exogenous calibration variable that should reduce $PM_{2.5}$ through atmospheric washout, and an instrumental variables extension uses national furniture demand interacted with baseline county exposure to address potential simultaneity. Across all specifications, the estimated elasticities are small and statistically indistinguishable from zero, there is no evidence that the employment to pollution relationship has shifted over the sample period, and precipitation is strongly and negatively related to $PM_{2.5}$, indicating that furniture employment in this setting does not generate detectable county-level particulate impacts.

Keywords: air quality; manufacturing; $PM_{2.5}$; North Carolina; employment elasticity; satellite data; instrumental variables
JEL Classification: Q53, Q56, R11, C23, C26, L60

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- Data Availability Statement: All datasets are publicly available; see Appendix A for sources and links.

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1. Introduction

North Carolina's furniture manufacturing industry has anchored the economy for more than a century and remains a major regional employer whose environmental footprint carries direct policy relevance. Fine particulate matter ($PM_{2.5}$) is a major public health concern because epidemiological research shows that exposure contributes to multiple severe health outcomes. This includes ischemic heart disease, stroke, lung cancer, chronic obstructive pulmonary disease, respiratory infections, and ultimately reduced life expectancy with substantial global mortality (Dockery et al., 1993; Pope et al., 2009; World Health Organization, 2021; Apte et al., 2018). Beyond health impacts, $PM_{2.5}$ exposure also reduces economic productivity. Fu et al. (2021) estimate that a 1 $\mu g/m^3$ decrease in $PM_{2.5}$ increases manufacturing labor productivity by 0.82 percent, underscoring the broader economic relevance of particulate pollution for industrial regions. Furniture production processes generate particulates within this size range, and facility-level studies consistently document elevated $PM_{2.5}$ concentrations and respiratory symptoms among workers in wood-product environments (Goldsmith and Shy, 1988; Jacobsen et al., 2008; Tasdemir et al., 2024). These findings establish that fine particulates are produced within the industry and motivate an examination of whether changes in sector-level employment translate into observable differences in ambient county-level $PM_{2.5}$.

A key empirical challenge is North Carolina's limited regulatory air-quality monitoring network. The state operates only 48 designated monitoring sites, many of which do not report continuous $PM_{2.5}$ measurements, leaving substantial gaps in rural and manufacturing-intensive areas (North Carolina Department of Environmental Quality, 2024; U.S. Environmental Protection Agency, 2024). Satellite-derived $PM_{2.5}$ helps overcome this limitation by providing complete, high-resolution coverage across all counties. The dataset used in this study integrates NASA aerosol optical depth retrievals with ground-based calibrations to generate uniform surface concentration estimates at a

0.01-degree grid resolution, approximately 1.1 km north–south by 0.9 km east–west in North Carolina (Shen et al., 2024). This spatial precision enables consistent analysis across counties, including those without regulatory monitors, and supports empirical assessment of pollution in historically under-monitored regions.

This study evaluates whether employment in North Carolina's furniture and wood-products manufacturing sector predicts ambient $PM_{2.5}$ using a balanced county–quarter panel spanning 2014 through 2023. Two research questions guide the analysis:

1. **RQ1: Do changes in furniture and wood-products employment predict county-level $PM_{2.5}$?** Addressed using the Employment-Based Scale Elasticity Model (Model A).

2. **RQ2: Has the employment–pollution relationship changed over time**? Addressed using the Time-Varying Employment to $PM_{2.5}$ Relationship (Model B).

Understanding whether changes in furniture manufacturing employment correspond to measurable differences in ambient $PM_{2.5}$ carries both environmental and economic relevance. A finding of no relationship would suggest declining pollution intensity relative to employment levels and may indicate that modern production technologies or regulatory controls effectively limit particulate emissions. A positive relationship, even if modest, would have implications for county-level zoning, environmental permitting, and industrial policy, particularly in regions considering further manufacturing development or evaluating the adequacy of existing air-quality protections.

The empirical strategy uses county and quarter fixed effects with weather controls, allowing the analysis to isolate within-county changes in employment from seasonal and regional variation in air quality. Precipitation serves as an important calibration variable because it is exogenous to manufacturing activity and physically expected to reduce $PM_{2.5}$ through atmospheric washout. To address potential simultaneity between employment and pollution, the analysis also incorporates an instrumental variables extension.

Across all specifications, we find no statistically significant relationship between changes in employment and satellite-based $PM_{2.5}$, and no evidence that the employment–pollution relationship shifts over time. Precipitation behaves as expected, exhibiting a strong negative association with $PM_{2.5}$ that reinforces the validity of the satellite-based outcome measure. Instrumental variables estimates, while imprecise, align with the primary finding: over the 2014–2023 period, changes in furniture manufacturing employment do not generate detectable county-level particulate impacts in these nine North Carolina counties.

2. Literature Review

Research linking economic activity to ambient air quality spans two central areas in environmental economics. One area examines how particulate pollution affects health, labor markets, and productivity. A second area studies how production activity and industrial structure shape pollution levels. This paper contributes to the second area by evaluating whether employment in a single manufacturing sector in North Carolina predicts county-level $PM_{2.5}$ (RQ1) and whether that relationship has changed over time (RQ2). The first area is discussed only to establish why $PM_{2.5}$ is an important outcome variable that requires accurate measurement in regions with limited monitoring.

2.1 Pollution, Health, and Economic Outcomes

A large amount of empirical literature shows that exposure to $PM_{2.5}$ increases cardiopulmonary mortality and reduces life expectancy. Foundational cohort and national panel studies demonstrate higher mortality in more polluted cities (Dockery et al., 1993) and show that reductions in fine particulates yield measurable increases in longevity (Pope et al., 2009; Apte et al., 2018). These findings inform current World Health Organization guidelines (World Health Organization, 2021).

Economists have shown that pollution affects labor markets and productivity across a wide range of settings. Studies document that pollution reduces physical output among agricultural and factory workers, lowers cognitive performance in service-sector

environments, and depresses hours worked and household earnings (Graff Zivin and Neidell, 2012; Chang et al., 2016, 2019; He and Ji, 2021). Natural experiments support these causal interpretations by showing that cleaner air increases labor supply and long-run earnings (Hanna and Oliva, 2015; Borgschulte et al., 2024; Isen et al., 2017). Together, these studies establish that $PM_{2.5}$ is an economically meaningful outcome and that even modest changes in fine particulates can have measurable microeconomic and macroeconomic consequences. However, this literature treats pollution as the explanatory variable. It does not address whether employment in a specific production sector predicts ambient $PM_{2.5}$ at the county scale, which is the focus of RQ1.

2.2 Production Activity, Industrial Structure, and Ambient Pollution

Environmental economics explains how production influences pollution through changes in output scale, industrial composition, and adoption of cleaner technologies (Antweiler et al., 2001). Empirical research consistently finds that pollution-intensive activity increases emissions unless offset by improvements in abatement or production methods (Antweiler et al., 2001; Cole and Elliott, 2004). Evidence from U.S. manufacturing demonstrates substantial reductions in emissions despite stable output, indicating that production practices heavily influence ambient pollution levels (Shapiro and Walker, 2018). Regional and county-level evidence shows that economic activity affects local air quality, with pollution falling during economic downturns and rising in areas with more pollution-intensive industry profiles (Davis, 2012; Zhang et al., 2022).

These contributions establish that production affects ambient pollution, but they do not resolve the central questions motivating this study. Existing work aggregates across many industries or relies on national-level output measures. Very few studies exploit within-county variation in employment, and none evaluate whether county-level $PM_{2.5}$ responds to employment changes in a single manufacturing sector in North Carolina. Equally important, existing studies provide little direct evidence on whether the strength of the employment–pollution relationship has shifted over time at the industry level, which

is the focus of RQ2. The models in the present study offer industry-specific, time-varying estimates that speak to both of these questions.

2.3 Furniture Manufacturing, Particulates, and the North Carolina Context

Furniture and wood-products manufacturing involves cutting, sanding, burning, milling, and finishing processes that generate respirable particulates. Occupational evidence documents elevated respiratory symptoms and accelerated lung-function decline among furniture workers (Goldsmith and Shy, 1988; Jacobsen et al., 2008), and exposure assessments show that wood-product occupations experience among the highest particulate concentrations in U.S. manufacturing (Teschke et al., 1999). Recent studies of modern wood-product facilities confirm that these processes generate fine particulate emissions with potential for outdoor dispersion (Tasdemir et al., 2024). International evidence from regions with concentrated furniture production finds elevated PM-bound particulates in ambient air, although estimates focus on elemental composition rather than sector-specific elasticities (Caliskan et al., 2025).

In North Carolina, source-apportionment work identifies wood-related industrial sources as contributors to ambient $PM_{2.5}$ in furniture-manufacturing regions (Tippett et al., 1998). Monitoring limitations create an empirical challenge. The state's air-quality network is sparse, and several major furniture-manufacturing counties lack continuous $PM_{2.5}$ monitoring (North Carolina Department of Environmental Quality, 2024; U.S. Environmental Protection Agency, 2024). Satellite-derived $PM_{2.5}$ provides spatially complete coverage at high resolution and has been validated against regulatory monitors (Shen et al., 2024; van Donkelaar et al., 2016). These data sources allow county-level analysis of the furniture sector's potential contribution to ambient $PM_{2.5}$, which would otherwise be infeasible.

2.4 Contribution

This paper contributes to the environmental economics literature in two ways that correspond directly to RQ1 and RQ2. First, the study provides the first empirical test of whether county-level $PM_{2.5}$ responds to employment fluctuations in a single, regionally concentrated manufacturing industry (Models A1 through A4). The estimated elasticities are small and statistically indistinguishable from zero, which suggests that any scale-based emissions response from furniture manufacturing is modest relative to the natural variation in ambient particulates. It could also suggest that the scale effects of furniture production appear only at spatial or temporal resolutions finer than county-quarter averages, or through pollutants other than $PM_{2.5}$, pointing toward future research using localized sensors or alternative environmental indicators. This question has not been examined in prior work because most studies aggregate across many industries or rely on national output measures rather than within-county variation. Employment serves as a proxy for production activity and thus for potential scale effects. The county–quarter empirical design isolates within-county variation, enabling a focused test of whether changes in local manufacturing employment translate into detectable changes in satellite-measured $PM_{2.5}$.

Second, the study evaluates whether the employment–pollution relationship has changed over time (Models B1 through B4). The trend interaction directly tests whether the elasticity has weakened as the industry has modernized. No prior research evaluates time variation in employment-based pollution elasticities for a single manufacturing sector at the county level for North Carolina. The findings speak directly to the tentative feasibility of sustainable industry growth in a region where manufacturing remains economically important and monitoring networks are limited.

3. Data

3.1 County Selection and Panel Structure

The analysis uses a balanced county–quarter panel covering nine North Carolina counties from 2014Q1 through 2023Q4 (40 quarters; 360 observations). The study counties are Buncombe (FIPS 37021), Burke (37023), Catawba (37035), Cleveland (37045), Guilford (37081), Haywood (37087), Orange (37135), Rockingham (37157), and Sampson (37163). A Map of these counties is available in Figure 1.

County selection was guided by two criteria central to the identification strategy. First, each of these counties provides uninterrupted Quarterly Census of Employment and Wages (QCEW) reporting for NAICS 337 (Furniture and Related Product Manufacturing) and related wood-products industries across the 2014–2023 period. Many North Carolina counties exhibit disclosure suppression or partial reporting in these industries, whereas the selected counties maintain continuous series for employment, establishments, and total wages. This ensures that within-county variation in employment is measured consistently across the entire sample, which is essential for estimating Models A and B.

Second, all nine counties align cleanly with the high-resolution satellite $PM_{2.5}$ data and NOAA/Meteostat weather observations, permitting construction of a fully balanced panel for the core variables used in the fixed-effects and IV specifications. Several counties with meaningful manufacturing activity lack complete pollution or weather coverage; excluding them avoids nonrandom missingness that could compromise inference.

Beyond data completeness, these nine counties constitute a substantively meaningful share of North Carolina's furniture and wood-products industrial base. According to the U.S. Census Bureau's County Business Patterns (CBP), Burke, Catawba, and Guilford rank among the highest-employment counties in NAICS 337 statewide throughout the past decade, while Buncombe, Cleveland, Haywood, Orange, Rockingham, and Sampson host persistent clusters of wood-products, upholstered furniture, and finishing operations. [1]

[1]Sources: U.S. Census Bureau, County Business Patterns (CBP), NAICS 337 county-level employment;

These counties reflect the long-standing concentration of production in western and central North Carolina and include both high-employment hubs and adjacent counties linked through labor markets, supply chains, and shared meteorological conditions.

This combination of sectoral relevance and data reliability produces a panel that is both economically representative and statistically robust. It provides sufficient within-county variation in employment, full coverage for satellite-derived $PM_{2.5}$ and weather controls, and the cross-county heterogeneity required for the shift–share instrument used in the IV/2SLS estimation.

3.2 Data Sources and Core Variables

The empirical analysis relies on a focused set of variables aligned directly with the elasticities estimated in Section 4. All variables are constructed at the county–quarter level and derived from publicly documented data systems whose measurement properties support within-county identification.

Ambient $PM_{2.5}$ concentrations are taken from the Atmospheric Composition Analysis Group (ACAG) surface dataset, which integrates satellite aerosol optical depth retrievals with chemical transport modeling and EPA monitor calibrations at a spatial resolution of 0.01° (approximately 1 km). Monthly gridded values are averaged within county boundaries and aggregated to quarterly means. The dependent variable is defined as $y_{itq} = \ln(PM_{2.5,itq})$. Satellite-derived $PM_{2.5}$ is necessary in this context because several study counties lack continuous regulatory monitoring, and existing monitors are not uniformly representative of industrial or residential areas. The ACAG dataset provides complete spatial coverage and has been validated extensively against ground measurements, making it suitable for detecting incremental changes in county-level fine particulates.

Furniture and wood-products employment is measured using Quarterly Census

North Carolina Department of Commerce, Labor and Economic Analysis Division (LEAD), *Furniture Manufacturing in North Carolina*; Quarterly Census of Employment and Wages (QCEW), 2014–2023.

of Employment and Wages (QCEW) data from the North Carolina Department of Commerce. Quarterly average employment in NAICS 337 and closely related wood-products categories is aggregated by county. This variable enters all models in log form as $E_{itq} = \ln(\text{Employment}_{itq})$ and provides the within-county variation required to estimate scale elasticities (Models A1–A4) and the evolution of those elasticities over time (Models B1–B4).

Quarterly weather data (mean temperature and total precipitation) comes from NOAA-based Meteostat archives, using ASOS/AWOS stations selected for representativeness and completeness. Weather variables enter in logarithms as P_{itq} and T_{itq}. Precipitation functions as a physical calibration variable because wet deposition mechanically reduces $PM_{2.5}$ concentrations. A negative coefficient on P_{itq} therefore provides a direct internal validity check on both the satellite pollution data and the fixed-effects specification. Details on station selection criteria and the full list of ASOS/AWOS stations used for each county are provided in Appendix B1 and Appendix B2.

The IV/2SLS specifications use a shift–share instrument of the form

$$Z_{itq} = \text{National furniture and wood-products demand indicator}_t \times s_{i,\text{base}},$$

where $s_{i,\text{base}}$ is county i's baseline employment share in the furniture and wood-products sector. This design satisfies two necessary conditions for econometric identification. First, national demand shifts affect the output and employment of North Carolina furniture producers through product-market linkages but do not directly influence local particulate levels, ensuring relevance without violating the exclusion restriction. Second, the shift–share form provides cross-sectional heterogeneity in exposure: counties with historically larger furniture sectors respond more strongly to national demand fluctuations than counties with smaller baseline shares. This structure supplies exogenous time variation in employment that is distinct from local regulatory changes,

weather-driven pollution shocks, or county-specific economic cycles. There is a possibility that employment and ambient $PM_{2.5}$ are jointly determined. For example, firms may adjust production in response to local pollution episodes such as wildfires, which can lead to attenuation or bias in ordinary least squares estimates. The IV strategy isolates the component of employment driven by national demand, yielding a consistent estimate of the causal elasticity of particulate concentrations with respect to sector employment. Together, these data provide a unified and internally consistent foundation for estimating the scale elasticity in Model A, its temporal evolution in Model B, and the causal effect of employment on county-level $PM_{2.5}$ through the IV/2SLS specification.

3.3 Variable Construction

All variables are constructed at the county–quarter level to align with the panel structure of the empirical models. The dependent variable, employment, and weather controls enter all specifications in logarithms. This transformation reduces skewness, stabilizes variance, and allows coefficients in Models A and B, as well as in the IV/2SLS framework, to be interpreted directly as elasticities. Accordingly, the core variables are defined as

$$y_{itq} = \ln(\mathrm{PM}_{2.5,\,itq}), \qquad E_{itq} = \ln(\mathrm{Employment}_{itq}),$$

$$P_{itq} = \ln(\mathrm{Precipitation}_{itq}), \qquad T_{itq} = \ln(\mathrm{Temperature}_{itq}).$$

To evaluate whether the employment–pollution relationship evolves over time, Models B1–B4 include an interaction between employment and a linear quarterly trend. The trend variable, Trend_{tq}, runs from 1 (2014Q1) to 40 (2023Q4). This structure allows for a parsimonious test of whether the elasticity changes systematically over the study period without imposing nonlinearities or higher-order terms.

A central requirement of the analysis is a fully balanced panel. All nine counties report complete $PM_{2.5}$ and meteorological data for every quarter in the 2014–2023 window. QCEW employment data are similarly comprehensive. Fewer than ten percent of

county–quarter employment values required linear interpolation (Appendix C). This limited and mechanically implemented imputation preserves the statistical properties of the panel while avoiding artificial trends that could confound the time-varying elasticity estimates. No interpolation was required for $PM_{2.5}$ or weather variables.

The full set of variables used in estimation is therefore:

$$\{\, y_{itq},\ E_{itq},\ P_{itq},\ T_{itq},\ Z_{itq},\ \text{Trend}_{tq},\ \alpha_i,\ \lambda_{tq} \,\},$$

where α_i and λ_{tq} denote county and quarter fixed effects. This construction yields a clean, internally consistent dataset suited to estimating both the level elasticity in Model A and its potential evolution in Model B, as well as the causal IV estimates.

3.4 Data Summary

The combined dataset provides a strong empirical foundation for estimating both the contemporaneous employment–pollution elasticity (Models A1–A4) and its evolution over time (Models B1–B4). Several features of the data environment support credible identification.

First, the satellite-based $PM_{2.5}$ series delivers complete spatial coverage at high resolution, which avoids the measurement gaps and siting concerns created by North Carolina's sparse regulatory monitoring network. Figure 2 showcases key frames from an animation of our entire North Carolina PM2.5 Dataset for every county that runs 2000-2023.

Second, the QCEW employment data provide consistent, industry-specific measures of furniture and wood-products employment that exhibit meaningful within-county variation, which is essential for identifying scale effects in a fixed effects setting. Figure summaries of county-mean employment over time are provided in Appendix E,F. Third, the NOAA-based precipitation and temperature variables supply physically interpretable sources of variation. These meteorological fluctuations influence atmospheric washout and dispersion but do not respond to short-run changes in county manufacturing activity,

which reinforces internal validity.

The dataset also supports an instrumental variables approach through a shift–share design that interacts national furniture and wood-products demand indicators with predetermined county industrial structure. These national demand movements originate outside local environmental, policy, or economic conditions in North Carolina and therefore provide plausibly exogenous movements in employment for the IV and 2SLS specifications.

Taken together, the full panel offers a clean and internally consistent basis for estimating small elasticities and for assessing whether the employment–pollution relationship has changed over the 2014 to 2023 period. The combination of full spatial coverage in pollution data, reliable county-level employment measures, physically grounded weather controls, and a defensible external demand instrument ensures that the empirical results are supported by a transparent and well-defined data environment. Appendices E, F, G, H provide descriptive visual evidence on employment trends and $PM_{2.5}$ dynamics, both in aggregate and by county, which illustrate the temporal variability, cross-county differences, and wildfire-driven spikes that motivate the fixed effects framework and help contextualize the regression results.

3.5 Descriptive Statistics

Table 1 reports descriptive statistics for all variables used in the empirical models. County–quarter $PM_{2.5}$ concentrations average 7.1 $\mu g/m^3$, and the corresponding logged values center around 1.95. These levels are consistent with the moderate regional pollution typical of North Carolina during the 2014 to 2023 period. Employment in furniture and wood-products industries averages roughly 1,575 workers per county–quarter, although the standard deviation is large relative to the mean. This dispersion confirms that counties differ meaningfully in the scale of manufacturing activity, which is important for estimating elasticities in the fixed effects framework.

The weather variables reflect substantial but realistic seasonal variation. Precipitation

averages more than 300 mm per quarter and varies widely across counties and seasons, while temperatures span the range expected for North Carolina's climate. These meteorological patterns provide variation that is orthogonal to short-run changes in manufacturing activity, which strengthens identification in Models A1 through A3 and B1 through B3.

The shift–share instrument Z_{itq} is standardized to have mean zero and unit variance and is constructed by interacting each county's baseline furniture and wood-products employment share with two national demand shifters: the Producer Price Index for lumber and wood products and the U.S. series on new privately owned housing units started. Quarter-to-quarter movements in lumber prices and national housing starts reflect changes in downstream demand for wood-intensive consumer durables, including furniture, but have no direct mechanical effect on ambient $PM_{2.5}$ in a specific North Carolina county. For example, an increase in new home construction in Texas or California raises national demand for furniture yet does not alter local particulate levels in Catawba or Guilford counties except through its impact on the production and employment decisions of North Carolina furniture manufacturers. By scaling this shift–share index to mean zero and unit variance, the instrument's distribution is driven by these external demand shocks rather than by local economic or environmental conditions. This construction is central to the IV and 2SLS specifications because it introduces plausibly exogenous variation in employment that is orthogonal to county-specific shocks, regulatory changes, or weather-driven pollution events.

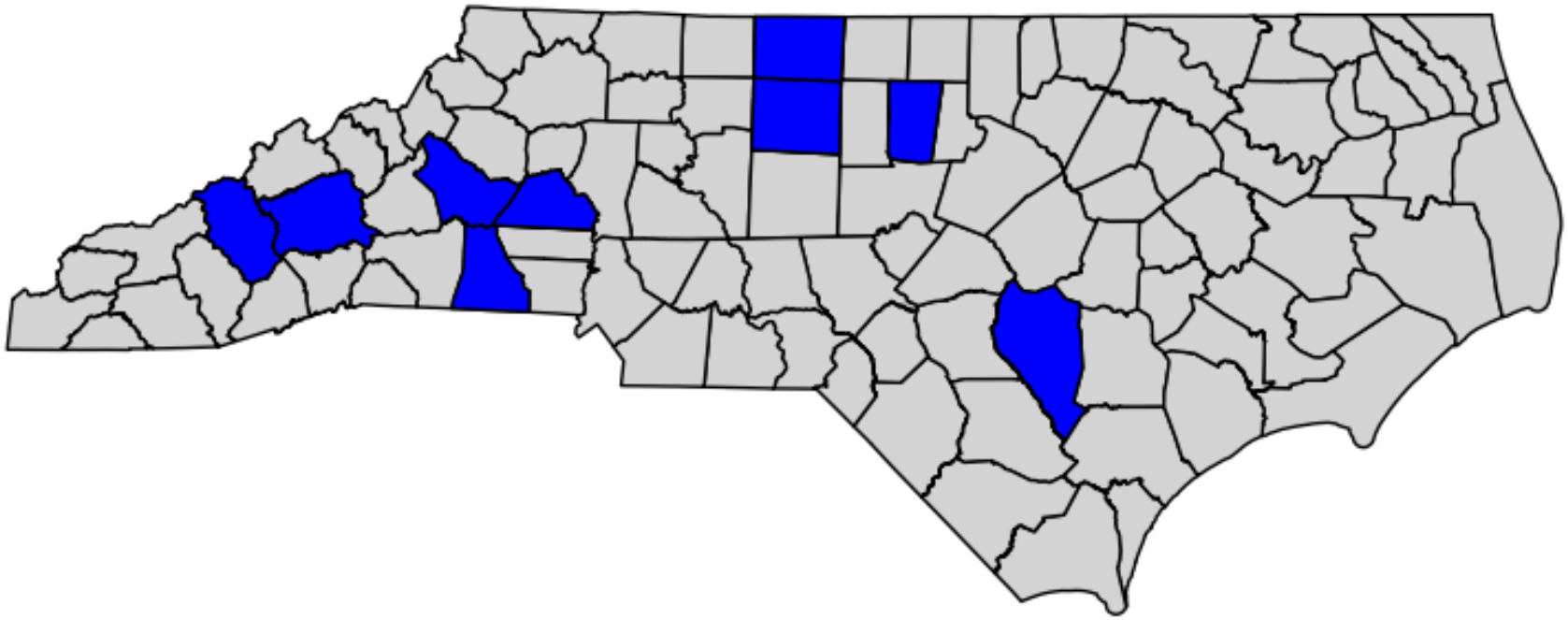
Overall, the descriptive patterns indicate that the dataset contains adequate variation in pollution, employment, and weather. Employment is relatively stable within counties over time, $PM_{2.5}$ displays moderate quarter-to-quarter changes, and weather variables provide meaningful exogenous fluctuations. These characteristics support credible estimation of both the contemporaneous and time-varying elasticities examined in the empirical analysis.

Table 1: **Descriptive Statistics for Core Variables (2014–2023)**

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
$PM_{2.5}$ (µg/m^3)	360	7.14	1.20	4.82	14.38
ln($PM_{2.5}$) (y_{itq})	360	1.95	0.16	1.57	2.67
Employment (count)	360	1,575	2,703	13	9,331
ln(Employment) (E_{itq})	360	6.83	1.21	2.56	9.14
Precipitation (mm)	360	308.31	126.99	9.90	676.08
ln(Precipitation) (P_{itq})	360	5.62	0.53	2.29	6.52
Temperature (°C)	360	15.60	6.66	3.32	26.82
ln(Temperature) (T_{itq})	360	2.64	0.49	1.20	3.29
National series used in the IV					
Housing Starts (thousands of units)	40	1,299.7	201.9	934	1,716
Standardized Housing Starts	40	0.00	1.00	-1.79	2.04
Lumber & Wood Products PPI (index, 2014=100)	40	115.80	14.95	100.0	145.4
Standardized Lumber PPI	40	0.00	1.00	-1.05	1.96
Shift–share instrument constructed for each county					
Shift–Share Instrument Z_{itq}	360	0.00	1.00	-2.48	2.91
Trend (quarter index) (Trend$_{tq}$)	360	20.50	11.69	1	40

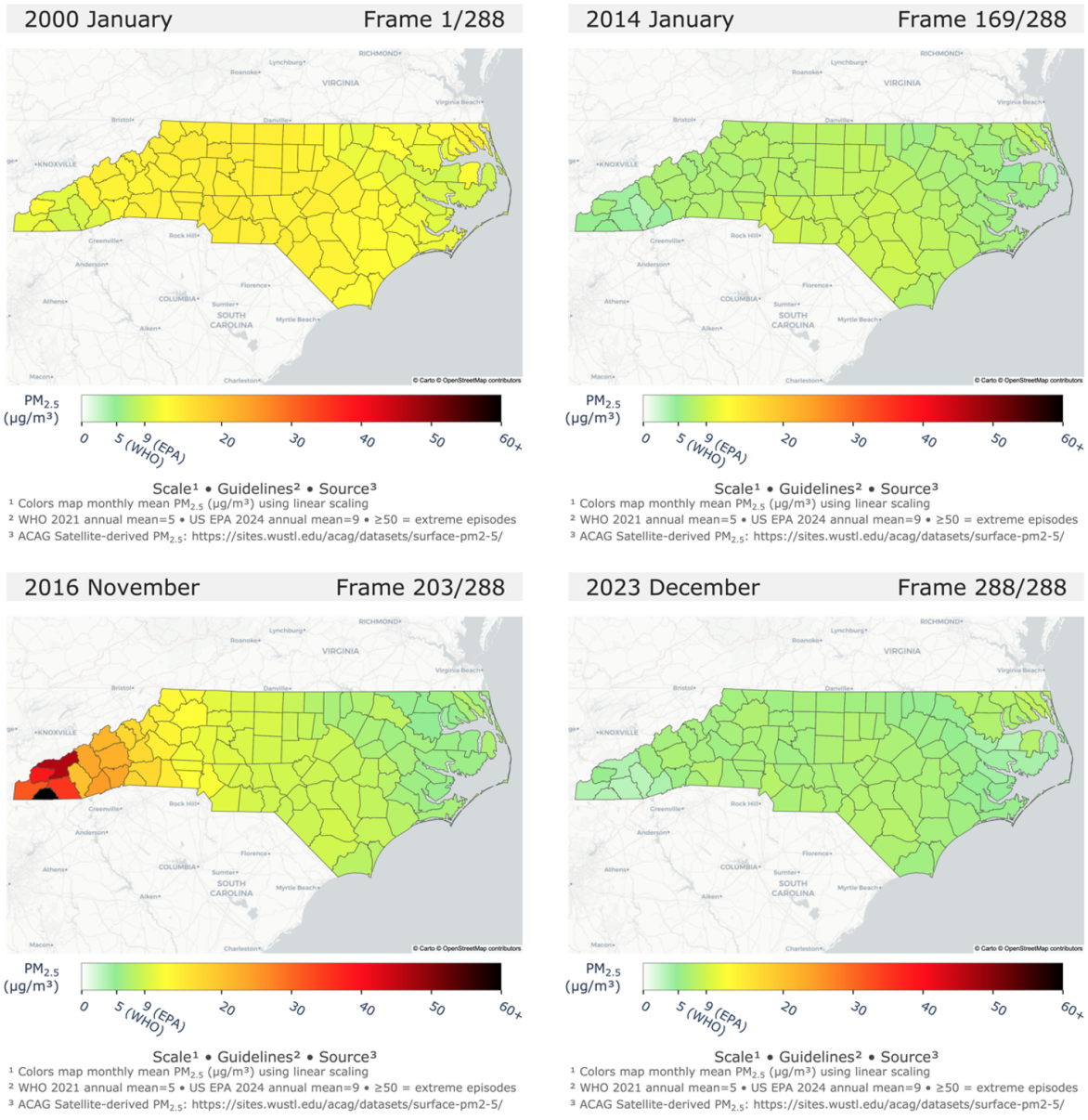
Notes: Statistics are reported for the balanced 2014Q1–2023Q4 panel of nine North Carolina counties. Variables enter the regressions in the logarithmic forms shown. National housing starts and lumber prices enter only in the construction of the shift–share instrument. Z_{itq} interacts each national series with the county's baseline furniture employment share. The quarter index runs from 1 to 40 and appears in Models B1–B4.

Figure 1: Geographic Distribution of the Nine Study Counties in North Carolina



Note: The figure shows the nine North Carolina counties included in the balanced 2014–2023 county–quarter panel used in Models A and B: *Buncombe, Burke, Catawba, Cleveland, Guilford, Haywood, Orange, Rockingham,* and *Sampson.* These counties were selected based on (i) long-term completeness of employment data from the Quarterly Census of Employment and Wages (QCEW), (ii) continuity of merged multi-source weather and satellite $PM_{2.5}$ data, and (iii) their representativeness within North Carolina's furniture and wood-products manufacturing geography. Satellite-derived $PM_{2.5}$ (ACAG, 0.01-degree resolution) ensures full spatial coverage despite sparse ground-monitor availability in several manufacturing counties.

Figure 2: Monthly Mean Satellite-Derived $PM_{2.5}$ Levels for North Carolina Counties: Selected Reference Months from 2000–2023



Note: This figure displays four reference months of satellite-derived $PM_{2.5}$ from the Atmospheric Composition Analysis Group (ACAG), reported as county-level monthly means. **Top left:** January 2000, the beginning of the ACAG dataset. **Top right:** January 2014, the start of the study period (Models A and B). **Bottom left:** November 2016, the study period's highest $PM_{2.5}$ month due to regional wildfire smoke. **Bottom right:** December 2023, the end of the study period. Colors reflect linear scaling relative to WHO (2021) and U.S. EPA (2024) guideline values. Source: Atmospheric Composition Analysis Group (ACAG), `https://sites.wustl.edu/acag/datasets/surface-pm2-5/`.

4. Empirical Analysis

This section presents the empirical models used to evaluate the study's two research questions. First, we examine whether quarterly changes in furniture and wood-products employment predict county-level $PM_{2.5}$ concentrations (Models A1–A4). Second, we test whether this employment–pollution relationship has changed over the 2014–2023 period (Models B1–B4). All specifications exploit within-county variation through county and quarter fixed effects, ensuring that identification arises from deviations inside counties over time rather than from cross-sectional differences.

The empirical strategy progresses from descriptive association models (A1–A3), which rely on conditional independence assumptions, to models that incorporate an instrumental variable (A4 and B4). Given the possibility that employment and $PM_{2.5}$ may be jointly determined by local economic conditions, weather events, or county-level shocks, the IV/2SLS specifications are essential for obtaining causal interpretation. The dataset imposes limits on precision, but the research design follows established econometric practice and produces internally coherent estimates. Where the data constrains inference, we note the limits clearly and interpret results conservatively.

4.1 Model A: Contemporaneous Employment–Pollution Elasticity

Model A1: Baseline FE OLS (no weather controls)

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta\, E_{itq} + \varepsilon_{itq}, \tag{A1}$$

Model A1 provides a baseline elasticity estimate using only fixed effects. Identification relies on the assumption that conditional on county and quarter fixed effects, employment is uncorrelated with unobserved determinants of $PM_{2.5}$. Given the strong influence of weather on particulates, A1 serves primarily as a reference point.

Model A2: Adding precipitation

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta\, E_{itq} + \phi\, P_{itq} + \varepsilon_{itq}, \tag{A2}$$

Precipitation enters as an exogenous physical control that reduces $PM_{2.5}$ through atmospheric washout. A correctly signed coefficient on P_{itq} provides an internal validity check on the satellite $PM_{2.5}$ outcome measure.

Model A3: Adding precipitation and temperature

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta\, E_{itq} + \phi\, P_{itq} + \kappa\, T_{itq} + \varepsilon_{itq}, \tag{A3}$$

Temperature captures seasonal variation in atmospheric stability and particulate formation. Together, precipitation and temperature account for key meteorological determinants of county-level $PM_{2.5}$.

Model A4: IV/2SLS with weather controls

First stage:

$$E_{itq} = \alpha_i^E + \lambda_{tq}^E + \pi\, Z_{itq} + \rho\, P_{itq} + \psi\, T_{itq} + u_{itq}, \tag{A4.1}$$

Second stage:

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta^{IV}\, \widehat{E}_{itq} + \phi\, P_{itq} + \kappa\, T_{itq} + \varepsilon_{itq}, \tag{A4.2}$$

The IV specification addresses potential simultaneity between employment and pollution. Local employment may respond to local economic cycles, policy changes, or environmental conditions. If pollution influences labor supply, or if firms adjust production in response to local shocks correlated with $PM_{2.5}$, OLS estimates of β may be biased.

The shift–share instrument Z_{itq} interacts national furniture-sector demand indicators with each county's baseline industrial share. This design satisfies two requirements for identification: (1) national demand fluctuations drive employment but do not directly affect local particulate levels in North Carolina; (2) baseline industry shares introduce cross-county heterogeneity in exposure, generating first-stage variation that is plausibly exogenous to county-specific pollution shocks.

While the sample size limits the precision of estimated IV effects, the method is theoretically appropriate. The resulting β^{IV} estimates therefore represent the best

available causal evidence given existing data constraints. Future funding for expanded data collection, with $PM_{2.5}$ and weather monitors placed directly onsite at furniture manufacturing facilities, would substantially enhance the validity of this study by reducing measurement error, strengthening the relevance of proposed instruments, and enabling far more credible IV identification in subsequent analyses. Additionally more complete QCEW economic data would allow enhanced study of more counties or other potential industries of interest. Table 2 reports the estimated coefficients for Models A1 through A4.

4.2 Model B: Time-Varying Employment–Pollution Elasticity

Model B1: Baseline trend interaction

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta E_{itq} + \theta(E_{itq} \times \text{Trend}_{tq}) + \varepsilon_{itq}, \tag{B1}$$

The interaction between employment and a linear time trend tests whether the elasticity changes systematically over the decade. A statistically significant θ would indicate that the pollution intensity of employment is evolving.

Model B2: Adding precipitation

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta E_{itq} + \theta(E_{itq} \times \text{Trend}_{tq}) + \phi P_{itq} + \varepsilon_{itq}, \tag{B2}$$

Model B3: Adding precipitation and temperature

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta E_{itq} + \theta(E_{itq} \times \text{Trend}_{tq}) + \phi P_{itq} + \kappa T_{itq} + \varepsilon_{itq}, \tag{B3}$$

Models B2 and B3 parallel Models A2 and A3, ensuring that any detected time variation is not an artifact of omitted weather effects.

Model B4: IV/2SLS with trend interaction and weather controls

First stage:

$$E_{itq} = \alpha_i^E + \lambda_{tq}^E + \pi Z_{itq} + \rho P_{itq} + \psi T_{itq} + u_{itq}, \tag{B4.1}$$

Second stage:

$$y_{itq} = \alpha_i + \lambda_{tq} + \beta^{IV}\widehat{E}_{itq} + \theta^{IV}(\widehat{E}_{itq} \times \text{Trend}_{tq}) + \phi P_{itq} + \kappa T_{itq} + \varepsilon_{itq}, \qquad \text{(B4.2)}$$

B4 evaluates whether any causal time variation exists in the employment elasticity. Although power is limited, the IV approach ensures that inferred changes are attributable to externally driven shifts in employment rather than to local confounding. Table 3 presents the results for Models B1 through B4.

4.3 Interpretation of Results

Across all Model A specifications, the employment coefficient remains small and statistically indistinguishable from zero. The negative and precisely estimated precipitation coefficients validate the satellite $PM_{2.5}$ measure and confirm that the empirical framework captures meaningful variation in ambient particulates.

The IV model produces an estimate very similar to the OLS coefficients. Given the limited sample size, this alignment does not necessarily imply that employment has no causal effect; it indicates that any such effect, if present, is modest relative to the natural meteorological and seasonal variation in county-level $PM_{2.5}$. Thus, the analysis provides evidence of an upper bound on the employment elasticity rather than precise point identification. Appendix G and Appendix H complement these regression results by plotting quarterly $PM_{2.5}$ per employee at the aggregate and county levels, highlighting both the modest downward trend and the wildfire-related spikes that the panel models attribute primarily to meteorological and regional pollution shocks rather than to furniture employment.

Model B results indicate that the employment–pollution elasticity has not changed materially over the study period. Appendix D provides quarter-specific elasticities that visually reinforce this pattern of negligible temporal variation. The interaction terms are small and statistically insignificant across all specifications, including the IV model. This

suggests that either (1) the pollution intensity of furniture-sector production has remained stable over the past decade, or (2) any meaningful changes occur at a scale too small to be detected by county-level, quarterly variation.

Overall, the empirical results show that, under current data limitations, county-level satellite $PM_{2.5}$ does not exhibit detectable responses to employment changes in the wood-products sector. The fixed effects and IV/2SLS strategies are methodologically appropriate and internally consistent, and the patterns across models provide coherent evidence even where precision is limited.

Table 2: **Model A Results (Employment–$PM_{2.5}$ Relationship in Levels)**

	(1) A1 Baseline FE OLS	(2) A2 + Precipitation	(3) A3 + Precipitation, Temperature	(4) A4 IV IV 2SLS + Weather
Employment (log) E_{itq}	-0.0059	-0.0125	-0.0146	-0.1431
	(0.0224)	(0.0220)	(0.0220)	(0.1355)
	[0.798]	[0.586]	[0.524]	[0.292]
Precipitation (log) P_{itq}		-0.0227*	-0.0203*	-0.0263***
		(0.0098)	(0.0101)	(0.0063)
		[0.049]	[0.079]	[<0.001]
Temperature (log) T_{itq}			0.1196	0.1399
			(0.1359)	(0.1335)
			[0.405]	[0.295]
County fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Observations	360	360	360	360
R^2	0.8561	0.8583	0.8595	0.8595
Within R^2	0.0002	0.0152	0.0233	0.0233

Notes: Dependent variable is $\ln(PM_{2.5})$. Standard errors clustered at the county level. Coefficients are reported with clustered standard errors in parentheses and p-values in square brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3: **Model B Results (Time-Varying Employment–$PM_{2.5}$ Relationship)**

	(1) B1 Trend Interaction FE OLS	(2) B2 + Precipitation	(3) B3 + Precipitation, Temperature	(4) B4 IV IV 2SLS + Trend + Weather
Employment (log) E_{itq}	-0.0010	-0.0090	-0.0106	-2.2617
	(0.0214)	(0.0221)	(0.0214)	(6.5706)
	[0.962]	[0.695]	[0.634]	[0.731]
Employment × Trend	0.000188	0.000120	0.000141	-0.0034
	(0.000142)	(0.000131)	(0.000140)	(0.0115)
	[0.221]	[0.383]	[0.345]	[0.766]
Precipitation (log) P_{itq}		-0.0213*	-0.0187	-0.1605
		(0.0105)	(0.0109)	(0.4326)
		[0.076]	[0.126]	[0.711]
Temperature (log) T_{itq}			0.1238	0.3577
			(0.1399)	(0.7221)
			[0.402]	[0.621]
County fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Observations	360	360	360	360
R^2	0.8567	0.8585	0.8597	0.8597
Within R^2	0.0039	0.0167	0.0253	0.0253

Notes: Dependent variable is $\ln(PM_{2.5})$. Standard errors clustered at the county level. Coefficients are reported with clustered standard errors in parentheses and p-values in square brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5. Conclusion

This paper examined whether employment in North Carolina furniture and wood-products manufacturing predicts county-level $PM_{2.5}$ and whether this relationship has changed over time. These questions were motivated by the industry's long-standing economic importance, the public health relevance of fine particulates, and the persistent data limitations created by North Carolina's sparse regulatory monitoring network. Using satellite-derived $PM_{2.5}$, county-level employment from the QCEW, and NOAA weather controls in a balanced panel from 2014 to 2023, the analysis estimated contemporaneous elasticities in Model A and time-varying elasticities in Model B, with an instrumental variables extension to address possible simultaneity.

The empirical results indicate no statistically significant relationship between quarterly changes in furniture-sector employment and satellite-measured $PM_{2.5}$ at the county level. The estimated elasticities are small across all Model A specifications, and Model B shows no meaningful change in the elasticity over time. Precipitation behaves consistently with atmospheric expectations, entering negatively and reinforcing the internal validity of the satellite pollution series and the fixed effects framework. IV estimates support the same general conclusion, though the precision of the estimates is limited by moderate first-stage strength. Taken together, the evidence suggests that, at the county scale and with currently available data, short-term changes in employment do not produce detectable changes in average $PM_{2.5}$ concentrations for the nine study counties.

These findings matter for how North Carolina evaluates the environmental implications of its manufacturing base. The absence of detectable county-level effects should not be interpreted as evidence of zero emissions from furniture production. Instead, it reflects the fact that the available data aggregate pollution spatially and temporally in ways that may conceal localized impacts near facilities. Employment is an imperfect proxy for production activity, and satellite $PM_{2.5}$ smooths important local variation, particularly in communities where industrial and residential areas are close together. As a result, the main conclusion

of the analysis is necessarily limited to the county scale: within this geographic unit, and over the past decade, changes in employment do not appear to influence ambient particulate concentrations in a way that is detectable with current data.

A key implication for policy is that more localized measurement is needed to support evidence-based decisions. Several study counties lack continuous ground monitoring, and the reliance on satellite data highlights the need for a monitoring network that can capture conditions near furniture manufacturing clusters, where exposures may be more concentrated. With improved monitoring, policymakers would be better positioned to evaluate whether the industry's recent stability and modest growth can occur without compromising air quality in nearby communities.

Improved economic data would also strengthen future research. Facility-level information on production volumes, technologies, abatement systems, energy use, and material inputs would allow researchers to distinguish scale effects from technological change. These distinctions matter for policy design. If modernization is reducing emissions per unit of output, then the industry may have a feasible path to sustainable growth. If local impacts emerge only close to facilities, then targeted mitigation rather than county-wide regulation may be more effective.

Future work would benefit from the installation of $PM_{2.5}$ sensors on-site at furniture and wood-products facilities, as well as in adjacent residential areas. These sensors could capture fine-grained spatial and temporal patterns that satellite averages cannot observe. Combining such measurements with detailed production data would allow researchers to estimate emissions intensity, identify cleaner production methods, and evaluate the environmental effects of technological upgrades. These improvements would also permit more precise estimation of the employment to pollution elasticity and may reveal small-scale relationships that are not visible in county averages. Appendix I shows other possible pollutants of interest for future research and the collection of data from onsite monitoring.

With better data, policymakers could design more tailored strategies to support sustainable industry growth. North Carolina's furniture sector remains economically important, and credible evidence on its environmental footprint would help guide zoning, permitting, and economic development incentives. Enhanced monitoring and more transparent data systems would allow the state to pursue a path that aligns manufacturing expansion with community health protections and long-term environmental goals.

In sum, the findings provide a baseline estimate of the county-level relationship between employment and fine particulates in furniture-producing regions of North Carolina. The results do not indicate detectable county-scale impacts, but they also highlight the need for more granular measurement in order to evaluate localized effects and to inform policy in a way that supports both economic development and environmental quality. Further research that incorporates higher-resolution economic and environmental data would significantly advance understanding of this sector and help chart a path toward sustainable regional growth.

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7. Appendix

Appendix A. Data Sources

County-level employment and wage data were obtained from the North Carolina Department of Commerce, Quarterly Census of Employment and Wages (QCEW). This dataset provides detailed information on establishments, employment, and total wages by county and industry. Data were retrieved from the North Carolina Department of Commerce's Data Delivery System.

North Carolina Department of Commerce. (n.d.). *Quarterly Census of Employment and Wages (QCEW) Data Delivery System.* Retrieved September 10, 2025, from `https://d4.nccommerce.com/qcewselection.aspx`

Annual population estimates were collected from the North Carolina Office of State Budget and Management (OSBM) LINC Portal, which provides demographic and economic data at the county level. These data were used to interpolate quarterly population figures for scaling and per-capita analysis.

North Carolina Office of State Budget and Management. (2023). *County Population Estimates, 2014–2023. LINC Data Portal.* Retrieved October 15, 2025, from `https://linc.osbm.nc.gov/explore/assets/county_estimates/export/?page=1&refine=area%3ABuncombe&refine=area%3ABurke&refine=area%3ACatawba&refine=area%3ACleveland&refine=area%3AGuilford&refine=area%3AHaywood&refine=area%3AOrange&refine=area%3ARockingham&refine=area%3ASampson`

Weather variables were obtained from Meteostat, which aggregates temperature and precipitation data from NOAA and other meteorological sources. Quarterly means were computed for each county's nearest weather station to control for climate variability.

Meteostat. (2024). *Historical Weather Data for North Carolina Counties (Temperature and Precipitation).* Retrieved October 11, 2025, from `https://meteostat.net/en/`

Air pollution data were sourced from the Atmospheric Composition Analysis Group (ACAG) at Washington University in St. Louis. The ACAG surface $PM_{2.5}$ dataset provides annual mean concentrations of fine particulate matter and its subcomponents, derived from satellite remote sensing and chemical transport models.
Shen, S., Li, C., van Donkelaar, A., Jacobs, N., Wang, C., & Martin, R. V. (2024). *Enhancing Global Estimation of Fine Particulate Matter Concentrations by Including Geophysical a Priori Information in Deep Learning. ACS ES&T Air.* `https://sites.wustl.edu/acag/surface-pm2-5/`. DOI: `10.1021/acsestair.3c00054`

National macroeconomic indicators were added to control for cyclical trends and to serve as instrumental variables. The Producer Price Index for Lumber and Wood Products and New Privately Owned Housing Units Started were retrieved from the Federal Reserve Bank of St. Louis FRED database. These indicators capture fluctuations in construction demand and commodity prices relevant to North Carolina's wood and furniture industries.
Federal Reserve Bank of St. Louis. (2025). *Producer Price Index by Commodity: Lumber and Wood Products (WPU082101).* Retrieved October 15, 2025, from `https://fred.stlouisfed.org/series/WPU082101`

The Consumer Price Index for All Urban Consumers (CPIAUCSL) was obtained from the Federal Reserve Bank of St. Louis FRED database. This index measures inflation in the overall cost of goods and services purchased by urban consumers in the United States and was used to adjust nominal wages and prices to real 2014Q1 values.
Federal Reserve Bank of St. Louis. (2025). *Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL].* Retrieved October 15, 2025, from `https://fred.stlouisfed.org/series/CPIAUCSL`

This series from the U.S. Census Bureau and HUD, accessed via FRED, records the monthly number of new privately owned housing units started in the United States (in thousands of units, seasonally adjusted annual rate). In the present study, it was used as

a national economic indicator representing construction demand relevant to the furniture and wood-product manufacturing context.

U.S. Census Bureau & U.S. Department of Housing and Urban Development. (2025). *New Privately-Owned Housing Units Started: Total Units [HOUST]. FRED, Federal Reserve Bank of St. Louis.* Retrieved October 15, 2025, from `https://fred.stlouisfed.org/series/HOUST`

Appendix B1. Weather Station Selection and Validation

Quarterly weather data (2014–2023) for each of the nine study counties were constructed using data from the nearest high-quality ASOS/AWOS meteorological stations provided by Meteostat and NOAA's National Centers for Environmental Information (NCEI). Stations were chosen based on (1) proximity to the county centroid, (2) continuous reporting of temperature and precipitation, and (3) representativeness of local climatic conditions. Where a county lacked a complete in-county station, the closest ASOS station with full data coverage was used. All stations report through the Automated Surface Observing System (ASOS) or Automated Weather Observing System (AWOS), ensuring consistent calibration and measurement standards. The final dataset provides a spatially consistent and reproducible record of quarterly meteorological conditions.

Appendix B2. Weather Station Source Identification

County (FIPS)	Station Name	ICAO / WMO ID	Elevation (m)	County Relation	Rationale for Selection
Buncombe (37021)	Asheville Regional Airport	KAVL / 72315	661	In-county	Primary ASOS for western NC; full continuous record; represents mountains climate.
Burke (37023)	Foothills Regional Airport	KMRN	393	In-county	Located in Morganton; complete daily temp & precip; ideal for piedmont foothills.
Catawba (37035)	Hickory Regional Airport	KHKY	353	In-county	Full ASOS coverage; continuous 2014–2023 record.
Cleveland (37045)	Charlotte Douglas Intl. (primary), Shelby KEHO (backup)	KCLT / KEHO	228	Adjacent/In-county	KCLT ensures reliable precipitation data; KEHO used for local verification.
Guilford (37081)	Piedmont Triad Intl. Airport	KGSO / 72317	270	In-county	Major ASOS hub; complete 10-year coverage.

Haywood (37087)	Asheville Regional (primary), Andrews–Murphy KRHP (backup)	KAVL / KRHP	661 / 518	Adjacent-county	Closest long-term ASOS to Haywood; captures high-elevation gradients.
Orange (37135)	Horace Williams Airport (UNC–Chapel Hill)	KIGX	141	In-county	Local AWOS station; strong correlation with RDU; excellent continuity.
Rockingham (37157)	Greensboro (KGSO) / Mount Airy KMWK	KGSO / KMWK	270 / 377	Adjacent-county	Combines regional ASOS and nearby AWOS to represent northern Piedmont climate.
Sampson (37163)	Fayetteville Regional Airport	KFAY / 72314	56	Adjacent-county	Closest ASOS with continuous precipitation and temperature reporting for coastal plain.

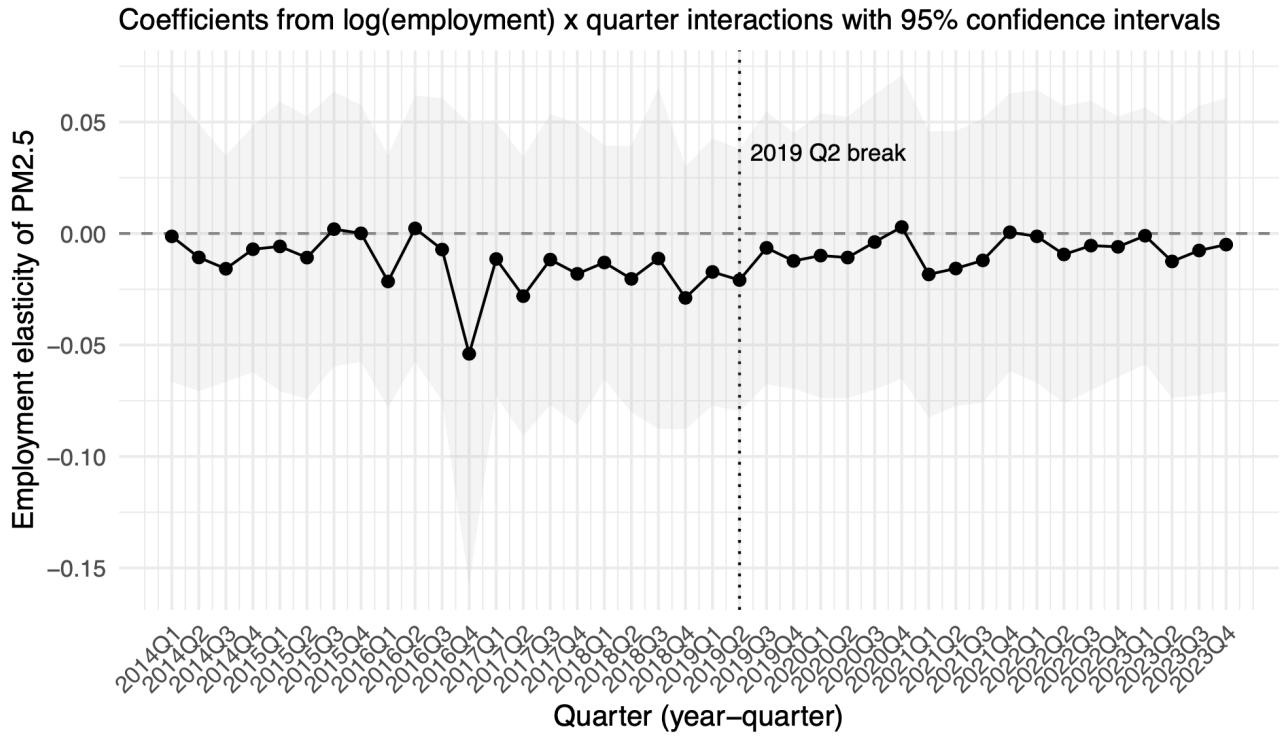
Notes: Station selection prioritized proximity, continuous data availability, and representativeness of local climatic conditions. All selected ASOS/AWOS stations provide consistent, standardized measurements suitable for quarterly aggregation and cross-county comparability.

Appendix C. Interpolated Data Observations (2014–2023)

#	Observation_Row_ID_County_Date_Row	Observation_Date
1	37021_41640_1	1/1/14
2	37021_41730_2	4/1/14
3	37021_45108_39	7/1/23
4	37023_45017_78	4/1/23
5	37023_45108_79	7/1/23
6	37023_45200_80	10/1/23
7	37045_41640_121	1/1/14
8	37045_41730_122	4/1/14
9	37045_41821_123	7/1/14
10	37045_41913_124	10/1/14
11	37045_42005_125	1/1/15
12	37045_42095_126	4/1/15
13	37045_42186_127	7/1/15
14	37045_42278_128	10/1/15
15	37135_43466_261	1/1/19
16	37135_43556_262	4/1/19
17	37135_43647_263	7/1/19
18	37135_43739_264	10/1/19
19	37135_43831_265	1/1/20
20	37135_43922_266	4/1/20
21	37135_44013_267	7/1/20
22	37135_44105_268	10/1/20
23	37157_44562_313	1/1/22
24	37157_44652_314	4/1/22
25	37157_44743_315	7/1/22
26	37157_44835_316	10/1/22
27	37157_44927_317	1/1/23
28	37157_45017_318	4/1/23
29	37157_45108_319	7/1/23
30	37157_45200_320	10/1/23

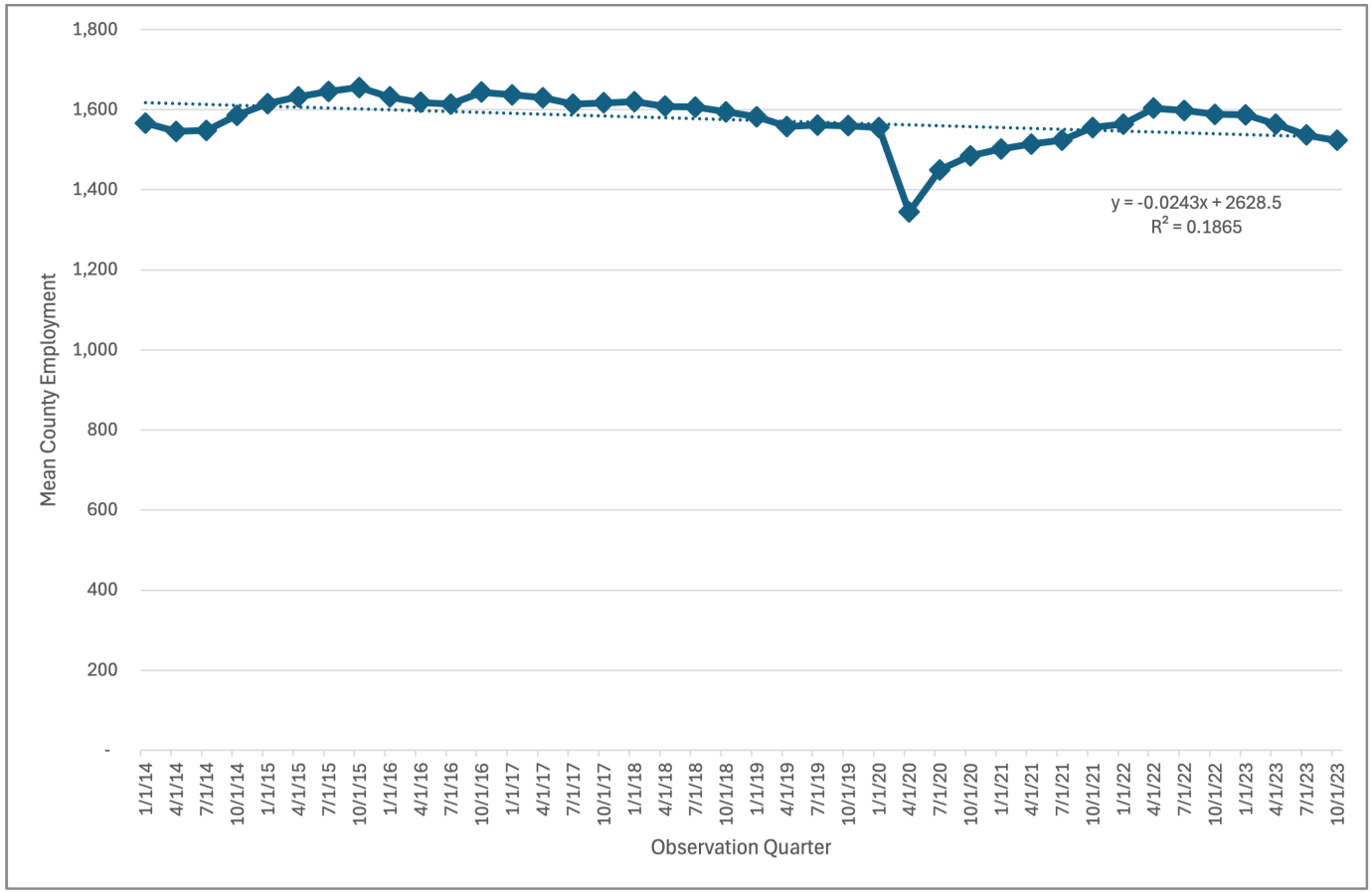
Notes: These rows correspond to county–quarter observations with missing employment values in the QCEW dataset. To maintain a balanced panel for all counties from 2014–2023, linear interpolation was applied to fill these gaps. 30/360 observations of county–quarter employment observations required imputation for a total of 8.3 percent. No counties with gaps longer than eight consecutive quarters were included in our data.

Appendix D. Quarter-specific Employment Elasticities (2014–2023)



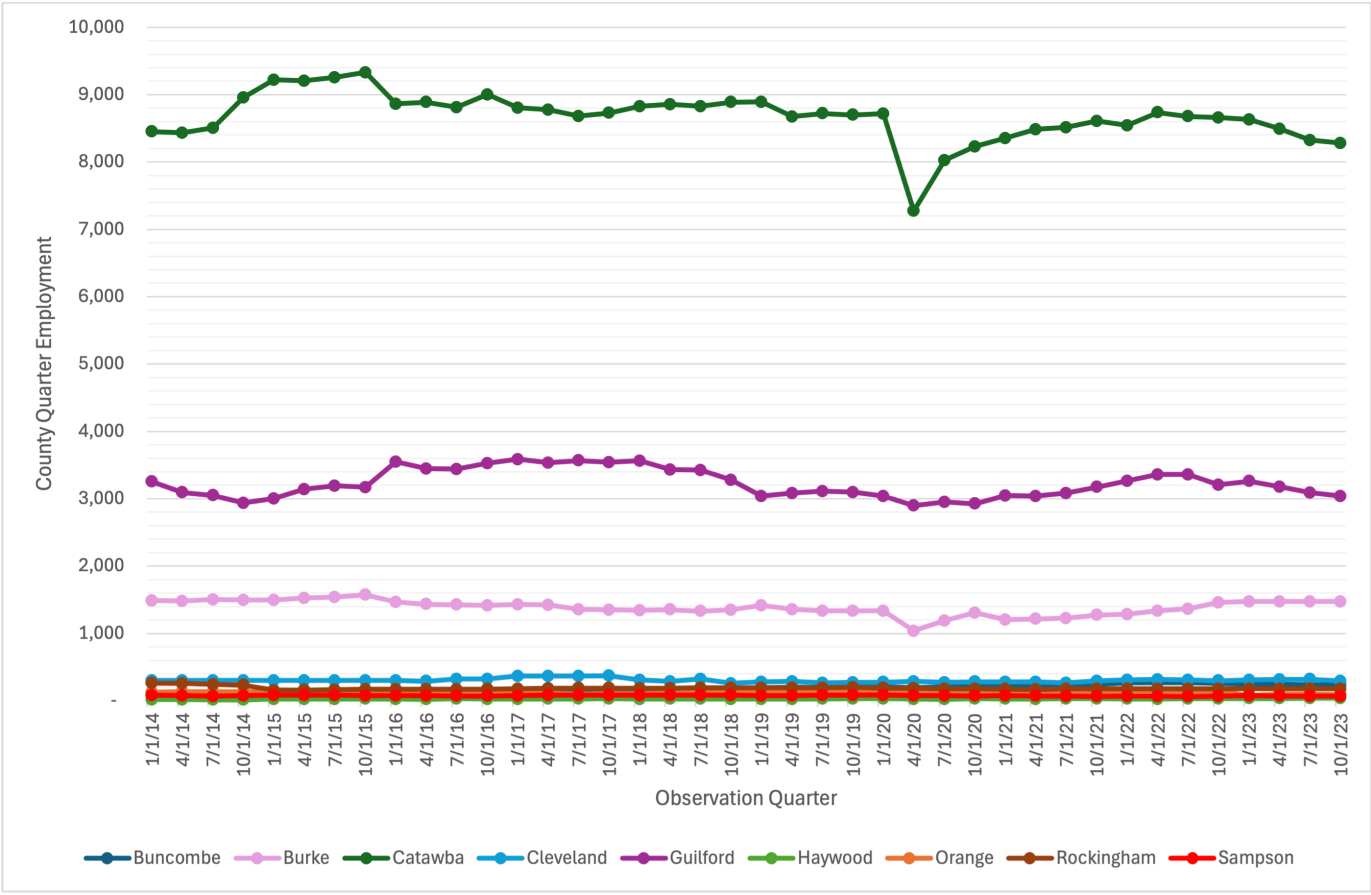
Notes: Quarter-specific employment elasticities with 2019Q2 marked as a visual reference point. Point estimates and confidence intervals are obtained from fixed-effects panel regressions of log $PM_{2.5}$ on log employment, quarter by quarter, across the nine study counties.

Appendix E. Mean County Employment Over Time (2014–2023)



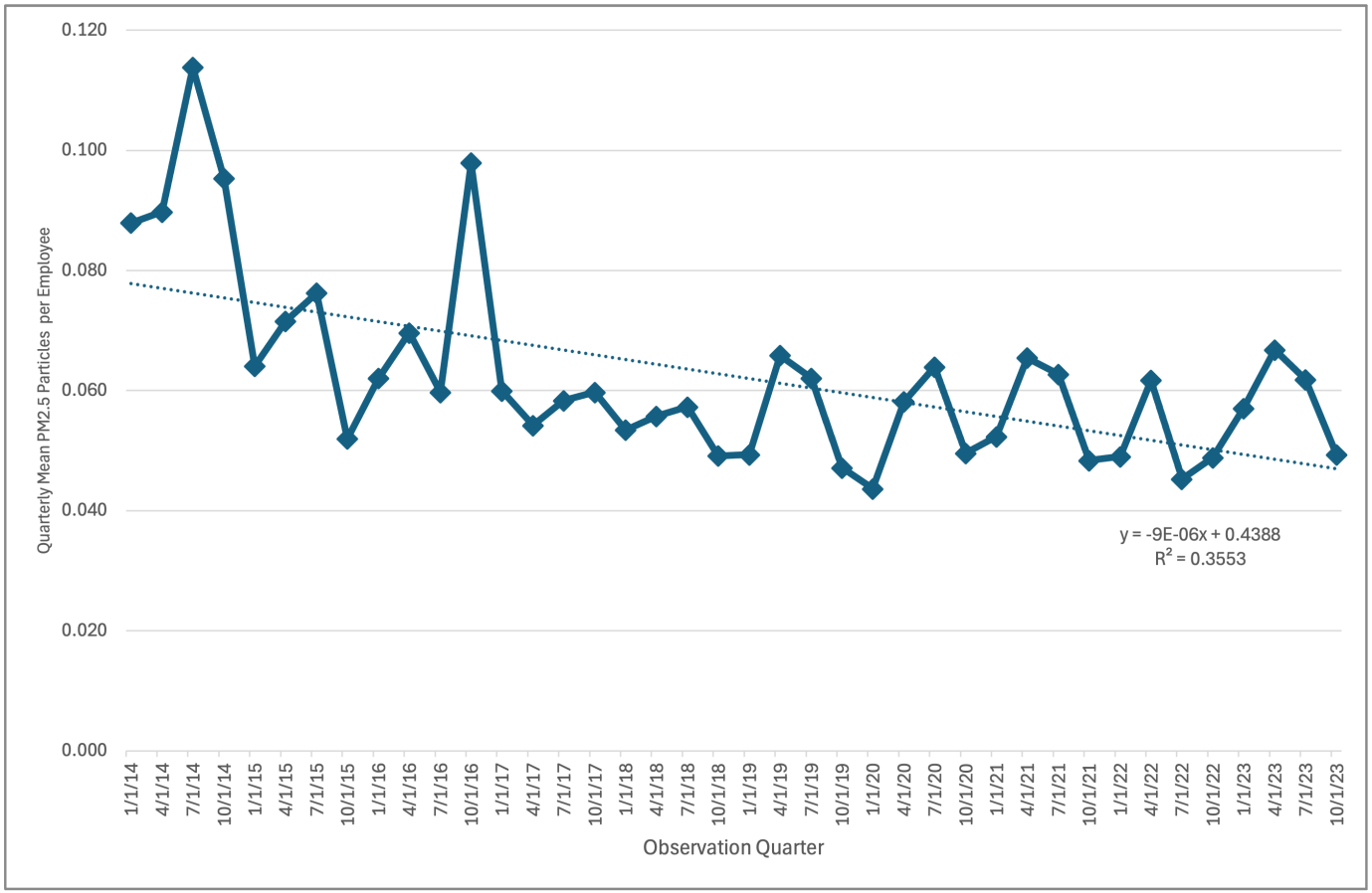
Notes: Mean County Employment (vertical axis) plotted by Observation Quarter (horizontal axis), averaged across the nine study counties for 2014–2023. The fitted linear trend line and reported R^2 summarize the overall time trend in mean county employment.

Appendix F. Mean Quarterly Employment by County (2014–2023)



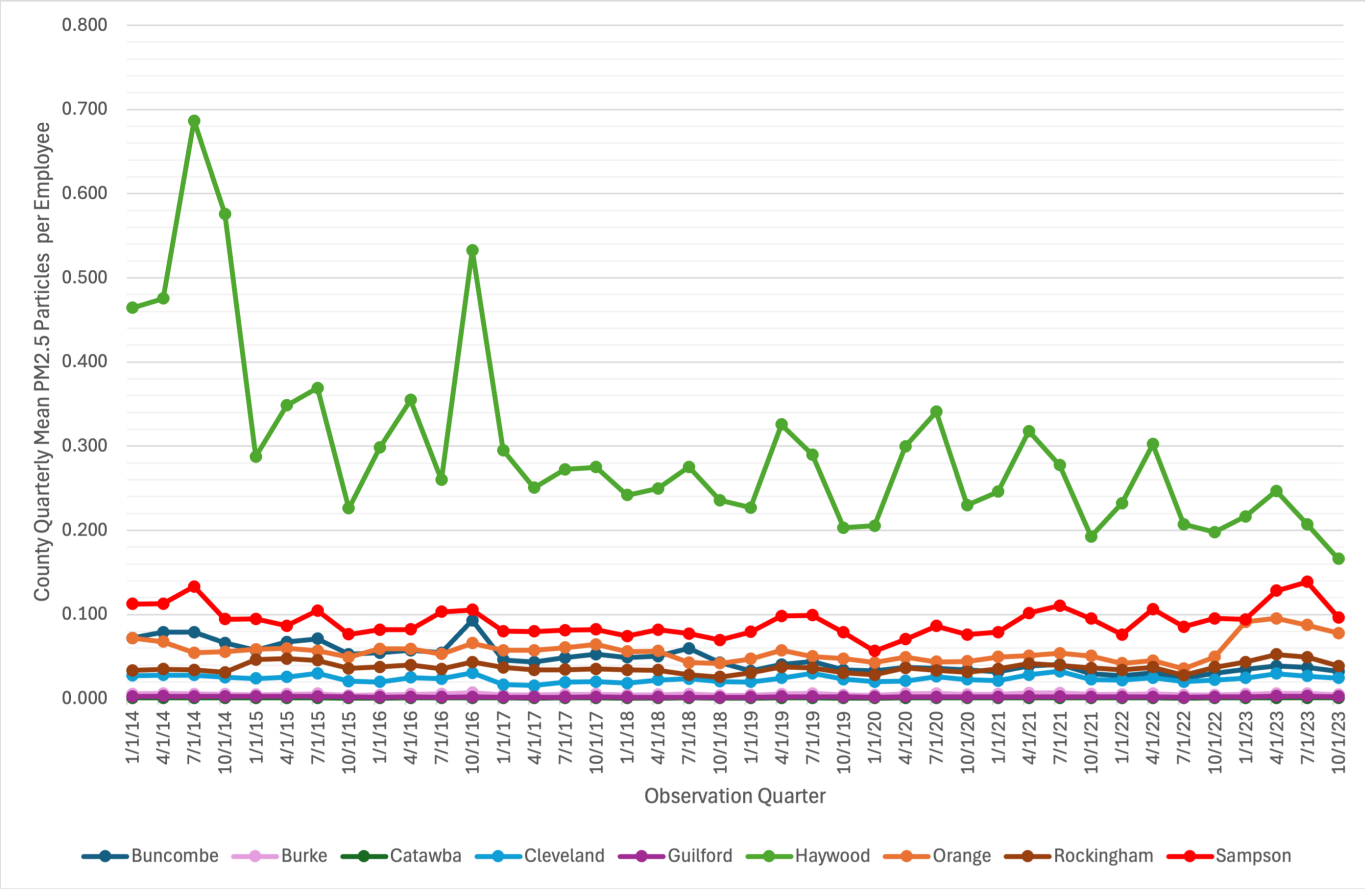
Notes: County Quarter Employment (vertical axis) for each of the nine study counties, plotted by Observation Quarter (horizontal axis) from 2014–2023. This highlights cross-county differences in employment levels and their evolution over time.

Appendix G. Quarterly Mean $PM_{2.5}$ Particles per Employee (2014–2023)



Notes: Quarterly Mean $PM_{2.5}$ Particles per Employee (vertical axis) across all nine counties, plotted by Observation Quarter (horizontal axis) for 2014–2023. The fitted linear trend line and reported R^2 quantify the overall downward trend in $PM_{2.5}$ per worker over the sample period. Pronounced wildfire-related spike in observation quarter 10/1/16.

Appendix H. County Quarterly Mean $PM_{2.5}$ Particles per Employee by County (2014–2023)



Notes: County quarterly mean $PM_{2.5}$ particles per employee (vertical axis) by observation quarter (horizontal axis), 2014–2023. The figure shows county-specific variation in $PM_{2.5}$ per employee, with pronounced wildfire-related spikes in Haywood and Buncombe counties around 10/1/16.

Appendix I. Pollutants Associated with Furniture Manufacturing and Their Likely Sources

#	Pollutant	Typical Sources Within Furniture and Wood-Products Manufacturing
1	$PM_{2.5}$	Generated during sanding, cutting, sawing, CNC machining, and finishing operations; can also form from combustion of wood waste or fossil-fuel heat sources.
2	PM_5	Produced by intermediate-size dust emissions from sanding, routing, and milling; these particles remain airborne and disperse beyond the immediate workstation.
3	PM_{10}	Generated primarily from coarse sawdust during cutting, planing, and initial shaping of lumber and engineered wood products.
4	Wood Dust (respirable/inhalable)	Emitted during sanding, sawing, routing, drilling, and milling of solid wood, MDF, plywood, and particleboard; concentrations rise in areas with inadequate dust extraction.
5	Combustion Particulates	Released when facilities burn wood scrap, fuel biomass boilers, or operate natural gas or diesel-fired equipment for heat, drying, or power generation.
6	Formaldehyde	Off-gassed from urea–formaldehyde and phenol–formaldehyde resins used in MDF, particleboard, veneers, adhesives, and certain pressed-wood substrates.

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#	Pollutant	Typical Sources Within Furniture and Wood-Products Manufacturing
7	Toluene	Emitted from solvent-based stains, varnishes, lacquers, spray finishes, and industrial cleaning products.
8	Xylene	Released during spray finishing, coating, varnishing, and solvent-based cleaning of equipment and spray booths.
9	Benzene	Present in trace quantities in certain solvent blends, adhesives, and finishing chemistry; may also be produced in small amounts by combustion processes.
10	Ethylbenzene	Found in solvent-borne stains, coatings, sealants, and lacquer thinners commonly used in finishing operations.
11	Methanol	Produced during curing of some resins and adhesives, and emitted from certain solvent-based coatings and cleaning solvents.
12	Acetone	Used in fast-evaporating coatings, cleaning agents, and thinners; increasingly common in low-HAP lacquer and polyurethane formulations.
13	Methyl Ethyl Ketone (MEK)	A component of high-performance solvent-based finishes, stains, and industrial lacquer thinners.
14	Methyl Isobutyl Ketone (MIBK)	Emitted from industrial coatings, sealants, stains, and solvent blends used in finishing booths.

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#	Pollutant	Typical Sources Within Furniture and Wood-Products Manufacturing
15	Styrene	Released from fiberglass-reinforced components, laminates, edge-banding adhesives, and certain resin-based decorative surfaces.
16	Phenol	Off-gassed from phenol–formaldehyde resins used in exterior-grade plywood, engineered wood laminates, and industrial adhesives.
17	Ethylene Glycol Ethers	Emitted from glycol-based solvents used in waterborne coatings, stains, and finishes that require slow evaporation or flow control.
18	Naphthalene	Present in some wood preservatives, stains, and solvent blends; can also arise from combustion of treated or resin-heavy wood scrap.
19	TDI and MDI (Isocyanates)	Emitted during spraying of polyurethane foams, adhesives, or high-performance coatings used in cushioning, upholstery, and specialty finishes.
20	Carbon Monoxide (CO)	Produced by incomplete combustion in biomass boilers, forklifts, curing ovens, and backup generators.
21	Nitrogen Oxides (NO_x)	Emitted from combustion equipment such as dryers, boilers, heaters, and fossil-fuel engines used onsite for heat or power.
22	Sulfur Dioxide (SO_2)	Generated primarily from combustion of fossil fuels with sulfur content (e.g., diesel, certain oils) used in heating or process equipment.

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#	Pollutant	Typical Sources Within Furniture and Wood-Products Manufacturing
23	Ammonia	Released by some waterborne coatings, catalyzed finishes, resin-curing processes, and urea-containing adhesive systems.
24	Urea–Formaldehyde and Phenol–Formaldehyde Resins	Off-gas from MDF, particleboard, plywood, and veneer products during machining, curing, and storage, especially when newly manufactured.

Notes: This appendix summarizes common pollutants found in furniture and wood-products manufacturing and identifies the specific production processes, materials, and equipment that typically generate each emission source.