Statistics Poland

Full Capacity Utilisation and Beyond?

A Sectoral Analysis of Capacity Utilisation Distributions in Poland Using Business Tendency Surveys

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Outline

Research Motivation

Capacity utilisation *CU* is

- A key indicator of an economy's cyclical position (Bierbaumer-Polly and Hölzl, 2016; DG ECFIN, 2023; Bachmann and Steiner, 2024)
- An essential explanatory variable in a macroeconomic production function (Greenwood et al., 1986; Wen, 1998; Christiano et al., 2005; Smets and Wouters, 2007)
- Captures the business cycle component in unadjusted total factor productivity indices and output gap (Planas et al., 2010, 2013; Havik et al., 2014; Blondeau et al., 2021; Błażej et al., 2025)

Problem: Comprehensive economy-wide *CU* measures are often unavailable

- Most studies rely on several survey-based series for manufacturing, construction and services as proxies
- These approaches overlook **heterogeneous developments across all sectors and main determinants of capacity utilisation**

Research Motivation

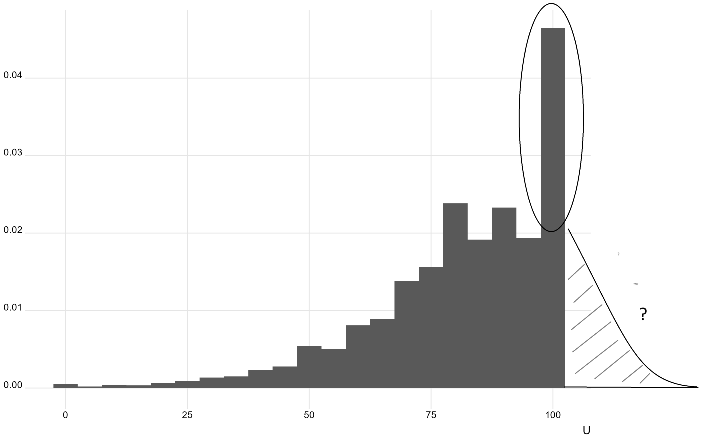

Figure 1: Empirical distribution of survey-based capacity utilisation $CU \in [0, 100]$ in Poland for 2008-2023, 18.6% of observations indicate 100, **indicating right-censoring**.

The Right-Censoring Problem

- By definition, capacity utilisation is bounded at 100%
- BTS data frequently cluster responses at this upper limit
- Firms may temporarily exceed "normal" capacity through:
  - Running additional shifts or overtime
  - Delaying maintenance
  - Employing reserve or outdated equipment
- Such cases are usually reported as 100% capacity utilisation
- **Result:** Right-censored variable where 100% may reflect unobserved latent values
- Standard OLS is inappropriate due to censoring bias

Literature Context

Foundational Work

- **Corrado and Mattey (1997); Graff and Sturm (2012):** Survey-based *CU* indicators align with poutput and output gaps
- **Basu et al. (2006); Fernald (2012); Gradzewicz et al. (2018)**: Structural interpretation of *CU* within production function framework
- **Malgarini and Paradiso (2013):** BTS-based *CU* indicators in EU context

Recent Developments

- **Lima and Malgarini (2016):** Survey data improves real-time output gap estimates
- **Bassi (2019)** Time-varying NAIRCU concepts
- **Our study:** First comprehensive sectoral analysis of *CU* using mixed-effects Tobit model and massive imputation methods

Research Gaps and Contribution

Current Limitations

- Manufacturing-only proxies misrepresent economy-wide dynamics of *CU*
- Neglect of full sectoral heterogeneity and determinants of *CU*
- Inappropriate econometric treatment of censored *CU*

Our Contribution

- **Micro-econometric approach** using firm-level data to estimate *CU*
- Analysis of Business Tendency Survey (BTS) and Annual Non-financial Enterprise Survey ANFES)
- **Mixed-effects Tobit model** to handle right-censoring in sample (Amemiya, 1984; Honore et al., 2000)
- Combining non-probability sample and full statistical survey **through mass imputation** based on Mixed-effects Tobit model (Kim et al., 2021)
- Comprehensive sectoral analysis for Poland (2008-2023)

Mixed-Effects Tobit Model

Observed capacity utilization (in logs) for firm j in period t:

$$cu_{jt} = \begin{cases} cu_{jt}^* & \text{if } cu_{jt}^* < 100 \\ 100 & \text{if } cu_{jt}^* \geq 100 \end{cases}$$

Prediction of **latent capacity utilization:**

$$\mathbb{E}(CU_j^* | X_j, \zeta_j) = X_j\beta + Z\zeta_j$$

$$CU_j^* | X_j, \zeta_j \sim \mathcal{N}(X_j\beta + Z\zeta_j, \operatorname{diag}(\sigma_\varepsilon^2))$$

where $CU_j^* = (cu_{j1}^*, \ldots, cu_{jt}^*, \ldots, cu_{jT}^*)$

- $X_j = (x_{j1}, \ldots, x_{jp})$: Matrix of p covariates observed over T periods for firm j
- ζ_j: Firm-specific random effects $\sim \mathcal{N}(0, \sigma_\zeta^2)$
- $Z = [1, 1, \ldots, 1]$ is a $T \times 1$ vector of covariates associated with random effects
- Accounts for intra-firm correlation in panel data

Likelihood Function

Conditional Density

$$f(cu_{jt}|x^Z_{jt}) = \begin{cases} \frac{1}{\sigma_\varepsilon}\phi\left(\frac{cu_{jt}-x^Z_{jt}}{\sigma_\varepsilon}\right) & \text{if } cu_{jt} = cu^*_{jt} \\ 1-\Phi\left(\frac{100-x^Z_{jt}}{\sigma_\varepsilon}\right) & \text{if } cu_{jt} = 100 \end{cases}$$

where $X^Z_j = X_j\beta + Z\zeta_j = (x^Z_{j1}, x^Z_{j2}, \dots, x^Z_{jT})'$

Firm-Level Likelihood

$$L_j(\beta, \sigma^2_\varepsilon, \sigma^2_\zeta) = \int_{\mathbb{R}} f(CU_j|X^Z_j)\frac{1}{\sigma_\zeta}\phi\left(\frac{\zeta_j}{\sigma_\zeta}\right)d\zeta_j$$

- $\phi(\cdot)$: Standard normal density, $\Phi(\cdot)$: Standard normal CDF
- $\log f(CU_j|X^Z_j) = \sum_{t=1}^T \log f(cu_{jt}|x^Z_{jt})$
- Parameters **estimated via maximum likelihood** using sample BTS∩ANFES

Massive Imputation and Weighting Methods for *CU*

The mixed-effects Tobit model estimated on **non-probability sample BTS $\cap$ ANFES** provides the forecasting formula for latent capacity utilization:

$$\hat{cu}^*_{jt} = X_{jt}\hat{\beta} + \hat{\zeta}_j \tag{1}$$

We apply the **massive imputation approach** proposed by Kim et al. (2021):

1. We employ model (1) to **predict latent capacity utilization** $\hat{cu}^*_{jt}$ for all firms in the statistical ANFES survey ($j \in$ ANFES)
2. For each period t, we apply the **standard GREG weighting method** to account for missing values in the ANFES dataset. The weights d^{ANFES}_{jt} are calibrated on aggregate totals of labor and revenues in NACE sections of non-financial enterprises in Poland.

The mean estimator of latent capacity utilization in sector $S \subset$ ANFES is:

$$\widehat{CU}_{S,t} = \frac{\sum_{j\in S} d^{\text{ANFES}}_{jt}\hat{cu}^*_{jt}}{\sum_{j\in S} d^{\text{ANFES}}_{jt}} \tag{2}$$

Data Sources

Annual Non-Financial Enterprises Survey (ANFES)

- Census of enterprises with 10+ employees
- Manufacturing, construction, and service sectors
- Financial statements and activity reports
- 75,000 firms annually

Business Tendency Survey (BTS)

- Quarterly survey on capacity utilisation in manufacturing, construction and services
- Stratified proportional sampling
- 10,000 firms per year
- Harmonised EU methodology

Non-probability sample (BTS $\cap$ ANFES)

- **Sample period:** 2008-2023 (16 years)
- **Panel structure:** Unbalanced panel linked via REGON IDs

Key Variables

Dependent Variable - Logs of Capacity Utilisation CU

- Percentage [0, 100] from BTS surveys
- Subjective survey-based answers to a question regarding capacity utilisation in each company: *'At what capacity is your company currently operating (as a percentage of full capacity)?'*
- Right-censored at 100%

Explanatory Variables (logs)

- **Production factors:** Output (Y), Capital (K), Labour (L)
- **Input costs:** Materials (M), Investment outlays (I)
- **Performance:** Profit margins (P)
- **Firm characteristics:** Size, age, ownership, export status
- **Market competitiveness:** Herfindahl-Hirschman Index
- **Controls:** Sectoral, regional, temporal effects

All monetary variables deflated to constant 2015 prices using sector-specific deflators.

Sample Characteristics

Final Dataset BTS $\cap$ ANFES

- **Total observations:** 113,809
- **Uncensored:** 93,134 (81.8%)
- **Right-censored:** 20,675 (18.2%)
- **Number of firms:** 23,186
- **Time period:** 2008-2023

Censoring by Sector

- **Manufacturing:** 8.5% report 100% capacity utilisation
- **Construction:** 18.4% report 100% capacity utilisation
- **Services:** 30.3% report 100% capacity utilisation

Capacity Utilization Censoring

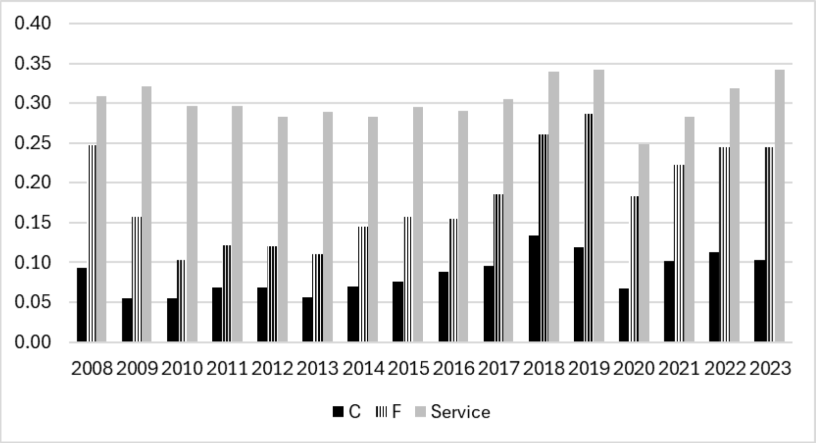

Figure 2: The share of firms declaring 100% capacity utilization within the sectors

Capacity Utilisation by Firm Characteristics

Characteristic	Share (%)	Mean	Std. Dev.	Range
Investment Level				
Low	64.96	82.40	17.56	[0, 100]
Moderate	16.92	81.36	16.51	[0, 100]
High	18.12	81.81	17.94	[0, 100]
Firm Size				
Small	45.88	79.72	19.82	[0, 100]
Medium	29.81	81.98	17.52	[0, 100]
Large	24.31	84.28	14.68	[0, 100]
Ownership				
Foreign-owned	10.22	83.74	16.21	[0, 100]
State-owned	3.72	82.23	17.13	[0, 100]
Private domestic	86.06	80.98	18.50	[0, 100]
Sectors				
Manufacturing (C)	30.29	79.13	16.26	[0, 100]
Construction (F)	32.94	79.66	19.34	[0, 100]
Services	33.78	85.65	17.83	[0, 100]

Capacity Utilisation by Firm Characteristics

Characteristic	Share (%)	Mean	Std. Dev.	Range
Firm Age				
0-3	0.13	80.93	19.51	[0, 100]
3-5	2.28	83.64	16.96	[0, 100]
5-10	13.53	82.82	18.14	[0, 100]
10-20	41.20	81.24	18.13	[0, 100]
20+	42.87	81.24	18.08	[0, 100]
Export Level				
No export	75.29	81.33	19.25	[0, 100]
Moderate export	10.03	80.72	16.15	[0, 100]
High export	7.68	83.43	15.36	[0, 100]
Market competition				
High	48.73	82.15	17.77	[0, 100]
Moderate	50.74	80.87	18.35	[0, 100]
Low	0.53	81.75	20.28	[0, 100]

Estimation Results: Main Effects

Table 1: Average Marginal Effects

Variable	dy/dx	Std. Err.	z-stat	P>|z|	[95% Conf. Interval]
Output (y)	0.053***	0.002	26.270	0.000	[0.049, 0.057]
Capital (k)	-0.046***	0.001	-34.250	0.000	[-0.049, -0.044]
Labour (l)	-0.003	0.003	-0.890	0.375	[-0.008, 0.003]
Materials (m)	0.024***	0.001	18.050	0.000	[0.021, 0.026]
Investment (i)	0.008***	0.001	9.810	0.000	[0.007, 0.010]
Profit margin (p)	0.110***	0.007	16.050	0.000	[0.096, 0.123]

Estimation Results: Firm Characteristics Effects

Variable	Coefficient	z-stat	Significance
Investment Level (vs. High)			
Low investment	0.009***	2.86	Higher CU
Moderate investment	0.004*	1.70	Slightly higher CU
Firm Size (vs. Small)			
Medium firms	0.011***	2.89	Higher CU
Large firms	0.005	0.88	No significant effect
Export Activity (vs. No export)			
Moderate export	-0.009***	-2.75	Lower CU
High export	-0.002	-0.52	No significant effect
Market Competition (vs. High)			
Moderate competition	-0.015***	-6.46	Lower CU
Low competition	-0.039***	-3.26	Much lower CU

Estimation Results: Firm Characteristics Effects

Variable	Coefficient	z-stat	Significance
Firm Age (vs 0-3)			
3-5	-0.32	0.752	Insignificant
5-10	-0.46	0.646	Insignificant
10-20	-0.41	0.682	Insignificant
20+	-0.57	0.567	Insignificant
Ownership (vs State-owned)			
Foreign-owned	0.013	1.58	Insignificant
Private domestic	0.005	0.70	Insignificant

Estimation Results: Time and Regional Effects

Time Effects: Economic Cycles

- **Crisis periods:**
  - 2009-2014: Significant negative effects (-0.017 to -0.083)
  - 2020: COVID-19 impact (-0.041***)
- **Expansion periods:**
  - 2017-2019: Strong positive effects (0.021*** to 0.058***)
  - Peak in 2018: +0.058***
- **Recovery:**
  - 2021-2023: Gradual recovery
  - 2022-2023: Return to positive territory

Regional Effects

- Regional effects are limited.
- Only two regions — Lubuskie and Lubelskie — demonstrate statistically significant deviations from the reference region (Mazowieckie).

Estimation Results: Sectoral heterogeneity

Variable	Coefficient	z-stat	Interpretation
Production Function Variables (Section C)			
Output (y)	0.045***	12.92	Positive scale effect
Capital (k)	-0.070***	-27.73	Capital intensity reduces CU
Labour (l)	0.020***	4.64	Labour intensity increases CU
Materials (m)	0.023***	9.97	Material usage increases CU
Investment (i)	0.014***	11.09	Investment boosts CU
Profit margin (p)	0.147***	12.03	**Strongest effect**
Sectoral Effects (vs. Manufacturing)			
Construction (F)	-0.315***	-11.31	Lower base CU
Services	-0.014	-0.55	No significant difference

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Estimation Results: Sectoral Heterogeneity

Construction vs. Manufacturing

- **Capital effect** less negative (+0.020***)
- **Labour effect** more negative (-0.032***)
- **Materials effect** more positive (+0.022***)
- **Profit margin effect** weaker (-0.056***)

Services vs. Manufacturing

- **Capital effect** much less negative (+0.052***)
- **Labour effect** more negative (-0.041***)
- **Materials effect** less positive (-0.019***)
- **Investment effect** weaker (-0.013***)
- **Profit margin effect** weaker (-0.061***)

Implication: Different production technologies and capacity constraints across sectors.

Model Predictions: Handling Censoring

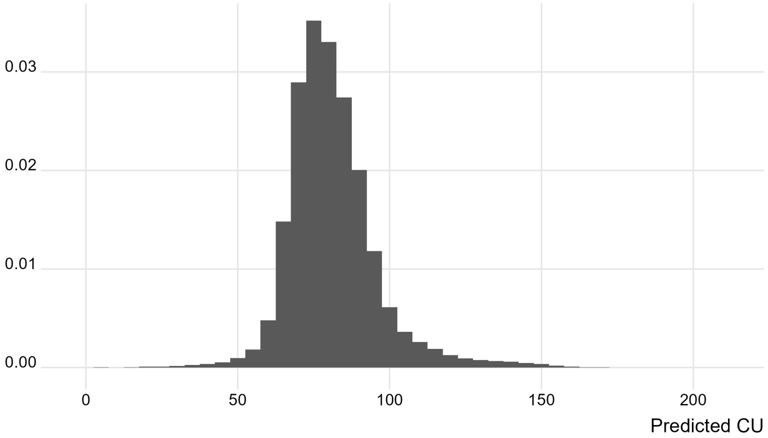

Figure 3: Empirical distribution of Predicted *CU* (*ANFES*) in Poland for 2008-2023

Model Predictions: Handling Censoring

Variable (Sample)	Obs.	Mean	Std. Dev.	Range
Observed *CU* (BTS)	150,264	81.51	18.09	[0.0, 100.0]
Predicted *CU* (ANFES∩BTS)	113,999	86.41	21.36	[0.8, 194.5]
Predicted *CU* (ANFES)	677,980	80.67	14.39	[0.8, 211.0]

Key Insights

- Model predicts values **exceeding 100%**, confirming latent over-utilisation
- ANFES∩BTS predictions have higher mean (86.41%) than observed (81.51%)
- ANFES predictions cover also firms not included in BTS
- **Maximum predicted:** 211% capacity utilisation

Predicted Sectoral Capacity Utilisation Rates

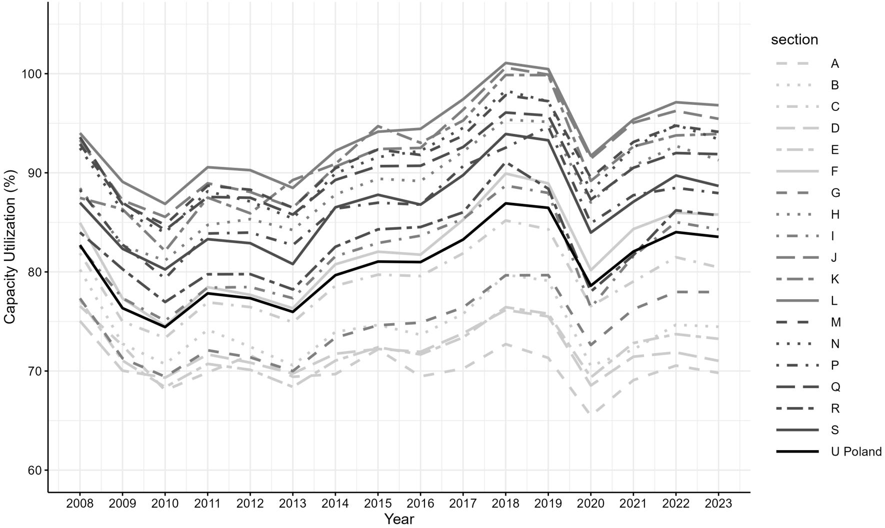

Figure 4: Predicted values of capacity utilization rates across sections

Predicted Sectoral Capacity Utilisation Rates

- **Overall range:** 74.53% (2010) to 87.03% (2018)
- **Crisis impact:** Sharp decline 2009-2013, 2020 drop to 78.68%
- **Recovery:** Peak 2018-2019, rebound to 83.71% by 2023

High-Utilisation Sectors

- Sections J, K, L, M, N, Q consistently above 90%
- Some exceed 100% in 2018-2019 (e.g., J at 100.82%)
- By 2023: 95.78%-96.77% range

Moderate-Utilisation Sectors

- **Agriculture (A):** Lowest, dropped to 64.44% in 2020
- **Manufacturing (C):** Tracks overall trend
- **Construction (F):** Moderate levels with high volatility

Economic significance

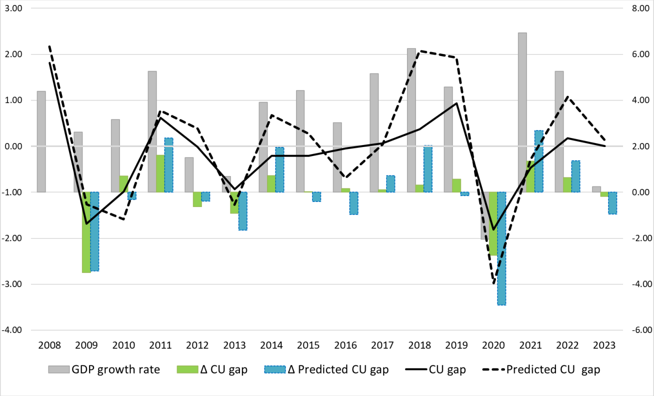

Figure 5: CU gaps vs GDP growth rates

Correlation	CU gap	Predicted CU gap	Δ CU gap	Δ Predicted CU gap
GDP growth rate	53.9%	65.9%	68.5%	84.4%

Key Findings: Determinants

Production Determinants

- **Profit margin:** Strongest positive effect (elasticity: 0.147)
- **Output:** Consistent positive scale effects across sectors
- **Capital:** Negative effect suggests capital intensity reduces CU
- **Investment:** Positive but differentiated sectoral effects

Firm Characteristics

- **Size:** Medium firms achieve highest utilisation
- **Investment:** Low-moderate investment firms outperform high
- **Competition:** Strong positive relationship with market competition

Sectoral Patterns

- **Services:** Consistently highest utilisation

Policy Applications

Macroeconomic Policy

- **Inflation monitoring:** High CU indicates potential price pressures
- **Monetary policy:** Sectoral CU provides granular economic slack measures
- **Business cycle analysis:** Real-time capacity indicators

Structural Policy

- **Investment incentives:** Target sectors with persistent under-utilisation
- **Competition policy:** Link between market competition and efficiency
- **Export promotion:** Mixed effects suggest nuanced approach needed

Crisis Management

- **Early warning:** Rapid CU decline signals economic stress
- **Recovery monitoring:** Track sectoral recovery patterns
- **Support targeting:** Identify most affected sectors

Thank you for your attention!

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Sample Coverage: ANFES

- Firm-level dataset covering small, medium, and large Polish non-financial companies from 2008 to 2023
- All data are reported in the Annual Non-Financial Enterprises Survey (ANFES, SP) conducted by Statistics Poland.
- final sample:
  - consists of over 1 mln observations accounting for 87% of all observations recorded in survey over 2008–2023; 192 000 firms;
  - includes on average over 65 000 enterprises annually;
  - The enterprises recorded an average employment of 5.14 million **full-time equivalents per year** and **average annual revenues** of PLN 3,222 billion.
  - It **covers, on average, approximately 44% of the GVA and 53% of the employment in the total economy.**

Sectoral Sample Coverage: ANFES∩BTS

Variable	Final sample (ANFES∩BTS)			
	Total economy	Manufacturing	Construction	Service
Employment	21.77	46.39	34.64	20.34
GVA	16.78	36.96	20.61	14.37
Capital	15.94	53.43	35.15	17.26

Table 2: Sectoral sample coverage

Empirical distributions of CU in manufacturing

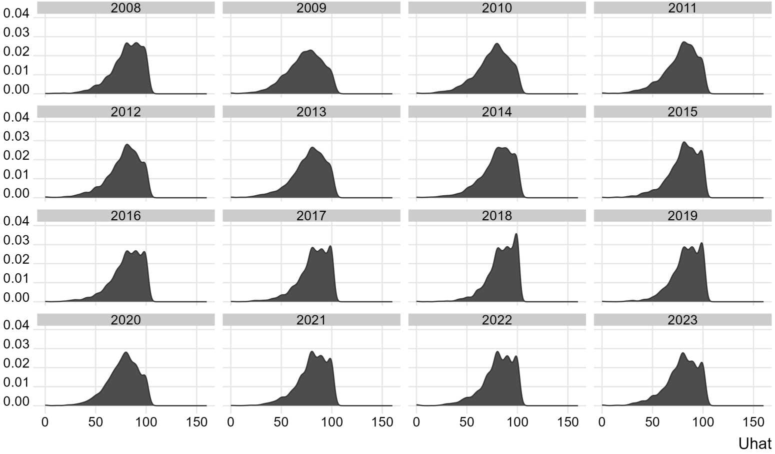

Figure 6: Empirical distributions of CU in section C, BTS sample

Distributions of predicted *CU* in manufacturing

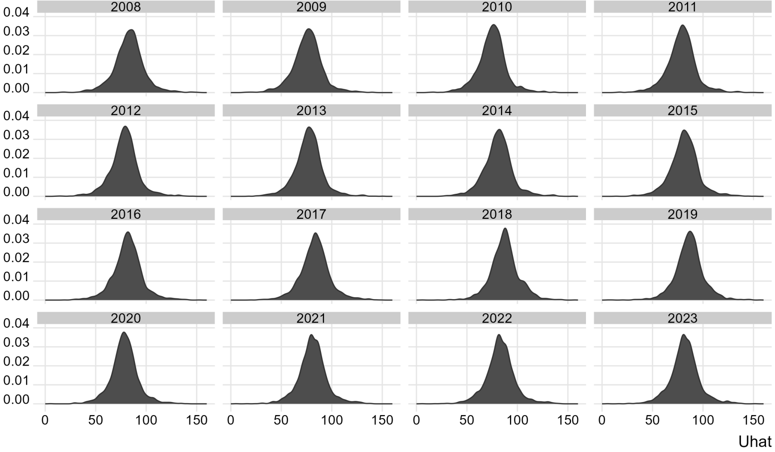

Figure 7: Distributions of predicted *CU* in section C, ANFES sample.

Empirical distributions of *CU* in construction

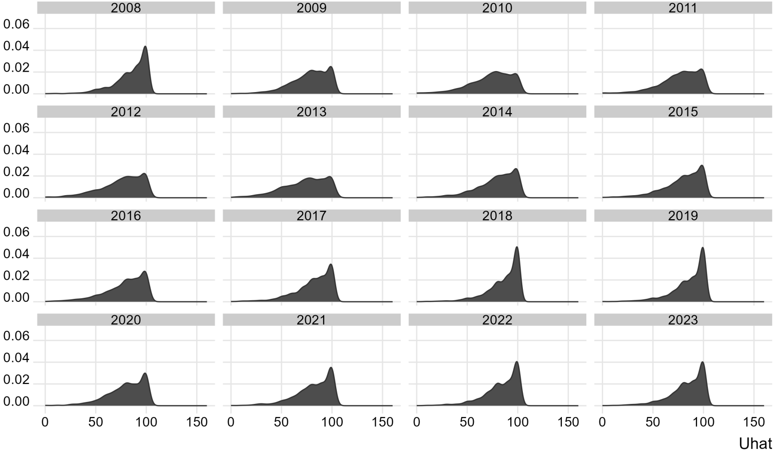

Figure 8: Empirical distributions of *CU* in section C, BTS sample

Distributions of predicted *CU* in construction

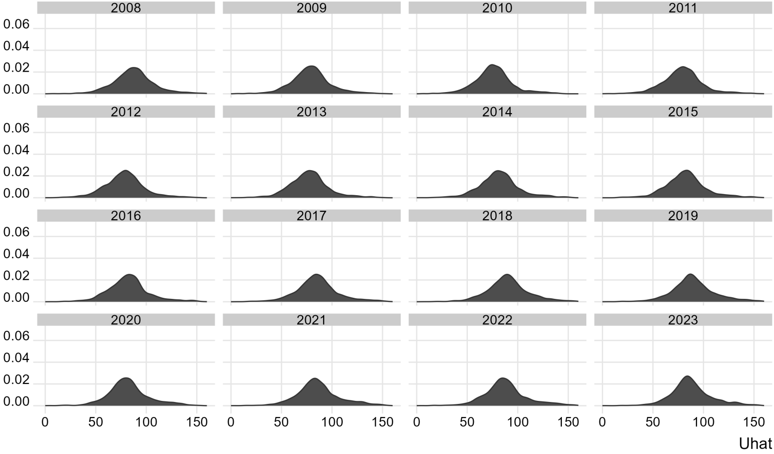

Figure 9: Distributions of predicted *CU* in section C, ANFES sample.

Empirical distributions of *CU* in Services

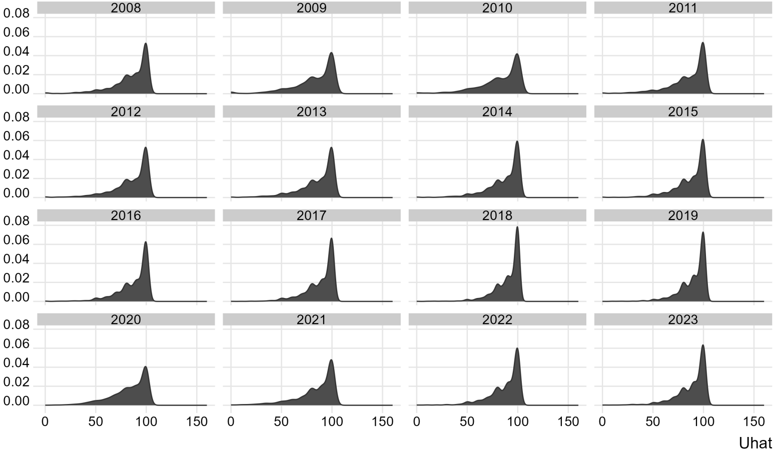

Figure 10: Empirical distributions of *CU* in Services, BTS sample

Distributions of predicted *CU* in Services

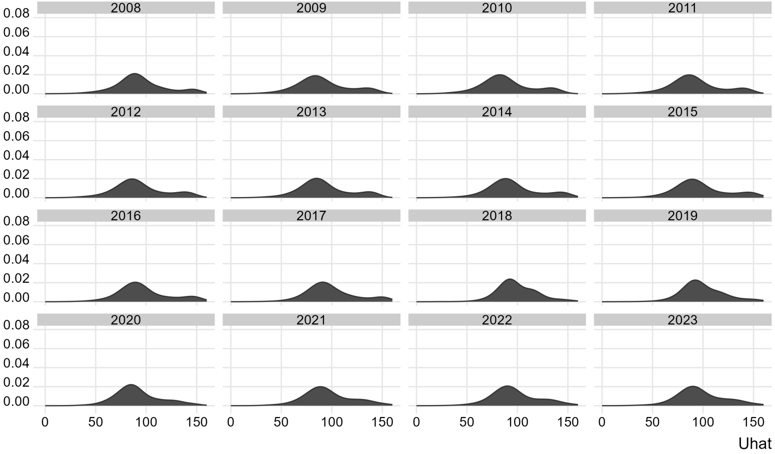

Figure 11: Distributions of predicted *CU* in Services, ANFES sample.