Understanding Profitability: The Role of Technology and Market Power

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Outline

- Introduction and contribution
- Model for Decomposing Profitability
- Model-based clustering algorithm
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Introduction

- **Does firm profitability reflect market power, or a return to production technology?**
- Examining this question informs us on how firm-level decisions, policy interventions, and major shocks alter the relative importance of each driver.
- Also, depending on the source of profitability, firms will respond differently to shocks and incentives.
  - $\rightarrow$ In particular, the responsiveness of firms to productivity changes, which could contribute to solving the **productivity puzzle**.

Introduction

- This study decomposes observed gross profitability into **three sources**:
  - production technology (returns to scale);
  - product market power;
  - labor market power.
- Then, it clusters firms according to these three dimensions.

Literature review

- **Production-function approach:** Hall (1988); De Loecker and Warzynski (2012); De Loecker (2011).
- **Joint product and labour market power:** Dobbelaere and Mairesse (2013); Caselli et al. (2021); Yeh et al. (2022).
- **Biased technical change:** Doraszelski and Jaumandreu (2018); Raval (2023); Demirer (2020); Azzam et al. (2025).
- **Profitability decomposition:** Azzam et al. (2025); Dobbelaere et al. (2025).
- **Clustering:** Cheng et al. (2023); Aglio and Bartelsman (2025).

Contribution

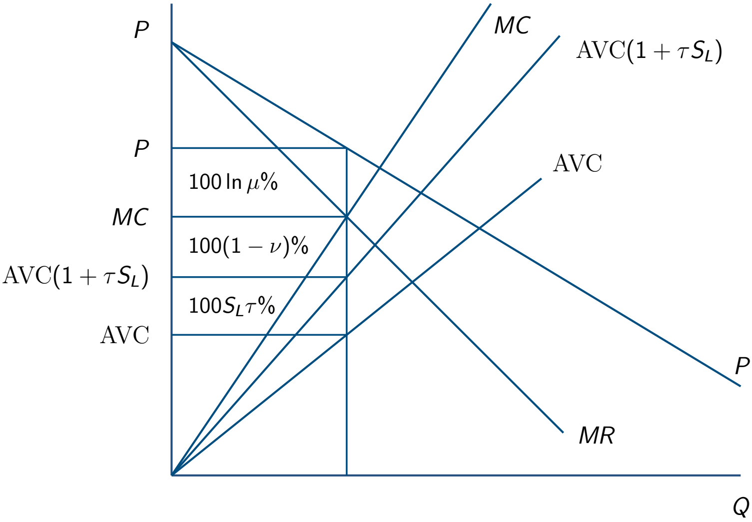
- We introduce a **model-based stratification** framework that clusters firms along three economic primitives: technology (output elasticity), residual demand elasticity, and labour supply elasticity.
- This allows us to understand the link between profitability and firms' performance.

Model: decomposition of profitability

- Short-run profitability depends on wedges between marginal benefits and marginal costs.
- Product market power: price is set above marginal cost according to the **markup** $\boldsymbol{\mu}$.
- Technology: the **short-run elasticity of scale** $\boldsymbol{\nu}$ determines the gap between marginal cost and average variable cost.
- Labor market power: the **markdown** $\boldsymbol{\tau}$ raises the marginal cost wedge through the labor cost share S_L.

$$\ln \frac{R_{it}}{VC_{it}} = -\ln \nu + \ln \mu_{it} + \ln(1 + S_{Lit}\tau) + \varepsilon_{it}$$

Model: decomposition of profitability



Model: production technology

- Taking a first-order approximation to the unspecified firm **production function** $Q_{it} = F(K_{it}, \exp(\omega_{Lit})L_{it}, M_{it})\exp(\omega_{Hit} + \varepsilon_{it})$, in logs:

$$q_{it} = \beta_0 + \beta_L(\omega_{Lit} + l_{it}) + \beta_M m_{it} + \beta_K k_{it} + \omega_{Hit} + \varepsilon_{it}$$

Model: market power

- We remain agnostic about the nature of competition in the product market and the labour market.
- We only assume that imperfect competition in the labour market might result in a wage markdown τ. Following Card et al. (2018), workers have firm-specific amenity, and the wage markdown is the reciprocal of the elasticity of labour supply.
- Imperfect competition in the product market result in a residual demand elasticity and, hence, price-cost markup μ_{it}.
- Firm-level prices are not observed. We, therefore, specify the firm **revenue function** under CES demand, as follows:

$$rev_{it} - p_{st} = \frac{\eta - 1}{\eta} q_{it} + \frac{1}{\eta} q_{st} + \frac{1}{\eta} \xi_{st} + \epsilon_{it}$$

Model-based clustering algorithm

- **Firms are clustered** according to the following equations:
  - Firm revenue function

$$r_{it} = \rho r_{it-1} + \frac{\eta - 1}{\eta}\Big[\beta_0' + \lambda(k_{it} - \rho k_{it-1}) + \nu\big(m_{it} - k_{it} - \rho(m_{it-1} - k_{it-1})\big) \\ - \nu(1+\tau)\frac{\sigma}{1-\sigma}(x_{it} - \rho x_{it-1})\Big] + \frac{1}{\eta}(q_{st} - \rho q_{st-1}) + \frac{1}{\eta}(\xi_{st} - \rho \xi_{st-1}) + e_{it}$$

  - Labour supply equation

$$\delta l_{it} = \beta \delta w_{it} + X_{it} + \nu_{it}$$

- Firms are clustered along the three primitives that determine profitability:
  - scalability of production ν;
  - elasticity of residual demand η;
  - elasticity of labor supply / markdown τ.

Model-based clustering algorithm

- Initial clustering is based on **empirical distributions** of:
  - labour productivity;
  - revenue-costs share;
  - labour response to wage changes.
- Then, the algorithm **jointly estimates** the firm revenue function together with labour supply elasticity and **clusters** firms in order to minimize the following GMM criterion:

$$Q(\beta, C) = \sum_{i=1}^{N} \sum_{e \in [C_i]} \frac{m_e(Y_i, X_i, \beta_{(C_i)})' W_{i,e} m_e(Y_i, X_i, \beta_{(C_i)})}{TSS_e}$$

- The main parameters of each equation are cluster-specific and depend on the cluster C_i, to which firm i is assigned. The instruments used in the revenue function regression are lagged variable inputs, capital and its lag, lagged wages, the lagged wage share, and the downstream demand indicators.

Model-based clustering algorithm

0. Initialize cluster membership C from empirical distributions.

For iterations $s \geq 1$:

1. Estimate cluster-specific parameters by GMM, conditional on C_s:

$$\hat{\beta}_s = \arg\min Q(\beta, C_s).$$

2. Reassign firms to clusters by minimizing $Q(\hat{\beta}_s, C)$ over C.

3. Assess convergence: $|Q(\beta_s, C_s) - Q(\beta_{s-1}, C_{s-1})| \leq \epsilon$: if convergence, stop; otherwise, repeat from point (1).

Model-based clustering algorithm

4. After the clustering process, compute coefficient minimizing the cluster-level GMM coefficient, where equations are stacked:

$$Q(\beta, C) = \sum_{c=1}^{N_c} m(Y_c, X_c, \beta_{C_c})' W_c m(Y_c, X_c, \beta_{C_c})$$

5. Finally, compute optimal weighting matrices $W^o_{i,e}$ for each firm i and W_c for each cluster c, using the 1^{st} stage estimation; then, repeat the GMM estimation algorithm with the optimal weighting matrices.

Data

- Sources: Dutch Business Register (BDK), Business Demographics (ABR), Production Statistics Survey (PS), matched employer–employee records from the Dutch Social Statistical Database (SPOLIS).
- Dutch business economy, 2010 – 2019.
- Around 180 thousand firm-year observations.
- Downstream demand instruments are built from OECD Inter-Country IO tables and from CBS Dutch IO tables.

Preliminary results: classification comparison

- The model-based clustering fits the production and labor-supply equations better than sectoral classifications.

Table: Heterogeneity in Clusters vs Sectors

RSS	Production	Labour elasticity
Total sample	17143	11184
1-digit NACE	17080	11134
2-digit NACE	15685	10929
Labour market regions		11107
Clusters	**14465**	**10375**

Preliminary results: average decomposition

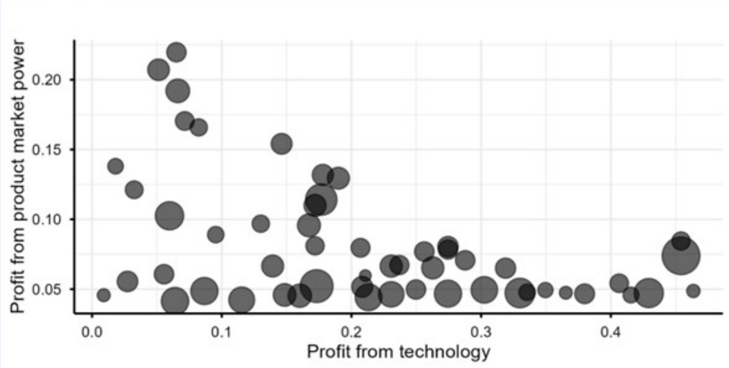
- Average explained profitability is about 30 percentage points.
- Technology explains the largest share, followed by product and labor market power.
- Approximate shares of explained profitability: **technology 60%**, **product market power 27%**, **labor market power 13%**.

Table: Main parameters estimates – average

	λ	ν	η	τ	$profit_{\nu}$	$profit_{\eta}$	$profit_{\tau}$	$profit_{exp}$	$profit$
Average	0.906	0.818	15.668	0.134	0.182	0.082	0.038	0.302	0.275

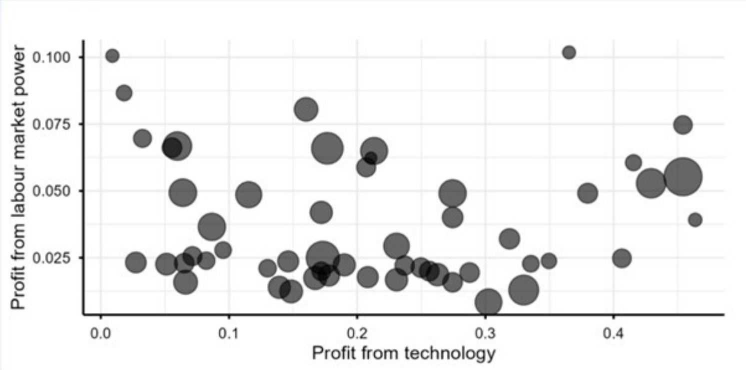
Preliminary results: Technology vs product market power

- Firms with higher profitability from product market power tend to have lower profitability from technology.
- Correlation: **-0.47**.



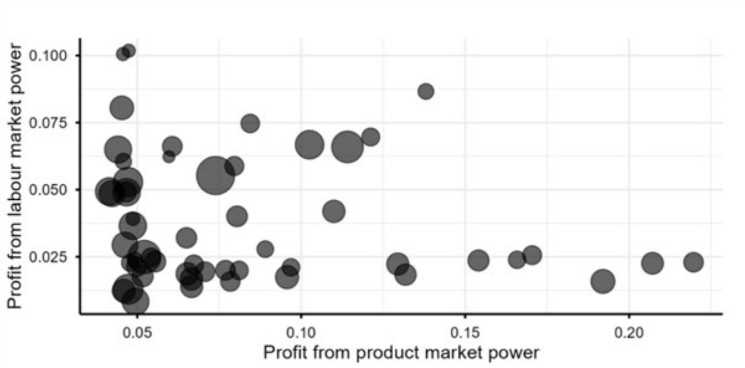
Preliminary results: Technology vs labour market power

- Profitability from technology and from labour market power are nearly uncorrelated.
- Correlation: **-0.02**.



Preliminary results: Product vs labour market power

- Profitability from product market power and from labour market power are negatively correlated.
- Correlation: **-0.17**.



Preliminary results: TFP and firm growth

Table: Productivity and growth

	(1) $\delta rrev_t$	(2) $\delta rrev_t$	(3) $\delta rrev_t$	(4) $\delta rrev_t$	(5) $\delta rrev_t$	(6) $\delta rrev_t$	(7) $\delta rrev_t$	(8) $\delta rrev_t$	(9) $\delta rrev_t$
$\delta\omega_{Ht}$	0.231***	-0.069***	0.183***	0.230***	-0.070***	0.184***	0.229***	-0.070***	0.188***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)	(0.009)	(0.006)
$\%profit_\eta$	0.063***			0.066***			0.063***		
	(0.006)			(0.006)			(0.006)		
$\delta\omega_{Ht} * \%profit_\eta$	-0.380***			-0.377***			-0.371***		
	(0.019)			(0.019)			(0.019)		
$\%profit_\nu$		0.054***			0.057***			0.056***	
		(0.005)			(0.005)			(0.005)	
$\delta\omega_{Ht} * \%profit_\nu$		0.377***			0.378***			0.381***	
		(0.015)			(0.015)			(0.015)	
$\%profit_\tau$			-0.185***			-0.207***			-0.202***
			(0.007)			(0.007)			(0.007)
$\delta\omega_{Ht} * \%profit_\tau$			-0.234***			-0.238***			-0.253***
			(0.022)			(0.022)			(0.022)
$k\ intensity_{t-1}$							-0.011***	-0.011***	-0.013***
$size_{t-1}$							-0.024***	-0.024***	-0.023***
Sector FE				Yes	Yes	Yes	Yes	Yes	Yes
Year FE				Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.012	0.013	0.014	0.019	0.021	0.022	0.025	0.027	0.028
Obs	177086	177086	177086	177086	177086	177086	177086	177086	177086

Preliminary results: TFP and firm growth

Table: Productivity and growth

	(1) δl_t	(2) δl_t	(3) δl_t	(4) δl_t	(5) δl_t	(6) δl_t	(7) δl_t	(8) δl_t	(9) δl_t
$\delta\omega_{Ht}$	0.136***	-0.041***	0.140***	0.134***	-0.043***	0.141***	0.122***	-0.043***	0.132***
	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)	(0.005)
$\%profit_\eta$	0.010*			0.014**			-0.004		
	(0.006)			(0.006)			(0.006)		
$\delta\omega_{Ht} * \%profit_\eta$	-0.180***			-0.176***			-0.161***		
	(0.018)			(0.018)			(0.018)		
$\%profit_\nu$		0.004			0.006			-0.009*	
		(0.005)			(0.005)			(0.005)	
$\delta\omega_{Ht} * \%profit_\nu$		0.244***			0.245***			0.232***	
		(0.015)			(0.015)			(0.015)	
$\%profit_\tau$			-0.018***			-0.029***			0.025***
			(0.006)			(0.007)			(0.007)
$\delta\omega_{Ht} * \%profit_\tau$			-0.255***			-0.262***			-0.263***
			(0.021)			(0.021)			(0.021)
$k\ intensity_{t-1}$							0.032***	0.032***	0.032***
							(0.001)	(0.001)	(0.001)
$size_{t-1}$							-0.059***	-0.059***	-0.059***
							(0.001)	(0.001)	(0.001)
Sector fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.005	0.006	0.005	0.009	0.010	0.010	0.049	0.050	0.050
Obs	177086	177086	177086	177086	177086	177086	177086	177086	177086

Conclusions

- This paper develops a novel **model-based stratification** framework that clusters firms along three dimensions of heterogeneity – production technology, demand rigidity in the product market, and the responsiveness of workers' labour supply to wages – to understand the sources of their profitability.
- Our preliminary results suggest that average profitability in the Dutch business economy is **about 60% explained by technology, 27% by product market power, and 13% by labour market power**.
- We also find substantial cross-firm heterogeneity in the drivers of profitability.
- Profitability from product market power is found to be strongly negative correlated with profitability from technology, and negatively correlated with profitability from labour market power.
- **Following productivity shock, growth is higher for firms gaining profit from technology, while it is hindered for firms gaining profits from product/labour market power**.

Thank you

Questions and comments are welcome

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