Heterogeneous Firms and the Phillips Curve
PRELIMINARY DRAFT
—comments welcome—

Daniele Aglio[1] and Eric Bartelsman[1]

[1]Vrije Universiteit, Amsterdam, and Tinbergen Institute

March 20, 2025

Abstract

This paper estimates the marginal cost and demand curves facing heterogeneous firms to provide evidence on the slope of the aggregate Phillips curve. The paper utilizes prices and quantities of outputs and factor inputs of French, Dutch, and Slovenian manufacturing firms along with exogenous downstream demand instruments from global input-output and trade data to identify the parameters. Model heterogeneity is addressed using a clustering method to classify firms according to their production technology and observed cost-shock pass-through. We find that more productive firms have flatter marginal cost curves and exhibit a lower price response to changes in output. The aggregate Phillips curve will be flatter when the more productive firms absorb a larger portion of demand shocks, which is generally the case. Further, idiosyncratic shifts in demand to clusters of firms with more rapidly rising marginal cost curves, or cost shocks to clusters of firms with high pass-through, could result in a steeper slope of the aggregate Phillips curve.

Acknowledgements This research received funding from the EU H2020 project grant *Microprod*, 2019-2022, and the EU TSI project from the European Commission, Directorate-general for Structural Reform Support under grant agreement No. 101101853 and No. 101140673. For more details, see the CompNet website at the following link: https://www.comp-net.org/eu-technical-support-instrument-tsi/overview/.

1 Introduction

Debates on monetary policy often have hinged on the slope of the Phillips curve, i.e., the relationship between economic slack and changes in prices or wages, conditional on expected inflation. The flattening of the slope of the Phillips curve in previous decades appears to have made it less useful for policy analysis, although this has been disputed by Hooper et al. 2020). Our paper provides a method for using firm-level data on outputs, inputs, and prices, together with micro-founded theory on firm-level pricing decisions and exogenous demand instruments, to estimate firm's price response to shocks. The paper presents a novel clustering method to aggregate firms while retaining the relevant heterogeneity, so that price behavior and cost and demand shocks that differ across the clusters could provide more timely estimates on the slope of the aggregate Phillips curve.

In the framework of the New Keynesian model (e.g. Gali 1999), the slope of the Phillips curve is determined by multiple factors. In the first place, an increase in price stickiness, modeled by a lower frequency with which firms can adjust prices (Calvo 1983 pricing), flattens the Phillips curve. A next macroeconomic determinant is the degree to which wages increase as labor markets tighten: a higher wage response leads to a steeper estimated Phillips curve for a given amount of cost pass-through. The reduced form relationship between activity and prices can also become steep when inflation expectations react positively to small shocks. With credible monetary policy, the estimated Phillips curve may be flatter by keeping expectations well anchored. In addition, the Phillips curve may not be linear, resulting in a lower price response when the slack is high. Finally, the slope of the Phillips curve is affected by supply shocks, such as an exogenous increase in prices of (imported) inputs.

A recent review by Baba et al. 2023 synthesizes the literature on estimating the Phillips curve slope, highlighting various factors other than economic slack that can explain recent

episodes of inflation and disinflation. Beyond the role of expectations and macro conditions in factor markets, research has explored the supply-side relationship between slack and prices in output markets. Boehm and Pandalai-Nayar (2022) show that US manufacturing industries' supply curves are convex and that inflationary pressures are higher when the production capacity limit is reached. Related, Gagliardone et al. 2023 find that the elasticity of marginal costs to the output gap is decreasing, hinting that supply shocks may still be relevant for the steepening of the slope of the Phillips curve, at the same time that demand shocks are less inflationary. Our evidence is not inconsistent, but allows empirically disentangling the role of supply and demand. Very similar in spirit to our theoretical, Andrés and Burriel 2018, model the flattening of the Phillips curve through the interaction between firm productivity heterogeneity and strategic competition. Finally, Fujiwara and Matsuyama 2022 show how increases in concentration and market power flatten the Phillips curve.

While the New Keynesian Phillips curve has been derived using micro-founded pricing behavior, empirical estimation often has taken place using macro time series, which confound micro decisions and market reactions. As stressed by Nakamura and Steinsson 2018, data on individual economic decision makers and appropriate exogenous variation is required to estimate micro-level supply and demand relations. We incorporate micro-theory, firm-level data, and instruments to estimate the level and slope of the supply curve and to estimate the slope and curvature of demand facing the firm.

Our contributions to the literature are fivefold. First, we derive a New Keynesian Phillips curve with firms that produce with heterogeneous technology and sell in monopolistically competitive markets facing residual demand curves with heterogeneous slopes and curvatures. In particular, we follow Mrázová and Neary 2017 in modeling demand from a 'firm's-eye view'. Second, in order to estimate firm's pricing behavior, we cluster the firms in our sample so that they have similar production technology and face similar demand curves within each cluster but have heterogeneous supply and demand estimates across clusters.

We implement an innovative clustering algorithm, in the spirit of Cheng et al. 2023, that provides the best fit for the production function and price pass-through regression equations. Third, we identify the supply and demand parameters using downstream Shea-type (Shea 1993a) instruments from global input-output data and global trade data linked to our firm sample. Fourth, our paper is the first to generate empirical results using the newly developed European microdata infrastructure (E. Bartelsman and MDI-Team 2024), which harmonizes firm-level data in multiple countries. In each country, firm-level panels are created by linking data sources such as the business register (BR), balance sheet and income statements (BS), structural business statistics (SBS), firm-level product prices and produced quantities (Prodcom), and firm-level trade data (ITGS). The MDI ensures such panels are harmonized in each participating European country.[1] The present paper focuses on France, and some cross-country comparisons are provided for the Netherlands and Slovenia.

Our fifth contribution is in our empirical findings, some corroborating earlier evidence, and some new results. We are the first to document that in manufacturing in multiple countries, the most productive firms have flatter supply curves. When faced with a shock in demand, their price response is modest. In addition, the most productive firms are found to exhibit higher volatility in output growth, implying a higher response in terms of output to industry- or firm-specific demand shocks. In addition, the output growth of the most productive cluster over the full sample period is substantially higher. This contributes to the flattening of the macro Phillips curve. Consistent with earlier findings in the literature, more productive firms are larger and have higher markups. The pass-through of cost shocks to price varies by demand cluster and seems slightly lower than estimated elsewhere, likely because we also control for differences in marginal cost.

The outline for the remainder of the paper is as follows: Section 2 lays out the theoretical New Keynesian framework with heterogeneous firms; Section 3 introduces the firm-level data

[1]To ensure replicability, the output generated in each country by analysis using MDI will be tagged uniquely, so that the exact source and version of underlying datasets, the precise harmonization routines, the version of R and all packages used, as well as the version of the MDI code and analytical code are documented and retrievable.

and the exogenous demand instruments; Section 4 describes our clustering algorithm using identified cost pass-through and production function estimates, and Section 5 reports our strategy for identifying and estimating micro pricing equations and provides empirical results; Section 6 extend the analysis to the full distribution of demand and supply among clusters; Section 7 implements the cross-country comparison, while Section 8 explores external validity of our results using evidence for a large sample of EU countries and business sectors from the CompNet database. Section 9 concludes.

2 The Theoretical Framework

2.1 The economic environment

Our analysis is based on a New Keynesian framework, the benchmark model for macro-monetary analysis and forecasting. The model is extended to allow for heterogeneity in supply and demand characteristics of firms making dynamic pricing decisions.

The economy in our model is populated by a representative household that consumes final output that is composed of a continuum of produced goods [0,1]. Each good is produced in a (symmetric) industry populated by N firms that compete à la Bertrand in monopolistic competition. In this market structure, firms internalize the effect of their pricing decision on the industry price since the number of firms is limited to N. By contrast, firms take the aggregate price level as given.

The model focuses on the response of firms to aggregate demand shocks and to firm-specific demand or supply shocks. Firm i, in sector s at time t, knows its own production technology and takes as given a residual demand curve for its output, $D_{ist}(p_{ist})$. Firms are constrained in their ability to make continuous price adjustments, à la Calvo.

Supply

We assume the following heterogeneous Cobb-Douglas firm production functions:

$$Y_{ist} = A_i(K_{ist}^{\alpha_i} L_{ist}^{(1-\alpha_i)})^{\gamma_i} \tag{1}$$

where Y_{ist}, K_{ist}, L_{ist}, are output, capital, and labour, respectively, of firm i, in industry s and time t. As will be derived below, the level of a firms' marginal costs depends on A_i and its slope on γ_i. As shown in Section 4, empirical support exists for a negative correlation between productivity and the slope of the marginal cost curve – more productive firms have flatter marginal cost curves. With heterogeneity in marginal cost curves across firms, there is no symmetry in steady state and firms have different market shares, while at the margin they will feature different responses to shocks.

Marginal costs are a function of input prices, output level, and firm technology, which, in the case of the above production function, can be expressed after cost minimization as:

$$MC_{ist}^{n} = \frac{C_{ist}}{A_i^{\gamma_i}} Y_{ist}^{\frac{1}{\gamma_i}-1} \tag{2}$$

where

$$C_{ist} = \left(\frac{W_t}{(1-\alpha)\gamma_i}\right)^{(1-\alpha)} \left(\frac{R_t}{\alpha\gamma_i}\right)^{\alpha}$$

Hence, A_i and γ_i are sufficient statistics to determine the level and slope of the marginal cost curve, conditional on market prices for inputs.

Demand

In the empirical sections of this paper, we do not take a stand on a particular functional form for industry demand and on the type of firm conduct. Instead, as advocated by Mrázová and Neary 2017, we consider the "firm's eye view" of demand, where the residual demand curve facing a firm can be sufficiently characterized by its elasticity and convexity,

which will be estimated. In particular, the firms' cost mark-up and pass-through decision depend on these residual demand characteristics.

In general, the residual demand elasticity is a negative function of the price response of competitors to firm i optimization. In this section we illustrate the function relating markups to market demand parameters and competitors' price behavior in the case of a nested CES function, without loss of generality. In the following equation we can think of firms (subscripts i) making up an industry (subscripts s).

With CES, the elasticity of the residual demand becomes:

$$\eta_{ist} = -\frac{\delta ln(D_{ist})}{\delta ln(P^o_{ist})} = \sigma - (\sigma - \epsilon)\zeta_{ist},$$

where the demand curve is given by D_{ist}, the firm price by P^o_{ist}, ϵ is the elasticity of substitution across industries, σ across firms within industries (and $\sigma > \epsilon$), $\zeta_{ist} = \frac{\delta p^{-i}_{st}}{\delta p^o_{ist}}$ and the rivals' price is P^{-i}_{st}

The industry price can be decomposed into the firm price and the rivals' price as follows :

$$P_{st} = \left[\frac{1}{N}(P^o_{ist}\omega^\sigma_{ist})^{1-\sigma} + \frac{N-1}{N}(P^{-i}_{st})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

Hence, the elasticity of industry price relative to firm i price can be written as:

$$\frac{\delta p_{st}}{\delta p^o_{ist}} = \underbrace{\frac{\omega^\sigma_{ist}}{N}\left(\frac{P^o_{ist}}{P_{st}}\right)^{1-\sigma}}_{s_{ist}} + \underbrace{\frac{N-1}{N}\left(\frac{P^{-i}_{st}}{P_{st}}\right)^{1-\sigma}}_{1-s_{ist}}\zeta_{ist}$$

In steady state, firms are in Nash-Bertrand equilibrium and do not have an incentive to change prices given the competitors' optimization. This implies that $\zeta_{is} = 0$ in steady state,

and the markup is log linearized as follows:

$$\hat{\mu}_{ist} = \mu_{ist} - \mu_{is} = -\Gamma_{is}(\hat{p}^o_{ist} - p^{-i}_{st}) + u^{\mu}_{ist}$$

where Γ_{is} denotes the markup elasticity with respect to firm price (where $\bar{x}$ stands for steady state value of x):

$$\Gamma_{is} = \frac{(\sigma - \epsilon)(\sigma - 1)(N-1)\bar{p}_s^{-i1-\sigma}\bar{p}_{is}^{1-\sigma}}{\eta_{is}(\eta_{is} - 1)N^2}$$

and

$$u^{\mu}_{ist} = \frac{(\sigma - \epsilon)(1 - s_{is})}{\eta_{is}(\eta_{is} - 1)}\zeta_{ist} + \frac{(\sigma - \epsilon)\sigma\bar{p}_{is}^{1-\sigma}}{\eta_{is}(\eta_{is} - 1)N}\left(1 - \frac{\bar{p}_{is}^{1-\sigma}}{N}\right) ln(\omega_{ist})$$

Similar functional forms for markups can be obtained with different demand specifications (for example, Kimball preferences), and parameters could be specific to the residual demand facing firm i. Below we describe the reset pricing, using the objects μ and Γ as they would be derived for any chosen demand system.

Pricing

Firms are restricted in their ability to adjust prices until some random window in time which occurs with probability $(1 - \theta)$, and are subject to expected residual demand D_{ist}. When able, firms choose a "reset price" P^o_{ist} to maximize the present discounted value of real profits:

$$\max_{P^o_{ist}} E_t\left\{\sum_{k=0}^{\infty}\theta^k\left[\Lambda_{t,k}\left(\frac{P^o_{ist}}{P_{st+k}}D_{ist+k} - TC(D_{ist+k})\right)\right]\right\}$$

denoting $\Lambda_{t,k}$ as the stochastic discount factor and P_{st} as the industry price, while $TC(D_{ist})$ are the real total costs. Therefore, the FOC of this problem can be represented as:

$$E_t\left\{\sum_{k=0}^{\infty}\theta^k\Lambda_{t,k}D_{ist+k}\left[\frac{P^o_{ist}}{P_{st+k}} - (1 + \mu_{ist+k})\frac{MC^n_{ist+k}}{P_{st+k}}\right]\right\} = 0 \tag{3}$$

where MC^n_{ist} are nominal marginal costs. In monopolistic competition, the log markup μ_{ist} is an inverse function of the firm residual demand elasticity $\eta_{ist} = -\frac{\delta ln(D_{ist})}{\delta ln(P^o_{ist})}$ that firms are facing at the margin, which in turn depends on the elasticity of substitution for market demand and the price reaction of competitors. Therefore, the log markup can be expressed as the usual Lerner index $ln\left(\frac{\eta_{ist}}{\eta_{ist}-1}\right)$, and the firm residual demand elasticity as:

$$\eta_{ist} = \eta_{ist}\left(\zeta_{ist}, \eta_d, \rho_d\right)$$

where $\zeta_{ist} = \frac{\delta p^{-i}_{st}}{\delta p^o_{ist}}$ is the price response of competitors to firm reset price, while η_d and ρ_d are parameters defining the elasticity and convexity of demand in the market in which the firm operates. It is important to stress that the relationship between markups and residual demand elasticity is a general result of simply assuming monopolistic competition.

Log-linearizing the FOC of equation 3 around the steady state, the reset price equals the discounted value of desired markups and expected marginal costs (where $\hat{x}$ stands for x log deviation from steady state):

$$\hat{p}^o_{ist} = (1-\beta\theta)E_t\sum_{k=0}^{\infty}(\beta\theta)^k(\hat{\mu}_{ist+k} + \hat{mc}^n_{ist+k}) \tag{4}$$

Given the above specifications, equation 4 can be rewritten as follows:

$$\hat{p}^o_{ist} = (1-\beta\theta)E_t\sum_{k=0}^{\infty}(\beta\theta)^k[(1-\Omega_{is})\hat{mc}^n_{ist+k} + \Omega_{is}p^{-i}_{st+k} + (1-\Omega_{is})u^{\mu}_{ist+k}] \tag{5}$$

where $\Omega_{is} = \frac{\Gamma_{is}}{1+\Gamma_{is}}$, which is increasing with the firm production technology level.

From the formula of MC^n_{ist}, log marginal costs are:

$$\hat{mc}^n_{ist} = \hat{c}_{ist} + v_i\hat{y}_{ist}$$

where the slope of the marginal costs relative to output is decreasing with production output elasticity:

$$v_i = \frac{1-\gamma_i}{\gamma_i} \tag{6}$$

while $\hat{c}_{ist}$ is not firm-specific in our model, but depends on the market cost of labor and capital, which is given from the point of view of a single firm, as we assumed above. Therefore, the price equation for each firm becomes:

$$\hat{p}^o_{ist} = (1-\beta\theta)E_t \sum_{k=0}^{\infty} (\beta\theta)^k [(1-\Omega_{is})(\hat{c}_{ist+k} + v_i \hat{y}_{ist+k}) + \Omega_{is} p^{-i}_{st+k} + (1-\Omega_{is}) u^{\mu}_{ist+k}] \tag{7}$$

From equation 7, it can be seen that firm technology is the crucial component of the firm supply curve: as γ_i rises (v_i diminishes), marginal costs become flatter, and competition effect on price decreases ($1-\Omega_{is}$ decreases). In this framework, even the competition mechanism results from higher production technology: lower marginal costs let the more productive firms grow larger and face lower competitive pressures. This implies that, at the occurrence of a demand shock, firms with a higher level of production technology react less in terms of prices and, consequently, owing to monopolistic competition, more in terms of output.

Then, leveraging the Calvo pricing mechanism:

$$E_t[p_{ist}|p_{ist-1}, p^o_{ist}] = (1-\theta)p^o_{ist} + \theta p_{ist-1}$$

and

$$\hat{p}_{ist} = (1-\theta)\hat{p}^o_{ist} + \theta \hat{p}_{ist-1} + \nu_{ist}$$

Consequently, the firms' pricing equation can be rewritten as:

$$\hat{p}_{ist} = (1-\theta)(1-\beta\theta)E_t \sum_{k=0}^{\infty}(\beta\theta)^k[(1-\Omega_{is})(\hat{c}_{ist+k} + v_i\hat{y}_{ist+k}) + \Omega_{is}\hat{p}^{-i}_{st+k}] + \theta\hat{p}_{ist-1} + \epsilon_{ist} \quad (8)$$

Given input prices and market structure, the higher the level of productivity at the firm, the flatter the firm supply curve. In fact, v_i decreases with productivity and factor output elasticities and denotes the lower increase in firm inputs needs after a demand increase. v_i is the slope of the firm marginal cost curve or supply curve. Moreover, $(1-\Omega_{is})$ denotes the strategic interaction effect as in Andrés and Burriel 2018, and it delivers a lower cost pass-through for firms characterized by higher productivity levels.

In the empirical section, we rely on equation 8 and estimate it for heterogeneous firms clustered according to their production technology and the elasticity and curvature of demandthey face. As stated above, the slope of firms' supply curves can also be affected by firm-specific demand characteristics. Hence, we control for demand conditions as observed by firm in our clustering analysis. Given our use of data at the annual frequency, as described in Section 3, the weight on future streams of output and related expectations becomes small. In fact, given standard estimated Calvo price stickiness parameters, firms are mainly free to adjust prices within one year. The same implication could be derived from agents' beliefs about effective monetary or fiscal policy responses to shocks in order to keep output on a balanced growth path.

2.2 Aggregating to the Phillips curve

Finally, we show that the macro Phillips curve can be seen as an aggregation of heterogeneous firms' pricing equations, again using the example of CES demand. The firm-level pricing equations are at the foundation of the economy-wide supply curve.

To derive the Phillips curve, we define the aggregate price index and the industrial prices as typical from a nested CES function:

$$P_t = \left(\int_0^1 \omega_{st}^{\epsilon} P_{st}^{1-\epsilon} \, ds \right)^{\frac{1}{1-\epsilon}}$$

$$P_{st} = \left[\sum_{i=1}^{N} \omega_{ist}^{\sigma} P_{ist}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

where ω_{st} and ω_{ist} are possible industry-specific and firm-specific demand shocks, respectively.

To aggregate, we recover the equations for prices in log deviations around the steady state (omitting the shocks for ease of notation):

$$p_t = \int_0^1 p_{st} ds$$

$$p_{st} = \frac{1}{N} \sum_{i=1}^{N} \bar{p}_{is}^{1-\sigma} \hat{p}_{ist}$$

The firm price equation in recursive form can be written as follows:

$$\hat{p}_{ist}^{o} = (1 - \beta\theta)[(1 - \Omega_{is})(\hat{c}_{ist} + v_i \hat{y}_{ist}) + \Omega_{is} p_{st}^{-i} + (1 - \Omega_{is}) u_{ist}^{\mu}] + \beta\theta E_t \hat{p}_{ist+1}^{o}$$

It is important to notice that, from CES specification, $\frac{\bar{p}_{is}^{1-\sigma}}{N} = s_{is}$. Hence, our aggregation is a weighted average of prices by steady-state firm revenue shares. It can be further shown that (thanks to Calvo iid draws and the law of large numbers):

$$p_t = \theta p_{t-1} + (1 - \theta) \hat{p}_t^{o}$$

where

$$\hat{p}_t^o = \int_0^1 \left(\frac{1}{N} \sum_{i=1}^{N} \bar{p}_{is}^{1-\sigma} \hat{p}_{ist}^o \right) ds$$

This way, aggregating recursive firm price equations, we obtain:

$$\hat{p}_t^o = \beta\theta E_t \hat{p}_{t+1}^o + (1-\beta\theta) p_t + (1-\Omega)(1-\beta\theta)\hat{c}_t^r + (1-\beta\theta) v\hat{y}_t + u_t \tag{9}$$

where

$$(1-\Omega) = \int_0^1 \left(\frac{1}{N} \sum_{i=1}^{N} \bar{p}_{is}^{1-\sigma} (1-\Omega_{is}) \right) ds$$

and

$$v\hat{y}_t = \int_0^1 (\frac{1}{N} \sum_{i=1}^{N} \bar{p}_i^{1-\sigma} (1-\Omega_{is}) v_i \hat{y}_{ist}) ds$$

From equation 9, it is then straightforward to compute the Phillips curve:

$$\pi_t = \beta E_t \pi_{t+1} + (1-\Omega)(1-\beta\theta)\hat{c}_t^r(\hat{y}_t) + (1-\beta\theta) v\hat{y}_t + u_t \tag{10}$$

The slope of the Phillips curve, given expectations and input prices, is a weighted average of each firm's supply curve and is flatter when the market share of more productive firms is higher. The Phillips curve can flatten even if the steady-state share of the more productive firms does not increase as long as these firms are the ones responding the most to temporary demand shocks. It is important to notice that we would find the same result if we used an atomistic basic NK model with heterogeneity in production technology. In atomistic monopolistic competition, $\zeta_{is} = 0$ and $s_i = 0$ for each firm i, and this would eliminate strategic interaction (Ω_{is} would be zero for all firms). However, our model predicts heterogeneous pricing curves beyond competition effects due to flatter marginal cost curves for more productive firms.

Furthermore, the aggregation to the macro-level Phillips curve shows us that it is not necessary to aggregate by industry. What matters is the production structure of firms and

the residual demand they face, with v being the weighted average across firms. In our empirical analysis, therefore, we consider only heterogeneity across technology and demand characteristics rather than heterogeneity across industries as defined by statistical agencies.

Finally, it must be noticed that the macro Phillips curve in equation 10 is characterized by a real input costs component c_t^r since we do not assume constant returns to scale in production technology. At the aggregate level, they are a function of the output gap, however they are driven by tightness in input markets. In any case, the higher the share of more productive firms with flatter derived input demand, the flatter the slope of the aggregate Phillips curve.

3 Data Description

In the main empirical analysis, we make use of the newly built micro data infrastructure (MDI), that harmonizes firm-level data on output, inputs, and prices at EU statistical agencies. Further, we employ national statistical institute (NSI) data for industry price deflators, as well as OECD input-output tables and UN Comtrade data for the construction of exogenous demand indicators.

The harmonized MDI firm-level panels are created under the EU *Technical Support Instrument* project[2], which involves the direct participation of NSI for data construction and harmonization, while national productivity boards (NPB) and several research institutes are data users and partners. A wide range of linkable firm-level datasets are available at NSIs, harmonized through the MDI.

The authors currently have direct access to the NSI data in France in order to develop the

[2]The MDI received funding from the H2020 project grant *Microprod*, 2019-222, and the EU TSI project, European Commission, Directorate-general for Structural Reform Support under grant agreement No. 101101853 and No. 101140673 (Austria). For more details, see the CompNet website at the following link: https://www.comp-net.org/eu-technical-support-instrument-tsi/overview/.

analytical research design. Presently, our main analysis will be related to France. We also will provide preliminary results from running the analysis remotely using the MDI set-up on harmonized panels from the Netherlands[3].

At the core of the MDI database is the *Statistical Business Register* (BR), which contains information on identifying firm characteristics. In MDI, the BR is the "backbone" or connection between various surveys and administrative datasets. In addition, the following datasets are available: *Balance Sheet and Income Statement* (BS), *Structural Business Statistics* (SBS), the *Community Innovation Survey* (CIS), the *ICT usage/E-Commerce Survey* (ICTEC), the *International Trade in Goods Statistics* (ITGS) and *International Trade in Services Statistics* (ITS), the *Foreign Affiliate Statistics* (FATS), *Firm Production Statistics* (Prodcom), and *Firm Energy Use* (ENER). For more details about each dataset, please see Appendix A.

The MDI harmonizes the linked panels in each country to have common units of observation, classifications, and variables: for example, the same variable names and definitions, the same industry and product codes, and so on. Consequently, the researcher's code can run unchanged in each country to generate output datasets with, for example, moments and regression parameters, that can be analyzed jointly in a multi-country setting.

In our empirical analysis, we use mainly two datasets from the MDI environment: Prodcom and SBS. Prodcom data report revenues and quantities by firm and 8-digit product, covering the economic activities of mining and quarrying, manufacturing, and materials recovery. The Prodcom datasets are relatively harmonized owing to Eurostat regulation. In the specific case of France, the survey covers a wider set of products, but we restrict the analysis to the harmonized set of products included in Prodcom for cross-country comparison

[3]Harmonized microdata panels also are under construction in Austria, Germany, Finland, Italy, Portugal, and Slovenia.

purposes[4]. The production dataset, SBS, covers the business economy's activities, including industry, construction, distributive trade, and services. Harmonization of the SBS is more difficult because only aggregated statistical output is harmonized at the EU level[5] and countries have some discretion on how to collect the underlying information. MDI harmonization takes place regarding the detail of coverage of size-class, sector (now NACE 2.1), and the statistical definition of the transmitted indicators. The following analysis is undertaken on the selection of firms that report information in both the SBS and Prodcom datasets.

We employ SBS for information about firms' revenues and production inputs, particularly labour and intermediate material expenses, as well as wages. For measures of the capital stock and interest paid by firms, we derive these indicators from the BS data that have been harmonized from the enterprise group to the firm level[6]. These data are used to implement our clustering analysis on firm production and costs pass-through, as we explain in Section 4.

Prodcom data are used to create prices at the firm level. We define the yearly price for each firm and product as the ratio between product revenues and quantities. Then, we define the firm-product price change as the ratio between the price in year t and $t-1$, and we aggregate to the firm level using a Törnqvist index, weighting over product revenue shares

[4]In France, INSEE undertakes a wider survey than Prodcom, called ProdFra (acronym for *Production Française*). The ProdFra headings are usually coded on 10 digits, the first eight repeating the Prodcom code if it exists. Furthermore, we exclude invoices relating to subcontracted orders in the computation of revenues and sales.

[5]EU Commission Regulation (EC) No 250/2009.

[6]Labour is defined as full-time equivalent and capital as tangible plus intangible fixed assets.

within each firm[7]. The resulting firm price change is, hence, as follows[8]:

$$\frac{P_{it}}{P_{it-1}} = \prod_{g \in i_g} \left(\frac{P_{git}}{P_{git-1}} \right)^{s_{git}}$$

In the expression above, P_{git} is the price index for product g, firm i, and year t, and s_{git} is the average firm revenue share of that product between year t and year $t-1$. This way, we create a firm price index: we normalize $P_{i,2010} = 1$ for all firms, and we accumulate forward an backward by the annual price change[9].

Similarly, we create a price change variable for competitors, i.e., all the firms except firm i in a given 4-digit industry, which is required for our firm pricing equation estimation. In this case, we use firm market share as Törnqvist index weight. The choice of the 4-digit industry as the market size is given by Table 1, which reports descriptive statistics from the Prodcom dataset. As it can be noticed, only at the 4-digit level do firms have a meaningful share of the market (1.04% of the market on average), and it is reasonable, hence, to assume strategic interaction[10]. From Table 1, it can also be seen that the distribution of firms is skewed to the right in terms of sales and labour, that firms are operating mostly in one 4-digit industry, and more than half of our sample produces more than one good.

Furthermore, it is instructive to test to what extent the pricing behaviour of firms reflects the aggregate price index. To do that, we aggregate our firm-level price changes,

[7]To construct the price change we need to harmonize the Prodcom codes across years. We do so thanks to official conversion tables provided by INSEE, the French NSI, and leveraging the firm-level data. In particular, we concord all one-to-one (the vast majority) and many-to-one matches. Also, we concord most of the one-to-many and many-to-many matches: in fact, if the concordance tables refer to a one-to-many or many-to-many match, but the single firm is producing only one good in year $t-1$ and t, we concord such codes straightforwardly. This way, we can concord up to more than 99% of the sample.

[8]We aggregate at the firm level products that are produced both in year $t-1$ and t, for which quantity unit of measure is comparable.

[9]For the years where firms are missing in the data, we fill the gap with 2-digit industry deflator change to complete the firm price series, and then we remove such observations from the final dataset.

[10]Similar results are provided for Belgium by Gagliardone et al. 2023.

Table 1: Descriptive statistics from the Prodcom dataset

	Average	5^{th} Pc	25^{th} Pc	Median	75^{th} Pc	95^{th} Pc
Revenue	22970.23	173.39	705.60	2343.02	8082.49	63791.01
Employees	66.45	1	5	14	38.5	230.25
Market Share within Manufacturing	0.00573%	0.00004%	0.00017%	0.00059%	0.00206%	0.01644%
Market Share within 2-digit industry	0.11670%	0.00099%	0.00437%	0.01376%	0.04741%	0.34173%
Market Share within 4-digit industry	1.04362%	0.00641%	0.02954%	0.09913%	0.38035%	3.71379%
Consecutive years in the sample	4.93	1	2	4	8	11
Number of industries	1.21	1	1	1	1	2
Number of products	4.72	1	1	2	5	12
Within firm revenue share of main industry	95.96%	64.35%	100%	100%	100%	100%

Note: Firm descriptive statistics from Prodcom. Employees are measured in full-time equivalents. Revenue is in thousands of Euros.

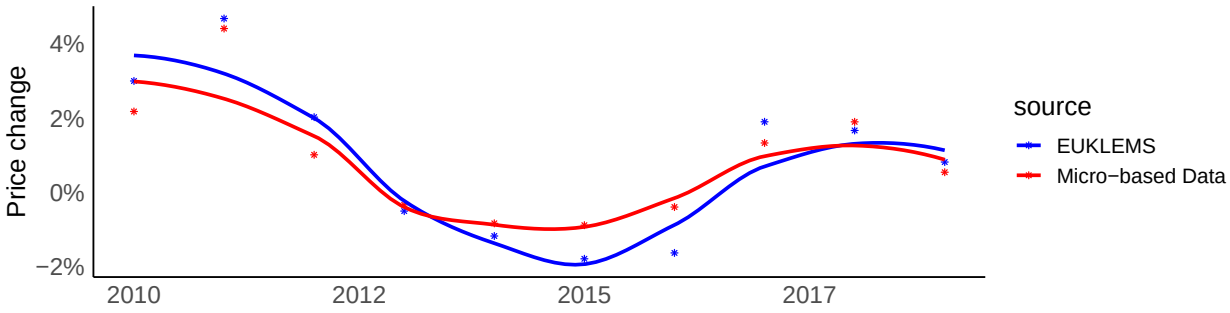
constructed as explained above, at the manufacturing level, again implementing a Törnqvist index weighting over market shares. We then compare our micro-based aggregate measure with the manufacturing gross output deflator from EU Klems[11].

As it can be seen in Figure 1, microdata manage quite well to replicate macro figures. On the one hand, this reveals the robustness of microdata. On the other hand, it also confirms that the aggregate price index consists of firms' pricing decisions.

In our estimation of firm-level price decision and supply curve slopes, we need exogenous

[11]Eu Klems data are available at https://euklems-intanprod-llee.luiss.it.

Figure 1: Aggregate price change in manufacturing: MDI and EU Klems



measures of demand shocks. We create two typologies of downstream demand indicators. The first one is constructed using the Inter-Country Input-Output (IO) Tables from the OECD[12]. These tables report intermediate expenses and output for 76 countries and the rest of the world at the 2-digit sectoral level or aggregation of sectors (NACE Rev.2 classification).

Revenues from the IO tables are in millions of US dollar Therefore, we firstly convert units into national currencies and, then, we deflate activities by industry deflators (or country GDP deflator, when sectoral deflators are not available)[13]. Afterwards, we calculate the downstream indicator for each country-sector as the weighted average of the annual percentage change in input expenses of its destination partners. The average is weighted over the previous year's shipment shares to each destination partner. From the computation are excluded the destinations whose input expenses in the country-sector shipments are more than 5%, as well as the destinations that represent more than 5% of the country-sector input expenses (Boehm and Pandalai-Nayar 2022 suggests this further condition)[14]. Consequently, our measure of downstream demand is robust to concerns of endogeneity regarding supply

[12]Available at https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm.

[13]Sectoral deflators are taken by Eurostat, the OECD Structural Analysis Database (STAN), or EU Klems; GDP deflators and exchange rates are provided by the World Bank.

[14]We also exclude domestic destination partners, to increase the exogeneity of the instrument. However, to improve predictive power, for each of the bottom 50% sectors in terms of export, we include the downstream shock of the domestic top 50% exporters, weighted by the shipment shares from the bottom exporter sector to the top exporter.

shocks in one industry affecting the partner industry. Our first instrument is, hence, a version of the Shea's instrument (Shea 1993a, Shea 1993b) of both domestic and foreign direct downstream demand:

$$DS_{st}^{Shea} = \sum_{j \in J_{st-1}} s_{jst-1} \Delta lnM_{jt}$$

where s_{jst-1} denotes the sales shares of industry s to destination j in year $t-1$, and ΔlnM_{jt} represents the aggregate growth rate of destination j's input expenses between years t and $t-1$.

Our second measure of demand shock is calculated as the world import growth rate, following the strategy of Dhyne et al. 2022. Export and import data are available in the UN Comtrade dataset[15] at the country-product level. Products are reported in millions of US dollars at the Harmonized System (HS) 6-digit level. Hence, we can construct the downstream indicator for each product as the total growth rate in world imports net of the imports from France. Imports are deflated by US GDP, which is a reasonable measure as a world import deflator (see, e.g., Gopinath, Boz, et al. 2020). This way, we can measure export-driven demand shock for each product in France. We then calculate a firm-specific shock weighting the product-level demand shocks with the firm revenue shares of such products, leveraging information from Prodcom:

$$DS_{it}^{wid} = \sum_{p \in \mathcal{P}_{pt-1}} s_{ipt-1} \Delta lnWID_{pt}$$

where s_{ipt-1} is the firm revenue share of product p for firm i in year $t-1$, and $\Delta lnWID_{pt}$ denotes the world demand growth rate for product p between years t and $t-1$.

We link the DS_{it}^{wid} instrument to our final firm-level dataset thanks to concordance tables

[15] Available at https://comtradeplus.un.org/.

between 8-digit Prodcom codes and 6-digit HS codes provided by Eurostat[16]. The DS_{st}^{Shea} is more easily linked since the first 4 digits of the Prodcom codes are identical to the NACE classification. After including all the relevant variables and cleaning data, the final firm-level annual dataset includes 146574 firm-level observations from 2011 to 2020, with a total of 33237 firms under analysis.

Thanks to these demand instruments, which now are standard in the literature, we can deal with endogeneity and estimate the supply curve for heterogeneous firms along the production technology distribution. Moreover, such shocks are different in nature. DS_{st}^{Shea} is closer to being an aggregate shock (at the industry level). All firms in the same industry are affected by the same shock coming from foreign downstream industries[17]. Hence, this indicator captures a global trend in demand for a particular domestic industry, directly affecting the industry demand for exporters and domestic firms. It is also correlated with domestic downstream indicators, proving it detects a general trend in demand for the whole industry. DS_{it}^{wid}, by contrast, is more firm-specific. In fact, it is again a foreign downstream indicator but specific to a particular product, and, as stated above, we weigh each product shock with a firm revenue share of that product. This way, we link the global trend directly to the firm basket of products and increase the micro-level variability of our demand shocks.

4 Clustering

Our objective is to estimate the coefficient v_i in equation 8 for heterogeneous firms. Such a parameter can be derived by estimating the coefficients of the output component and the competitors' price in equation 8. However, the strategic component $(1-\Omega_{is})$ could, in princi-

[16]Eurostat provides concordance tables between Prodcom and the Combined Nomenclature 8-digit codes, which are equal to the HS classification for what concerns the first six digits. We take the average export demand shock in case of a one-to-many match.

[17]For the few firms operating in different industries, DS_{st}^{Shea} is also weighted by the firm revenue shares. However, as shown by Table 1, even firms producing in different industries are mostly concentrated in the main one.

ple, be affected by firm-specific demand elasticity, as we explain in Section 2, and this could bias our estimates of the firm supply curve. We plan to estimate the demand and supply parameters firms that differ in these two dimensions. The firm subscript i in e.g. equation 8 will now refer to a group of firms that have been clustered together based on similarity in the esimates. This way, we aim to increase the precision in estimating v_i.

We propose an innovative algorithm to cluster firms simultaneously according to supply and demand dimensions. Some recent methodologies allow cluster observations across membership of multi-dimensional regression parameters. For example, Cheng et al. 2023 estimate multiple memberships in non-linear panel data and compute heterogeneous parameters across groups. Instead, we want to assign each firm membership according to two different regression models. For the supply dimension, we run production function estimations for five possible groups and cluster each firm according to the best fit to minimize a GMM criterion, assigning firms to their production technology level, from the least productive firms in the first group progressively to the most productive firms in the fifth group. Firms are considered to have higher technology level when they are characterized by larger TFP and output elasticities. On the demand side, given the focus on the margin of the residual demand curve, we estimate a cost pass-through equation and, again, we cluster firms according to the best fit (in the case of demand, we cluster in three possible groups, from the lowest level of pass-through, meaning higher demand elasticity, to the highest one). Both estimations are implemented contemporaneously, estimating the production function given the demand structure and vice versa.

Consistent with the model, we estimate a Cobb-Douglas specification for the production function. We implement a GMM estimation of a dynamic panel specification that uses capital and lagged inputs as instruments[18]. This methodology controls for possible productivity bias

[18] As it is standard in the literature, the model assumes that firm productivity evolves as an AR(1) process and it is correlated with variable inputs (l_{it} and m_{it}). The dynamic panel model quasi-differentiates variables

estimation, while keeping the algorithm procedure linear and tractable, as follows:

$$\delta y_{it} = \alpha + \beta_k \delta k_{it} + \beta_l \delta l_{it} + \beta_m \delta m_{it} + t + \epsilon_{it}$$

where y_{it}, k_{it}, l_{it}, m_{it}, and t are firm output, capital, full-time equivalent, intermediate expenses, and time, respectively[19]. All variables are in real log terms. We deflate firm output with firm price index computed as described in Section 3. Capital and intermediate inputs are, instead, deflated using 2-digit sector-specific deflators. Given the relatively short period in our sample, characterized by low inflation levels, the possible input price bias is also assumed to be negligible.

For the demand estimation, we follow Mrázová and Neary 2017, who show that in monopolistic competitive markets, the cost pass-through is a function of slope and curvature (or the elasticity and convexity) of the demand curve [20]. Given the supply curve, the slope and curvature of the demand curve determine the mark-up of price over marginal cost and the pass through of cost shocks. At present we cluster the firm based on the pass-through of costs, using the following equation:

$$\delta p_{it} = \beta_0 + \beta_d(\eta_d, \rho_d)\delta mc_{it} + \delta_t + \epsilon_{it}$$

where δp_{it} is the log difference of firm price, while δmc_{it} are residuals from a regression of firm log difference of marginal costs on our downstream demand shocks to mimic a supply cost shock. According to theory, the resulting β_d from the demand side clustering is a func-

to cancel out the lagged productivity shock. Then, through GMM estimation, we use lagged variable inputs (as well as current capital, the constant, and the time variable) as instruments to control for such bias.

[19]We do not include firm fixed effect since the production function literature theorizes that these could amplify the highly-persistent measurement error noise in capital stock; see, for example, Ackerberg et al. 2015.

[20]The authors, unlike us, assume constant marginal costs as well. We adjust their exposition to allow for an upward-sloping marginal cost curve. At the margin, it can still be a good approximation, and again, we are interested in detecting similarities among firms with respect to the residual demand they face. Therefore, a cost pass-through equation in a fashion similar to Mrázová and Neary 2017 reaches the purpose.

tion of the elasticity η_d and convexity ρ_d of firms' residual demand. We cluster the firms based on this parameter. From our theoretical framework (equation 2), marginal costs are proportional to unit variable costs, and, hence, mc_{it} can be proxied by a counterpart in the data. We measure unit variable costs as the ratio between the sum of wages, paid interest, and intermediate expenses, and real output (nominal sales deflated by firm-specific price).

Our interative procedure of estimation of the two equations and reassignment of firms to clusters based on residual sum of squares allows the clustering of firms according to these two dimensions in a reasonable span of time. After the clustering algorithm is concluded, a firm will be part of its assigned cluster for all the years it appears in the data: this is consistent with the idea of persistent production characteristics and but mostly is based on the pragmatic issue of computation speed. For more details on the algorithm, please see Appendix B[21].

To initialise our iterative procedure of estimation and assignment we start by classifying firms according to the empirical distribution of firms' labour productivity and the ratio of price and marginal cost growth rates. The distribution of such variables empirically suggests the division of firms into five technology clusters and three demand clusters. In fact, the distribution of firms' labour productivity is very skewed, with a thick right tale, which suggests considering separately such different firms. Instead, the distribution of the ratio of price and marginal cost growth rates is more normally distributed and, hence, allows the division of the firms into three separate clusters (two tales and the middle part of the distribution). Other methodologies, instead, propose penalty approaches to detect the number of clusters (see, for example, Ando and Bai 2016, Mehrabani 2023, and Su et al. 2016). However, these methods rely on the particular form and parametrization of the penalty function. Our approach aims at being more coherent with the data undr analysis. Then, our algorithm detects the

[21]In future work, we plan to explore firms' dynamics in switching groups.

clustering that minimizes the GMM criterion for each bin along both the production and demand dimensions. To our knowledge, this study is the first to explicitly consider both production and demand heterogeneity while estimating firms' supply curves.

Table 2: Number of firms by technology and demand cluster

	Demand 1	Demand 2	Demand 3
Technology 1	655	468	929
Technology 2	3974	2877	3603
Technology 3	5236	3664	4956
Technology 4	948	1312	3187
Technology 5	242	214	972
Cost pass-through	0.107	0.670	0.979

Note: *Cost pass-through* indicates the estimated coefficient for the demand side clustering.

Table 2 reports the result of the clustering analysis. The algorithm delivers a skewed distribution of firms along the production technology distribution, with around 70% of them in the second and third production groups, and a thicker right tail of more productive firms.

As for the demand side clustering, cost pass-through estimates align with available empirical evidence, suggesting a less than 100 percent price-cost transmission (e.g., Gopinath and Itskhoki 2010, De Loecker et al. 2016). Moreover, it is interesting to notice that the majority of the most productive firms (technology clusters 4 and 5) are located in the third demand cluster, where demand is more rigid and pass-through higher. Instead, less productive firms (technology clusters 1, 2, and 3) face higher demand elasticity (demand clusters 1 and 2). Therefore, the clustering result suggests a negative correlation between production technology and residual demand elasticity. This can be partly because the most productive firms are also larger, as shown below. Our model's strategic interaction in monopolistic

competition predicts that their competitors react strongly to their reset price increase, hence maintaining the residual demand more rigid.

Table 3: Descriptive statistics by technology cluster

Technology	*N° firms*	*TFP*	oe_{k+l}	oe_{k+l+m}	$oe_{k+l+m,\text{ACF}}$	*lprod*	*size*	$markup_m$	*marg. costs*
1	2052	0.188	0.179	0.818	0.911	4.47	4076.24	0.93	2.13
2	10454	0.411	0.186	0.831	0.926	4.89	5436.07	1.03	1.10
3	13856	0.649	0.228	0.859	0.931	5.24	11940.40	1.11	0.85
4	5447	1.028	0.297	0.897	0.950	5.68	39751.27	1.24	0.61
5	1428	1.585	0.453	0.984	0.962	6.41	75443.54	1.37	0.42

Note: *N° Firms* refers to the number of firms, *TFP* is total factor productivity which, together with the sum of output elasticities of capital and labour (oe_{k+l}) and total returns to scale (oe_{k+l+m}), is computed through the production function estimation by group in the cluster analysis; $oe_{k+l+m,ACF}$ is the sum of output elasticities from a output production function estimation with ACF methodology; *lprod* means labour productivity in logs; *size* is sales in thousands of euros; $markup_m$ is markup over intermediate inputs estimated as in Loecker and Warzynski 2012; *marg. costs* are marginal costs proxied by unit variable costs as computed in the main analysis.

To better acknowledge the differences among clusters, Table 3 shows descriptive statistics along the estimated technology distribution and the results from the production function estimation in the last round of the clustering algorithm. As it can be seen, estimated TFP is positively correlated with the sum of output elasticities. This result is robust to different production function estimation specifications, including Ackerberg et al. 2015 (ACF) methodology on output production function estimation. Furthermore, the sum of output elasticity positively correlates with labour productivity, measured as sales deflated by the firm price index over labour (full-time equivalent).

The model predictions for size, markups, and marginal costs are confirmed. As the firm increases production technology, it is found to be larger, with higher markups and lower marginal costs. In addition to that, from the CIS data, we find that only 50% of the employees in firms of technology clusters 1 and 2 use ICT, while the share increases to 53% for cluster 3 and 65% for cluster 4, until a percentage of 70% is found on the intensity of ICT

among the employees of technology cluster 5.[22].

Table 4: Growth in market shares and volatility of output change by production cluster

	δ_S	$se(\Delta_y)$
Production 1	− 33.0%	2842.93
Production 2	+ 8.49%	4808.45
Production 3	+ 9.80%	6207.88
Production 4	+ 5.45%	33410.13
Production 5	+ 25.5%	74304.47

Note: δ_S is the growth rate in 2-digit market shares between 2013 and 2019 for the cluster average firm, while $se(\Delta_y)$ is its volatility of output change.

Finally, Table 4 reports for each technology cluster the average firm growth rate in 2-digit industry market shares between 2013 and 2019 and the volatility of the change in production during the same period. Even during this short period, we observe reallocation in industries from the least productive to the most productive firms. More interestingly, the volatility of the output change is the highest for the most productive firms. This suggests that demand shocks are mostly met by firms at the technology frontier, meaning that these are the main suppliers at the margin, as predicted by theory and with deep implications for the aggregate supply curve slope. The more demand shocks are met by the most productive firms, the flatter the Phillips curve becomes.

5 Micro Results

The clustering analysis implemented in the previous section allows us to group firms according to their production technology level and detect differences in the residual demand they

[22]However, the statistics from the CIS data are based only on around 4% of the sample.

face. It delivers a population of firms classified only according to these two dimensions.

Based on such division, it is now possible to test whether firms' supply curves are heterogeneous across the production technology distribution, controlling for demand characteristics as well. To do that, we estimate firms' pricing equation 8 considering firm heterogeneity on these two dimensions. In particular, leveraging on the New Keynesian framework we described in Section 2, and considering we are employing annual data (for which firms can be considered allowed to optimize prices and, hence, weigh future streams negligibly), in our main analysis we estimate the following pricing equation:

$$\delta p_{it} = \beta_1 \delta y_{it} + \beta_{1c} \delta y_{it}{}^* D_c + \beta_2 \delta p_{st}^{-i} + \beta_{2c} \delta p_{st}^{-i*} D_c + \beta_3 \delta p_{it-1} + \delta_{st} + \delta_i + \epsilon_{it} \qquad (11)$$

where we implement 2SLS regressions to instrument firm real output increase δy_{it} by the downstream demand indicators we described in Section 3; δp_{it} and δp_{st}^{-i} are the log difference of firm and competitors' price at 4-digit industry level, respectively. We also add industry-year fixed effects δ_{st} to control for trends in industry input prices, and, this way, we want to mimic the component $\hat{c}_{ist}$ from the model pricing equation. Results are qualitatively similar when controlling at the 2-digit or 4-digit industry level. Moreover, we include firm fixed effects δ_i and lagged firm price log difference to control for the possibility that the firm pricing behaviour is outside the balanced growth path (which is implicitly assumed by the theoretical framework). In Appendix C, where results are shown to hold for several robustness checks, we also implement GMM estimations of equation 11, instrumenting competitors' prices as well with their lagged value to avoid the risk of endogeneity in the case of industry shocks affecting both firm and competitors' pricing decisions.

Finally, $\beta_{xc} D_c$ for $x \in \{1, 2\}$ represents all the interaction coefficients with different cluster membership specifications in comparison with the reference cluster (β_x). Together, they

represent $(1-\Omega_{is})v_i$ for each cluster from the theoretical model. Cluster membership interacts with demand shocks and, depending on the empirical model, with competitors' prices. The strategic competition effect Ω_{is} can be subtracted from the estimated coefficient of competitors' prices. Consequently, we can estimate our parameter of interest v_i for different groups of firms along the production technology distribution, net of the effect of strategic competition and controlling for residual demand characteristics. In all our regression specifications, observations are weighted by the revenue share to better mimic an aggregate supply curve slope.

We first analyze firms' pricing behaviour by comparing supply curves along the production technology distribution, without taking into account residual demand differences. Therefore, in this case, cluster interactions refer solely to the technology distribution.

Table 5 reports the results for the first stage of the demand instruments in the case of this first specification. Both types of downstream indicators are employed to increase the predictive power about firm sales increase. As it can be noticed, the DS_{st}^{Shea} instrument has a larger impact on firm-specific demand increase (a 1% increase in aggregate demand raises firm output by 3.3% for the reference group). Most interestingly, we see a reallocation effect since the higher the production technology, the more the cluster responds. DS_{it}^{wid}, instead, results less significant, although still detecting a significantly higher response of the most productive cluster to downstream demand shocks. Again, this implies a certain degree of reallocation within the industry from the least to the most productive firms. Similar results are found for the first stages of the other regression specifications (see Appendix C).

Table 6 shows the estimation results for the firm pricing equation by production technology cluster, where the first cluster is taken as reference. This first specification strongly points out a flattening supply curve along the production technology distribution. In fact,

Table 5: First stage of firm pricing equation by technology cluster

	δy_{it}
DS_{st}^{Shea}	3.308***
	(0.835)
$DS_{st}^{Shea} \times \text{tech}_2$	1.085*
	(0.560)
$DS_{st}^{Shea} \times \text{tech}_3$	1.576***
	(0.550)
$DS_{st}^{Shea} \times \text{tech}_4$	2.392***
	(0.550)
$DS_{st}^{Shea} \times \text{tech}_5$	2.297***
	(0.557)
DS_{it}^{wid}	-0.018
	(0.017)
$DS_{it}^{wid} \times \text{tech}_2$	-0.003
	(0.017)
$DS_{it}^{wid} \times \text{tech}_3$	0.014
	(0.017)
$DS_{it}^{wid} \times \text{tech}_4$	0.016
	(0.017)
$DS_{it}^{wid} \times \text{tech}_5$	0.031*
	(0.017)
Other regressors included	Yes
Sector-Year fixed effects	Yes
Firm fixed effects	Yes
Obs	146574
R^2	0.25

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15.

the least productive firms turn out to feature a steep curve, where a 1% increase in demand impacts prices by around 0.43%, while this slope decreases as the production technology increases until the most productive firms are characterized by a significantly flatter supply curve. This result is robust to including interaction with the competitors' price change and 4-digit industry-year fixed effects. The columns *Slope* report the significance from a t-test

of the difference between cluster c and cluster $c-1$ coefficients, where $c = \{1, 2, 3, 4, 5\}$, and confirm the significant flattening of the supply curves as production technology rises. Finally, the impact of strategic competition (the coefficient of competitors' price δp_{st}^{-i}) is found to be on average around 18%. This differs from, for example, Gagliardone et al. 2023, who find a flattening of the supply curves of around 50% due to competition interaction.

Table 6: Firm pricing equation by technology cluster

	(1)		(2)	
	δp_{it}	Slope	δp_{it}	Slope
δy_{it}	0.430***		0.435***	
	(0.084)		(0.085)	
$\delta y_{it} \times \text{tech}_2$	-0.075***	***	-0.090***	***
	(0.026)		(0.026)	
$\delta y_{it} \times \text{tech}_3$	-0.156***	***	-0.168***	***
	(0.025)		(0.026)	
$\delta y_{it} \times \text{tech}_4$	-0.196***	***	-0.206***	***
	(0.025)		(0.025)	
$\delta y_{it} \times \text{tech}_5$	-0.282***	***	-0.293***	***
	(0.026)		(0.026)	
δp_{st}^{-i}	0.180***			
	(0.007)			
δp_{it-1}	-0.181***		-0.174***	
	(0.007)		(0.006)	
δp_{st}^{-i}-Technology group fixed effects	No		Yes	
2 digit Industry-Year fixed effects	Yes		Yes	
Firm fixed effects	Yes		Yes	
Obs	146574		146574	
R^2	0.21		0.22	

Note: 2sls regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1, $^+$ < 0.15. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution.

This first result, hence, supports the theoretical framework in which the most productive

firms have flatter supply curves. However, as we discussed above, the firm-specific residual demand could differ for firms located at different levels of production technology. This is the case as shown in Section 4. We, hence, leverage multi-dimensional clustering, and the main pricing equation specification includes interaction with all the production-demand groups delivered by the clustering algorithm. This way, the heterogeneity in supply curves can be assessed while keeping demand characteristics fixed.

Table 7: Firm pricing equation by technology - demand cluster

	δp_{it}			Slope		
	demand_1	demand_2	demand_3			
$\delta y_{it} \times \text{tech}_1$	0.481**	-0.131	-0.171*			
	(0.217)	(0.105)	(0.101)			
$\delta y_{it} \times \text{tech}_2$	-0.201**	-0.143	-0.214**	***		***
	(0.099)	(0.097)	(0.097)			
$\delta y_{it} \times \text{tech}_3$	-0.222**	-0.221**	-0.295***		***	***
	(0.097)	(0.097)	(0.096)			
$\delta y_{it} \times \text{tech}_4$	-0.215**	-0.247**	-0.363***			***
	(0.096)	(0.097)	(0.096)			
$\delta y_{it} \times \text{tech}_5$	-0.323***	-0.307***	-0.402***	***	***	***
	(0.112)	(0.097)	(0.096)			
δp_{st}^{-i}	0.149***					
	(0.007)					
δp_{it-1}	-0.109***					
	(0.006)					
2 digit Industry-Year fixed effects	Yes					
Firm fixed effects	Yes					
Obs	146574					
R^2	0.21					

Note: 2sls regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15. Reference group is $prod_1 \times demand_1$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution for each demand cluster.

The results from the main specification are presented in Table 7. Now, three columns

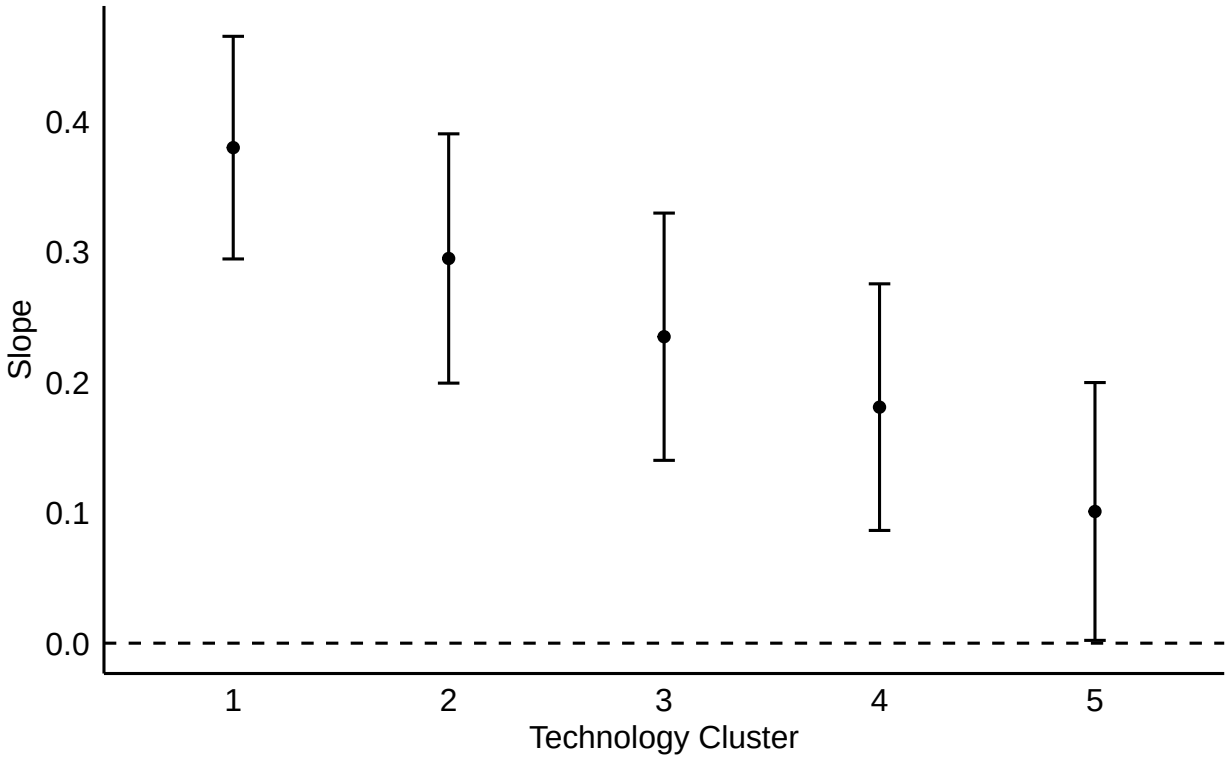
are reported for each demand cluster, and interaction coefficients are in comparison with the technology 1 - demand 1 group. The results still provide strong evidence of firms' supply curve flattening along the production technology distribution for each demand cluster. In particular, for demand group 3, where demand is more rigid, the slope of the supply curves is significantly decreasing between each consecutive production cluster, as stated by the *Slope* column. However, all demand clusters feature a significant flattening pattern along the technology distribution. The most productive firms (i.e., technology clusters 4 and 5), which are present mostly in demand clusters 2 and 3, have the flattest supply curves.

The results presented in Table 7 can now be considered cleaned from possible variability in terms of the residual demand firms face and be caused by the sole heterogeneity in production technology. Again, the results are robust to different industry fixed effects specifications and to the inclusion of interactions between competitors' prices and cluster membership. Strategic competition turns out to have a similar effect as in the previous specification, with an average flattening impact of around 15%.

Figure 2 summarizes the dynamics of the supply curves along the production technology distribution for the three demand clusters. The average pricing equation coefficient for each technology group across demand clusters, weighted by the total revenue share of the cluster, and its 95% confidence interval are presented in the graph, which shows a clear flattening of the firm price response as its productivity increases. Figure 2 is the firm-level counterpart of our aggregate empirical evidence in Figure 8b, which supports our micro findings for a broader set of countries and sectors (including services).

We further check the flattening of the supply curves along the production technology distribution with the following specification: we aggregate the production technology clusters to separate the least productive firms (groups 1, 2, and 3) from the most productive

Figure 2: Slope of pricing equations by technology group



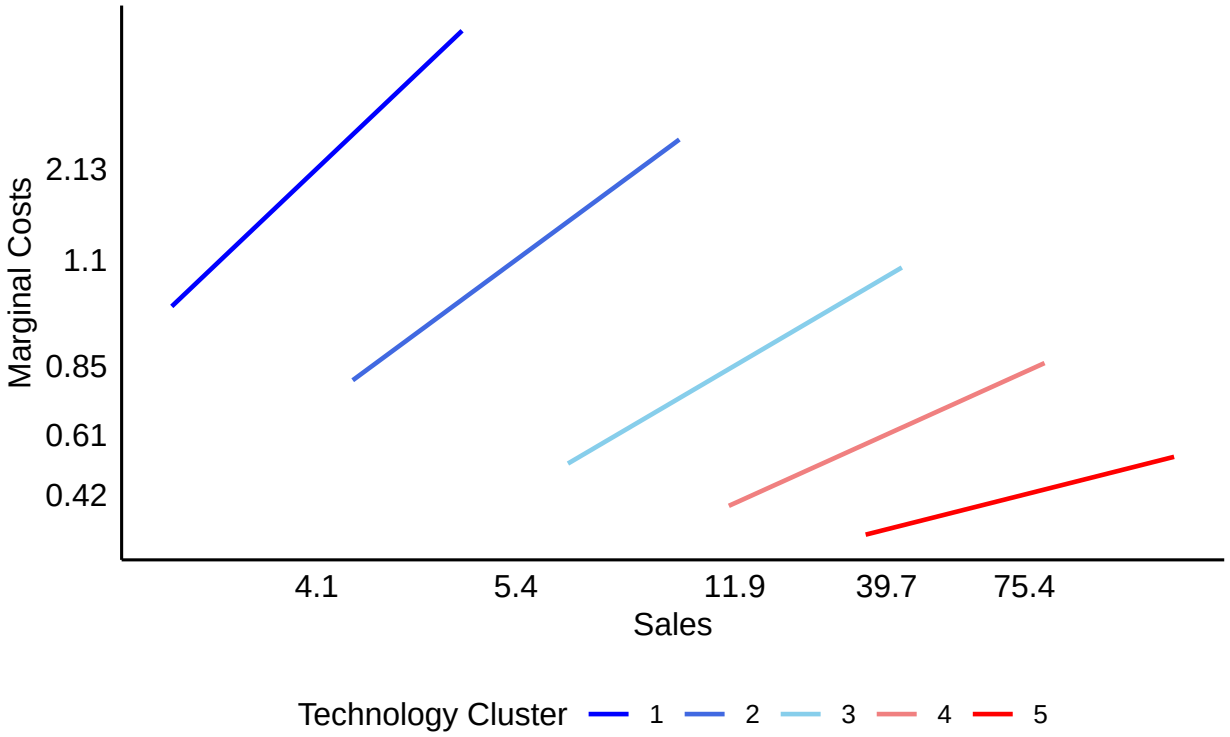
Note: Average coefficients by production technology group from regression in Table 7. 95% confidence intervals constructed based on variance-covariance matrix of coefficients.

firms (groups 4 and 5). We then regress our pricing equation clustering according to these aggregated clusters, always controlling for demand characteristics. Results are presented in Appendix Table C3. In this last specification, we detect a flattening of the supply curves in demand clusters 2 and 3. Appendix C also reports the same empirical models estimated through GMM, instrumenting competitors' prices as well with their lagged values, and the results still hold.

To summarize our findings, heterogeneity in production technology significantly impacts firms' pricing behaviour. Even after controlling for strategic competition and residual demand characteristics, the distribution of production technology predicts a flattening of the supply curves. As seen in Figure 2, from a price response of around 0.4% for the least pro-

ductive firms, the Phillips curve flattens along the production technology distribution until it reaches a price response of around 0.1%.

Figure 3: Heterogeneous production technology



Note: Calibrated firms' supply curve for each production technology cluster. Marginal costs and sales are data from table 3.

Furthermore, from the estimations of our main specification in Table 7, we can derive an average parameter v_i for each cluster of production technology. To this aim, we take the average slope coefficient of the pricing equation for each production technology cluster across demand groups, net of the strategic competition effect detected from the coefficients of competitors' prices. This way, the computed heterogeneous slopes of the supply curves result in 0.45, 0.35, 0.24, 0.18, 0.10 from the least to the most productive firms, with the γ_i parameter being 0.70, 0.74, 0.78, 0.83, 0.90, respectively. Hence, the heterogeneous supply curves along the production technology distribution can be represented in Figure 3. In the

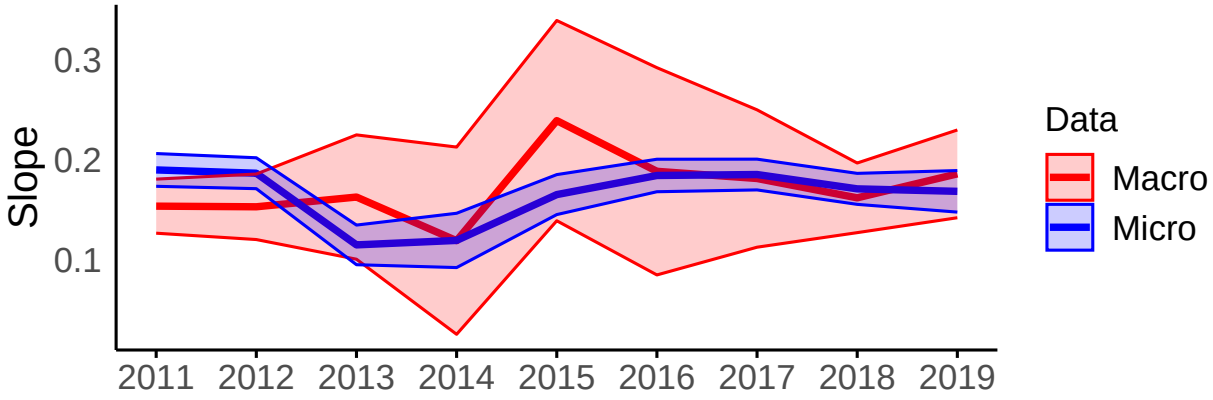
graph, the supply curves are calibrated around each cluster mean marginal costs and sales, whose data are taken from Table 3. As can be seen, the higher the production technology, the lower the marginal costs and the flatter the supply curve. This is expected from the model, where marginal costs are a function of productivity A_i and the output elasticity γ_i.

Given that the most productive firms are also larger and with higher markups, our results can also explain why a lower price response characterizes high markup firms and more concentrated markets (see, e.g., Fujiwara and Matsuyama 2022).

Finally, we show the power of firm-level data in replicating the Phillips curve's macro estimates. In Section 2, we explained that the macro Phillips curve is the weighted average of each firm supply curve, and it is, therefore, a weighted curve along firms' heterogeneity in production technology. Hence, an aggregate Phillips curve can be computed from micro evidence and compared with typical macro estimates.

We estimate a macro Phillips curve employing EU Klems data for the French manufacturing industry: the slope of the Phillips curve is computed through rolling regressions of sectoral price change on the output gap, controlling for lagged country inflation. Each regression spans five years, and the slope of the macro Phillips curve is estimated from 2011 to 2019 (the last available year from EU Klems). Then, an estimate of the macro Phillips curve is derived from our micro results. Again, the average coefficients for each production technology cluster are taken from Table 7 and weighed by the cluster share of output change in each year. The comparison between the macro and the micro-based Phillips curve can be seen in Figure 4. When aggregated at the manufacturing level, micro-based estimates can predict the macro Phillips curve slope quite well and are included in its confidence interval for most of the estimation period.

Figure 4: Slope of aggregate Philips curve, micro vs macro



Note: Macro Phillips slope derived from rolling regressions of inflation on output gap, based on EU Klems French manufacturing data, controlling for lagged country inflation. Micro-based Phillips curve slope is computed as the weighted average of the estimated slopes of firms' pricing equations from Table 7, with yearly change in cluster sales as weight.

The comparison suggests that now-casting the slope of the aggregate Phillips curve using microdata is an insightful exercise, even when micro data only become available with a lag (e.g., see E. J. Bartelsman and Wolf 2014).

6 Demand and Supply by Cluster

The focus of this paper is on the pricing behaviour of firms along the technology distribution. However, our clustering analysis allows us to include the demand side into the estimation of inflationary pressures. Thanks to the estimation of pricing equations and cost pass-through, we can compute estimates of the slope of marginal costs (γ_i), demand elasticity and cur-

vature (η_d and ρ_d), and markup estimates. We then center the demand and supply at the average (Y,P) for each cluster.

Table 8: Parameters and levels of demand and supply by cluster

cluster	γ	v	β_d	η_d	ρ_d	*size*	*mc*	*markup*
tech_1-demand_1	0.64	0.56	0.19	3.05	-4.70	7.83	3.61	0.79
tech_1-demand_2	0.71	0.41	0.74	10.05	0.60	8.14	1.78	0.96
tech_1-demand_3	0.74	0.36	0.95	23.35	0.91	8.54	1.71	0.97
tech_2-demand_1	0.75	0.33	0.16	10.04	-4.46	7.84	1.02	0.97
tech_2-demand_2	0.72	0.39	0.69	5.12	0.59	8.67	1.10	1.03
tech_2-demand_3	0.76	0.31	0.96	4.18	1.02	8.93	1.15	1.06
tech_3-demand_1	0.77	0.30	0.17	9.80	-3.74	9.03	0.85	1.06
tech_3-demand_2	0.77	0.30	0.68	7.75	0.66	9.52	0.84	1.09
tech_3-demand_3	0.82	0.22	0.96	4.83	1.08	9.51	0.85	1.13
tech_4-demand_1	0.76	0.31	0.28	2.52	-1.03	10.92	0.66	1.16
tech_4-demand_2	0.79	0.27	0.73	6.02	0.88	10.88	0.63	1.23
tech_4-demand_3	0.88	0.14	0.97	4.28	1.16	10.37	0.59	1.23
tech_5-demand_1	0.85	0.18	0.25	1.11	-1.55	10.34	0.36	1.12
tech_5-demand_2	0.83	0.20	0.79	10.25	1.00	11.57	0.44	1.27
tech_5-demand_3	0.92	0.09	0.97	2.36	1.28	11.20	0.42	1.43

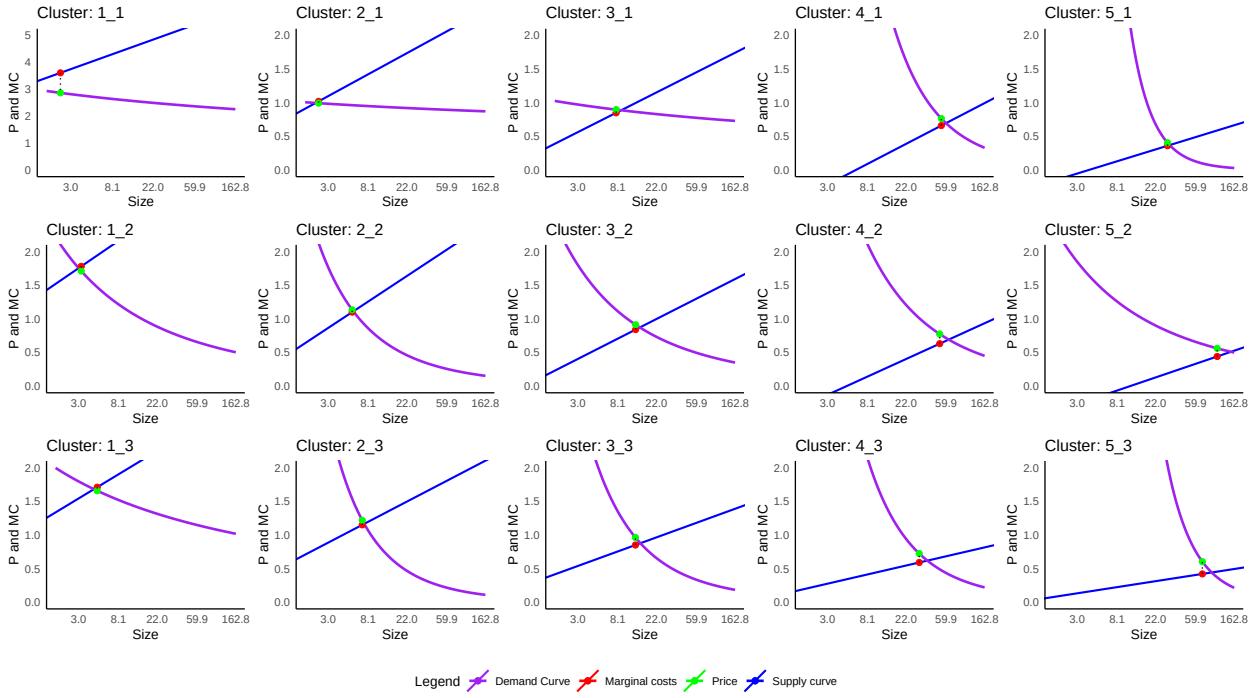
Note: parameters estimated through the clustering algorithm and the pricing equations: output elasticity γ, the slope of the supply curve v, cost pass-through coefficient β_d, demand elasticity η_d and curvature ρ_d, and markup computed as in Loecker and Warzynski 2012. Log of revenues (thousand euros) *size* and marginal costs *mc* from data.

The estimated demand and supply parameters are reported in Table 8, together with data on the size and marginal costs. Thanks to this information, we can represent in Figure 5 the local demand and supply curves for the firm in each clusters[23].

Detailed data on the firms in each cluster are reported in Appendix D. Generally, most

[23]For each cluster, the supply curves are computed as for Figure 3, while demand curves are constructed to have the slope depending on η_d at the (Q,P) point, and curvature depending on ρ_d. Parameters η_d and ρ_d are estimated as in Mrázová and Neary 2017 thanks to the cost pass-through coefficients and markups, taking into account non-constant returns to scale in production. Markups are computed as in Loecker and Warzynski 2012 and multiplied by marginal costs data to get the level of prices.

Figure 5: Distribution of demand and supply among clusters



Note: visualization of demand and supply, based on parameters and data from Table 8. In this figure, *Size* is in million euros.

productive firms are larger, pay higher salaries, enjoy higher profit margins, invest more in intangible assets and new marketing strategies, and export more.

This paper argues that the slope of the aggregate economic slack-inflation relationship depends on heterogeneous technology. However, actual price pass-through from cost shocks, or prices increases owing to shifts in demand, will depend on both supply and demand curves facing firms. When a firm is hit with an exogenous shock to demand for its products, its profit-maximizing response to output or price (i.e., cost markup) depends on the demand and supply characteristics. Given the demand curve, a firm with a flat marginal cost curve will respond more in output than price to a demand shock. Given a supply curve, a firm with more curvature in demand will see a higher increase (or lower decrease) in markup following a positive demand shock. Similarly, the optimal pass-through of an exogenous shock to costs, say a rise in the price of imported energy, depends on these characteristics, with

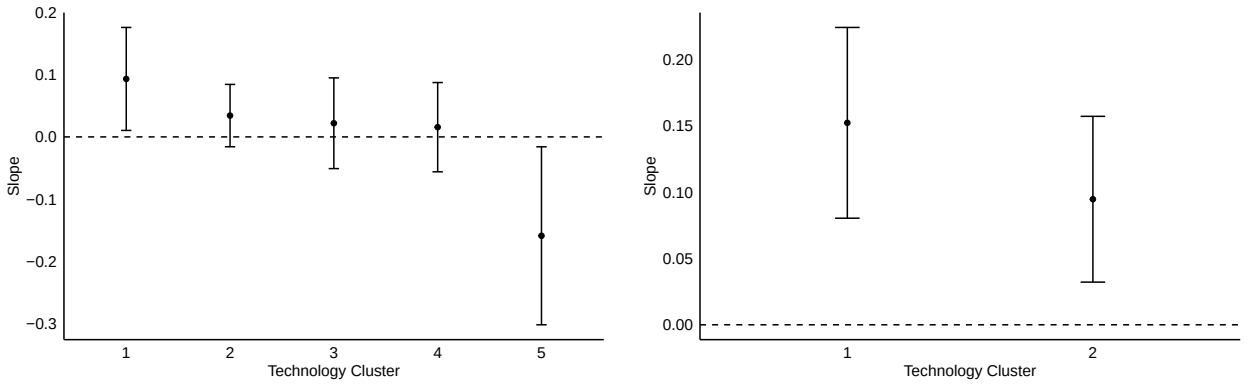
higher curvature leading to higher markups and, thus, cost pass-through.

We estimate parameters for supply and demand curves for all clusters, but can summarize the heterogeneity in slope of the aggregate Phillip Curve by technology. If demand rises and is disproportionately supplied by the highest productivity (lowest cost) firms, industry-level prices may rise less than if the demand is met by low-productivity firms, ceteris paribus. Similarly, cost shocks will have less aggregate impact if they hit firms with low cost pass-through.

7 Cross-Country Comparison

To widen the perspective of this study, some cross-country results from the MDI data are reported in this subsection. In particular, firms' pricing equation 8 is estimated in the case of the Netherlands and Slovenia for the same period as for France.

Figure 6: Slope of pricing equations by technology cluster - Netherlands and Slovenia

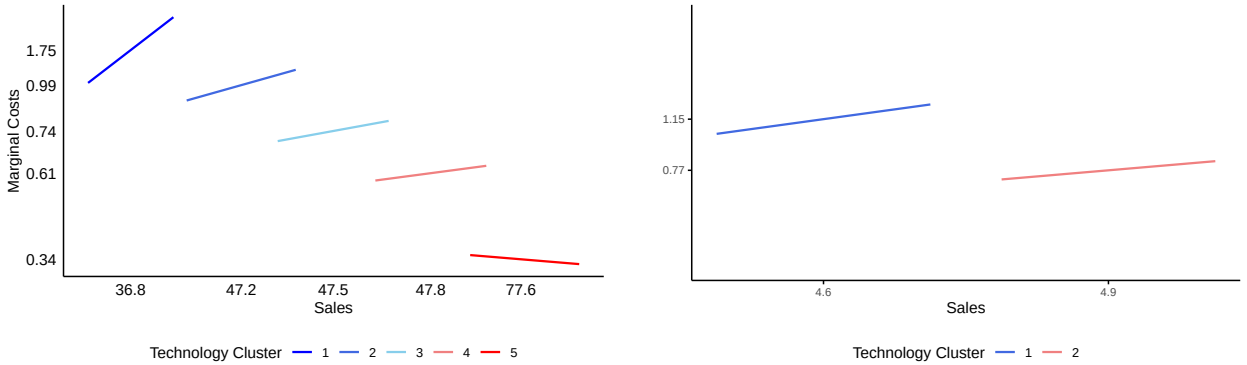


(a) Netherlands (b) Slovenia

Note: Average coefficients by production technology cluster from pricing equation in the Netherlands and Slovenia. 95% confidence intervals constructed based on variance-covariance matrix of coefficients.

As for the case of France, Dutch and Slovenian firms are clustered according to produc-

Figure 7: Heterogeneous production technology - Netherlands and Slovenia



(a) Netherlands (b) Slovenia

Note: Calibrated firms' supply curve for each production technology cluster. Marginal costs and sales are taken from data.

tion technology and demand characteristics[24], as explained in Section 4. Then, the firm pricing equation 8 is estimated for each technology-demand group, as in our main empirical analysis. The summary of the results is presented in Figure 6. As can be noticed, the flattening of the Phillips curves also characterizes Dutch and Slovenian firms, and they present a generally flatter curve than in France. We report the distribution of supply curves in Figure 7, computed as in the case of France.

The empirical findings in the Netherlands and Slovenia, therefore, confirm the main analysis and hints, together with the multi-country results in Section 8, that the production technology effect on firms' pricing behaviour has a general scope across countries and sectors.

8 External Validity beyond Manufacturing

The above analysis has been conducted for France, the Netherlands, and Slovenia. The MDI will allow replication in more countries over time. Unfortunately, the analysis is limited to

[24]For Slovenia, we analyze only two demand and two supply clusters, owing to the small number of firms in the sample.

the manufacturing sector, owing to availability of price data (from Prodcom), but also availability of the Comtrade data on international trade by detailed product class. In this section we extend the analysis to a wide set of countries and non-farm business sectors, using data from the CompNet database.[25] While richer in country and industry coverage, the CompNet data precludes identification of the underlying micro-level demand and supply curves using exogenous shocks. Building on the previous section's theoretical framework, we replicate the effect of production technology heterogeneity on the slope of the Phillips curve, in a more reduced form manner.

The CompNet datasets draw from various administrative, statistical, and public firm-level sources across numerous European countries and are constructed to be highly comparable across countries. CompNet data comprises micro-aggregated moments at different levels of (dis)aggreagtion, e.g., 2-digit industry or industry-by-size class. The 9^{th} vintage includes 21 European countries for the period 2004-2020 and covers most of the private non-farm business sector, including activities trade and services. A very useful feature of the CompNet database is the so-called *joint distribution* table. The joint distributions aggregate firm-level indicators along quantiles of a specific variable, creating "representative firms" for each quantile of the distribution of the specific variable by country, sector, and year. We analyse output, inputs, and wages for "representative firms" defined by their quintile location in the within-industry productivity (TFP) distribution, by 2-digit industry, country and year. Prior to aggregation, TFP at the firm level is estimated through OLS regressions with time fixed effects assuming the Cobb-Douglas production function.

As we showed in Section 2, productivity and costs are inversely related: if demand in an industry rises, and this demand is disproportionately supplied by the highest productivity/lowest cost firms, industry prices may well rise less than if low productivity firms, ceteris

[25]For more details, please see Haug et al. 2022.

paribus, meet the demand.

Given that there is no information about firm prices in the CompNet data, we first test our theoretical model on the input prices side. In particular, we estimate wage equations as follows:

$$\delta w_{csqt} = \alpha x_{csqt} + \beta \delta w_{csqt-1} + \gamma \pi_{ct-1} + \delta_{csq} + \delta_t + \varepsilon_{csqt} \tag{12}$$

where δw_{csqt} and x_{csqt}, are real wage growth rate and output gap in log-points, in country c, industry s, productivity quintile q, and year t. We control for lagged country-level inflation, π_{ct-1} from Eurostat[26]. Country-industry-quintile and year fixed effects are given, respectively by δ_{csq} and δ_t. The panel regression is shaped to correspond to the formula of marginal costs in equation 2 of the theoretical model, controlling for trends in industry input prices. Potential output and output gap are measured for the representative firms at each productivity level [27]. With this specification, which is standard in the New Keynesian macro literature, we aim to mimic at the aggregate level the dependence of marginal costs on the output gap and the general trends in input costs, as expressed in equation 2 of Section 2.

At the aggregate level, the resulting wage Phillips curve is reported in Table 9, both for manufacturing and the whole economy. On average, for a 1 percentage point increase in output gap, wages increase by 0.13% in the whole economy, and results are similar for the manufacturing as well. These findings are not directly comparable to macro estimates, given that the focus is on real wages and not on inflation. However, they are in line with estimates of the Phillips curve at the macro level. Recently, Ball and Mazumder 2021 report estimations of basic Phillips curve for the euro area around 0.22. Moreover, the slope of the Phillips curve in the ECB-BASE semi-structural model is estimated to be 0.12 (see Eser

[26] Available at https://ec.europa.eu/eurostat/databrowser/view/tec00118/default/table.

[27] We measure potential output as the estimated maximum production in each country, 2-digit industry, productivity quintile, and year, by a standard stochastic frontier model. The output gap is, then, measured as the log difference between actual real sales and potential output.

Table 9: Real wage growth on output gap

	Manufacturing		All Economy	
	(1)	(2)	(3)	(4)
	δw_{csqt}	δw_{csqt}	δw_{csqt}	δw_{csqt}
x_{csqt}	0.103***	0.096***	0.136***	0.123***
	(0.011)	(0.012)	(0.004)	(0.004)
δw_{csqt-1}	-0.305***	-0.296***	-0.311***	-0.313***
	(0.014)	(0.015)	(0.005)	(0.006)
π_{ct-1}		0.120***		0.119***
		(0.052)		(0.025)
Constant	0.057***	0.049***	0.0548***	0.0481***
	(0.005)	(0.006)	(0.010)	(0.011)
Country-Industry-Quintile FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	16,607	14,577	35,600	27,611
R-squared	0.169	0.161	0.167	0.163

Source: CompNet 9^{th} vintage and Eurostat.
Notes: panel regressions at the country-industry-productivity quintile level of real wage growth on output gap, lagged real wage growth, lagged country-level inflation (models 2 and 4), and year fixed effects. Standard errors clustered at industry-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

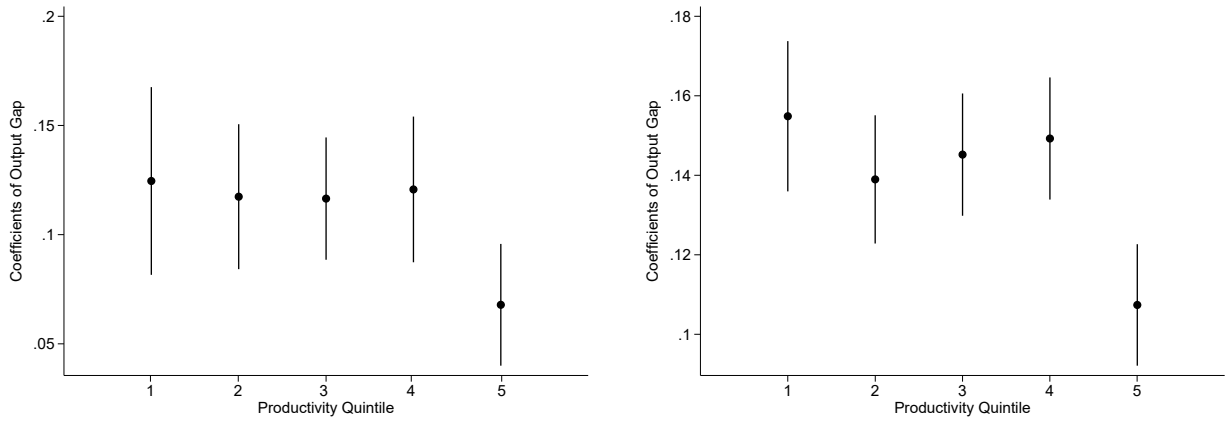
et al. 2020).

However, the most intriguing finding emerges when performing estimations of firms' pricing behavior along the productivity distribution. We estimate our wage-to-output relation 12 for each quintile of firms along the TFP distribution, controlling also for labor market power as well[28]. As shown in Figure 8, the most productive firms are characterized by a less responsive wage increase when their available production capacity changes, in both manufacturing and the whole economy.

In a related reduced-form equation, we regress real sales growth by industry-quintile on industry aggregate real sales growth, interacted with productivity quintile dummies. As

[28]Labour market power is defined as the ratio between firms' markup over labor and markup over intermediate input (markdown). For reference, see Dobbelaere and Mairesse 2013 and Mertens 2019.

Figure 8: Slope of the firms' wage equation along the TFP distribution



(a) Manufacturing (b) All industries

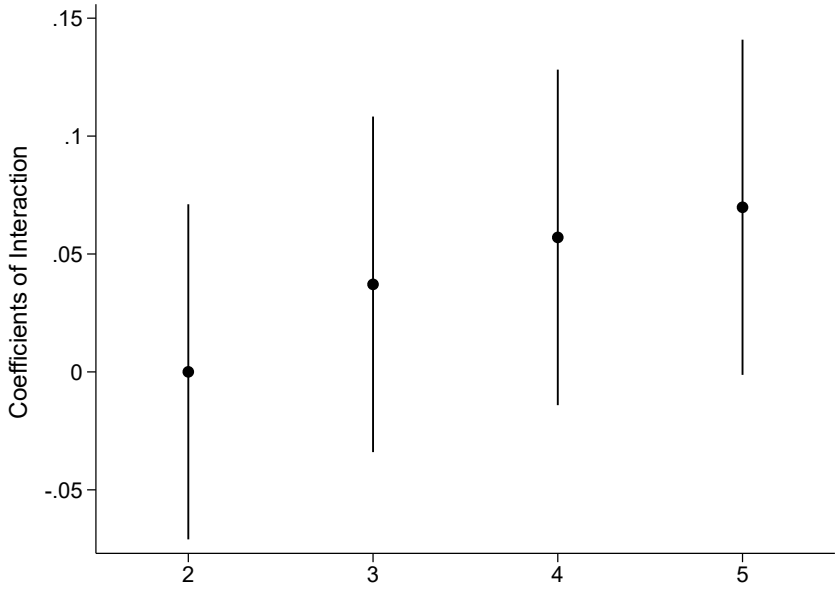
Source: CompNet 9^{th} vintage and Eurostat.
Note: Coefficients of the output gap, derived from panel regressions at the country-industry-productivity quintile level of real wage growth on the output gap, lagged real wage growth, lagged country-level inflation, labour market power, and year fixed effects for the period 2004-2020. Regressions are taken separately for each productivity quintile group of firms. All available industries and countries are pooled. 90% confidence intervals are included.

Figure 9 reports, sales growth responds more to increases in aggregate sales for higher productivity quintiles. This reduced-form empirical evidence, which is coherent with our first stage IV regressions with microdata, suggests that the marginal firm responding to demand shocks or, more generally, to an increase in aggregate demand is the most productive firm with the lowest marginal costs. Hence, heterogeneous productivity, combined with lower price response and higher demand response from more productive firms, implies a flatter aggregate supply curve.

The above evidence gives some support that our main findings for the manufacturing sector in a limited set of countries could also hold for a larger set of countries in a wide selection of sectors. Unfortunately, this evidence remains from reduced-form regressions of quintile wage changes on output gaps, or from quintile market share changes on industry output change, and the interpretation relies on consistency with comparative statics from a postulated model.

Figure 9: Increase in production along the TFP distribution

Year-on-year changes, TFP quintile 1 as reference



Source: CompNet 9^{th} vintage.
Note: Coefficients of interaction between aggregate real sales growth and productivity quintile dummies, derived from panel regressions at the country-industry-productivity quintile level of real sales growth on country-industry production growth dummy (1 if growth rate is positive, 0 otherwise), interaction of the dummy with productivity quintiles, and year fixed effects, for the period 2004-2020. All available industries and countries are pooled. 90% confidence intervals are included.

9 Conclusion

We cluster firms with an innovative algorithm that detects similarities among firms in terms of production technology and demand characteristics. Then, we estimate firms' pricing equations in the context of a New Keynesian model and document that the most productive firms have flatter supply curves, even after controlling for differences in firm residual demand and net of strategic competition. The more productive firms are larger and respond more in output and less in price to demand shocks. Production technology matters for firm pricing decisions, and the slope of the aggregate Phillips curve depends on the weighted average of the slopes of the different firm supply curves.

The main empirical findings are based on French firm-level data on manufacturing. Also,

they are supported by a similar analysis of the Dutch and Slovenian industries, covering the same set of economic activities, and by cross-country analysis of micro-based data regarding several European countries for the entire business economy (including services).

Moreover, thanks to our clustering analysis, we estimate demand elasticity and curvature for for heterogeneous groups of firms. Therefore, we are able to analyze the distribution of demand and supply curves among firms. These clusters differ in terms of supply and demand parameters, as well as several characteristics. In particular, more productive firms are found to be larger, with higher markups, exhibiting lower marginal costs, and facing more rigid residual demands on average.

The pricing equation is far more informative than the Phillips curve because it allows to disentangle supply shocks, idiosyncratic demand shocks, and aggregate demand shocks. Therefore, if we want to understand risks to inflation, other than through inflation expectations, we need to analyze the nature of the shock, determine the price response of the 15 clusters, and aggregate (also considering change in market share owing to differential market selection). The analysis of demand and cost shocks impact on aggregate pricing requires the joint analysis of production technology and demand conditions.

Therefore, our clustering method can be an important toolkit to build appropriate time-series of heterogeneous agents for macro research and forecasting. In fact, traditional macroeconomic frameworks, such as the Phillips curve, can be derived using micro theory but are generally estimated using macroeconomic time series. In this paper, we show considerable heterogeneity in the parameters at the micro level which could result in unstable macro estimates. Our clustering method provides a flexible way to capture the heterogeneity while aggregating the micro data into a limited number of sub-aggregates. Having estimates of how such heterogeneous clusters respond to shocks, together with information on the nature

of shocks faced by each cluster, can lead to better and more timely macro forecasts.

Moreover, an interesting future extension of this framework is the creation of cross-country panel data for each cluster and including them in macro analysis. Furthermore, it is intriguing to understand the selection process of firms into clusters and if it changes over time.

It is important to note that we employ relatively aggregate demand measures to instrument firm demand shocks. They work sufficiently well, but finding a closer measure of a firm-specific demand shock would be very effective and better track demand-driven increases in firm sales. Also, future research can incorporate the analysis with the estimation of demand systems.

Finally, our indentified findings mostly relate to the manufacturing sector, although CompNet data help make more general statements about firms' pricing behaviour outside manufacturing and in many other countries. It is, hence, a natural further step in this field to include a larger part of the economy, in particular, services. Currently, data are mostly available for firm input prices. Although this can already shed light on the heterogeneity in marginal cost curves, output price statistics outside of manufacturing would be very valuable.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer (2015). "Identification properties of recent production function estimators". In: *Econometrica* 83.6, pp. 2411–2451.

Ando, Tomohiro and Jushan Bai (2016). "Panel data models with grouped factor structure under unknown group membership". In: *Journal of Applied Econometrics* 31.1, pp. 163–191.

Andrés, Javier and Pablo Burriel (2018). "Inflation and optimal monetary policy in a model with firm heterogeneity and Bertrand competition". In: *European Economic Review* 103, pp. 18–38.

Baba, Chikako, Mr Romain A Duval, Romain Duval, Ting Lan, and Petia Topalova (2023). *The 2020-2022 Inflation Surge Across Europe: A Phillips-Curve-Based Dissection*. International Monetary Fund.

Ball, Laurence and Sandeep Mazumder (2021). "A Phillips curve for the euro area". In: *International Finance* 24.1, pp. 2–17.

Bartelsman, Eric and MDI-Team (2024). *MDI Users' Guide*. Tech. rep. CompNet-MDI, www.comp-net.org.

Bartelsman, Eric J and Zoltan Wolf (2014). "Forecasting aggregate productivity using information from firm-level data". In: *Review of Economics and Statistics* 96.4, pp. 745–755.

Boehm, Christoph E and Nitya Pandalai-Nayar (2022). "Convex supply curves". In: *American Economic Review* 112.12, pp. 3941–3969.

Calvo, Guillermo A (1983). "Staggered prices in a utility-maximizing framework". In: *Journal of monetary Economics* 12.3, pp. 383–398.

Cheng, Xu, Frank Schorfheide, and Peng Shao (2023). *Clustering for Multi-Dimensional Heterogeneity with an Application to Production Function Estimation*. Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.

De Loecker, Jan, Pinelopi K Goldberg, Amit K Khandelwal, and Nina Pavcnik (2016). "Prices, markups, and trade reform". In: *Econometrica* 84.2, pp. 445–510.

Dhyne, Emmanuel, Ayumu Ken Kikkawa, Toshiaki Komatsu, Magne Mogstad, and Felix Tintelnot (2022). *Foreign demand shocks to production networks: Firm responses and worker impacts*. Tech. rep. National Bureau of Economic Research.

Dobbelaere, Sabien and Jacques Mairesse (2013). "Panel data estimates of the production function and product and labor market imperfections". In: *Journal of Applied Econometrics* 28.1, pp. 1–46.

Eser, Fabian, Peter Karadi, Philip R Lane, Laura Moretti, and Chiara Osbat (2020). "The Phillips curve at the ECB". In: *The Manchester School* 88, pp. 50–85.

Fujiwara, Ippei and Kiminori Matsuyama (2022). *Competition and the Phillips curve*. Centre for Economic Policy Research.

Gagliardone, Luca, Mark Gertler, Simone Lenzu, and Joris Tielens (2023). *Anatomy of the Phillips Curve: Micro Evidence and Macro Implications*. Tech. rep. National Bureau of Economic Research.

Gali, Jordi (1999). "Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations?" In: *American economic review* 89.1, pp. 249–271.

Gopinath, Gita, Emine Boz, Camila Casas, Federico J Díez, Pierre-Olivier Gourinchas, and Mikkel Plagborg-Møller (2020). "Dominant currency paradigm". In: *American Economic Review* 110.3, pp. 677–719.

Gopinath, Gita and Oleg Itskhoki (2010). "Frequency of price adjustment and pass-through". In: *The Quarterly Journal of Economics* 125.2, pp. 675–727.

Haug, Peter, Jonathan Deist, Tommaso Bighelli, Mirja Hälbig, Verena Plümpe, and Alessandro Zona (2022). "User Guide for the 9th Vintage of the CompNet Dataset". In.

Hooper, Peter, Frederic S Mishkin, and Amir Sufi (2020). "Prospects for inflation in a high pressure economy: Is the Phillips curve dead or is it just hibernating?" In: *Research in Economics* 74.1, pp. 26–62.

Loecker, Jan De and Frederic Warzynski (2012). "Markups and firm-level export status". In: *American economic review* 102.6, pp. 2437–2471.

Mehrabani, Ali (Aug. 2023). "Estimation and identification of latent group structures in panel data". In: *Journal of Econometrics* 235.2, pp. 1464–1482. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2022.12.002. URL: https://www.sciencedirect.com/science/article/pii/S030440762200207X (visited on 12/03/2024).

Mertens, Matthias (2019). *Micro-mechanisms behind declining labour shares: Market power, production processes, and global competition*. Tech. rep. IWH-CompNet Discussion Papers.

Mrázová, Monika and J Peter Neary (2017). "Not so demanding: Demand structure and firm behavior". In: *American Economic Review* 107.12, pp. 3835–3874.

Nakamura, Emi and Jón Steinsson (2018). "Identification in macroeconomics". In: *Journal of Economic Perspectives* 32.3, pp. 59–86.

Shea, John (1993a). "Do supply curves slope up?" In: *The Quarterly Journal of Economics* 108.1, pp. 1–32.

— (1993b). "The input-output approach to instrument selection". In: *Journal of Business & Economic Statistics* 11.2, pp. 145–155.

Su, Liangjun, Zhentao Shi, and Peter CB Phillips (2016). "Identifying latent structures in panel data". In: *Econometrica* 84.6, pp. 2215–2264.

Appendix

Appendix A. Further Details about the MDI Database

The MDI database provides the following data[29]:

- *Statistical Business Register.* BR is central in producing business statistics and is the starting point for establishing statistical survey frames. The BR contains information on identifying characteristics such as ID numbers, names and addresses, demographic characteristics, economic activity, legal form, and institutional sector code, as well as information on control and ownership relations for enterprises, their local and legal units, and enterprise groups. In MDI, the BR serves as a "backbone" or connection between various surveys and administrative datasets.

- *Balance Sheet and Income Statement.* BS is generally sourced from the tax authority, leveraging compulsory tax declarations firms submit before paying their taxes. They normally cover the universe of companies, unless some small firms rely on personal taxes instead of corporate taxation, which is possible in most European countries. Data harmonization is provided by a standard reclassification of the most common items of the Balance Sheet/Income Statement developed by the CompNet team in its almost 10 years of work, in strong collaboration with the National Statistical Offices.

- *Structural Business Statistics.* SBS describes the economic activities within the business economy, including industry, construction, distributive trade, and services. SBS indicators at the detailed sector level are transmitted to Eurostat and published by all European Statistical System (ESS) members (EU Member States, Norway and Switzerland, some candidate and potential candidate countries). Harmonization of the SBS has taken place regarding the detail and coverage of the sectors (now NACE 2.1) and

[29]Information reported in this appendix is taken from the MDI manual, currently under drafting.

the statistical definition of the transmitted indicators (Commission Regulation (EC) No 250/2009). Generally, the SBS indicators in each country are collected at the level of individual enterprises engaged in economic activity.

- *Firm Production Statistics.* Prodcom provides statistics on the production of manufactured goods by enterprises in EU countries. These statistics are part of European business statistics and are collected by the national statistical institutes under the European business statistics regulation. Prodcom data cover the economic activities of mining and quarrying, manufacturing, and materials recovery. It delivers information about firm sales and sold quantity by product (at the 8-digit level).

- *Community Innovation Survey.* CIS is part of the EU science and technology statistics and provides mostly qualitative information on firms' innovative activity. Surveys are carried out every two years by EU member states and several ESS member countries voluntarily. The harmonized survey contains information on the types of innovation and various aspects of the development of an innovation, such as the type of funding and innovation expenditures. The CIS covers both innovation outputs and the innovative process and inputs (type of funding, R&D expenditure) and distinguishes four innovation types: process, product, organizational, and marketing, thus covering both innovative property as well as capabilities and organizational capital. Additionally, the CIS asks about the novelty of the innovation, i.e. whether it is new for the market, new to the country, developed by the firm or was adopted, and thus provides information about the innovative value.

- *ICT usage/E-commerce Survey.* ICTEC is an annual survey conducted since 2002, which collects information on the use of information and communication technology, the internet, e-government, e-business and e-commerce in enterprises. Like the CIS, the EC survey contains mostly qualitative data. The ICT use survey measures various dimensions of firm technology use. Besides software and databases being considered

as an integral part of intangibles, the adoption of certain technologies also provides information about firms' organizational capital and ICT capabilities both in the firms' internal operations and regarding the firms' supplier and buyer relationships. The qualitative information in the survey can be used to construct an ICT intensity index which allows for variation in the underlying source variables, thereby overcoming the issue with changing survey questions and the saturation of certain variables over time.

- *International Trade in Goods Statistics* and *International Trade in Services Statistics*. ITGS measure the value and quantity of goods traded between EU Member States (intra-EU trade) and goods traded by EU Member States with non-EU countries (extra-EU trade) broken down by types of goods (Combined Nomenclature) and by partner countries. The providers of statistical information differ between intra and extra EU-trade. In the first case, it corresponds to all taxable persons reporting transactions exceeding a certain threshold fixed by member states; in the second case, it corresponds to administrative data from the customs declarations lodged by natural or legal persons in the customs administration. ITS typically cover trade services, i.e., transactions paid for the services that have taken place between the residents and non-residents.

- *The Foreign Affiliate Statistics*. FATS are distinguished into inward FATS, i.e. the activity of foreign affiliates resident in the compiling country, and the outward FATS, that is, the activity of foreign affiliates abroad but controlled by the compiling country. FATS allows to qualitatively assess the degree of economic activity of a domestic enterprise abroad and identify foreign-controlled firms.

- *International Sourcing Survey*. ISS gathers data on international organizations and the sourcing of business functions in 16 European countries, covering the period 2014-2016 or 2015-2017, depending on the country. The survey results cover nearly 60,000 businesses with over 50 employees. However, since the survey is still in the pilot stage, the survey design varies across countries.

- Moreover, data on firm energy use (ENER) and demographics (FD) are also available from Eurostat for some countries. ENER provides data on expenditures and quantities of several renewable and non-renewable energy sources, whereas FD informs about firm entry-exit and mergers-acquisitions.

Appendix B. Clustering Methodology

The computation details of the clustering algorithm are reported below. Firms are clustered according to the best fit in terms of GMM criterion from a production function estimation and a cost pass-through regression. A firm will be part of the assigned cluster for all the years it appears in the data. After initialization (0), the algorithm proceeds in two stages: (1) the 1^{st} stage with a preliminary weighting matrix and (2) the 2^{nd} stage with an optimal matrix.

0) Initialization: initial clustering of firms into technology groups $\hat{G}_0$ and demand groups $\hat{D}_0$. Initial clusters are based on empirical distribution of firms according to labour productivity and price change - marginal cost change ratio. Moreover, initial weighting matrix W_i for each firm i, based on intruments $(Z_i'Z_i)$.

1) 1^{st} stage GMM estimator with initial weighting matrix W_i. The GMM criterion to be minimized is the following:

$$(\hat{\beta}, \hat{G}, \hat{D}) = \text{argmin } Q(\beta, G, D)$$

where

$$Q(\beta, G, D) = \sum_{i=1}^{N} Q_i(\beta, G, D)$$

and

$$Q_i(\beta, G, D) = (Y_i - \beta_{(G_i,D_i)}X_i)'Z_iW_iZ_i'(Y_i - \beta_{(G_i,D_i)}X_i).$$

For iterations $s \geq 1$:

(a) min $Q(\beta, G, D)$ over $\hat{\beta}$;

(b) min $Q(\beta, G, D)$ over $\hat{G}$;

(c) min $Q(\beta, G, D)$ over $\hat{\beta}$;

(d) min $Q(\beta, G, D)$ over $\hat{D}$;

(e) Assess convergence: $|Q(\beta_s, G_s, D_s) - Q(\beta_{s-1}, G_{s-1}, D_{s-1})| \leq \epsilon$: if convergence, stop; otherwise, repeat from point (a).

2) Compute optimal weighting matrices W_i^o for each firm i, using the 1^{st} stage estimation.

3) 2^{nd} stage GMM estimator: repeat the GMM estimation algorithm of the 1^{st} stage, now with the optimal weighting matrix W_i^0.

Appendix C. Further Empirical Results

Further IV Results

This subsection reports the first stage of the firm pricing equation based on production technology and demand group (Table 7 in the main text).

Moreover, the firm pricing equation by aggregate production technology and demand group is shown, with the related first stage. Aggregate production group 1 is the sum of the first three production clusters, while the two more productive clusters are merged in the aggregate production group 2. Results are qualitatively similar to the main specifications presented in the main text and, again, robust to the inclusion of different industry fixed effects or the interaction between competitors' price response and cluster membership. In particular, for this specification, we observe a flattening of the supply curve in demand clusters 2 and 3.

Table C1: First stage of firm pricing equation by technology - demand cluster

	δy_{it}		
DS_{st}^{Shea}	-0.044	DS_{it}^{wid}	0.011
	(2.048)		(0.070)
$\times$ tech_demand$_{1,2}$	5.075**		-0.030
	(2.151)		(0.076)
$\times$ tech_demand$_{1,3}$	3.296		-0.032
	(2.067)		(0.074)
$\times$ tech_demand$_{2,1}$	5.268***		-0.047
	(1.969)		(0.071)
$\times$ tech_demand$_{2,2}$	4.395**		-0.035
	(1.950)		(0.070)
$\times$ tech_demand$_{2,3}$	5.042***		-0.016
	(1.947)		(0.071)
$\times$ tech_demand$_{3,1}$	5.324***		-0.011
	(1.946)		(0.070)
$\times$ tech_demand$_{3,2}$	5.056***		-0.017
	(1.943)		(0.070)
$\times$ tech_demand$_{3,3}$	5.468***		0.000
	(1.942)		(0.071)
$\times$ tech_demand$_{4,1}$	8.642***		-0.015
	(1.944)		(0.070)
$\times$ tech_demand$_{4,2}$	5.723***		0.014
	(1.942)		(0.070)
$\times$ tech_demand$_{4,3}$	5.554***		0.009
	(1.941)		(0.070)
$\times$ tech_demand$_{5,1}$	5.733***		0.033**
	(2.101)		(0.014)
$\times$ tech_demand$_{5,2}$	7.745***		0.002
	(1.949)		(0.062)
$\times$ tech_demand$_{5,3}$	5.322***		0.101**
	(1.944)		(0.043)
Other regressors included		Yes	
Sector-Year fixed effects		Yes	
Firm fixed effects		Yes	
Obs		146574	
R^2		0.25	

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15.

Table C2: First stage of firm pricing equation by technology - demand aggregated cluster

	δy_{it}		
DS_{st}^{Shea}	5.194***	DS_{it}^{wid}	-0.005
	(0.645)		(0.005)
$\times$ aggtech_demand$_{1,2}$	-0.406**		-0.010*
	(0.179)		(0.005)
$\times$ aggtech_demand$_{1,3}$	0.035		0.011**
	(0.172)		(0.005)
$\times$ aggtech_demand$_{2,1}$	3.277***		0.001
	(0.200)		(0.005)
$\times$ aggtech_demand$_{2,2}$	0.878***		0.003
	(0.176)		(0.005)
$\times$ aggtech_demand$_{2,3}$	1.171***		0.013**
	(0.162)		(0.006)
Other regressors included			Yes
Sector-Year fixed effects			Yes
Firm fixed effects			Yes
Obs			146574
R^2			0.26

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15.

Table C3: Firm pricing equation by technology - demand aggregated cluster

	δp_{it}			Slope	
	demand_1	demand_2	demand_3		
$\delta y_{it} \times \text{agg_tech}_1$	0.183***	0.027**	-0.050***		
	(0.043)	(0.012)	(0.011)		
$\delta y_{it} \times \text{agg_tech}_2$	0.003	-0.052***	-0.154***	***	***
	(0.011)	(0.017)	(0.012)		
δp^{-i}_{st-1}	0.050***				
	(0.002)				
δp_{it-1}	-0.035***				
	(0.002)				
2 digit Industry-Year fixed effects		Yes			
Firm fixed effects		Yes			
Obs		146574			
R^2		0.21			

Note: 2sls regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15. Reference group is $prod_1 \times demand_1$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution for each demand cluster.

GMM Results

This subsection reports the GMM results for the same empirical models of the pricing equations as exposed in the main text, as a robustness check. Results are very similar to the analysis in the main text.

Table C4: Firm pricing equation by technology cluster

	(1)		(2)	
	δp_{it}	Slope	δp_{it}	Slope
δy_{it}	0.461***		0.426***	
	(0.087)		(0.094)	
$\delta y_{it} \times \text{tech}_2$	-0.074*	***	-0.105**	***
	(0.039)		(0.042)	
$\delta y_{it} \times \text{tech}_3$	-0.181***	***	-0.192***	***
	(0.038)		(0.042)	
$\delta y_{it} \times \text{tech}_4$	-0.243***	***	-0.241***	***
	(0.038)		(0.042)	
$\delta y_{it} \times \text{tech}_5$	-0.366***	***	-0.336***	***
	(0.039)		(0.042)	
δp_{st}^{-i}	0.110***			
	(0.029)			
δp_{it-1}	-0.215***		-0.144***	
	(0.010)		(0.010)	
δp_{st}^{-i}-Technology cluster fixed effects	No		Yes	
2 digit Industry-Year fixed effects	Yes		Yes	
Firm fixed effects	Yes		Yes	
Obs	146574		146574	
R^2	0.20		0.21	

Note: gmm regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution.

Table C5: Firm pricing equation by technology - demand cluster

	δp_{it}			Slope		
	demand_1	demand_2	demand_3			
$\delta y_{it} \times \text{tech}_1$	0.395***	-0.144	-0.192*			
	(0.089)	(0.105)	(0.101)			
$\delta y_{it} \times \text{tech}_2$	-0.195**	-0.139	-0.219**	***		
	(0.099)	(0.097)	(0.097)			
$\delta y_{it} \times \text{tech}_3$	-0.216**	-0.216**	-0.291***		***	***
	(0.097)	(0.097)	(0.096)			
$\delta y_{it} \times \text{tech}_4$	-0.195**	-0.241**	-0.359***			***
	(0.096)	(0.095)	(0.096)			
$\delta y_{it} \times \text{tech}_5$	-0.327***	-0.287***	-0.396***	***	***	***
	(0.112)	(0.097)	(0.096)			
δp_{st}^{-i}	0.109***					
	(0.029)					
δp_{it-1}	-0.092***					
	(0.008)					
2 digit Industry-Year fixed effects	Yes					
Firm fixed effects	Yes					
Obs	146574					
R^2	0.21					

Note: gmm regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15. Reference group is $prod_1 \times demand_1$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution for each demand cluster.

Table C6: Firm pricing equation by technology - demand aggregated group

	δp_{it}			Slope	
	demand_1	demand_2	demand_3		
$\delta y_{it} \times \text{agg_tech}_1$	0.202***	0.039**	-0.082***		
	(0.048)	(0.018)	(0.016)		
$\delta y_{it} \times \text{agg_tech}_2$	0.018	-0.070***	-0.235***	***	***
	(0.017)	(0.018)	(0.016)		
δp_{st}^{-i}	0.079***				
	(0.029)				
δp_{it-1}	-0.101***				
	(0.009)				
2 digit Industry-Year fixed effects	Yes				
Firm fixed effects	Yes				
Obs	146574				
R^2	0.21				

Note: gmm regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1, $^{+}$ < 0.15. Reference group is $prod_1 \times demand_1$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution for each demand cluster.

Appendix D. Descriptive Statistics by Technology - Demand Cluster

Table D1: Shares, sectors, and growth by cluster

cluster	$s_{c,rev}$	$s_{c,va}$	$s_{c,lab}$	$s_{ind,rev}$	$s_{ind,va}$	$s_{ind,lab}$	$sector_1$	$sector_2$	$sector_3$	$sector_4$	$sector_5$	*Growth*
tech_1-demand_1	0.17%	0.03%	0.02%	0.02%	0.01%	0.03%	25	23	28	26	14	-5.18%
tech_1-demand_2	0.20%	0.20%	0.34%	0.02%	0.02%	0.04%	28	28	23	16	14	-0.30%
tech_1-demand_3	0.48%	0.51%	0.87%	0.04%	0.04%	0.05%	28	28	23	16	31	-0.58%
tech_2-demand_1	1.20%	1.32%	2.08%	0.02%	0.02%	0.03%	25	18	22	16	23	-0.92%
tech_2-demand_2	3.18%	3.58%	4.71%	0.06%	0.06%	0.07%	25	16	22	23	31	+0.77%
tech_2-demand_3	5.06%	5.57%	7.26%	0.08%	0.07%	0.08%	25	23	16	31	28	+0.92%
tech_3-demand_1	5.59%	6.26%	7.79%	0.07%	0.07%	0.07%	25	22	18	23	28	+2.29%
tech_3-demand_2	9.16%	9.97%	11.69%	0.10%	0.11%	0.11%	25	23	22	31	16	+1.80%
tech_3-demand_3	12.45%	13.64%	15.60%	0.10%	0.10%	0.10%	25	23	28	31	22	+1.80%
tech_4-demand_1	7.25%	8.50%	6.21%	0.55%	0.61%	0.51%	38	25	28	23	20	+3.04%
tech_4-demand_2	12.61%	12.76%	10.45%	0.40%	0.38%	0.36%	25	28	23	20	22	+2.71%
tech_4-demand_3	20.04%	20.70%	20.46%	0.20%	0.21%	0.20%	25	28	18	31	23	+2.26%
tech_5-demand_1	4.31%	3.80%	2.36%	0.72%	0.69%	0.70%	38	25	28	23	26	+6.16%
tech_5-demand_2	3.57%	2.54%	1.54%	0.48%	0.43%	0.33%	28	13	25	26	20	+3.44%
tech_5-demand_3	14.72%	10.60%	8.37%	0.41%	0.35%	0.32%	28	18	25	20	26	+3.35%

Note: $s_{c,x}$ for $x \in \{rev, va, lab\}$ are cluster shares in revenue, value-added, or employment (fte) over the total sample, while $s_{ind,x}$ are the 2-digit industry shares for the average cluster firm; $sector_n$ for $n \in \{1, 2, 3, 4, 5\}$ are the top n most common NACE 2-digit industry by cluster; *Growth* is the average revenue growth rate.

Table D2: Descriptives by cluster

cluster	*lprod*	wages	$wages_{emp}$	$size_{rev}$	se($size_{rev}$)	$size_{emp}$	se($size_{emp}$)	*profit margin*	$share_{EXP}$	inv_{INTAN}
tech_1-demand_1	4.40	0.87	34.89	2.51	6.61	20.28	179.25	-1%	33.2%	57.72
tech_1-demand_2	4.45	0.74	35.41	3.43	6.97	19.62	39.83	7%	44.9%	36.44
tech_1-demand_3	4.52	1.02	40.13	5.12	8.92	29.06	59.42	10%	48.7%	43.87
tech_2-demand_1	4.88	0.50	37.48	2.53	6.58	14.10	33.59	11%	28.1%	13.54
tech_2-demand_2	4.89	1.14	37.42	5.85	12.04	31.23	103.89	13%	41.5%	25.69
tech_2-demand_3	4.90	1.49	44.76	7.53	14.14	41.15	121.24	13%	50.2%	33.79
tech_3-demand_1	5.20	1.42	40.49	8.37	21.65	37.42	113.16	17%	41.8%	33.51
tech_3-demand_2	5.25	2.23	39.28	13.61	29.86	57.82	155.11	16%	48.9%	60.48
tech_3-demand_3	5.27	2.42	66.81	13.55	29.47	62.04	177.19	16%	52.3%	64.31
tech_4-demand_1	5.63	12.02	59.15	55.25	149.14	229.95	973.77	21%	54.7%	438.71
tech_4-demand_2	5.69	7.34	46.84	53.03	144.05	157.34	481.03	18%	58.7%	454.08
tech_4-demand_3	5.68	5.64	40.49	31.81	104.74	124.88	614.11	17%	56.1%	306.54
tech_5-demand_1	6.58	28.31	39.28	30.80	143.03	530.98	5510.30	22%	56.7%	4201.73
tech_5-demand_2	6.51	8.68	66.81	106.37	290.29	163.81	445.10	16%	70.8%	1115.89
tech_5-demand_3	6.36	10.56	59.15	73.47	220.40	213.79	1106.91	17%	66.7%	512.22

Note: *lprod*, wages, $wages_{emp}$, $size_{rev}$, se($size_{rev}$), $size_{emp}$, se($size_{emp}$), *profit margin*, $share_{EXP}$, and inv_{INTAN} are log of labour productivity (2010 thousand euros over fte), wages (million euros) and wages by employee (thousand euros), total revenue (million euros) and its standard deviation, total employment (fte) and its standard deviation, operational profit over revenue, share of exporters, and investment in intangible assets (thousand euros), respectively.

Table D3: Market strategy by cluster

cluster	*new design*	*new promotion*	*new placement*	*new pricing*
tech_1-demand_1	17.50%	20.00%	12.50%	15.00%
tech_1-demand_2	11.25%	11.25%	8.75%	8.75%
tech_1-demand_3	17.31%	16.67%	10.26%	11.54%
tech_2-demand_1	9.84%	10.51%	4.70%	6.49%
tech_2-demand_2	13.47%	14.90%	8.17%	8.94%
tech_2-demand_3	18.36%	18.53%	9.27%	9.77%
tech_3-demand_1	13.17%	13.88%	6.67%	8.81%
tech_3-demand_2	17.18%	18.11%	8.06%	10.42%
tech_3-demand_3	17.50%	17.83%	8.42%	10.96%
tech_4-demand_1	24.63%	28.36%	14.55%	15.30%
tech_4-demand_2	20.37%	23.39%	11.48%	13.63%
tech_4-demand_3	21.78%	22.33%	10.86%	14.50%
tech_5-demand_1	35.71%	35.71%	21.43%	14.29%
tech_5-demand_2	12.24%	20.41%	11.22%	7.14%
tech_5-demand_3	24.77%	24.54%	14.91%	14.91%

Note: percentage of firms that significantly changed the aesthetic design or packaging (*new design*), used new media or techniques for product promotion (*new promotion*), employed new methods for product placement or sales channels (*new placement*), and implemented new methods of pricing goods or services (*new pricing*). Data from the CIS survey (around 5.4% of the total sample).