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Abstract

This paper provides theory and evidence on micro-level pricing behavior needed to model an aggregate New Keynesian Phillips Curve. We start with individual firms that are heterogeneous in their production technology and in the demand curves they face. We estimate the parameters of supply and demand curves by utilizing prices and quantities of outputs and factor inputs of firms along with exogenous downstream demand instruments from global input-output and trade data. The research addresses model heterogeneity using a clustering method to classify firms according to their production technology and observed price pass-through. The results show that more productive firms exhibit a lower price response to changes in demand. We find that the aggregate price response to demand shocks will be smaller when more productive firms absorb a larger portion of demand shocks, which generally is the case. At the same time, our results imply that 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, will result in a higher aggregate price response. Finally, this paper provides a framework to incorporate heterogeneous pricing behavior into an estimate of the slope of the aggregate Phillips Curve.

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1 Introduction

Understanding how inflation responds to economic activity is central to monetary policy. A large literature documents that estimates of the Phillips curve slope have declined over time, conditional on inflation expectations. While this flattening is not uncontested, the time-variation of the slope has raised concerns about using traditional macroeconomic slack indicators for real-time monetary policy decisions (Hooper et al. (2020), Ball and Mazumder (2021), Eser et al. (2020), Hobijn et al. (2023)).

Standard explanations for changes in the slope of the empirical correlation between inflation and the output gap emphasize nominal rigidities, inflation expectations, and non-linearities in response to economic slack. A complementary set of explanations points to structural changes in the economy, including globalization, changes in market structure, and the growing importance of large, productive firms. These forces suggest that inflation dynamics may depend not only on aggregate conditions, but also on how demand and cost shocks are distributed across firms with different technologies and pricing behavior.

The slope of the aggregate Phillips curve will reflect how heterogeneous firms adjust prices and quantities in response to shocks. Firms' price adjustment depends on how the shock affects its costs and whether the costs can be passed through to its customers. Firms that can expand output with relatively flat input requirements will have a lower cost increase from a demand shock than firms with a steeper supply curve. The slope and curvature of the demand curve facing the firms restricts the ability to pass through costs. If demand expansions are disproportionately absorbed by more productive and scalable firms, aggregate inflation will respond less to changes in economic activity even if nominal rigidities and expectations remain unchanged. Over recent decades, technological change and market reallocation have plausibly increased the macroeconomic importance of firms with higher scalability.

Recent inflation dynamics underscore the relevance of this mechanism. The inflation surge in 2021-2022 reflected a combination of demand recovery and supply disruptions, but these shocks were highly uneven across sectors and firms (Baba et al. (2023)). As a result, aggregate inflation depended not only on the magnitude and nature of shocks, but also on which firms and sectors they affected. Even if growth in the market share of technologically advanced firms has flattened the Phillips curve secularly, idiosyncratic shocks can generate sizable inflation responses when they disproportionately hit firms with steep marginal cost curves or high price pass-through.

This paper asks a simple but previously unanswered empirical question: how does firm-level heterogeneity in both technology and demand conditions affect the aggregate Phillips Curve? In particular, we ask how structural shifts towards technologically advanced firms affect aggregate price and quantity responses to aggregate demand shocks, but also how shocks that affect firms differently lead to identifiable variation over time in the slope of the aggregate Phillips curve.

To answer this question, we build on three strands of the literature: the representative-firm New Keynesian Phillips curve of Gali (1999), theories of firm-level competition and pricing behavior (Fujiwara and Matsuyama (2026)), and the recent micro-founded pricing framework of Gagliardone et al. (2025). Our key departure from the existing literature is that we allow the structural pricing parameters to differ systematically across firms. We identify the heterogeneous parameters using firm-level data and aggregate the resulting pricing equations into a time-varying aggregate Phillips curve. We refer to this object as the Micro-aggregated Phillips Curve (MAPC).

We estimate the model using detailed panel data on prices, quantities, and inputs for French manufacturing firms, together with downstream demand instruments constructed from global input-output tables and firm-level trade data. Rather than imposing a representative-firm structure or estimating average pricing responses across firms, we allow the structural parameters governing pricing behavior to differ systematically across groups of firms.

To isolate the role of supply- and demand-side heterogeneity, we deliberately abstract from several other mechanisms that influence inflation dynamics, including equilibrium feedback through monetary policy and inflation expectations, as well as movements along aggregate input supply curves. These effects are absorbed by time-varying fixed effects in the empirical analysis. The resulting framework is intentionally partial equilibrium, allowing the contribution of heterogeneous production technology and demand conditions to the aggregate Phillips curve to be identified separately from other determinants of inflation.

An econometric challenge is that firms differ simultaneously in their production technologies and in the demand conditions they face. These two dimensions of heterogeneity need not coincide with conventional industry classifications, so restricting structural parameters to be common within industries pools data from firms with different supply and demand characteristics. We therefore apply the latent-panel clustering approach of Cheng et al. (2025) as extended by Aglio and Bartelsman (2026), to group firms according to common production and demand parameters rather than statistical industry codes. The resulting classification preserves the economically relevant heterogeneity for pricing decisions while remaining sufficiently parsimonious to aggregate heterogeneous firm-level supply curves into a macro Phillips curve. Within this framework, the slope of the micro-aggregated Phillips curve is an expenditure-weighted average of firm-level supply curves, with the weights evolving as demand reallocates across groups of firms with different production technologies and pass-through behavior.

Our main findings are as follows. More productive firms have flatter marginal cost curves, adjust quantities more strongly, and exhibit lower price responses to demand shocks. These firms also account for a disproportionate and increasing share of output adjustments following demand fluctuations. As a result, aggregate inflation responds less to changes in economic activity when demand shocks are absorbed primarily by highly productive firms. At the same time, sector-specific demand or cost shocks concentrated in firms with steep marginal costs or high price pass-through generate larger inflation responses, even in an economy characterized by a flat average Phillips curve. We provide some robustness by replicating our main empirical work for French manufacturing firms in the Netherlands and Slovenia using the newly developed European microdata infrastructure (Bartelsman and MDI-Team (2026)), with similar results. Further, we expand beyond manufacturing by applying a reduced-form specification to all non-farm business sectors using CompNet data for 21 EU countries and show that more productive firms have flatter marginal costs outside of manufacturing as well.

The remainder of the paper is organized as follows. Subsection 1.1 places our work in the context of recent literature. Section 2 presents a framework with heterogeneous firm pricing and derives the aggregate Phillips curve as an aggregation of firm-level pricing decisions. Section 3 describes the firm-level data and the construction of downstream demand instruments. Section 4 presents the clustering methodology. Section 5 reports the estimation of firm-level pricing equations and empirical results. Section 6.1 provides checks on external validity of our results, and Section 7 concludes.

1.1 Related literature

This paper relates to several strands of the literature on inflation dynamics and the Phillips curve and to recent work on the econometrics of latent group structure in panel data.

Flattening and time variation of the Phillips curve. A large literature documents the time variation in the relationship between inflation and economic activity. Early contributions emphasize nominal rigidities and expectations formation (e.g., Calvo (1983); Bullard and Mitra (2002)), while more recent work highlights state-dependent pricing and time-varying parameters (Costain et al. (2022)). Empirical studies for the euro area and the United States confirm substantial variation in Phillips curve estimates across periods and policy regimes (Ball and Mazumder (2021); Eser et al. (2020); Hooper et al. (2020)). Our paper complements this literature by emphasizing firm-level heterogeneity, especially with respect to production technology, as a structural determinant of aggregate inflation responses.

Supply conditions and the Phillips curve. Several papers study how heterogeneity across sectors and production networks shapes aggregate inflation. Imbs et al. (2011) show that aggregation across sectoral Phillips curves generates persistence and slope attenuation at the macro level. More recent work highlights the role of production networks and intermediate inputs in shaping the Phillips curve (Rubbo (2023); Höynck (2025)). The paper closest to our framework is Gagliardone et al. (2025), who derive micro-founded New Keynesian pricing equations with strategic complementarities and possible marginal-cost curvature. Our framework builds directly on this insight, but differs by taking into account the importance of firm-level heterogeneity, in both supply and demand. In particular, we differ on how the marginal-cost term is brought to the data. Whereas the empirical specification in Gagliardone et al. (2025) absorbs firm-level movements along the marginal cost curve into residual or fixed-effect components, we explicitly estimate movement along marginal cost curves. This allows us to estimate how the slope of marginal costs with respect to output varies across firms and how this heterogeneity maps into the slope of the MAPC. While we do not directly consider the convexity of the aggregate marginal cost curve as in Boehm and Pandalai-Nayar (2022), the aggregate slope is not constantin our approach. We also differ from most of the empirical literature by not relying on (dis)aggregation at the industry level. Our work strongly suggests that it is unlikely that analysis even at the 4-digit industry level can capture the relevant heterogeneity in supply and demand conditions (see Figure 4 and

Table 4).

Market structure, demand, and price pass-through. A growing literature emphasizes the role of globalization, competition, and market structure in explaining muted inflation responses. Theoretical work links increased trade exposure or market concentration to lower pass-through and flatter Phillips curves (Guilloux-Nefussi (2020); Fujiwara and Matsuyama (2026)). Empirical studies document substantial heterogeneity in price adjustment and pass-through across firms, driven by differences in productivity, markups, and demand conditions (Gopinath and Itskhoki (2010); Amiti et al. (2019); De Loecker et al. (2016); Forlani et al. (2023)). Our demand-side approach is closest to the firm-level framework of Mrázová and Neary (2017). It differs from models in which strategic complementarity arises from oligopolistic interaction under CES demand. With CES demand, strategic complementarity is primarily tied to market structure or firm size: we allow the pass-through object itself to differ across firms facing different residual demand conditions.

Identification of demand and supply and aggregation using micro data. Some of our empirical findings on the effect of shocks on inflation under conditions of heterogeneous supply and demand have been foreseen by Andrés and Burriel (2018), who present a theoretical model where the flattening of the Phillips curve results from the interaction between firm heterogeneity in production and strategic competition among firms. We provide a richer theoretical framework which we also bring to micro data. Further, we employ exogenous micro variation in order to identifying structural relationships for macro analysis, as advocated by Nakamura and Steinsson (2018). We identify firm-level supply and demand parameters using downstream demand instruments derived from input-output and trade linkages (Shea (1993a,b); Dhyne et al. (2025)). Methodologically, our clustering approach relates to recent work on latent group heterogeneity in panel data Bonhomme and Manresa (2015); Ando and Bai (2016); Su et al. (2016); Mehrabani (2023). In particular, our algorithm follows Cheng et al. (2025), who cluster firms based on heterogeneity in output elasticities of production. We extend their approach to a system of multiple equations, as discussed in Aglio and Bartelsman (2026).

2 Theoretical Framework

The economic environment

Our analysis is based on a New Keynesian framework, the benchmark model for macro-monetary analysis and forecasting. The exposition of our framework closely follows Gagliardone et al. (2025). Our model explicitly incorporates heterogeneity in both supply- and demand-side conditions faced by firms making pricing decisions. We show that structural parameters from both sides are needed to estimate a micro-founded pricing equation. The modeling exercise provides a tractable framework for estimation of heterogeneous demand and supply parameters using firm-level data, but also allows aggregation into time-varying parameters of an aggregate New Keynesian supply curve that are based on identified micro-level price behavior and time-varying market shares.

The economy has a representative household that consumes final output composed of a continuum of produced goods. The market for each good is supplied by a finite number of firms that compete à la Bertrand in monopolistic competition. Firms are heterogeneous in the residual demand curves they face, with variation across firms in optimal price pass-through of cost shocks. Firms are heterogeneous in their production technology, so that there is variation across firms in derived factor demand following demand shocks. Finally, firms are limited in their ability to adjust their price, as in Calvo (1983).

Pricing behavior

We start with the firm-level pricing problem that lies at the heart of the NK sticky-price model. Firms in market m are monopolistically competitive and face a residual demand curve, $Y_{it} = D_i(\frac{P_{it}}{P_t}, \frac{P^c_{mt}}{P_t}, Y_t; \phi_i)$, where P^c_{mt} is the average competitors' price in market m, and ϕ_i are firm i specific demand parameters. Firms take the aggregate price level, P_t and output, Y_t as given. With probability $(1-\theta)$, firms can choose a "reset price", $P^o_{i,t}$, to maximize the present discounted value of expected real profit:

$$\max_{P^o_{it}} \sum_{k=0}^{\infty} \theta^k E_t \left[\Lambda_{t,k} \frac{P^o_{it} D_i(\frac{P^o_{it}}{P_{t+k}}, \cdot) - TC_i(D_i(\frac{P^o_{it}}{P_{t+k}}, \cdot))}{P_{t+k}} \right],$$

where $\Lambda_{t,k}$ is the stochastic discount factor between time $t+k$ and t, P_t the aggregate price, and $TC_i(Y_{it})$ denotes the firm's nominal total cost as a function of its output. One can derive the FOC for optimal P^o_{it} as:

$$\sum_{k=0}^{\infty} \theta^k E_t \left[\frac{\Lambda_{t,k}}{P_{t+k}} D_i(\frac{P^o_{it}}{P_{t+k}}, \cdot)(1-\eta_{i,t+k}) \left(P^o_{it} - \mu_{i,t+k} MC_i(D_i(\frac{P^o_{it}}{P_{t+k}}, \cdot)) \right) \right] = 0, \tag{1}$$

where $MC_i(Y_i)$ is the firm's nominal marginal cost function, $\eta_{it} = -\frac{\partial D_i(\cdot)}{\partial P_{it}} \frac{P_{it}}{Y_{it}}$ is the firm's residual demand elasticity and $\mu_{i,t} = \frac{\eta_{i,t}}{\eta_{i,t}-1}$ is the optimal markup under flexible prices.[1]

The optimal reset price trades off future profit gains and losses that arise because shocks cause the fixed reset price to deviate from the frictionless optimum. Note that typical simplifications used in the literature to solve for the reset price, such as constant demand elasticity and markup or constant marginal cost, either in the cross-section or over time, are relaxed in this specification.

Nevertheless, progress can be made by solving for the reset price in deviations from steady state following shocks to fundamentals. In our case, the steady-states for output, price, and markup and the behavioral responses to shocks can differ across firms in the cross section,

[1] In the literature, it is common to drop the $(1-\eta)$ term that multiplies the deviation between price and markup times marginal cost. When η depends on price, as it does in this paper, as well as in Gagliardone et al. (2025), higher η increases the sensitivity of profits to output changes and penalizes more heavily deviations from optimal pricing. However, when solving the system in deviations from steady-state, the $(1-\eta)$ term is only of second-order importance.

depending on their firm-specific demand and supply parameters.

Household Preferences and Demand

The representative household has utility defined over consumption of a composite good, C_t:

$$U_t = \frac{C_t^{1-\sigma}}{1-\sigma}, \tag{2}$$

where $C_t = \left[\int_{m=0}^{1} C_{mt}^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}}$, with substitution elasticity ξ across markets m.[2] Each market $m \in [0,1]$ delivers a consumption bundle C_{mt} to the household that is aggregated from deliveries from individual firms, C_{imt}. In our specification, we have an implicit Kimball aggregator that is defined with the following local properties (ω_i being the share of firm i in market m):

$$\sum_{i \in m} \omega_i \Psi_{im}(\frac{C_{imt}}{C_m t}) = 1, \tag{3}$$

and

$$\frac{P_{imt}}{P_m t} \propto \Psi'_{im}(\frac{C_{imt}}{C_m t}), \tag{4}$$

with regularity conditions $\Psi'_i > 0$ and $\Psi''_i < 0$.

In particular, we consider a firm-specific Klenow-Willis (Klenow and Willis (2016)) type aggregator, Ψ_i, where the pass-through parameter will differ across groups of firms.[3] In section 4 we discuss how we find the mapping $g_d : \mathcal{I} \to \{1, ..., D\}$ that allocates firm i to 'demand group' d, or $d = g_d(i)$. Firms in group d share the demand function:

$$\Psi_i(\frac{C_{it}}{C_t}) = 1 + \frac{\eta_i \rho_d}{(\eta_i - 1)(1-\rho_d)} \left[\left(1 + (\frac{1}{\rho_d} - 1)(\frac{C_{it}}{C_t} - 1) \right)^{\frac{\eta_i - 1}{\eta_i}} - 1 \right], \tag{5}$$

with demand elasticity η_i and proportional pass-through parameter ρ_d that is common among

[2] Without loss of generality, we are assuming symmetry across markets.

[3] For purposes of exposition, we drop the notation for the nested (symmetric) markets m, and will only discuss demand for products from firm i.

all firms in the group, i.e. $i \in \mathcal{I}_d \equiv \{i : g_d(i) = d\}$ group d.

Production Technology

We assume that goods are produced using the following heterogeneous-firm production functions:

$$Y_{it} = A_{st}(K_{it}^{\alpha_s^k} L_{it}^{\alpha_s^l} M_{it}^{(1-\alpha_s^k-\alpha_s^l)})^{\gamma_s} \tag{6}$$

where Y_{it}, K_{it}, L_{it},M_{it} are output, capital, labor, and materials, respectively, of firm i at time t, and α_s^x, γ_s and A_{st} are production function parameters for firms belonging to "supply group" $s = g_s(i)$. In section 4 we discuss how we find the mapping g_s that allocates firms to groups, $s = g_s(i)$, in order to minimize production function heterogeneity across firms in a group.

Marginal costs are a function of factor input prices that are exogenous to the firm, and firm-level output and technology. Within each group of firms, the production function parameters do not vary across firms, so that marginal costs for all firms $i \in I_s \equiv \{i : g_s(i) = s\}$ within a group s can be written as:

$$MC_{it} = \frac{C_{st}}{A_{st}^{1/\gamma_s}} \frac{1}{\gamma_s} Y_{it}^{\nu_s} \tag{7}$$

where $\nu_s = \frac{1-\gamma_s}{\gamma_s}$ and

$$C_{st} = \left(\frac{R_t}{\alpha_s^k}\right)^{\alpha_s^k} \left(\frac{W_t}{\alpha_s^l}\right)^{\alpha_s^l} \left(\frac{P_{Mt}}{1-\alpha_s^k-\alpha_s^l}\right)^{(1-\alpha_s^k-\alpha_s^l)}.$$

The level of a firms' marginal costs decreases in A_{st} and its upward slope with respect to output Y decreases with γ_s. While A_{st} and γ_s both are estimated freely, we will show in Section 4, that in the data, average total factor productivity and the slope of the marginal cost curve are found to be negatively correlated across firm groups – more productive firms have flatter marginal cost curves.

The optimal reset price

The steps in the literature that are used to go from the exact Calvo-style FOC to a New Keynensian Phillips Curve, by traversing through a per-period desired price and the deviation-from-steady-state reset price can be used in our setting as well. In our problem, the steady-state will differ by clusters of firms j defined by their supply and demand group, $j = (s, d)$. Starting from the FOC for the optimal reset price (equation 1), and using notation $\mathcal{H}_{j,t+k}(\cdot) = D_j(\frac{P^o_{jt}}{P_{t+k}}, \frac{P^c_{j,t+k}}{P_{t+k}}, Y_{t+k})(1 - \eta_{j,t+k})\left(P^o_{jt} - \mu_{j,t+k} MC_j(D_j(\frac{P^o_{jt}}{P_{t+k}}, \frac{P^c_{j,t+k}}{P_{t+k}}, Y_{t+k}))\right)$, the FOC of the pricing equation becomes:

$$\sum_{k=0}^{\infty} \theta^k E_t \left[\frac{\Lambda_{t,k}}{P_{t+k}} \mathcal{H}_{j,t+k} \left(\frac{P^o_{jt}}{P_{t+k}}, \frac{P^c_{jt+k}}{P_{t+k}}, Y_{t+k}, D_j(\cdot), MC_j(\cdot) \right) \right] = 0. \tag{8}$$

It should be noted that P^o_{jt} term shows up both directly as part of revenue, through demand for the group's products, and indirectly through the group's elasticity, markup, and marginal costs that depend on demand.

For each group we denote steady state values for the variables $\bar{P}_j$, $\bar{Y}_j$,$\overline{MC}_j$, $\bar{\mu}_j$,and $\bar{P}^c$. In case of zero-inflation, each firm's reset price is its steady-state price, $\bar{P}^o_j = \bar{P}_j$ and the steady-state FOC collapses to $\bar{P}_j = \bar{\mu}_j \overline{MC}_j$. The steady-state values differ across groups of firms j, owing to heterogeneity in A_s, γ_s, and ρ_d.

Now, define P^{flx}_j as the price that the firm would pick in any period if there were no restrictions and firms did not care about future periods, such that $\mathcal{H}_j\left(\frac{P^{flx}_j}{P}, \frac{P^c_j}{P}, MC_j, Y\right) = 0$ in each period. In steady state, $\bar{P}^{flx}_j = \bar{P}_j$.

Near the steady state, we can write the first-order approximation of the future terms as

$\mathcal{H}_j(\cdot) \approx \mathcal{H}_j' \left(\hat{P}^o_{j,t} - \hat{P}^{flx}_{j,t+k}\right)$, and we can define the deviations of the flexible price around its type-j steady state: $\hat{P}^{flx}_{j,t} = \rho_d \hat{MC}_{j,t} + (1-\rho_d)\hat{P}^c_{j,t}$.[4]

Therefore, the Calvo reset price, in relative deviations from steady state becomes: $\hat{p}^o_{jt} = (1-\beta\theta)\sum_{k=0}^{\infty}(\beta\theta)^k E_t\left[\rho_d \hat{mc}_{j,t+k} + (1-\rho_d)\hat{p}^c_{j,t+k} + \sum_{l=1}^{k}\pi_{j,t+l|t}\right]$, where $\hat{p}^o_{jt} \equiv \hat{P}^o_{jt} - \hat{P}_{jt}$ and $\hat{p}^c_{jt} \equiv \hat{P}^c_{jt} - \hat{P}_{jt}$, mc are real marginal costs, β is the steady state of the stochastic discount factor and $\sum_{k=1}^{\infty}\pi_{j,t+k|t} = \hat{P}_{j,t+k} - \hat{P}_{jt}$.

While we cannot get an exact price index – as defined by Diewert (1976) – for firms in group j using the Kimball aggregator, as a first order approximation the Calvo price index relation $\pi_{jt} = \frac{1-\theta}{\theta}(\hat{P}^o_{jt} - \hat{P}_{jt})$ still holds. Stating the reset equation in recursive form, and using the marginal cost equation 7 to separate the effect of output and factor prices, we can write the reset price for firms in group $j = (s, d)$ as:

$$\hat{p}^o_{jt} = (1-\beta\theta)\left[\rho_d \hat{c}_{jt} + \rho_d \nu_s \hat{y}_{jt} + (1-\rho_d)\hat{p}^c_{jt}\right] + \beta\theta E_t(\hat{p}^0_{j,t+1} + \pi_{j,t+1}), \tag{9}$$

noting that ρ_d varies between groups $d = g_d(i)$ and ν_s varies between groups $s = g_s(i)$

Finally, we can write the NK supply curve for firms in group j, using the Calvo price-index relation as:

$$\pi_{jt} = \kappa\left[\rho_d \hat{c}_{jt} + \rho_d \nu_s \hat{y}_{jt} + (1-\rho_d)\hat{p}^c_{jt}\right] + \beta E_t \pi_{j,t+1} \tag{10}$$

with $\kappa = \frac{(1-\theta)(1-\beta\theta)}{\theta}$ and $\hat{c}_{jt}$ gives possible changes to real marginal costs other than through changes in output.[5] Note that a firm's pricing decision separates the idiosyncratic output-

[4]Note that the source of strategic complementarity, $(1-\rho_d)$ matters for interpretation. For example, in oligopolistic extensions of CES demand, incomplete pass-through can arise because firms internalize the effect of their own price on an aggregate price index; the resulting strategic-complementarity term is then governed by market shares or concentration. We instead allow firms to face residual demand curves with heterogeneous elasticity and curvature. The associated pass-through parameter, ρ_d, is therefore a structural feature of the demand curve that a firm faces, rather than a mechanical function of the number of firms in an industry. This distinction permits firms in the same narrowly defined industry to differ in their response to common cost and demand shocks.

[5]In this paper we are interested in the effects of heterogeneity of the slope of marginal costs with respect to output, and in our empirical analysis control for changes in marginal costs resulting from movements

response term (governed by ρ_d, ν_s) and a forward-looking aggregate term.

The micro-aggregated Phillips curve

The previous section derived a type-specific New Keynesian supply curve for firms in cluster $j = (s, d)$, where s indexes supply groups and d indexes demand groups. We now show how to aggregate these heterogeneous pricing equations to obtain the Micro Aggregated Phillips Curve (MAPC).

To first order, aggregate inflation is the expenditure-share weighted average of group-level inflation rates. Under the Kimball aggregator, the exact market price index is implicit, but its first-order log change is given by the Divisia approximation using steady-state expenditure shares. Let ω_j denote the aggregate steady-state expenditure share of group j, obtained by aggregating shares of firms of type j within markets and market shares in final expenditure, or $\omega_j = \int_0^1 \left[\sum_{i \in m: g(i)=j} \omega_{imt}\right] dm$ we then have $\pi_t = \sum_j \omega_j \pi_{j,t}$. Substituting the cluster-level New Keynesian supply curve yields

$$\pi_t = \kappa \sum_j \omega_j \left[\rho_d \hat{c}_{jt} + \rho_d \nu_s \hat{y}_{jt} + (1 - \rho_d)\hat{p}^c_{jt})\right] + \beta E_t \pi_{t+1} \tag{11}$$

where $\hat{p}^c_{jt}$ denotes the competitors' price gap relative to the group-j price. Thus, the aggregate Phillips curve is a composition-weighted average of heterogeneous firm-level supply curves.[6]

Given our production technology, marginal-cost fluctuations can be written in terms of changes in marginal cost "levels" that depend on productivity and factor costs – $\hat{c}_{jt}$ – and

along input supply curves.

[6]Because the Calvo aggregate framework linearly separates expectational shifts (the $\beta E_t \pi_{t+1}$ term) from the slope, the structural slope for cluster j and for the aggregate relies entirely on ρ_d and ν_s. Owing to our assumption that these parameters are structural and invariant to the source of shocks, our partial-equilibrium estimates map perfectly to the general equilibrium aggregate slope.

marginal costs changes arising from firm's own output changes through the marginal cost curve slope – $\nu_s \hat{y}_{jt}$ that varies by supply group.

Thus, firms with flatter marginal-cost curves contribute less to aggregate inflation for a given change in output. Similarly, firms with lower pass-through ρ_d contribute less to inflation because they place greater weight on competitors' prices and absorb more of marginal-cost movements into markups.

Assuming a uniform proportional shock where all groups experience the same output gap ($\hat{y}_{jt} = \hat{y}_t$), the slope of the aggregate Phillips curve depends on the joint distribution of steady-state revenue and the estimated parameters: The slope of the MAPC for an aggregate demand shock is thus proportional to $\sum_j \omega_j \rho_{d(j)} \nu_{s(j)}$. In general, the aggregate slope is time varying as it depends on the distribution of the shocks as well as the responses, and is proportional to $\left(\sum_j \omega_j \rho_{d(j)} \nu_{s(j)} \hat{y}_{jt}\right) / \left(\sum_j \omega_j \hat{y}_{jt}\right)$

This is the central empirical mapping. The micro evidence from demand groups, ρ_d, and supply technology groups, ν_s and A_s, can be incorporated directly into the aggregate Phillips curve by assigning each firm to a group $j = (g_s(i), g_d(i))$ and aggregating the slope of each group j using its expenditure share.[7]

A natural implication of the framework is that aggregation need not follow conventional industry classifications. The parameters governing firm-level pricing decisions in the model — pass-through ρ_d and marginal-cost curvature ν_s — are not primarily industry-specific objects, but firm-level characteristics reflecting residual demand conditions and production

[7]In our interpretation of developments of the slope of the MAPC, we treat ρ_d and ν_s as structural parameters, while allowing the expenditure weights ω_{jt} to evolve slowly over time. These movements capture changes in technology, product quality, consumer tastes, and market composition. The contemporaneous MAPC slope evolves with the composition of expenditure across firm groups, and depends critically on the time-varying distribution of shocks.

technologies. As we will show in section 4.5, firms within narrowly defined industries often display substantial heterogeneity in pricing behavior, markup adjustment, and cost pass-through, while firms in different industries may exhibit similar values of ρ_d and ν_s. As a result, aggregating at the industry level attenuates the economically relevant sources of heterogeneity that determine aggregate inflation. What matters for the slope of the micro-aggregated Phillips curve is therefore the distribution of expenditure across firms with different pass-through and marginal-cost characteristics, rather than the distribution across statistical industry categories.

3 Data Description

Our research makes use of the Micro Data Infrastructure (MDI; Bartelsman and MDI-Team (2026)), a harmonized research environment that integrates firm-level administrative and survey data within the secure computing systems of participating European National Statistical Institutes (NSIs).[8] The MDI links longitudinal firm-level datasets through identifiers derived from the Statistical Business Register and harmonizes units of observation, classifications, and variable definitions across countries, while recording dataset versions, software environments, and analytical code to ensure full replicability. One particular strength of the MDI is that it allows for replication of single-country micro-data analysis in a practical and cost effective manner.

Our main analysis uses French firm-level data to construct the main datasets and variables.[9] The variables used in the analysis are drawn from three linked datasets: Structural Business Statistics (SBS), Balance Sheet data (BS), and Firm Production Statistics (Prod-

[8]The MDI received funding from the H2020 project grant *Microprod*, 2019–222, and the EU-TSI project from the European Union under grant agreements No. 101101853 and No. 101140673. For details on participating countries and available datasets and variables, see the MDI catalogue and the MDI manual.

[9]The firm-level data of the French NSI, INSEE, is accessed remotely via the French research service CASD.

com[10]). We replicate the analysis through the MDI installed at the remote research data service of Statistics Netherlands and Slovenia, and provide robustness by using CompNet panel data for a larger sample of countries and industries. Further, the paper uses Comtrade data and OECD Inter-Country Input-Output data to create downstream demand indicators.

Firm-level revenues, compensation, and intermediate material expenditures, in euros, and employment, in full time equivalents, are sourced from the SBS dataset. Firm-level capital is constructed from the BS dataset and is measured as the book value of tangible and intangible fixed assets.

Firm-level price indexes are constructed using product-level revenue and quantity information from the Prodcom dataset. For each firm i, product g, and year t, we compute a unit value:

$$P_{git} = \frac{\text{Revenue}_{git}}{\text{Quantity}_{git}},$$

and a firm-level price relative:

$$\frac{P_{it}}{P_{i,t-1}} = \prod_{g \in \mathcal{G}_i} \left(\frac{P_{git}}{P_{gi,t-1}} \right)^{s_{git}},$$

where s_{git} denotes the average revenue share of product in g in firm i's between years t and $t-1$. If a firm–product–year observation is missing, both the corresponding price relative and its revenue share are excluded from the aggregation. The remaining revenue shares are renormalized so that they sum to one within each firm-year. If a firm-year price relative cannot be computed, we replace it with the price relative of the firm's four-digit industry price.

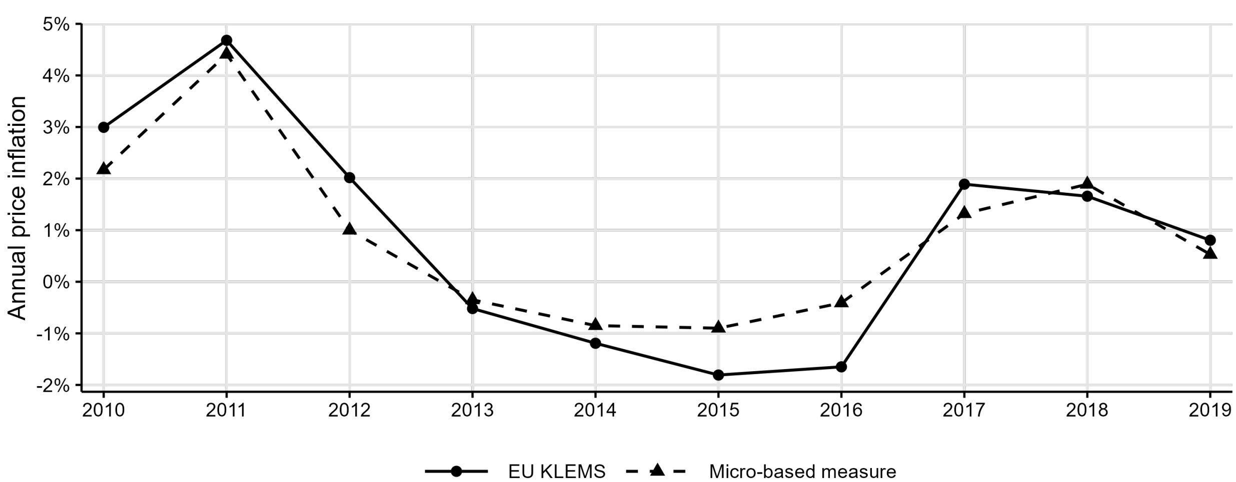
[10]In France, INSEE undertakes a wider survey than Prodcom, called ProdFra (acronym for Production Française). The ProdFra headings are usually coded on 10 digits, the first eight repeating the Prodcom code if it exists. In our analysis, we include only products available in Prodcom, for cross-country comparison.

The firm-year price relatives are chained forward to obtain the firm-level price index P_{it}, with the base year normalized such that $P_{i,2010} = 1$.

Even with granular Prodcom data, there could still be mismeasurement of prices versus quantities. Our MDI data harmonization takes into account the unit of measurement in each observation of Prodcom so that unit-values are based on common units for each product code. However, the firm-level price index could have remaining unobserved quality components. In our empirical procedure these will be absorbed by the mark-up estimate. Under our assumption that the unobserved perceived quality is time-invariant at the firm-product level over our horizon, our pass-through (=change in markup) estimate by demand group will capture true pricing changes.

As a check on the quality of the Prodcom price data, we construct a total manufacturing price inflation series by weighted aggregation of firm-level price relatives. The resulting micro-based series closely tracks the EU KLEMS manufacturing deflator over 2010–2019, with a correlation of approximately 0.96 (see Figure 1).

Figure 1: Aggregate manufacturing price inflation: micro-based measure and EU KLEMS



To measure price developments among competitors, we construct a competitor price index, P^c_{it}. For each firm i in year t, competitors are defined as all firms other than firm i operating in the same four-digit industry classification. The competitor price relative is computed as the revenue-weighted average of firm-level price relatives of all other firms in the same industry, excluding the focal firm. Chaining these price relatives over time yields the competitor price index, P^c_{it}. We choose 4-digit industry as the appropriate market definition, as at higher levels of aggregation market shares of the largest firms are so low that the market will not exhibit meaningful strategic interaction between firms.[11]

Demand Instruments To estimate firm-level price responses to demand fluctuations, we need to identify the slope of the supply curve. This requires exogenous shifts in demand, for which we propose two 'dowstream' instruments.[12] The first is defined at the industry–year level using international input–output linkages, while the second is defined at the firm–year level using product-level trade flows.

The instruments follows the logic of the downstream demand instrument proposed by Shea (1993a,b) and applied in recent work such as Boehm and Pandalai-Nayar (2022). The first measure is closest to the Shea-specification and uses the OECD Inter-Country Input–Output (ICIO) tables, which report intermediate input flows between industry-country pairs at the two-digit NACE Rev.2 industry level for 76 countries and the rest of the world.[13] We construct, for each industry in France, a downstream demand indicator based on the

[11] In our pricing equation, the competitor's price variation is needed to estimate the pass-through parameter. To avoid bias in estimating pass-through, a firm-level price index that relied on the 4-digit proxy for a missing price relative, is set to missing and thereby excluded in estimation of the price equation.

[12] We assume that exogenous demand shocks take the form of proportional shifts in the level of residual demand, leaving invariant structural demand parameters η_d and ρ_d (consistent with the "firm's eye view" of Mrázová and Neary (2017)).

[13] Data are available at OECD Inter-Country Input-Output tables.

growth in input expenditures of its downstream industry-country pairs.

$$DS^{Shea}_{mt} = \sum_{j \in J_{mt-1}} s_{mjt-1} \Delta ln M_{jt}$$

where s_{mjt-1} denotes the sales shares of industry m to destination j in year $t-1$, and $\Delta ln M_{jt}$ represents the aggregate growth rate of destination j's real input between years t and $t-1$.

The ICIO flows are reported in current U.S. dollars. We first convert these values into national currencies and deflate them using sectoral price deflators when available (from Eurostat, OECD STAN, or EU KLEMS), or the country GDP deflator otherwise. To strengthen exogeneity, we exclude destination industries if: 1) j's input expenses are purchased for more than 5% from m, or 2) m's input expenses are purchased for more than 5% from j. Domestic destinations are also excluded to reduce potential simultaneity between domestic supply shocks and downstream demand.

Our second measure also is in the spirit of Shea and captures the potential impact of global shocks at the product level using international trade data from the UN Comtrade database.[14]. The data report bilateral trade flows at the six-digit Harmonized System (HS) level.

For each product, p, we construct a world demand indicator defined as the growth rate of world imports excluding imports from France, $\Delta ln WID_{pt}$.

Trade values are reported in current U.S. dollars and are deflated using the U.S. GDP deflator, which is commonly used as a proxy for a global import price index (see, e.g., Gopinath et al. (2020)). We then construct a firm-level demand shock by aggregating these product-

[14]Available at UN Comtrade.

level demand indicators using firm-specific revenue weights derived from the Prodcom data:

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

where s_{ipt-1} and $\mathcal{P}_{it-1}$ are the share of firm i's revenue from product p and firm i's product portfolio, respectively, in year $t-1$.

To link Comtrade data to ProdCom data, we use Eurostat concordance tables between eight-digit Prodcom codes and HS6 product codes. When a Prodcom code corresponds to multiple HS products, the corresponding demand shock is computed as the average across matched HS codes.

The estimation sample includes firms in industries covered by Prodcom (primarily manufacturing and related sectors) that can be consistently linked across the SBS and BS datasets. Requiring an inner merge ensures that all firms have complete information on inputs, financial variables, and prices. After adding the downstream demand indicators, the final firm panel contains 146,574 firm–year observations for the period 2011–2020, covering 33,237 firms.

In summary, the firm panel provides measures of revenue and material expenditures, full-time equivalent workers, compensation of employees, the firm-level price index, competitors' price index, and exogenous downstream demand indicators. The logarithm of real output, y, is computed as the log of revenue deflated by the firm-level price index, log labor input, l, is the log of FTE workers, log real intermediate input, m, as the log of material expenditures deflated by sectoral price indices and log real capital, k, is the log of book value deflated by sectoral capital price indices. Firm-level marginal costs, mc_{it} are proxied by unit variable costs, defined as the ratio of total variable expenditures (labor compensation plus intermediate input expenditures) to output. These data are used to estimate how firms adjust prices in response to demand and cost fluctuations, which allows us to recover the parameters underlying the slope of the macro Phillips curve. Table 1 reports descriptive statistics for our sample.

Table 1: Descriptive statistics

	Mean	Median	95^{th} Percentile
Revenue	22.97	2.34	63.79
Employment	66.45	14	230.25
Number of products	4.72	2	12
Firm's industry share	1.04%	0.1%	3.71%

Note: Descriptive statistics from the firm panel used in the empirical analysis. *Revenue* is reported in million euros. *Employees* are measured in full-time equivalents. *Products* correspond to 8-digit Prodcom product classes. *Shares* are based on revenue at 4-digit NACE.

4 Clustering

The micro-founded NK pricing equation (eq. 10) derived in Section 2 is rewritten below. The equation depends on two structural parameters for heterogeneous supply and demand, ν_s and ρ_d. An important contribution of this paper is to provide a method to map each firm i to a supply group, s, and a demand group, d, or more generally to cluster $j = (g_s(i), g_d(i))$ along the dimensions of supply and demand. Our method is similar in spirit to k-means clustering: we allocate firms to a supply or demand group in order to improve model homogeneity within a group while allowing model heterogeneity across groups.

$$\pi_{jt} = \kappa\rho_d\hat{c}_{jt} + \kappa\rho_d\nu_s\hat{y}_{jt} + \kappa(1-\rho_d)\hat{p}^c_{jt} + \beta E_t\pi_{j,t+1}.$$

As typical in panel data estimation, to have sufficiently large samples while allowing some degree of model heterogeneity, parameters are restricted to be constrained across units in a group, while being allowed to vary across groups. The traditional approach in empirical studies with firm-level data, is to allow the parameters to vary across groups defined by a particular level of aggregation of the industry classification. However a statistical "industry" is not necessarily designed to be comprised of firms with a common production technology and facing the same demand conditions. As noted by McGuckin (1993), classification systems such as the U.S. Standard Industrial Classification mix different organizing principles: some industries are defined by production technologies, others by product markets, and others by materials used. For example, a market may be served by goods produced with different technologies (e.g., wooden and metal park benches), while similar production technology may by used to serve distinct markets (e.g., men's and women's garments). As a result, firms within the same industry code may face very different marginal cost structures and competitive environments.

Thus, a key empirical challenge is that the two dimensions of heterogeneity do not necessarily align. Firms with similar production technologies may face different competitive environments and therefore exhibit different strategic complementarity. In contrast, firms facing similar demand conditions may operate with different marginal cost structures. Estimating the pricing equation while ignoring this two–dimensional heterogeneity would therefore pool firms with different structural parameters and bias the estimated price responses. To address this issue, we map firms into clusters that are homogeneous along both supply and demand dimensions. Within each cluster, j, firms share common production function parameters that determine the level and slope of marginal costs and common demand parameters that determine price pass-through. We treat this partition of our dataset as a fixed economic environment and in further statistical analysis treat the classification in the same way that researchers treat statistical agency classifications, such as NAICS or NACE.

The remainder of this section proceeds as follows. We first describe the estimation of the production parameters and the demand parameters. Next, we describe the iterative algorithm used to assign firms to groups, then discuss the resulting distribution of firms across supply and demand groups. Finally, we reflect on the usefulness and validity of the clustering procedure.

4.1 Heterogeneity in Production technology

Consistent with the model, we estimate a Cobb–Douglas production function using a dynamic panel GMM specification. The estimating equation is:

$$\delta y_{it} = \alpha_s + \alpha_s^k \delta k_{it} + \alpha_s^l \delta l_{it} + \alpha_s^m \delta m_{it} + \alpha^t t + \epsilon_{it},$$

where y_{it}, k_{it} , l_{it}, and m_{it} are log of output, capital, labor, and intermediate inputs, respectively, as described in section 3, and t is time. The operator δ denotes in this case first quasi-differences of the variable (i.e., for any variable x, $\delta x_t = x_t - \rho x_{t-1}$). The returns-to-scale parameter is computed as $\gamma = \alpha^k + \alpha^l + \alpha^m$.

The estimation follows an approach often used in the production-function literature, assuming that firm-level productivity evolves as an AR(1) process correlated with variable inputs. The dynamic specification quasi-differences the variables to remove the productivity shock, while lagged inputs, as well as current capital, serve as instruments in the GMM estimation. The estimated production parameters determine the slope of the marginal cost curve, through $\nu = (1-\gamma)/\gamma$, as well as its level through total factor productivity productivity (TFP), which is computed for each supply group as the difference between output and the elasticity-weighted contributions of capital, labor, and intermediate inputs.

4.2 Heterogeneity in Demand

Consistent with our model of demand, we need to classify groups of firms by their cost pass-through in order to take equation 10 to the firm-level data. We specify a simple reduced-form pricing model to separate firms with heterogeneous pass-through parameter, ρ_d, with the cluster algorithm targeting the homogeneity of the model within groups.

We estimate

$$\delta p_{it} = \alpha + \alpha^t t + \rho_d \delta \hat{mc}_{it} + \epsilon_{it},$$

where δp_{it} denotes the log first-difference in the firm price index, $\delta \hat{mc}_{it}$ represents an exogenous shock to marginal costs, t is time, and α and α^t are a constant and time trend. To isolate cost shocks, we construct $\delta \hat{mc}_{it}$ as the residual from a regression of the log first-difference of marginal cost, δmc_{it} on downstream demand shocks.

4.3 Clustering algorithm

We implement the two-dimensional clustering algorithm proposed by Aglio and Bartelsman (2026), which assigns firms to groups based on their fit to the two empirical relationships. In our implementation for this paper, the clustering procedure alternates between estimating the production function and the cost pass-through group-specific parameters and reassigning firms across groups, first along the supply dimension and then along the demand dimension, to minimize the GMM objective function. The final cluster of a firm, $j = (g_s(i), g_d(i))$, is the combination of its supply-group mapping $g_s(i)$ and its demand-group mapping $g_d(i)$. To reduce computational complexity, it is assumed that each firm stays in its assigned cluster for the entire period. Based on evidence on the lumpiness and persistence of firm production technologies, the assumption seems justifiable (for example, see Cooper and Haltiwanger (2006), who observe infrequent investment spikes; see also Syverson (2011) for survey on persistent productivity differences across firms). Details of the algorithm are provided in Appendix A.

To initialize the procedure, firms are sorted according to labor productivity and to the ratio of price to marginal cost growth. Visual inspection of the empirical distributions of these variables suggests partitioning firms into five production clusters and three demand clusters. In particular, the distribution of labor productivity exhibits a pronounced right tail, indicating an important group with frontier technologies, while the distribution of price–cost growth ratios is closer to symmetric and supports the partitioning into three demand groups. In Appendix A, we show our decision tree based on observables that is used to determine the number of clusters.

4.4 Clustering results

In this section we provide descriptive results, and refer to Appendix A for econometric details. Table 2 shows estimates of TFP, A_s and the slope of the supply curve, ν_s, by supply group in the left panel, and the pass-through parameter, ρ_d, by demand group in the right panel. Productivity increases and the supply curve slope decreases monotonically from supply group 1 to supply group 5. In supply group 5, marginal costs are nearly flat, with a slope of 0.016. Cost pass-through increases monotonically from demand group 1 to demand group 3, from a value of .107 to .979, consistent with empirical evidence that price-cost transmission is typically incomplete (Gopinath and Itskhoki (2010), De Loecker et al. (2016)).[15] In the remainder of the paper, we will generally refer to increasing supply group and increasing demand group, but may refer to higher productivity or flatter marginal cost for the former, and to higher pass-through for the latter.

Figure 2 shows some distributional features of the clusters. Panel (a) reports share of firms per cluster, with the supply group in rows and the demand group in columns, and row and column totals. Similarly, Panel (b) reports the revenue share of firms per cluster (averaged over time).

[15] As a robustness check, we use computed TFP as an exogenous (negative) cost shock (see, e.g., Foster et al. (2008)), and estimate the same cost pass-through equation with qualitatively similar results; 0.17 for demand group 1, 0.75 for 2, and 0.83 for demand group 3.

Table 2: Supply and Demand group parameters

Supply	TFP	SC-Slope (ν_s)	Demand	Pass-through (ρ_d)
1	.007	.222	1	.107
2	.133	.203	2	.670
3	.622	.164	3	.979
4	.949	.115		
5	1.340	.016		

Figure 2: Shares by cluster
(in percent)

Note: The shares by cluster are shaded with a heatmap given in the legend. The marginal distributions by supply and demand group are given by the right column and bottom row, respectively.

The firms initially were distributed uniformally along the supply and demand groups. After clustering, the share of firms is bell-shaped by supply group. The share of revenue increases monotonically with cost pass-through, for all supply groups, except in the highest supply group, where the increase is not monotonic. Along supply groups, revenue shares increase through the fourth supply group and then decline, for all demand groups. Slightly more than fifty percent of total revenue is generated by firms in the highest two supply and two demand groups.

In Appendix B, we show similar heatmaps for average firm size and price-cost markups by cluster. Average firm size increases by demand group in the two lowest productivity groups, but is hump shaped in the higher productivity groups. The highly productive firms can scale without significantly raising costs, but likely demand such that it is more profitable to retain mark-ups. Markups are increasing by supply groups, for all demand groups, while they are generally declining in cost pass-through, albeit at a steeper rate for the high supply groups.

Table 3: Descriptive statistics and estimated parameters by supply cluster

Supply	*N^o firms*	*size*	*lprod*	*mc*	γ	α_{k+l}	*markup*	γ^{ACF}
1	2052	4.08	4.47	2.13	.818	.179	.93	.911
2	10454	5.44	4.89	1.10	.831	.186	1.03	.926
3	13856	11.94	5.24	.85	.859	.228	1.11	.931
4	5447	39.75	5.68	.61	.897	.297	1.24	.950
5	1428	75.44	6.41	.42	.984	.453	1.29	.962

Note: *N^o firms* refers to the number of firms; *size* is average sales per firm in millions of euros; *lprod* means labor productivity in logs; *mc* are marginal costs proxied by unit variable costs as computed in the main analysis; $\gamma = \alpha_k + \alpha_l + \alpha_m$; $\alpha_{k+l} = \alpha_k + \alpha_l$; the *markup* is over intermediate inputs and estimated as in Loecker and Warzynski (2012); γ^{ACF} is the sum of output elasticities from a output production function estimation with ACF methodology.

Table 3 reports descriptive statistics across the production technology groups. The number of firms, firm size, labor productivity and marginal costs can all be computed directly from the data for firms in each supply group. The next columns show the sum of capital and labor output elasticities, and the markup, both of which require parameters from the production function estimation. All economic measures increase monotonically by supply group, except marginal costs which decrease monotonically. Returns to scale estimated using the approach of Ackerberg et al. (2015), γ^{ACF}, is positively correlated with TFP and negatively with the slope of the marginal cost curve, ν, shown in Table 2).

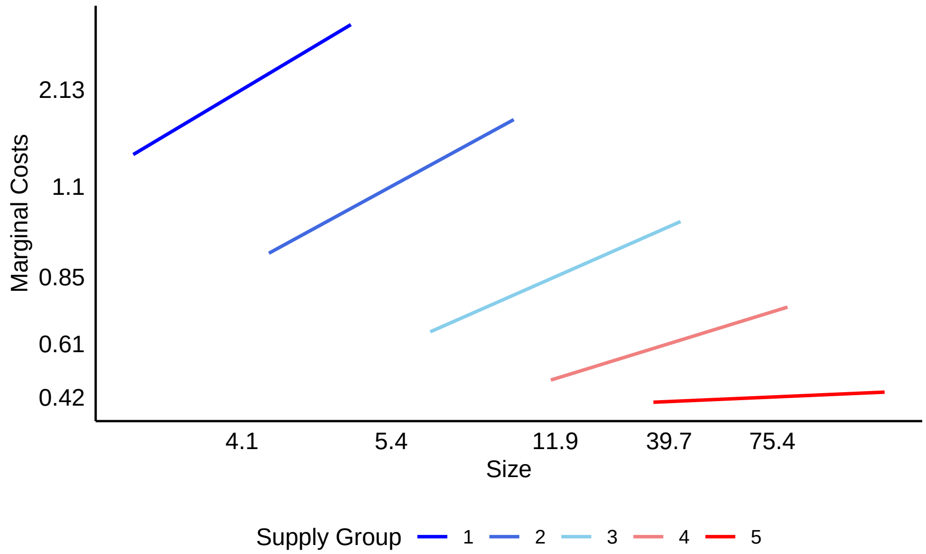
The information on marginal costs, average firm size, and the estimated slope of the marginal cost curve is used in Figure 3. The figure shows for each supply group, a linear marginal cost curve with its estimated slope, centered around each group's marginal cost and average firm size (in million Euro). The figure highlights that higher supply groups have lower marginal costs and flatter supply curves, and result in larger firms, on average. A wide variety of summary statistics by supply and demand cluster are shown in Appendix B, for example industry composition, wages, export intensity, price-cost markups, and innovation scores.

4.5 Validation

Clustering firms according to production and demand characteristics allows economically meaningful heterogeneity across clusters while improving model homogeneity within supply and demand groups. We provide evidence on the first point by considering marginal cost curves from production function estimation where parameters are constrained within 2-digit industries and contrasting them with marginal cost curves based on estimation where parameters are constrained within supply group. We provide evidence on model homogeneity through clusteringin Table 4.

Figure 4 displays results for five groups of industries, by allocating the 2-digit industries

Figure 3: Heterogeneous production technology

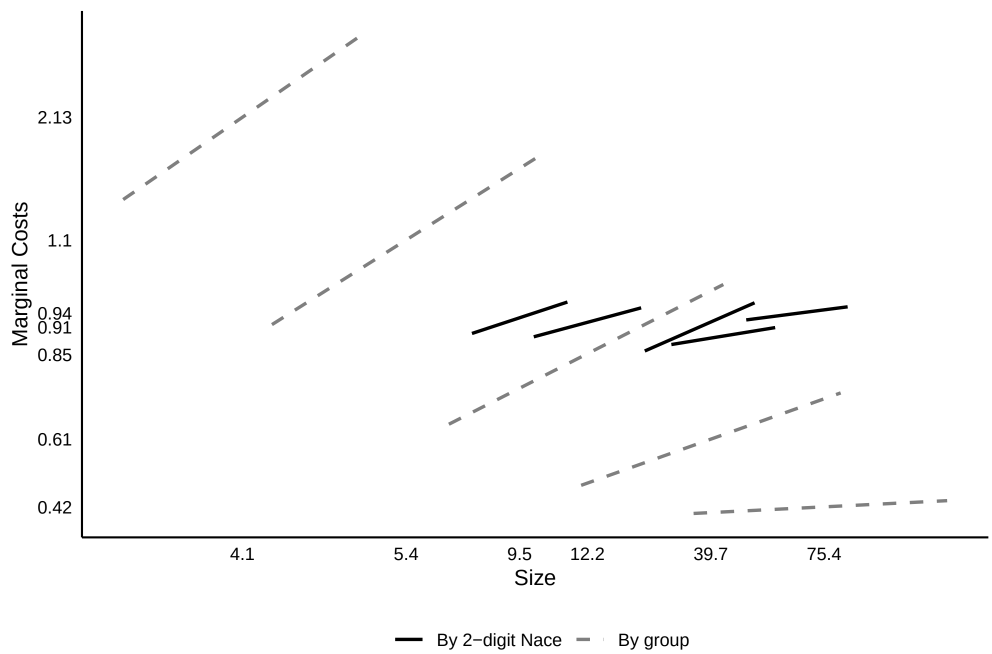


Note: Firms' supply curves, by supply group. Data on marginal costs and average firm size are shown in Table 3 and the estimated slope of the marginal cost curve is shown in Table 2.

into five industry-groups, based on the 2-digit industry's average level of productivity. For each group, we take the weighted averages of the 2-digit industry production function parameters and data. The figure then shows for each industry-group (in black lines) the average marginal costs, the average marginal cost slope parameter and the average firm size. The industry-based marginal cost curves are shown alongside the supply-group based marginal cost curves (dotted lines) that already were shown in Figure 3. Not much meaningful heterogeneity remains in the industry-based groups that could be used for distinguishing the effect of structural change on the aggregate Phillips curve slope.

On model homogeneity, Table 4 compares the fit of our regressions when allowing parameters to vary by groups of firms clustered using our algorithm versus allowing parameters to vary by various "levels" of industry disaggregation in the NACE classification hierarchy. For both the production function estimation and the cost pass-through estimation, the clustering classification with parameter variation across five and three supply and demand groups, respectively, yields a substantially lower sum of squares residuals than even the 4-digit NACE

Figure 4: Industries vs Supply Groups



Note: Firms' supply curves, by supply group and based on 2-digit industries. 2-digit industry data are aggregated into five groups, based on the industry's average level of productivity.

classification with parameter variation across roughly 200 manufacturing industries.

Table 4: Model Fit (RSS), by classification level

Classification:	Clusters	1-digit NACE	2-digit NACE	3-digit NACE	4-digit NACE
Supply (eq. 4.1)	13312.77	24639.16	20561.64	22491.83	26585.04
Demand (eq. 4.2)	1933.78	3018.09	2964.39	2921.25	2876.60

Note: The table shows the total residual sum of squares (RSS) for regression models that are estimated with parameters constrained to be common across firms belonging to the same classification cell. Note that the Demand equation is estimated with OLS, so that the RSS declines by construction when parameter restrictions are loosened from 1-digit to 4-digit. By contrast, the GMM used for the Supply equation minimizes a weighted moment criterium that is not equal to RSS.

5 Micro Results

The empirical objective is to estimate the heterogeneous parameters entering the MAPC. We begin by estimating the cluster-level pricing equation implied by our theoretical framework.

We rewrite equation 10 below for ease of exposition.

$$\pi_{jt} = \kappa\rho_d\hat{c}_{jt} + \kappa\rho_d\nu_s\hat{y}_{jt} + \kappa(1-\rho_d)\hat{p}^c_{jt} + \beta E_t\pi_{j,t+1}$$

To move from theory to our empirical firm-level specification, we use the the algorithm implemented in the previous section to map each firm to one of the fifteen clusters, $j = (g_s(i), g_d(i))$, based on their production technology and their proportional cost pass-through. Next, we absorb the expectations for price changes, $E_t\pi_{j,t+1}$, as well as the marginal costs that vary through movements along the input supply curves, $\hat{c}_{jt}$, with market-year fixed effects.[16] This results in the following micro pricing equation to be estimated:

$$\delta p_{it} = \beta^y_j \delta\hat{y}_{it} + \beta^c_d \delta p^c_{it} + \alpha_i + \alpha_{mt} + \epsilon_{it} \tag{12}$$

where δp_{it} and δp^c_{it} are the log first-difference of firm i's price and the competitors' price, respectively, and $\delta\hat{y}_{it}$ is the predicted value of a first stage regression of output growth on the downstream instruments (described in Section 3). The parameters β^y_j, which represent the NK equation parameters $\kappa\rho_d v_s$, are allowed to vary by cluster $j = (g_s(i), g_d(i))$. The parameters β^c_d, which represent the NK equation parameters $\kappa(1-\rho_d)$, are allowed to vary by demand group $d = g_d(i)$. The parameters α_i are firm fixed effects. Because we do not have input market specific indicators in our data, we proxy the market-year fixed effects, α_{mt}, with either 2-digit or 4-digit NACE industry-year dummies, with qualitatively similar results. In all our regression specifications, observations are weighted by their revenue share.

Table C2 in Appendix C.1 reports the results for the first stage estimation of firm output growth on the two downstream indicators interacted with supply and demand cluster

[16] The effect of changes in the position of the marginal cost curve on prices is the main object in the estimation of Gagliardone et al. (2025), who sweep out effects arising from heterogeneous marginal cost curve slopes. If we include $\hat{c}_{jt}$, proxied by firm-level TFP estimates from the clustering procedure, in our estimation, the slope parameters are little changed.

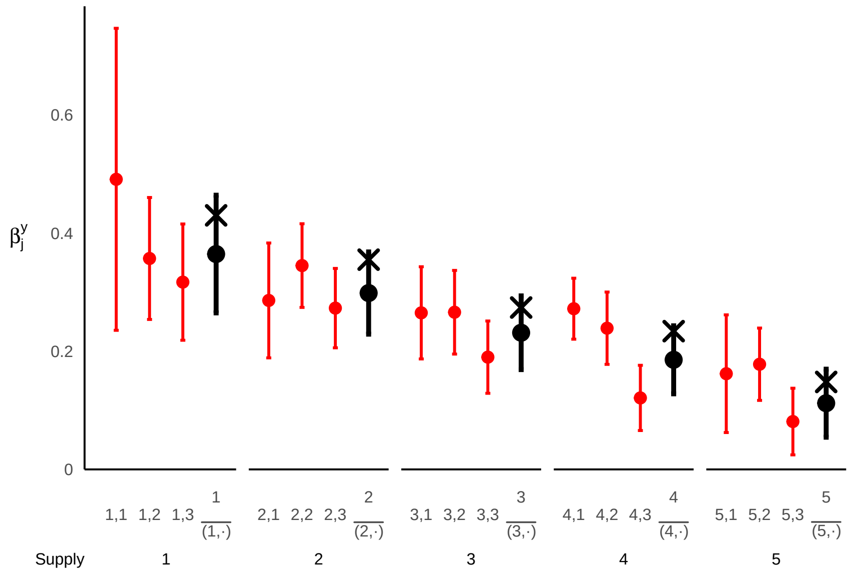
dummies. To start, the F-test confirms that the instruments are relevant and that despite insignificance of the trade-based instruments, we reject that the instruments are jointly weak. Consistent with profit maximization in monopolistic competitive markets, we expect that firms with flatter marginal cost slope are more likely to accommodate demand shocks. We apply a slope test to confirm that the coefficients on the exogenous demand shocks increase by supply cluster, for both instruments.

Before analyzing the detailed results of the second stage estimation of the firm-level pricing equation, we summarize the main result of this paper in Figure 5. The figure shows, in black dots, the supply-cluster average parameter $\bar{\beta}^y_{s,\cdot} = \sum_d w_{s,d}\beta^y_{s,d}$ with its confidence interval, for each supply cluster, where $w_{s,d} = \frac{y_{s,d}}{\sum_d y_{s,d}}$ is the revenue share. The response of prices to demand shocks declines monotonically by supply cluster. Firms in the highest-productivity cluster exhibit approximately one-third the price response of firms in the lowest-productivity cluster. The average response in each supply cluster is lower than the price response when the parameter estimation does not control for variation across the demand clusters, i.e., $\bar{\beta}^y_{s,\cdot} < \beta^y_s$, where β^y_s is labeled with a black 'x'. The figure further shows the full set of β^y_j estimates for all clusters $j = (s, d)$.

Turning to full estimation results in Table 5, the coefficients $\beta^y_{j=(s,d)}$ used in Figure 5 and their standard errors are shown in supply row s and demand column d. To test whether the slope coefficients decline significantly with our supply groups, for each demand group, we multiply each coefficient with a matched element of linearly increasing vector with mean zero, and test whether the sum is negative, ie $H0 : t_d = 0$, $H1 : t_d < 0$, where $t_d = -2\beta^y_{1,d} - 1\beta^y_{2,d} + 0\beta^y_{3,d} + 1\beta^y_{4,d} + 2\beta^y_{5,d} < 0$). The significance of this one sided test for each demand group is shown in the table row labeled 'H1: $t_d < 0$'.

The coefficients on competitors' prices, β^c_d are all significant and decline by demand group,

Figure 5: Slope of pricing equations by cluster



Note: estimated β_j^y by supply-demand cluster from Table 5 (in red), and their weighted averages by supply group (in black dot). 95% confidence intervals constructed based on variance-covariance matrix of coefficients. Estimated β_s^y that only varies by supply group is also reported (in black X).

with group three having the highest pass-through. $\beta_{\cdot,3}^y < \beta_{\cdot,1}^y$ is lower for the demand group 3 than for group 1, for all supply groups. The coefficient of competitors price on own price, β_d^c declines by demand cluster. Lower strategic complementarity also implies higher cost pass-through. Combining these results, we can infer that the slope parameter ν within each supply group increases with strategic complementarity. We return to this in our conclusion section, but point out the possibility that ρ and ν are not independent objects, but that firms may invest both to improve their supply and to influence demand to allow higher pass-through.

In robustness checks, Appendix C, we document different versions of our pricing equation, namely i) where β_s^y varies across supply groups and β^c is fixed for all firms, with the pricing equation estimated with instrumental variables, and ii) and iii), where both parameters specifications are estimated using GMM. In the GMM version, the competitors' price

Table 5: Firm pricing equation by supply - demand cluster

		δp_{it}		
	supply	demand		
		1	2	3
β^y_{sd}	1	0.491**	0.357***	0.317***
		(0.213)	(0.086)	(0.082)
	2	0.286***	0.345***	0.273***
		(0.081)	(0.059)	(0.056)
	3	0.265***	0.266***	0.190***
		(0.065)	(0.059)	(0.051)
	4	0.272***	0.239***	0.121***
		(0.043)	(0.051)	(0.046)
	5	0.162**	0.178***	0.081*
		(0.083)	(0.051)	(0.047)
β^c_d		0.233***	0.134***	0.043**
		(0.011)	(0.013)	(0.019)
2 digit Industry-Year fixed effects			Yes	
Firm fixed effects			Yes	
H1: $t_d < 0$		-2.96***	-3.64***	-5.22***
Obs			146574	
R^2			0.21	

Note: 2sls regression at the firm level. observation weighted by the share of nominal revenue. Standard error clustered by 2-digit sector shown in parenthesis. *** p<0.01, ** p < 0.05, * p < 0.1. t_d shows significance of the one-sided t-test that the coefficients jointly decrease by supply cluster ($t_d = -2\beta^y_1 - \beta^y_2 + \beta^y_4 + 2\beta^y_5 < 0$).

variable is identified through a separate set of moment conditions based on its lagged values. The size of β^y and its variation between supply groups is quantitatively very similar across specifications, although the slope parameter on output in the GMM version is lower in the highest supply group. Instrumenting the competitor's price in the GMM does not meaningfully change the estimates of strategic complementarity.

It should be noted that our micro pricing equation provides evidence on the structural parameters υ_s and ρ_d of the NK equation 10 up to an unknown factor $\kappa = \frac{(1-\theta)(1-\beta\theta)}{\theta}$, with $\rho_d = 1 - \frac{\beta_d^c}{\kappa}$ and $\upsilon_s = \sum_d \omega_{sd} \frac{\beta_{sd}^y}{\kappa - \beta_d^c}$. Our clustering algorithm provides another set of estimates of υ_s and ρ_d through estimation of separately identified production function and shock pass-through equations. The direct cluster estimates of υ_s and ρ_d are positively correlated with the estimates derived through the micro pricing equation, where the correlation depends on the value of κ. As a back-of-the-envelope consistency check, and assuming no heterogeneity in κ, we can find a value of κ that minimizes the weighted sum of the sum of squared differences between the two estimates, weighting the slope parameter difference more strongly. With this calibrated value of $\kappa = 1.58$, and picking a value for the steady state stochastic discount rate of 0.96 (at an annual rate), we get an annual hazard of not adjusting prices (θ) of 0.31, which compares well with a standard value used in the literature of 0.74 at a quarterly frequency (details of the calibration are shown in Appendix C.6).[17]

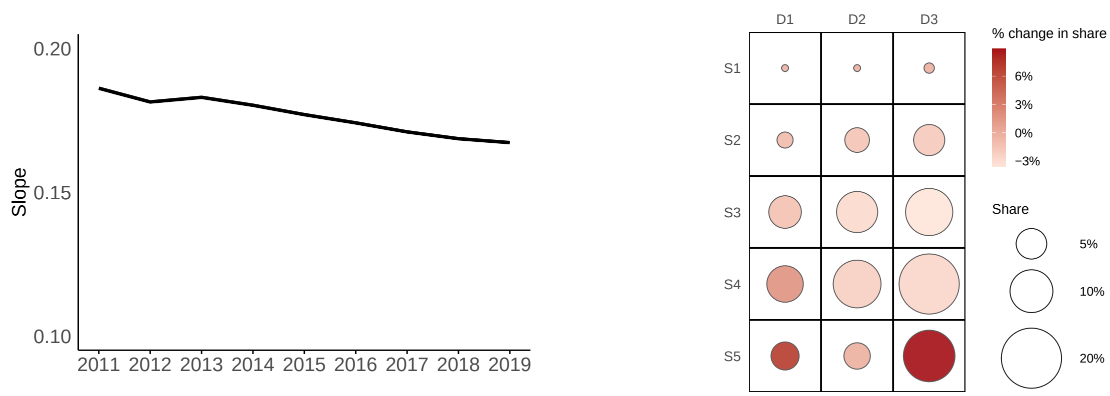
We summarize the micro evidence: i) Supply groups differ strongly in ν_s and demand groups differ strongly in ρ_d; ii) Overall, the price response of firms to demand shocks decreases with productivity, for each demand group and on average across demand groups; iii) Within each supply cluster, the revenue share of firms increases in pass-through; iv) Interestingly, within supply clusters we see that, with constant κ, pass-through and supply-curve slope are negatively correlated—high pass-through firms in a supply cluster have flatter slopes than firms in that supply cluster with lower pass-through; v) The numerically different parameter estimates from the clustering procedure and from the micro pricing estimation can best be reconciled with a Calvo price stickiness parameter of 0.31 (or 0.74 at a quarterly frequency). In the next subsection, we turn to the implication of our findings that the micro-level heterogeneity of firms matters for the aggregate Phillips curve.

[17]We weight the slope differences with 0.9 and the pass-through with 0.1. Equally weighting the sum of squared residuals for the two parameters increases the stickiness parameter to .37 (quarterly .78). If we use the κ that provides the best fit for only the pass-through parameter, θ increases to 0.6 (.88 quarterly), which is above the plausible range.

5.1 From micro to macro

In Section 2, we derived the MAPC as the weighted average of each (group of) firm's supply curve. In this section, we sketch how practitioners can use firm-level panel data estimates of NK supply curves by supply and demand cluster for policy analysis. First we show how the MAPC slope changes as the revenue share of clusters evolve over time. This slope provides the aggregate price response if all clusters receive the same effective demand shock. Next, we show for years 2020 to 2022 the relation between the historically estimated slope of each clusters' supply curve and the effective demand response to downstream demand shocks.

Figure 6: Micro-aggregated Phillips curve

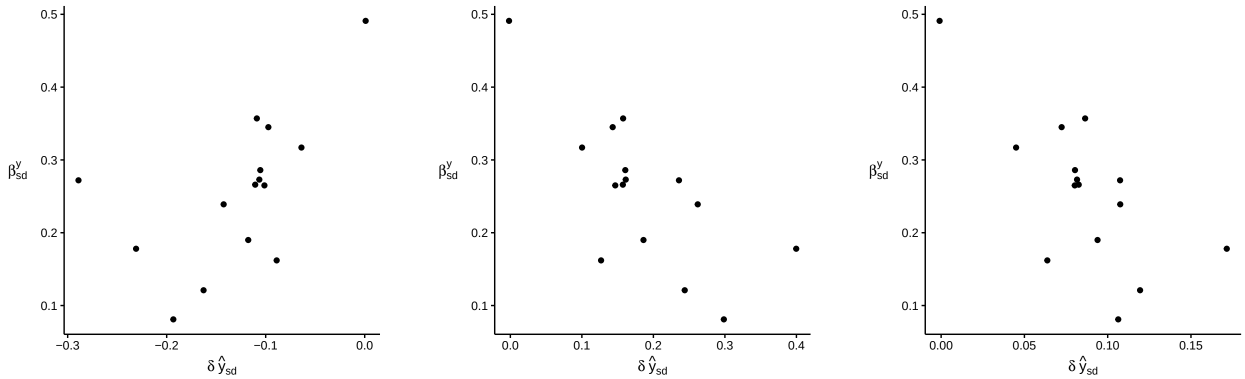


(a) Slope of the MAPC (b) Change in cluster shares

Note: MAPC slope is computed as the weighted average of the estimated slopes of firms' pricing equations from Table 5. Weights are revenue shares in each cluster.

The MAPC is a weighted average of the fixed slope estimates of the micro pricing equation for each cluster. The slope coefficients for each supply cluster are shown in Table 5 and the weights are annual revenue shares of each cluster. Another way to interpret our micro-aggregated slope is through our assumption that each cluster has its own time-invariant Phillips curve. The aggregate price effect sums the change in a cluster's output gap times its slope, weighted by revenue shares. In Figure 6a, it is assumed that each cluster faces the same output gap. In general, for real time policy analysis, the output gaps are based on the cluster-specific response to shocks and the slope of the MAPC is the revenue share weighted

Figure 7: Slope and demand shocks by cluster



(a) 2020 (b) 2021 (c) 2022

Note: β^y_{sd} is the cluster-specific slope of the pricing equation in Table 5; $\delta\hat{y}_{sd}$ is the cluster-specific weighted average of output growth explained by downstream demand indicators.

price response (cluster-specific slope time shock) divided by the revenue share weighted cluster output gap.

Differing weighting schemes can be considered to extrapolate the slope of the MAPC, depending on the analysis being conducted. The micro-aggregation we display, using time varying revenue shares as weights, is meant to provide evidence on secular changes in the Phillips curve owing to structural change in the economy towards firms with lower marginal costs and flatter marginal cost curves. Our evidence shows a rather stable Phillips curve, with a slope that declines slightly over time. Panel (b) of Figure 7) shows the weights for each cluster (area of circle), but also that the weights grow most over our sample period for clusters with the lowest slope coefficient.

As a display of shocks that can hit different clusters differently, we look at the downstream Shea instruments for the years 2020 through 2021, and use the first-stage coefficients to computer the effective demand shock for each cluster. The supply curve slope for each cluster is then displayed on vertical axis of scatter plots, with the 'predicted' output change on the horizontal axis, in a panels (a) through (c) of Figure 7 for each of the years. While in

2020 the firms with the flattest supply curve had the largest negative demand shock, those same firms had the largest positive shocks in 2021. Clusters with higher slopes had smaller negative and positive shocks in 2020 and 2021, respectively. Panel (c), 2022, shows a similar pattern to 2021, albeit with smaller positive shocks.

A practical advantage of the framework is that estimation of the micro-level parameters can be separated from their macroeconomic application. The demand and supply parameters, together with the expenditure shares of the clusters, can be computed periodically using detailed firm-level panel data. The micro-level work could be done by replicating our methodology[18] on other available micro data sources. Macroeconomic analysis can then be conducted using only the resulting cluster-level aggregates, without requiring access to the underlying confidential microdata. To get an estimate of the contemporaneous MAPC slope one could use revenue impacts of recent and current shocks applied to the appropriate clusters, with their slopes estimated on historical data. The micro-aggregated data include information on e.g. trade intensity, energy intensity, and labor composition by cluster. This information allows linking tariff shocks, energy prices, or differential wage developments to each cluster in order to update weights. While the micro data needed to estimate the slope for each cluster only becomes available with a lag of two or three years, combining the micro-aggregated information with more contemporaneous aggregate variation has been shown to improve macro forecasts when structural micro parameters are stable (see Bartelsman and Wolf (2014)).

6 External validity

To broaden the scope of the study, we replicate the micro-level analysis for other countries using the MDI and we extend the analysis to the entire business sector using micro-aggregated data (CompNet).

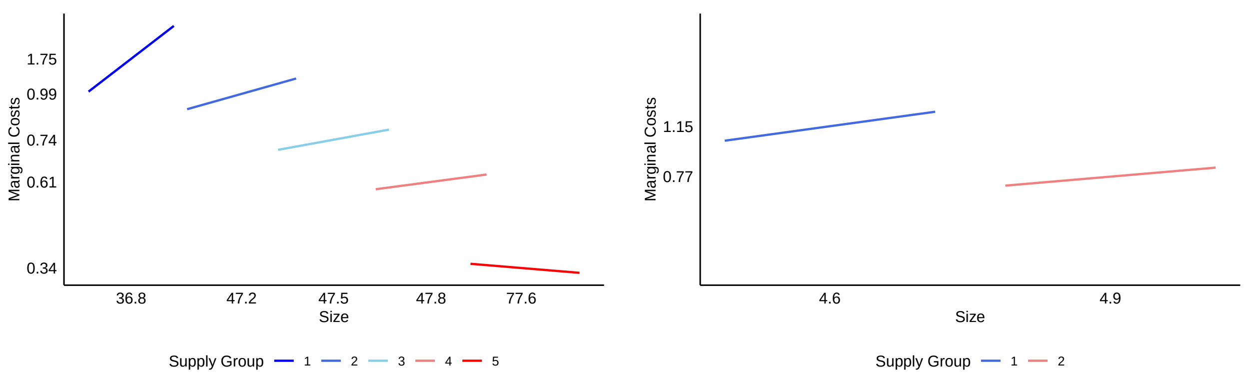
[18]Codes will be available online.

6.1 Cross-country evidence

We replicate the analysis, including data preparation, clustering, and estimation of the firm-level pricing equation using data from the Netherlands and Slovenia for the same sample period.[19]

The replication starts with clustering of firms according to production technology and demand characteristics.[20] Figure 8 shows the level and slope of the marginal cost curves as well as the average firm size by supply group for manufacturing firms in the Netherlands and Slovenia. The pattern of higher productivity and flatter marginal cost curves and increasing firm size by supply cluster is qualitatively similar to that seen for France in Figure 3. Next, the firm pricing equation, (eq. 12), is estimated at the firm-level with parameters varying by cluster. The average slope of β_s^y by supply group is presented in Figure 9.

Figure 8: Heterogeneous production technology - Netherlands and Slovenia



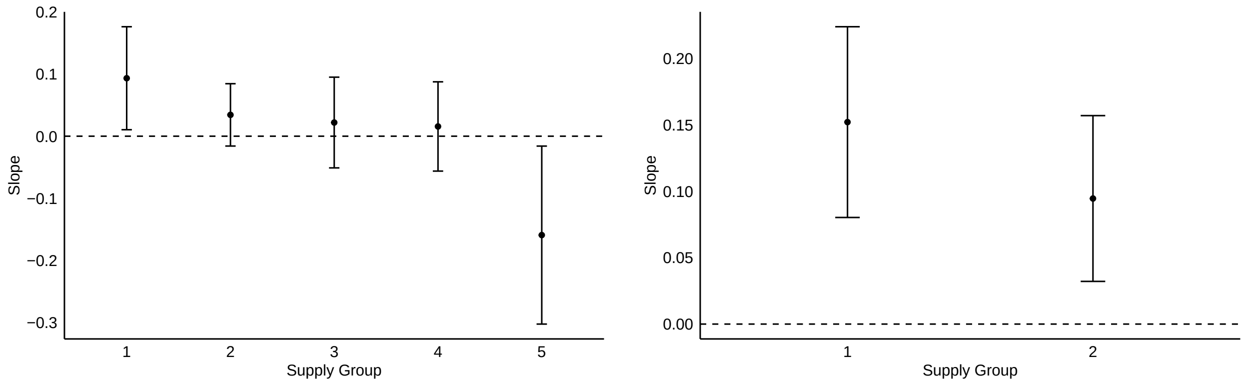
(a) Netherlands (b) Slovenia

Note: Firms' supply curves, by supply group. Marginal costs and average firm size taken from data, while slopes are estimated through the clustering procedure.

[19]The cross-country estimates are from a previous version of the current methodology.The supply curve estimation is identical, but the clustering is based on estimating the production function with OLS rather than GMM. We will update this section, conditional on available funding, using an exact replication of the current research code in a future 'launch' of the MDI for a larger selection of countries.

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

Figure 9: Slope of pricing equations by technology cluster - Netherlands and Slovenia



(a) Netherlands (b) Slovenia

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

6.2 Beyond manufacturing

The above analysis is limited to the manufacturing sector, owing to availability of micro price data (from Prodcom), and the Comtrade data on international trade by detailed product class. In this section, we extend the analysis to non-farm business sectors and to a wider set of countries, using micro-aggregated data from the CompNet database.[21] While we cannot replicate exactly our micro-data analysis, we show that, using a similar specification, the findings for manufacturing and the rest of the economy are substantively similar. While the CompNet data is richer than the micro data in country and industry coverage, it does not allow identification of the underlying micro-level demand and supply clusters using exogenous shocks. Instead, we define supply groups by firm-level productivity levels, making use of our empirical observation that across supply groups, supply curve slopes are negatively correlated with productivity. In estimation of the pricing equation, our slope parameters are allowed to vary by firm productivity quintile, and we find that the most productive quintiles have smaller slopes, both in manufacturing and beyond.

The data used in this extension are micro-aggregated moments, from the so-called *joint*

[21]For more details, please see Haug et al. (2022).

distribution table of CompNet. The joint distribution table includes firm-level indicators aggregated along quintiles of a specific variable, creating 'representative firms' for each quintile of the distribution of the specific variable by country, sector, and year. In our analysis, we use micro-aggregated 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.

Unfortunately, there is no information on prices by productivity quintile in the CompNet data. Instead test our theory on the input price side. This proxy deviates from our micro based work above, where we sweep out changes in marginal costs arising from movements along the input supply curve.[22] In particular, we estimate the following wage growth vs output-gap equation:

$$\delta w_{ciqt} = \beta_q^y x_{ciqt} + \alpha^w \delta w_{ciqt-1} + \alpha^\pi \pi_{ct-1} + \alpha^\psi \psi_{ciqt} + \alpha_{ciq} + \alpha_t + \varepsilon_{ciqt} \tag{13}$$

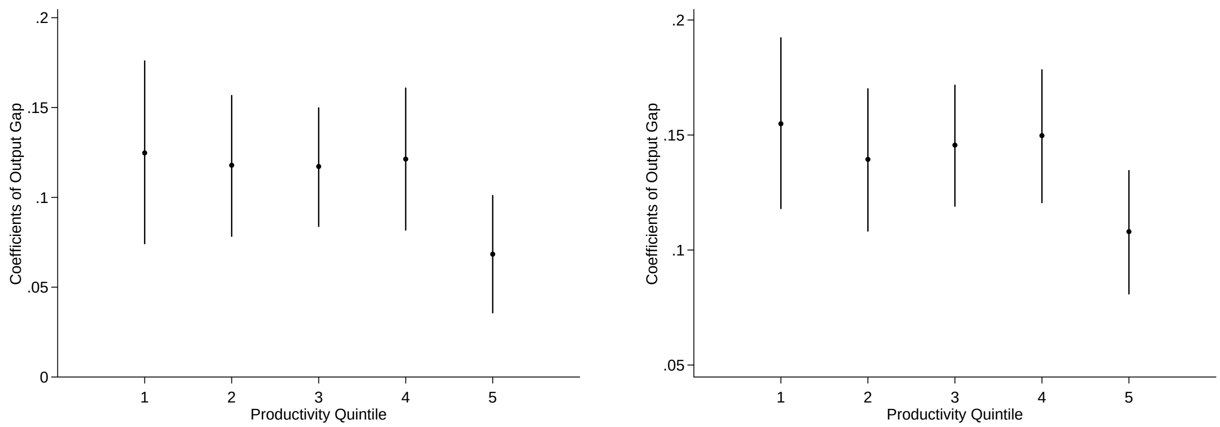
where δw_{ciqt} is real wage growth and x_{ciqt} is the output gap in log-points in country c, industry i, productivity quintile q, and year t. We allow the slope coefficient (the effect of tightening output gap on wage inflation), β_q^y, to vary by productivity quintile. We control for lagged wage growth and country-level inflation, π_{ct-1}, which serves as a proxy for inflation expectations. We also include markdown ψ_{ciqt} to control for variation in monopsony power, as well as country-industry-quintile fixed effects, α_{ciq}, and year fixed effects, α_t, to absorb time-invariant differences across labor markets and common aggregate trend over time. Potential output and the output gap are computed for the representative firm at each productivity quintile.[23] Equation 7 of the theoretical model implies that derived labor de-

[22] The proxy is valid under the assumption that all firms have the same monopsony power in the labor market. In our estimation we control for variation in monopsony power.

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

mand should respond less strongly to output for firms with a flatter slope, ν.

Figure 10: 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, labor 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. 95% confidence intervals are included. The coefficient for the fifth quintile differs significantly from those of the other quintiles at the 5% level, except in the comparison with the second quintile in the "All industries" sample, where the difference is significant only at the 15% level.

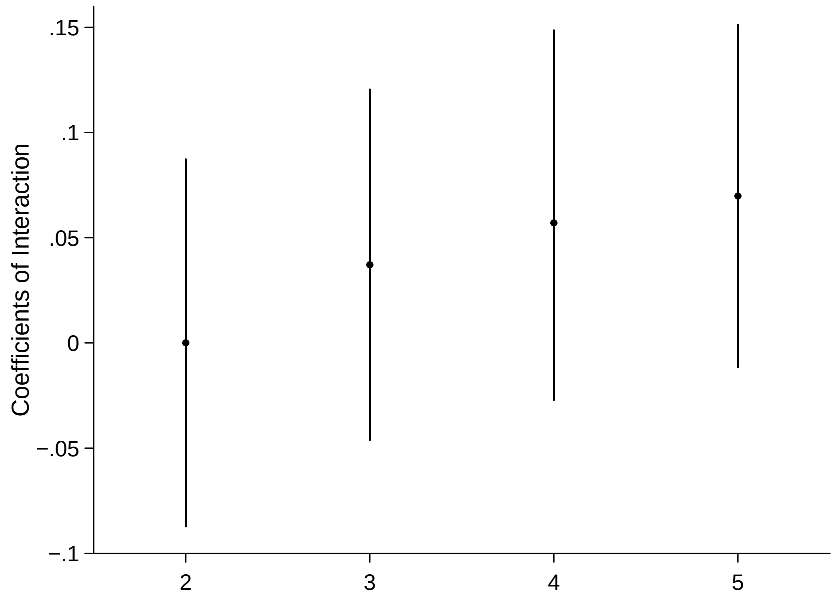
We estimate the wage-to-output relation 13 for each quintile supply group, controlling for labor market power.[24] Figure 10 shows the slope of our equation, by quintle for manufacturing (panel a) and all industries (panel b). The most productive firms show a less responsive wage increase when their available production capacity changes, both for manufacturing and for the whole economy. For comparison with estimates in the macro literature, Appendix Table C8 shows estimates where β^y does not vary by supply group. Our average macro response is in line with the slope estimate of 0.12 used in the ECB-BASE semi-structural model (see Eser et al. (2020)).

In a related reduced-form equation, we regress real sales growth by industry-quintile on

[24]Labor 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 (2022).

Figure 11: 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. 95% confidence intervals are included.

industry aggregate real sales growth, interacted with productivity quintile dummies. As Figure 11 reports, sales growth responds more to increases in aggregate sales for higher productivity quintiles. This reduced-form empirical evidence, consistent 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 firm with the lowest marginal costs. We find that heterogeneous productivity matters, with a lower slope and a higher demand response from more productive firms, similarly for manufacturing and the whole economy.

7 Conclusion

This paper studies how heterogeneity in firms' production technology and demand conditions shapes the aggregate Phillips curve. Building on recent literature on the Phillips Curve, we show that the relevant structural parameters differ systematically across firms and can be identified from firm-level data. This allows us to construct a Micro-Aggregated Phillips Curve (MAPC), where aggregate inflation dynamics depend on both heterogeneous pricing behavior and the evolving composition of economic activity.

Our findings point to a coherent mechanism. Firms differ substantially in both production technology and demand conditions, and this heterogeneity is only imperfectly captured by conventional industry classifications. More productive firms have flatter marginal-cost curves and respond to demand shocks more through quantities than through prices. During our sample period, these firms also increase their revenue shares, implying that structural change itself contributes to a gradual flattening of the micro-aggregated Phillips curve.

The contribution of our paper is methodological as much as empirical. Rather than inferring the aggregate Phillips curve parameters from macro time series or from average firm-level panel data response, we estimate its underlying, heterogeneous, structural components before aggregation. The structural parameters and other micro-aggregated information are then used for further macro analysis. The resulting MAPC separates estimation of microeconomic behavior from macroeconomic analysis, providing a practical framework for updating Phillips-curve estimates as the composition of firms evolves. Statistical agencies periodically could release estimated slopes, revenue shares, and other cluster characteristics, while central banks could update MAPC estimates in near real time.

Our framework deliberately isolates one driver of the Phillips curve slope. We abstract from general-equilibrium feedback through expectations and monetary policy, absorb common input-cost movements into fixed effects, estimate with annual manufacturing data, and rely on imperfect demand instruments. While these choices limit the scope of the model, they also allow the role of heterogeneous production technology and demand conditions to inflation dynamics to be identified separately.

Despite these simplifications, our evidence suggests that supply-side heterogeneity is an economically important determinant of inflation dynamics. We confirm that the results extend to countries other than France. While our identification relies on manufacturing data, the evidence from the CompNet analysis suggests that the underlying mechanism extends beyond manufacturing.

Our explorations and findings leave us with some thoughts for future research. One intriguing finding is that firms with higher pass-through exhibit flatter implied supply curves, conditional on supply group and no heterogeneity in price stickiness. This suggests that production technology and demand conditions may themselves be jointly determined. Our current framework treats them as separate dimensions because this separation permits identification. Instead, investments in production technology, scalability, product differentiation, branding, and customer relationships may jointly determine the firm's position in both dimensions. Firms may invest not only to increase expected profits, but also to reduce the sensitivity of profits to demand and supply shocks, with implications for stabilization policy. Further research could explore how firm investment may trigger transitions of firms into different clusters. Alternatively, research could explore interaction between price stickiness and price pass-through.

A second avenue of research concerns extending the micro-data framework beyond manufacturing. Since output prices are rarely observed outside manufacturing, future work could combine wage or other input prices and instruments for labor- or input-market shocks to identify firms' pricing behavior indirectly.

We close with the observation that the Phillips curve need not be viewed as representing the behavior of a representative firm. Instead, it can be constructed from the pricing behavior of heterogeneous firms. As richer micro data become available, this micro-aggregation approach offers a promising route toward macro models that remain empirically grounded while explicitly accounting for structural change.

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Appendix

A Clustering methodology

The details of the clustering estimation are reported below. Firms are clustered according to the best fit in terms of the GMM criterion, where a production function estimation (the supply group) and a cost pass-through regression (the demand group) are stacked. Y_i, X_i, and Z_i then represent the dependent variable, the regressors, and instruments, respectively, of the two equations on which the clustering procedure is based. 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. The algorithm is the following:

0) Initialization: initial clustering of firms into supply groups $\hat{G}_s^0$ and demand groups $\hat{G}_d^0$. Initial clusters are based on firm-level empirical distribution of labor productivity and the ratio of price to marginal cost growth, and the number of clusters is selected using a rule based on the shape of the distribution. Specifically, the number of groups is increased by three for each peak in the distribution. To take into account possible high variation in the data, an additional group is added if the standard deviation is larger than 1 (the standard deviation of the standard Normal distribution) and the coefficient of variation exceeds 0.5, while two additional groups are added if it exceeds 0.75. Finally, one further group is included whenever the skewness of the distribution is statistically different from 0.

   Given that, in our sample, the labor productivity distribution features only one pick, standard deviation equal to 156.36 and a coefficient of variation equal to 0.69, and skewness equal to 1.98 (statistically significantly different from zero, after implementing a bootstrap test), the number of supply groups is determined to be 5; instead, the number of demand groups is set to be 3, since the distribution of the ratio of price to marginal cost growth has one pick, standard deviation equal to 0.86, and skewness equal to 0.31 (not statistically significantly different from zero). Initial weighting matrix W_i for each firm i is 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:

$$(\hat{\beta}, \hat{G}_s, \hat{G}_d) = \text{argmin } Q(\beta, G_s, G_d)$$

where

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

and

$$Q_i(\beta, G_s, G_d) = \frac{(Y_i - \beta_{(g_s(i), g_d(i))} X_i)'}{N_i} Z_i W_i Z_i' \frac{(Y_i - \beta_{(g_s(i), g_d(i))} X_i)}{N_i},$$

N_i being the number of observations of firm i.

For iterations $r \geq 1$:

(a) min $Q(\beta, G_s, G_d)$ over β, given $\hat{G}_s^{r-1}, \hat{G}_d^{r-1}$);

(b) min $Q(\beta, G_s, G_d)$ over G_s, given $\hat{\beta}, \hat{G}_d^{r-1}$);

(c) min $Q(\beta, G_s, G_d)$ over β, given $\hat{G}_s^{r}, \hat{G}_d^{r-1}$);

(d) min $Q(\beta, G_s, G_d)$ over G_d, given $\hat{\beta}^r, \hat{G}_s^{r}$);

(e) Assess convergence: $|Q(\hat{\beta}^r, \hat{G}_s^r, \hat{G}_d^r) - Q(\hat{\beta}^{r-1}, \hat{G}_s^{r-1}, \hat{G}_d^{r-1})| \leq \epsilon$: if convergence, stop; otherwise, repeat from point (a).

(f) Then, post-clustering estimation computes coefficient minimizing the cluster-level

GMM coefficient:

$$Q(\beta, G_s, G_d) = \sum_{c=1}^{C} \frac{N_c}{N} (Y_c - \beta_{(g_s(c),g_d(c)} X_c)' Z_c W_c Z_c' (Y_c - \beta_{(g_s(c),g_d(c)} X_c)$$

where C is the number of clusters and N_c is the number of observations in cluster c.

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.

The methodology follows Aglio and Bartelsman (2026), but clusters firms separately along the supply and demand dimensions, rather than using the full set of supply-demand intersections. As a result, the estimated structural parameters are group-specific rather than cluster-specific. Table A1 reports the estimates of our clustering algorithm.

Table A1: Clustering estimation

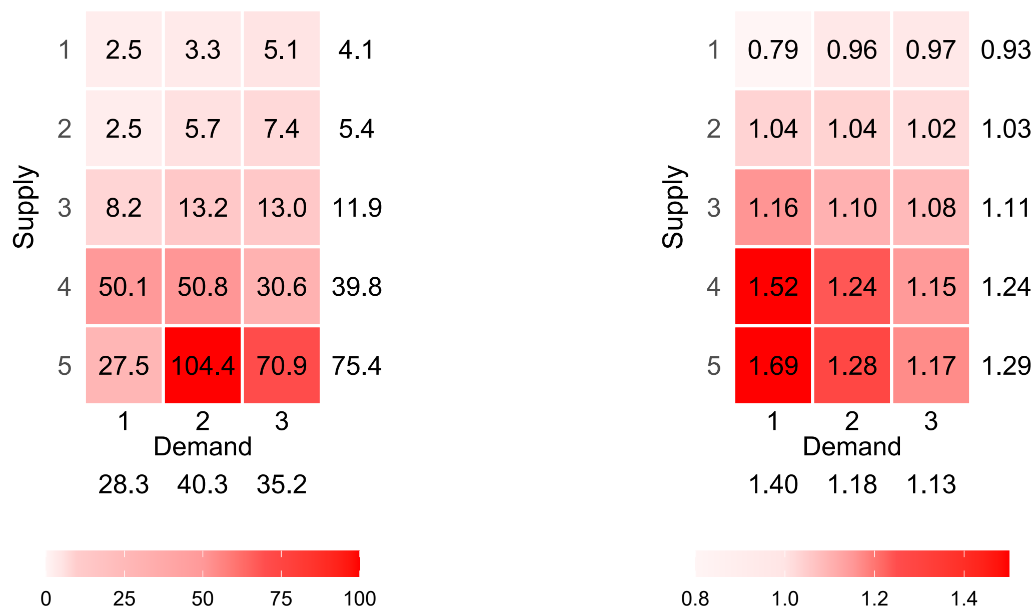
	Production function				Cost pass-through	
Supply	α_s^k	α_s^l	α_s^m	α_s	Demand	ρ_d
1	-0.032	0.211***	0.639***	1.469***	1	0.107***
	(0.057)	(0.078)	(0.072)	(0.124)		(0.006)
2	0.021	0.165***	0.645***	1.389***	2	0.670***
	(0.022)	(0.026)	(0.025)	(0.044)		(0.003)
3	0.072***	0.156***	0.631***	1.684***	3	0.979***
	(0.022)	(0.030)	(0.028)	(0.046)		(0.001)
4	0.091***	0.206***	0.600***	1.744***		
	(0.029)	(0.038)	(0.033)	(0.054)		
5	0.124***	0.329***	0.531***	2.324***		
	(0.060)	(0.086)	(0.062)	(0.127)		
					α	0.028***
						(0.004)
α^t	0.014***				α^t	-0.001
	(0.002)					(0.001)
ρ	0.660***					
	(0.072)					
R^2	0.74				R^2	0.75

B Descriptives by supply - demand cluster

This section reports several descriptives by cluster.

Figure B1: Size and markup by cluster

(a) Size (b) Markup



Note: *Size* is sales in millions of euros; *Markup* is over intermediate inputs and estimated as in Loecker and Warzynski (2012). The marginal distributions by supply and demand group are given by the right column and bottom row, respectively.

Table B1: Sectors by cluster

supply-demand cluster	sector_1	sector_2	sector_3	sector_4	sector_5
1-1	25	23	28	26	14
1-2	25	28	23	16	14
1-3	25	28	23	16	31
2-1	25	18	22	16	23
2-2	25	16	22	23	31
2-3	25	23	16	31	28
3-1	25	22	18	23	28
3-2	25	23	22	31	16
3-3	25	23	28	31	22
4-1	38	25	28	23	20
4-2	25	28	23	20	22
4-3	25	28	18	31	23
5-1	38	25	28	23	26
5-2	28	13	25	26	20
5-3	28	18	25	20	26

Note: sector_n for $n \in \{1, 2, 3, 4, 5\}$ are the top n most common NACE 2-digit industry by cluster.

Table B2: Descriptives by cluster

supply-demand cluster	N^o firms	size	lprod	mc	payroll	wages	employment	profit margin (%)	share_{EXP} (%)	inv_{INTAN}	markup
1-1	655	2.51	4.40	3.64	0.87	34.89	20.28	-1	33.2	57.72	0.79
1-2	468	3.33	4.45	1.78	0.74	35.41	19.62	7	44.9	36.44	0.96
1-3	929	5.12	4.52	1.72	1.02	40.13	29.06	10	48.7	43.87	0.97
2-1	3974	2.53	4.88	1.03	0.50	37.48	14.10	11	28.1	13.54	1.04
2-2	2877	5.75	4.89	1.10	1.14	37.42	31.23	13	41.5	25.69	1.04
2-3	3603	7.43	4.90	1.16	1.49	44.76	41.15	13	50.2	33.79	1.02
3-1	5236	8.17	5.20	0.85	1.42	40.49	37.42	17	41.8	33.51	1.16
3-2	3664	13.21	5.25	0.84	2.23	39.28	57.82	16	48.9	60.48	1.10
3-3	4956	13.05	5.27	0.85	2.42	66.81	62.04	16	52.3	64.31	1.08
4-1	948	50.05	5.63	0.66	12.02	59.15	229.95	21	54.7	438.71	1.52
4-2	1312	50.83	5.69	0.63	7.34	46.84	157.34	18	58.7	454.08	1.24
4-3	3187	30.61	5.68	0.59	5.64	40.49	124.88	17	56.1	306.54	1.15
5-1	242	27.50	6.58	0.36	28.31	39.28	530.98	22	56.7	4201.73	1.69
5-2	214	104.37	6.51	0.44	8.68	66.81	163.81	16	70.8	1115.89	1.28
5-3	972	70.87	6.36	0.42	10.56	59.15	213.79	17	66.7	512.22	1.17

Note: *N^o firms*, *size*, *lprod*, *mc*, payroll, wages, *employment*, *profit margin*, $share_{EXP}$, inv_{INTAN}, and *markup* are number of firms, average sales per firm (millions euros), log of labor productivity (2010 thousand euros over fte), marginal costs proxied by unit variable costs as computed in the main analysis, payroll (million euros), wage (thousand euros), operational profit over revenue, share of exporters, investment in intangible assets (thousand euros), and markup over intermediate inputs as in Loecker and Warzynski (2012), respectively.

Table B3: Market strategy by cluster

supply-demand cluster	new design (%)	new promotion (%)	new placement (%)	new pricing (%)
1-1	17.50	20.00	12.50	15.00
1-2	11.25	11.25	8.75	8.75
1-3	17.31	16.67	10.26	11.54
2-1	9.84	10.51	4.70	6.49
2-2	13.47	14.90	8.17	8.94
2-3	18.36	18.53	9.27	9.77
3-1	13.17	13.88	6.67	8.81
3-2	17.18	18.11	8.06	10.42
3-3	17.50	17.83	8.42	10.96
4-1	24.63	28.36	14.55	15.30
4-2	20.37	23.39	11.48	13.63
4-3	21.78	22.33	10.86	14.50
5-1	35.71	35.71	21.43	14.29
5-2	12.24	20.41	11.22	7.14
5-3	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).

C Further empirical results

C.1 First stage of the pricing equation by supply-demand cluster

This section reports the first stage of the firm pricing equation by supply-demand cluster (Table 5 in the main text).

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

		δy_{it}		
	supply		demand	
		1	2	3
β_{sd}^{Shea}	1	-0.043	4.880***	3.154
		(1.987)	(1.825)	(1.871)
	2	5.067***	4.220***	4.848***
		(1.387)	(1.373)	(1.350)
	3	5.121***	4.861***	5.261***
		(1.345)	(1.338)	(1.337)
	4	8.340***	6.388***	6.344***
		(1.335)	(1.344)	(1.331)
	5	5.818***	7.470***	6.219***
		(1.710)	(1.367)	(1.343)
β_{sd}^{wid}	1	0.011	-0.018	-0.020
		(0.068)	(0.047)	(0.042)
	2	-0.035	-0.023	-0.005
		(0.032)	(0.035)	(0.049)
	3	0.000	-0.005	0.011
		(0.035)	(0.033)	(0.034)
	4	-0.004	0.025	0.020
		(0.031)	(0.034)	(0.031)
	5	0.043***	0.013	0.109***
		(0.013)	(0.024)	(0.021)
Other regressors included			Yes	
Sector-Year fixed effects			Yes	
Firm fixed effects			Yes	
H1: $t_d^{Shea} > 0$		4.73***	3.64***	3.89***
H1: $t_d^{wid} > 0$		1.61*	1.52	1.89**
Obs			146574	
R^2			0.25	
F test			193.4***	

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$. t_d shows significance of the one-sided t-test that the coefficients jointly increase by supply cluster ($-2\beta_1^y - \beta_2^y + \beta_4^y + 2\beta_5^y > 0$).

C.2 Pricing equation by supply group

This section reports the firm pricing equation results by supply group and the related first stage.

Table C2: First stage of firm pricing equation by supply group

		δy_{it}
	supply	
β_{sd}^{Shea}	1	3.308***
		(0.835)
	2	4.393***
		(0.421)
	3	4.884***
		(0.417)
	4	5.700***
		(0.418)
	5	5.605***
		(0.429)
β_{sd}^{wid}	1	-0.018
		(0.017)
	2	-0.021
		(0.015)
	3	-0.004
		(0.006)
	4	-0.002
		(0.004)
	5	0.031***
		(0.014)
Other regressors included		Yes
Sector-Year fixed effects		Yes
Firm fixed effects		Yes
H1: $t_d^{Shea} > 0$		5.55***
H1: $t_d^{wid} > 0$		2.31**
Obs		146574
R^2		.25
F test		454.2***

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$. t_d shows significance of the one-sided t-test that the coefficients jointly increase by supply cluster ($-2\beta_1^y - \beta_2^y + \beta_4^y + 2\beta_5^y > 0$).

Table C3: Firm pricing equation by supply group

		δp_{it}
	supply	
β^y_{sd}	1	0.430***
		(0.084)
	2	0.355***
		(0.023)
	3	0.274***
		(0.022)
	4	0.234***
		(0.021)
	5	0.148***
		(0.024)
β^c_d		0.180***
		(0.007)
2 digit Industry-Year fixed effects		Yes
Firm fixed effects		Yes
H1: $t_d < 0$		-10.14***
Obs		146574
R^2		0.21

Note: 2sls regression at the firm level; observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. t_d shows significance of the one-sided t-test that the coefficients jointly decrease by supply cluster ($-2\beta^y_1 - \beta^y_2 + \beta^y_4 + 2\beta^y_5 < 0$).

C.3 Robustness - GMM results

This section reports the GMM results for the same empirical models of the pricing equations as exposed in the main analysis, as a robustness check.

Table C4: Firm pricing equation by supply group

		δp_{it}
	supply	
β^y_{sd}	1	0.461***
		(0.087)
	2	0.387***
		(0.035)
	3	0.280***
		(0.033)
	4	0.218***
		(0.032)
	5	0.095***
		(0.036)
β^c_d		0.110***
		(0.029)
2 digit Industry-Year fixed effects		Yes
Firm fixed effects		Yes
H1: $t_d < 0$		-10.56***
Obs		146574
R^2		0.20

Note: gmm regression at the firm level; 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. t_d shows significance of the one-sided t-test that the coefficients jointly decrease by supply cluster ($-2\beta^y_1 - \beta^y_2 + \beta^y_4 + 2\beta^y_5 < 0$).

Table C5: Firm pricing equation by supply - demand cluster

		δp_{it}		
	supply		demand	
		1	2	3
β^y_{sd}	1	0.403**	0.256***	0.207***
		(0.191)	(0.086)	(0.082)
	2	0.204***	0.261***	0.180***
		(0.081)	(0.057)	(0.055)
	3	0.183***	0.183***	0.106**
		(0.059)	(0.056)	(0.048)
	4	0.204***	0.157***	0.037
		(0.039)	(0.049)	(0.045)
	5	0.069	0.110**	-0.001
		(0.081)	(0.051)	(0.038)
β^c_d		0.231***	0.137***	0.045
		(0.035)	(0.034)	(0.031)
2 digit Industry-Year fixed effects			Yes	
Firm fixed effects			Yes	
H1: $t_d < 0$		-2.27***	-3.06***	-5.18***
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. t_d shows significance of the one-sided t-test that the coefficients jointly decrease by supply cluster ($-2\beta^y_1 - \beta^y_2 + \beta^y_4 + 2\beta^y_5 < 0$).

C.4 Regression on the whole sample

Table C6 reports the pricing equation estimates in the whole sample, without interacting with cluster membership.

Table C6: Firm pricing equation - whole sample

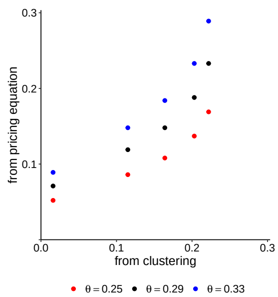
	2SLS δp_{it}	GMM δp_{it}
β^y	0.176*** (0.082)	0.169*** (0.079)
β^c	0.184*** (0.008)	0.152*** (0.041)
2 digit Industry-Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Obs	146574	146574
R^2	0.19	0.19

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.

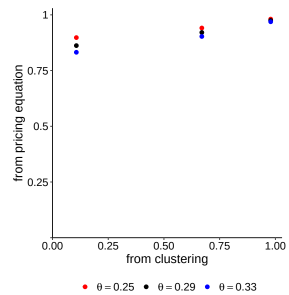
C.5 Comparing structural parameters from clustering and pricing equations

This section graphically compares the estimates of ν and ρ from the clustering procedure and from the results of the pricing equation in the main analysis.

Figure C1: Comparison of estimates from clustering and from pricing equation



(a) Slope of marginal costs, ν_s



(b) Cost pass-through, ρ_d

Notes: Comparison of $\nu_j = \frac{\bar{\beta}^y_{s,d}}{\kappa - \beta^c_d}$ vs ν_s from clustering (Panel (a)) and $\rho_d = \frac{\kappa - \beta^c_d}{\kappa}$ vs ρ_d from clustering (Panel (b)), for different calibrations of θ.

C.6 Calibration of structural parameters

Table C7 reports the results on the calibration of the structural macro parameters of our NK model. *kappa* is calibrated to minimize the squared distance between parameters from clusteering and pricing estimation, with weight equal to 0.9 for ν and 0.1 for ρ.

Table C7: Calvo price stickiness (θ) calibration

	ν			ρ	
Supply	clustering	pricing	Demand	clustering	pricing
1	.222	.250	1	.107	.853
2	.203	.202	2	.670	.915
3	.164	.159	3	.979	.972
4	.115	.127			
5	.016	.076			
β	.96	From the literature (quarterly 0.99)			
κ	1.58	Minimize sum of squared differences of parameters			
θ	.31	(quarterly 0.74)			

Note: κ calibrated to minimize the squared distance between parameters from clustering and pricing estimation, with weight equal to 0.9 for ν and 0.1 for ρ. θ solves $\kappa = \frac{(1-\theta)(1-\beta\theta)}{\theta}$, given β and κ.

C.7 Regression tables of Section 6.2

This section presents the regression results from the micro-based analysis using the 9^{th} Vintage of the CompNet dataset. Table C8 reports results for manufacturing and the whole economy, while Tables C9 and C10 by quintile along the productivity distribution.

Table C8: Real wage growth on output gap

	Manufacturing		All Economy	
	(1)	(2)	(3)	(4)
	δw_{ciqt}	δw_{ciqt}	δw_{ciqt}	δw_{ciqt}
x_{ciqt}	0.116***	0.108***	0.150***	0.137***
	(0.013)	(0.014)	(0.008)	(0.009)
δw_{ciqt-1}	-0.310***	-0.302***	-0.317***	-0.320***
	(0.013)	(0.014)	(0.009)	(0.010)
π_{ct-1}		0.125**		0.130***
		(0.052)		(0.042)
ψ_{ciqt}	-0.0357***	-0.0389***	-0.0305***	-0.0319***
	(0.006)	(0.006)	(0.004)	(0.005)
Constant	0.110***	0.104***	0.102***	0.0994***
	(0.010)	(0.011)	(0.009)	(0.010)
Country-Industry-Quintile FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	16,607	14,577	35,600	27,611
R^2	0.177	0.169	0.176	0.174

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), markdown, and year fixed effects. Standard errors clustered at industry-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table C9: Real wage growth on output gap by quintile of productivity - manufacturing

	Q1	Q2	Q3	Q4	Q5
	δw_{cit}	δw_{cit}	δw_{cit}	δw_{cit}	δw_{cit}
x_{cit}	0.125***	0.117***	0.117***	0.121***	0.068***
	(0.026)	(0.020)	(0.017)	(0.020)	(0.017)
δw_{cit-1}	-0.301***	-0.321***	-0.331***	-0.262***	-0.299***
	(0.019)	(0.021)	(0.028)	(0.024)	(0.020)
π_{ct-1}	0.044	0.126*	0.302***	0.108*	0.048
	(0.088)	(0.065)	(0.086)	(0.065)	(0.074)
ψ_{cit}	-0.098***	-0.061***	-0.051***	-0.030***	-0.023***
	(0.023)	(0.010)	(0.009)	(0.006)	(0.007)
Constant	0.181***	0.126***	0.113***	0.115***	0.078***
	(0.033)	(0.018)	(0.021)	(0.028)	(0.023)
Country-Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs	2,899	2,961	2,803	3,048	2,866
R^2	0.187	0.211	0.200	0.153	0.140

Source: CompNet 9^{th} vintage and Eurostat.
Notes: panel regressions at the country-industry level of real wage growth on output gap (x_{cit}), lagged real wage growth (δw_{cit-1}), lagged country-level inflation (π_{ct-1}), labor market power (ψ_{cit}), and year fixed effects. Standard errors clustered at industry-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table C10: Real wage growth on output gap by quintile of productivity - all industries

	Q1	Q2	Q3	Q4	Q5
	δw_{cit}	δw_{cit}	δw_{cit}	δw_{cit}	δw_{cit}
x_{cit}	0.155***	0.139***	0.145***	0.149***	0.107***
	(0.019)	(0.016)	(0.014)	(0.015)	(0.014)
δw_{cit-1}	-0.305***	-0.333***	-0.327***	-0.319***	-0.329***
	(0.014)	(0.018)	(0.020)	(0.020)	(0.021)
π_{ct-1}	0.052	0.146**	0.222***	0.145**	0.090
	(0.071)	(0.057)	(0.064)	(0.058)	(0.065)
ψ_{cit}	-0.077***	-0.053***	-0.043***	-0.028***	-0.017***
	(0.015)	(0.008)	(0.006)	(0.004)	(0.004)
Constant	0.169***	0.128***	0.103***	0.112***	0.069***
	(0.027)	(0.016)	(0.018)	(0.021)	(0.019)
Country-Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs	5,403	5,519	5,340	5,740	5,609
R^2	0.179	0.198	0.200	0.181	0.156

Source: CompNet 9^{th} vintage and Eurostat.
Notes: panel regressions at the country-industry level of real wage growth on output gap (x_{cit}), lagged real wage growth (δw_{cit-1}), lagged country-level inflation (π_{ct-1}), labor market power (ψ_{cit}), and year fixed effects. Standard errors clustered at industry-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.