# Anatomy of the Phillips Curve: Micro Evidence and Macro Implications

Luca Gagliardone* Mark Gertler† Simone Lenzu‡ Joris Tielens§

June, 2024

**Abstract**

We develop a bottom-up approach to estimating the slope of the primitive form of the New Keynesian Phillips curve, which features marginal cost as the relevant real activity variable. Using quarterly micro data on prices, costs, and output from the Belgian manufacturing sector, we estimate dynamic pass-through regressions that identify the degrees of nominal and real rigidities in price setting. Our estimates imply a high slope for the marginal cost-based Phillips curve, which contrasts with the low estimates of the conventional unemployment or output-based formulations in the literature. We reconcile the difference by demonstrating that, although the pass-through of marginal cost into inflation is substantial, the elasticity of marginal cost with respect to the output gap is low, at least for pre-pandemic data. We also illustrate the advantage of a marginal cost-based Phillips curve for characterizing the transmission of supply shocks to inflation.

**JEL: E30.**

* New York University. Email: luca.gagliardone@nyu.edu; † New York University and NBER. Email: mark.gertler@nyu.edu; ‡ New York University, Stern School of Business. Email: slenzu@stern.nyu.edu; § National Bank of Belgium and KU Leuven. Email: joris.tielens@nbb.be. We thank Fernando Alvarez, Ester Faia, Jordi Gali, Xavier Gabaix, Jonathon Hazell, Man Chon Iao, Virgiliu Midrigan, Alessio Moro, Carolin Pflueger, Luminita Stevens, Ludwig Straub, Gianluca Violante, Olivier Wang, Ivan Werning, Raf Wouters, and seminar participants at various institutions for helpful comments and conversations. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Bank of Belgium, the Eurosystem, or any other institution with which the authors are affiliated.

# 1 Introduction

Understanding the relation between inflation and real activity over the business cycle continues to be an important though unresolved matter in macroeconomics. At the heart of this inquiry lies the challenge of estimating the slope of the Phillips curve. To illustrate the issue, let us consider the New Keynesian version of the Phillips curve (NKPC), which is now the textbook formulation in the literature. Let $\pi_t$ denote inflation and $\widetilde{y}_t$ the output gap, the percentage difference between real output and its natural level. Then (what we will refer to as) the *conventional form* of the NKPC is given by:

$$\pi_t = \kappa \, \widetilde{y}_t + \beta \, \mathbb{E}_t \, \{\pi_{t+1}\} + u_t, \tag{1}$$

where $u_t$ is typically referred to as a cost-push shock, and $\beta$ is a subjective discount factor, typically a parameter close to unity. The NKPC asserts that inflation depends positively on both $\widetilde{y}_t$, which is interpreted as a measure of excess demand, and on expected future inflation. The main object of interest is $\kappa$, the slope coefficient on the output gap.

There are two interrelated sets of issues involved in uncovering $\kappa$. The first set revolves around the econometric identification of this parameter. First, as emphasized by McLeay and Tenreyro (2020), the output gap is an endogenous object. If the central bank acts to adjust $\widetilde{y}_t$ to stabilize $\pi_t$ in response to positive cost-push shocks, the estimate of $\kappa$ will be biased downward due to the negative correlation between $\widetilde{y}_t$ and $u_t$. Given the absence of good instruments for $\widetilde{y}_t$, the estimation of $\kappa$ using aggregate time-series data is problematic (Mavroeidis et al. 2014). Another identification issue involves trend inflation. The specification given by equation (1) presumes that trend inflation is constant. However, as emphasized by Hazell et al. (2022) and Jørgensen and Lansing (2023), shifts in trend inflation may confound the identification of the Phillips curve. For instance, if trend inflation decreases as output declines, and the regression model does not account for this correlation, the estimate of $\kappa$ will be upwardly biased.

These identification challenges have led researchers to employ regional data to estimate $\kappa$. Recent examples include Hooper et al. (2020), McLeay and Tenreyro

(2020), and Hazell et al. (2022).[1] Importantly, Hooper et al. (2020) and Hazell et al. (2022) allow for time fixed effects to control for shifting trend inflation. In the latter study, this identification approach yields an astonishingly small estimate of $\kappa$, which suggests that the Phillips curve is "flat". This view has become the conventional wisdom, at least for the pre-pandemic period.

The second set of considerations pertains to both the relevant measure of real activity that enters the Phillips curve and, consequently, the interpretation of the slope coefficient $\kappa$. In the underlying theory, firms set prices in response to current and anticipated movements in marginal cost. Thus, as emphasized by both Galí and Gertler (1999) and Sbordone (2002), the *primitive form* of the NKPC features real marginal cost (in percent deviations from trend) entering as the real activity variable. In fact, the conventional formulation of the NKPC in equation (1) only holds under specific conditions that establish a proportional relationship between marginal cost and the output gap. Among other things, wages must be perfectly flexible.[2] If these conditions are violated, then the output gap may not serve as an adequate proxy for real marginal cost, typically leading to a downward bias in the estimate of $\kappa$.[3] Moreover, even if all conditions that establish a proportional relationship are approximately met, it is crucial to recognize that the output-based slope $\kappa$ is ultimately the product of two parameters: the elasticity of inflation with respect to real marginal cost and the elasticity of marginal cost with respect to the output gap. The ability to separately identify the two coefficients is important for gaining a comprehensive understanding of inflation dynamics.

In this paper, we propose a novel empirical strategy to estimate the slope of the primitive form of the NKPC. The conventional estimation approach involves aggregating individual firm pricing decisions into a NKPC and then estimating its slope with aggregate data. Instead, we follow a bottom-up approach. We use micro data to estimate dynamic pass-through regressions that identify both the degree of nominal and real rigidities from short-run comovements in firm-level

[1] Also relevant is Beraja et al. (2019), which uses regional data to identify wage Phillips curves.

[2] Indeed, it is for this reason that New Keynesian DSGE models with wage rigidity include the marginal cost-based Phillips curve in the system of equations as opposed to the conventional one (see Galí 2015 chapter 6 and the references therein).

[3] These considerations also extend to formulations of the conventional NKPC that utilize the unemployment gap as a measure of economic activity instead of the output gap. They also apply to using an aggregate measure of real marginal cost such as the labor share.

marginal costs and prices. We the use these estimates to recover the NKPC slope and compute the implied aggregate pass-through.

In Section 2, we develop a theoretical framework starting from first principles that serves as the foundation of our estimation strategy. We derive an expression for firms' optimal reset prices in an environment with nominal rigidities and imperfect competition. As is standard, optimal reset prices depend on the expected path of marginal cost over the period the firm expects its price to be fixed. Moreover, due to the presence of strategic complementarities, firms factor in the expected path of competitors' prices, which reduces the pass-through of marginal cost. The slope of the Phillips curve is then a function of the two parameters capturing the degree of nominal price rigidities and the strength of strategic complementarity in price setting.

We estimate these structural parameters using micro data, which we describe in Section 3. We collect administrative data on product-level output prices, quantities, and production costs for manufacturing firms in Belgium, which we use to construct granular proxies of firms' marginal costs and competitor's prices. Our data extends the database originally assembled by Amiti et al. (2019) in terms cross-sectional and time-series coverage. Notably, our data is recorded at the quarterly (as opposed to annual frequency), which allows us to study the role of nominal rigidities in price setting at the business cycle frequency.

Section 4, we next map the theoretical model to the data to derive dynamic pass-through regressions that identify the structural parameters of interest. The use of micro data allows us to tackle the issues that hinder identification using aggregate data.[4] By including in our model a granular set of fixed effects, we address unobserved heterogeneity and confounding factors stemming from trends in output growth, trend inflation, and shifts in inflation expectations. In addition, we can construct powerful instruments for marginal cost and competitors' prices to tackle endogeneity and measurement issues. Our approach relates to the literature on incomplete pass-through of marginal cost into prices (Goldberg and

[4]Galí and Gertler (1999) originally estimated a marginal cost-based NKPC using aggregate data with the labor share as the measure of marginal cost. The use of micro data improves upon the identification as it addresses weak instruments concerns raised by Mavroeidis et al. (2014) and allows us to deal with trends in costs and prices. Moreover, the micro data also provides us with a richer measure of marginal costs that accounts for intermediate input costs along with labor costs.

Verboven 2001; Nakamura and Zerom 2010). In addition, in an environment with perfectly flexible prices, our dynamic pass-through framework nests as a special case the static pass-through regressions estimated in Amiti et al. (2019) using annual data.

In section 5 , we show that our analysis delivers sensible and robust estimates of the the parameters governing firms pricing behavior. We find a substantial degree of nominal rigidities (three to four quarters of price stickiness) and a meaningful role for strategic complementarities (reducing the pass-through of marginal cost shocks by about half). These estimates imply an economically significant slope of the marginal cost-based NKPC, tightly estimated in the range of 0.05 to 0.07. They also imply a substantial aggregate pass-through from marginal cost to inflation. To show this, in Section 6 we construct a proxy for aggregate marginal cost, which we feed into our model. The model-implied inflation series tracks the actual PPI data well. Fluctuations in marginal cost alone can account for at least seventy percent of the variation in inflation, without appealing, as is often done, to unobservable cost-push shocks or including lags of inflation.

These findings stand in contrast to the low slope's estimates found in the literature employing the conventional output-based formulation of the NKPC (Rotemberg and Woodford 1997, Hazell et al. 2022). In Section 7, we show how they can be reconciled. We make assumptions that allow us to obtain, as is standard, the output-based Phillips curve slope as the product of the marginal cost-based slope and the output elasticity of marginal cost (e.g., Galí 2015). We then develop an identification strategy to estimate the elasticity using the micro data and retrieve the implied slope of the output-based NKPC. For our pre-pandemic sample, we find a low elasticity of marginal cost to changes in output, which delivers point estimates of the output-based NKPC slope that are consistent with the literature. This suggests that the flat slope of the conventional NKPC does not stem from a limited transmission of fluctuations in marginal cost to inflation, but rather from the weak connection between movements in the output gap and marginal cost.

In Section 8, we proceed with an exercise in model validation using the cost-based NKPC to analyze the effects of supply shocks on inflation, specifically using the example of oil shocks. We trace out the impact of identified oil shocks

(Känzig 2021) on marginal cost and inflation. We show that the impulse-responses for inflation produced by a cost-based NKPC model calibrated to our estimates closely match the empirical impulse-responses estimated in the data, which validates our micro-based estimates. As we discuss, this exercise also illustrates the usefulness of the cost-based NKPC for analyzing supply-side shocks.

Concluding remarks are in Section 9.

# 2 Theoretical framework

This section presents the theoretical framework that underlies our empirical analysis. We formulate the minimum structure required to produce firm pricing equations that allow us to identify the slope of the aggregate Phillips curve. The framework features heterogeneous firms competing under imperfect competition and subject to nominal rigidity. Firms are granular. Granular firms internalize the impact of their pricing decisions on industry aggregates and are in turn influenced by the pricing decisions of their competitors. This model generates a micro-founded New Keynesian Phillips curve, the slope of which is a function of the structural parameters that govern firms' pricing behavior.

## 2.1 Preferences and pricing behavior

The economy is populated by heterogeneous producers (or firms), denoted by $f$, each operating in an industry $i \in I = [0,1]$. We denote by $\mathcal{F}_i$ the set of firms competing in industry $i$. While each firm is of measure zero relative to the economy as a whole and hence takes aggregate expenditure as given, it may be large relative to its industry and hence internalizes the effect of its pricing decisions on the consumption and price index within the industry.

Let $P_{ft}$ denote the price charged by each firm for a unit of its output, $P_{it}$ the industry price index, $\varphi_{ft}$ is a firm-specific relative demand shifter, and $Y_{it}$ the real industry output. For any industry $i$, we consider an arbitrary, invertible demand system that generates a residual demand function of the following form:

$$\mathcal{D}_{ft} := d(P_{ft}, P_{it}, \varphi_{ft})Y_{it} \qquad \forall f \in \mathcal{F}_i. \tag{2}$$

We assume firms face nominal rigidities as in Calvo (1983).[5] Each period firms face a probability $(1-\theta)$ of being able to change their price, independent across time and across firms, with $\theta \in [0,1]$. Thus, the price $P_{ft}$ paid by consumers in any given period is either the (optimal) reset price set by a firm that is able to adjust, denoted by $P^o_{ft}$, or the price charged in the previous period, $P_{ft-1}$.

The firms adjust their prices during the period in order to maximize expected profits. Their pricing decisions consider both the pricing choices made by competitors and the impact of their own price adjustments on their residual demand and the industry-wide price index. Additionally, nominal rigidities generate forward-looking pricing behavior, as firms take into account that it might not be possible to adjust prices every period. As a result, the optimal reset price set by firms that are able to adjust is a weighted average of current and expected future nominal marginal costs and markups. Let $\Lambda_{t,\tau}$ denote the stochastic discount factor between time $t$ and $t+\tau$, $TC_{ft} := TC(\mathcal{D}_{ft})$ the real total costs, and $MC^n_{ft}$ the nominal marginal cost of firm $f$. Then the optimal reset price $P^o_{ft}$ solves the following profit maximization problem:

$$\max_{P^o_{ft},\{Y_{ft+\tau}\}_{\tau\geq 0}} \mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \theta^{\tau} \left[ \Lambda_{t,\tau} \left( \frac{P^o_{ft}}{P_{t+\tau}} \mathcal{D}_{ft+\tau} - TC(\mathcal{D}_{ft+\tau}) \right) \right] \right\},$$

subject to the sequence of expected demand functions $\{\mathcal{D}_{ft+\tau}\}_{\tau\geq 0}$ in equation (2). The FOC of the problem is:

$$\mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \theta^{\tau} \Lambda_{t,\tau} \mathcal{D}_{ft+\tau} \left[ \frac{P^o_{ft}}{P_{t+\tau}} - (1+\mu_{ft+\tau}) \frac{MC^n_{ft+\tau}}{P_{t+\tau}} \right] \right\} = 0, \tag{3}$$

where $\mu_{ft}$ denotes the desired log markup.

According to equation (3), the optimal reset price depends on the expected path of marginal cost over the period the firm expects its price to be fixed, where $\theta^{\tau}$ is the probability the firm expects its price to be fixed $\tau$ periods from now. Moreover, in finding the optimal reset price, the firm factors in how its pricing decision today affects the expected path of desired markups, given by the Lerner

[5] In Appendix D we show that our identification approach and the estimated NKPC remain valid if the data-generating process features Ss-style price adjustments as in conventional menu cost models.

index:

$$\mu_{ft+\tau} := \ln\left(\frac{\epsilon_{ft+\tau}}{\epsilon_{ft+\tau}-1}\right), \tag{4}$$

where $\epsilon_{ft+\tau} := -\frac{\partial \ln \mathcal{D}ft+\tau}{\partial \ln P^o_{ft}}$ denotes the residual demand elasticity faced by firm $f$.

## 2.2 Technology

Firms are heterogeneous in their production technologies. We assume that a unit of output of $Y_{ft}$ is produced at a nominal marginal cost of:

$$MC^n_{ft} = C_{it}\mathcal{A}_{ft}Y_{ft}^{\nu_{ft}}, \tag{5}$$

where $C_{it}$ denotes the nominal marginal unit cost of the composite input factor (e.g., wages and intermediate goods); $\mathcal{A}_{ft}$ is a firm-specific cost shifter that affects the average unit cost of production and it is inversely related to the firm's total factor productivity (TFP); $\nu_{ft}$ is a firm-specific parameter that pins down short-run returns to scale in production (henceforth SR-RTS), given by $(1/(1+\nu_{ft}))$.[6] To derive the aggregate implications of the model, we assume that the economy displays constant returns to scale in the aggregate (i.e., $\nu_{ft} = 0$ on average). This assumption rules out macroeconomic complementarities due to the feedback of firms' pricing behavior on their respective marginal cost (see e.g. Galí 2015).[7] We relax this assumption in Appendix A.2. In Section 5.1, we show that our estimates of the Phillips curve are robust as the empirical evidence is broadly consistent with the constant returns to scale assumption at both the sectoral and aggregate levels.

## 2.3 The optimal reset price

We log-linearize the FOC in equation (3) around the symmetric steady state with zero inflation.[8] Denoting the variables in logs with lower-case letters, we obtain that the reset price satisfies:

[6]This functional form is rather general and consistent with standard production technologies used in the literature (see, e.g., Hottman et al. 2016). For instance, it nests Cobb-Douglas and CES as special cases.

[7]Macroeconomic complementarities can arise, for example, from roundabout production as in Basu (1995) or local input markets as in Woodford (2011).

[8]The choice of steady-state inflation is largely immaterial for our purposes but permits simpler notation. We relax it in the empirical analysis, where we allow for sector/industry-specific trends.

$$p^o_{ft} = (1-\beta\theta)\mathbb{E}_t\left\{\sum_{\tau=0}^{\infty}(\beta\theta)^\tau\left(\mu_{ft+\tau} + mc^n_{ft+\tau}\right)\right\}. \tag{6}$$

As we show in Appendix A.1, the log-linearized desired markup is a function that depends inversely on the gap between the firms' own reset price and the price of its competitors, which we denote by $p^{-f}_{it}$. Formally:

$$\mu_{ft} - \mu_f = -\Gamma\left(p^o_{ft} - p^{-f}_{it}\right) + u^\mu_{ft}, \tag{7}$$

where $\mu_f$ denotes the firm's steady state markup (with $\mu_f = \mu$ in the symmetric steady state); $\Gamma > 0$ denotes the markup elasticity with respect to prices and $u^\mu_{ft}$ is a shock to the desired markup. $u^\mu_{ft}$ is a firm-specific demand shock that generally depends on the demand shifter $\varphi_{ft}$ (equation A.4 of the Appendix). Under weak assumptions, this relationship holds for standard imperfectly competitive frameworks, including monopolistic competition with variable elasticity of demand (Kimball 1995), static oligopoly (Atkeson and Burstein 2008) and dynamic oligopoly (Wang and Werning 2022). These frameworks share the property that, in equilibrium, a firm's elasticity of demand declines as its market share increases. Thus the presence of strategic complementarities in price setting implies that a relative price increase lowers a firm's desired markup, dampening the response of prices to marginal cost.

Substituting the expression for $\mu_{ft+\tau}$ in the log-linearized FOC we obtain the following forward-looking pricing equation:

$$p^o_{ft} = (1-\beta\theta)\mathbb{E}_t\left\{\sum_{\tau=0}^{\infty}(\beta\theta)^\tau\left((1-\Omega)(mc^n_{ft+\tau} + \mu_f) + \Omega p^{-f}_{it+\tau}\right)\right\} + u_{ft}, \tag{8}$$

where $u_{ft} := (1-\beta\theta)(1-\Omega)\mathbb{E}_t\left\{\sum_{\tau=0}^{\infty}(\beta\theta)^\tau u^\mu_{ft+\tau}\right\}$ is a firm demand shock. The parameter $\Omega := \frac{\Gamma}{1+\Gamma}$ captures the strength of strategic complementarities and impacts the firm's pricing policy by muting the price response to changes in marginal costs. If the elasticity of demand is constant, as it is in the textbook New Keynesian model with monopolistically competitive firms, then desired markup $\mu_{ft}$ is also constant. In this case, $\Omega = 0$ and the optimal pricing equation simplifies to the familiar formulation where the reset price exclusively depends on the current and future stream of marginal costs. Competitors' prices are then irrelevant.

## 2.4 The New Keynesian Phillips Curve

As we show in Appendix A.2, the log-linear aggregate price index is given by:

$$p_t = (1-\theta)p_t^o + \theta p_{t-1}, \tag{9}$$

with $p_t$ and $p_t^o$ denoting the aggregate price indexes implied by equation (2), which average across firms and industries. Let $mc_t^n$ denote the aggregate log-nominal marginal cost, and define the aggregate real marginal cost and aggregate inflation as $mc_t = mc_t^n - p_t$ and $\pi_t = p_t - p_{t-1}$, respectively. Averaging the pricing equation in (8) across firms and industries and writing it in recursive form, we obtain an equation for the aggregate reset price:

$$p_t^o = (1-\beta\theta)\big((1-\Omega)(mc_t^n + \mu_f) + \Omega p_t\big) + \beta\theta\mathbb{E}_t p_{t+1}^o + \frac{\theta}{1-\theta}u_t, \tag{10}$$

where $u_t$ is an aggregate cost-push shock, as defined in the Appendix A.2. Combining equations (9) and (10) gives the *primitive* formulation of the NKPC curve:

$$\pi_t = \lambda\, \widehat{mc}_t + \beta\, \mathbb{E}_t\{\pi_{t+1}\} + u_t, \tag{11}$$

which asserts that inflation depends on real marginal cost in deviation from its steady state level and on expected future inflation. Under the assumption of constant SR-RTS in the aggregate, we obtain the standard expression for the slope of the cost-based NKPC curve:[9]

$$\lambda := \frac{(1-\theta)(1-\beta\theta)}{\theta}(1-\Omega). \tag{12}$$

Two observations are worth noting. First, the primitive form of the Phillips curve in equation (11) features the log deviation of real marginal cost from its steady state as the relevant real activity variable. In contrast, the conventional formulation of the Phillips curve, displayed in equation (1), uses the output gap or unemployment as a proxy for marginal cost. As we will discuss, the mapping between marginal cost and output gap is theoretically valid only under

[9] In an environment with cross-industry heterogeneity in the parameters $\theta$ and $\Omega$, aggregation across industries implies that the cost-based NKPC becomes $\pi_t = \lambda \cdot \widehat{mc}_t^r + Cov\left(\lambda_i, \widehat{mc}_{it}^r\right) + \beta\mathbb{E}_t\pi_{t+1}$, where $\lambda := \int \lambda_i di$, the slope in equation (12), and $\lambda_i := \frac{(1-\theta_i)(1-\beta\theta_i)}{\theta_i}(1-\Omega_i)$. Thus, the aggregate pass-through also depends on the cross-sectional covariances $Cov(\widehat{mc}_{it}^r, \theta_i)$ and $Cov(\widehat{mc}_{it}^r, \Omega_i)$. Understanding the quantitative importance of these terms is a challenging but interesting avenue for future research.

specific circumstances. Moreover, even when a proportionality between the two variables can be established, the elasticities of marginal cost to output gap and unemployment need not be equal to one. We return to these points in Section 7.

Secondly, the slope of the NKPC, $\lambda$, is a function of the primitives that govern the pricing behavior of the firms. As in standard New Keynesian models (e.g., Galí and Gertler 1999), high nominal rigidities and low discounting flatten the sensitivity of inflation to changes in real economic activity. Additionally, equation (12) shows how strategic complementarities also contribute to reducing the slope. Therefore, given a calibration of the discount factor $\beta$, estimates of the structural parameters $\theta$ and $\Omega$ pin down the slope of the Phillips curve.

Toward this end, we take the structural pricing equation (8) to the data. This exercise requires measures of prices and marginal costs, which we discuss in the next section. Notably, it is the use of firm-level data that permits the identification of the primitive parameters.

# 3 Data and measurement

We begin by introducing our dataset and highlighting its features that are relevant for measurement purposes. We then illustrate the procedure for constructing price and marginal cost measures using product-level and firm-level data.

## 3.1 Data

We assemble a micro-level dataset that covers the manufacturing sector in Belgium between 1999 and 2019, at the *business cycle frequency*. The dataset is compiled from administrative sources, extending and enriching the annual dataset used by Amiti et al. (2019). A unique feature is its ability to track quarterly product-level prices and quantities sold in the domestic market by both domestic and foreign producers, as well as quarterly information on production costs for domestic producers.

The PRODCOM dataset allows us to observe domestic firms' quarterly sales and physical quantities sold for each narrowly defined (8-digit PC codes) manufacturing product. We use this highly disaggregated information to calculate domestic unit values (sales over quantities) at the firm-product level.[10] We obtain similar data on foreign competitors from the administrative records of Belgian customs declarations. Specifically, for each manufacturing product sold by a foreign producer to a Belgian buyer, we observe quarterly sales and quantity sold for different products (8-digit CN codes), from which we compute unit values of foreign competitors in local markets.

We use detailed administrative data to measure firms' variable production costs. Specifically, we obtain information on firms' quarterly purchases of intermediates (materials and services) from their VAT declarations. Additionally, we draw upon firms' social security declarations to obtain a measure of their labor costs (the wage bill) on a quarterly basis.

Our final sample includes $4,598$ firms observed over 84 quarters (1999:Q1–2019:Q4), totaling $132,915$ observations. Appendix B provides detailed information on the data sources and data cleaning procedures. Table 1 presents summary statistics of our dataset. Several features of the data are worth noting.

First, our dataset covers the lion's share of domestic manufacturing production in Belgium. The average firm in our dataset employs 74 employees (measured in full-time equivalents) and has a domestic turnover (sales) of €6 million. The sales of the smallest firms in the sample are worth less than one-tenth of a thousandth of those generated by the largest producers.

Second, throughout the paper we adopt a narrow industry definition based on 4-digit NACE Rev.2 codes, the standard sector classification system in the European Union. Based on this classification, we sort firms into 169 manufacturing industries, distributed across 9 manufacturing sectors.[11] This classification optimally balances a coherent definition of the industry (which is mostly precise

[10] PRODCOM surveys all Belgian firms involved in manufacturing production with more than 10 employees, covering over 90% of production in each NACE 4-digit industry. The survey does not require firms to distinguish between production and sales to domestic and international customers. Therefore, we recover domestic values and quantities sold by combining information from PRODCOM with international trade data on firms' product-level exports (quantities and sales).

[11] The first four digits of the PRODCOM product classification coincide with the first four digits of the NACE Rev.2 classification and also to the first 4 digits of the CN product code classification used in the customs data. Following the official Eurostat classification system, we define manufacturing sectors by grouping 2-digit NACE Rev.2 codes, appropriately harmonized to account for changes in product classifications over time. See Appendix B for sectors' definitions.

if narrow) with the ability to identify an appropriate set of competitors (both domestic and foreign) competing to gain market share in Belgium. Table 1 shows that the vast majority of the firms in our sample specializes in only one manufacturing industry. Even for those firms that operate in multiple industries, the contribution of the main industry to total firm revenues is, on average, 98% (median 100%). For the few multi-industry firms, we treat each industry as a separate firm in accordance with the theoretical framework.[12]

Third, the typical sector is characterized by a large number of firms with small market shares—the average within-industry share is approximately 1.5% on average, with a median of 0.5%—and a few relatively large producers. To the extent that these large firms internalize the effect of their pricing and production decisions on industry aggregates and strategically react to the pricing decisions of their competitors, the monopolistic competition benchmark would be a poor approximation. The theoretical framework introduced in the previous section explicitly accounts for this.

Fourth, although the largest firms have nontrivial market shares in their industries, they are small compared to the volume of economic activity of their macro sector (e.g., textile manufacturing or electrical equipment manufacturing) and, even more so, compared to the volume of economic activity in the whole manufacturing sector in Belgium. It is therefore reasonable to assume that even the largest producers do not internalize the effect of their pricing and production decisions on the aggregate economy.

Finally, our data allow us to observe a long time series of both prices and marginal costs. On average, we observe firms for approximately 10 consecutive years (42 quarters). This feature of the data is particularly important for identification purposes. As we discuss below, a long time series enables us to include unit fixed effects in our empirical models to control for time-invariant confounding factors without suffering from the classical Nickell bias that frequently complicates the estimation of dynamic panel models.

[12] Because most firms operate in only one industry, and the main industry accounts for the lion's share of sales of multi-industry firms, all our results are essentially unchanged if we restrict the sample to the main industry for each firm.

**Table 1:** Summary statistics

| | Mean | $5^{st}$ pctle | $25^{th}$ pctle | Median | $75^{th}$ pctle | $95^{th}$ pctle |
|---|---|---|---|---|---|---|
| Number of industries within firm | 1.10 | 1.00 | 1.00 | 1.00 | 1.00 | 2.00 |
| Within firm revenue share of main industry | 98.22 | 86.57 | 100.00 | 100.00 | 100.00 | 100.00 |
| Firm's market share within industry | 1.72 | 0.06 | 0.22 | 0.53 | 1.36 | 6.57 |
| Firm's market share within sector | 0.21 | 0.01 | 0.02 | 0.05 | 0.13 | 0.70 |
| Firm's market share within manufacturing | 0.03 | 0.00 | 0.00 | 0.01 | 0.01 | 0.08 |
| Number of consecutive quarters in sample | 42.19 | 11.00 | 24.00 | 38.00 | 59.00 | 82.00 |

*Notes.* The summary statistics reported in this table refer to the sample of domestic producers in PRODCOM. The sample includes 4,598 firms observed over 84 quarters (1999:Q1–2019:Q4), totaling 132,915 observations.

## 3.2 Measurement

We now describe how to map the theoretical counterparts to the data. We use product-level prices, firm-level production costs, and information on prices of competitors (firms that operate in the same 4-digit industry) to construct measurable counterparts of prices and reset prices, which vary at the firm-industry-quarter level. Appendix B provides a detailed description of the procedure used to construct all our variables.

**Output prices.** The key variable of interest is the domestic price of goods charged by firms in the local market (Belgium). We construct a firm-industry price index that varies at the same level of our reset prices. We use the subscript $i$ to denote an industry, $f$ to denote a firm-industry pair, and $t$ to denote time (quarters). $s_{ft}$ denotes the revenue share of the firm in the industry.

We compute the change in the firm-industry price index, $P_{ft}/P_{ft-1}$, using the most disaggregated level allowed by the data. For domestic producers, the finest level of aggregation is the firm×8-digit PC product code level. For foreign competitors, it is the importing-firm×source country× 8-digit PC product code level.[13] Approximately half of the domestic firms in our sample are multi-product firms, meaning they produce multiple 8-digit products within the same industry. For these entities, we compute the price change by aggregating changes in product-level prices using a Törnqvist index: [14]

$$P_{ft}/P_{ft-1} = \prod_{p \in \mathcal{P}_{ft}} (P_{pt}/P_{pt-1})^{\bar{s}_{pt}}.$$

In the formula above, $\mathcal{P}_{ft}$ represents the set of 8-digit products manufactured by firm $f$, $P_{pt}$ is the unit value of product $p$ in $\mathcal{P}_{ft}$, and $\bar{s}_{pt}$ is a Törnqvist weight computed as the average of the sale shares between $t$ and $t-1$: $\bar{s}_{pt} := \frac{s_{pt}+s_{pt-1}}{2}$. Finally,we construct the time series of price levels by concatenating quarterly changes.[15]

Using a similar approach, we construct the price index of competitors for each domestic firm by concatenating quarterly changes as follows:

$$P_{it}^{-f}/P_{it-1}^{-f} = \prod_{k \in \mathcal{F}_i/f} (P_{kt}/P_{kt-1})^{\bar{s}_{kt}^{-f}}. \tag{13}$$

Here, $\bar{s}_{kt}^{-f} := \frac{1}{2}\left(\frac{s_{kt}}{1-s_{ft}} + \frac{s_{kt-1}}{1-s_{ft-1}}\right)$ represents a Törnqvist weight, constructed by averaging the residual revenue share of competitors in the industry at time $t$ (net of firm $f$ revenues) with that at time $t-1$.[16] Note that the set of domestic competitors for each Belgian producer, denoted as $\mathcal{F}_i$, includes not only other Belgian manufacturers operating in the same industry but also foreign

[13]In the raw customs data, products are measured using the more disaggregated CN 8-digit product classification. We map the CN product codes in the customs data to PC product codes used in PRODCOM using the official bridge tables available on the Eurostat web page. See Appendix B.1 for additional details.

[14]Given that our measure of reset prices varies at the firm-industry level and our assumption that the elasticity of substitution is common across all firm's products within an industry, we would obtain approximately the same parameter estimates running our models in the more granular dataset (with product-level price variation), as long as the product-level observations are weighted by the same Törnqvist weights, $\bar{s}_{pt}$, used in the aggregation.

[15] Let $t_f^0$ denote the first quarter when $f$ appears in our data. Starting from a base period $P_{f0}$, which we can normalize to one, prices are concatenated using the formula: $P_{ft} = P_{f0}\prod_{\tau=t_f^0+1}^{t}\left(P_{f\tau}/P_{f\tau-1}\right)$. The normalization of the level of the firm's price index in the base year, $P_{f0}$, is one rationale for the inclusion of firm fixed effects in our empirical specifications.

[16]As with the firm's price index, the level of the price index of competitors is constructed by normalizing the first period to one and concatenating quarterly changes. Also, in this case, the normalization is immaterial for estimation purposes as our empirical model always includes firm fixed effects.

manufacturers selling the same goods to Belgian customers.

**Marginal costs.** The cost structure outlined in equation (5) implies that a firm's nominal log-marginal cost is equal to log-average variable costs plus a term reflecting SR-RTS:

$$mc^n_{ft} = \ln(\text{TVC}_{ft}/Y_{ft}) + \ln(1 + \nu_{ft}). \tag{14}$$

Accordingly, we construct our empirical proxy of firms' marginal costs using variation in average variable costs. Returns to scale, which are not directly observable in the data, will enter the error term of our empirical models.

We measure total variable costs ($\text{TVC}_{ft}$) as the sum of intermediate costs (materials and services purchased) and labor costs (wage bill). Intermediate input costs account, on average, for 75 percent of total variable costs. They are also the most volatile cost component, with a within-firm coefficient of variation that is more than twice as large as that of labor costs (1.77 vs 0.77).

We obtain a firm-specific quantity index for domestic sales ($Y_{ft}$) by scaling a firm's domestic revenues by its domestic price index, such that $Y_{ft} = (PY)_{ft}/\bar{P}_{ft}$. For single-industry firms, $\bar{P}_{ft}$ coincides with the firm-industry price index $P_{ft}$, which was discussed earlier. For multi-industry firms, we aggregate industry prices $P_{ft}$ by using as weights the firm-specific revenue shares of each industry.[17]

# 4 Identification strategy

In this section, we present the identification strategy that enables us to estimate the structural parameters that pin down the slope of the primitive NKPC. We begin by mapping the theoretical model to the data to derive dynamic pass-through regressions with measurable counterparts. In doing so, we highlight

[17] Specifically, we apply the Törnqvist weight of each (4-digit) industry bundle $i$ produced by firm $f$ in quarter $t$, which is defined as $(s_{fit} + s_{fit-1})/2$, where $s_{fit}$ is the share of revenues of the firm coming from sales in industry $i$ in total sales across industries. The choice of $\bar{P}_{ft}$ has essentially no impact on our estimation results because, as we have shown, the majority of the firms in our data operate in only one industry, and the sales of those firms that produce goods in multiple industries are typically concentrated in their primary industry. In fact, our empirical results are robust to defining $\bar{P}_{ft}$ as the price of the main industry or using other aggregation methods (such as an arithmetic average or a CES aggregator).

the connection with static pass-through models. Next, we discuss the identifying assumptions and the instrumental variable approach used to tackle endogeneity issues.

## 4.1 Econometric framework for dynamic pass-through

Without loss of generality, prices and reset prices satisfy the following long-run cointegrating relationship:

$$p_{ft} = p^{o}_{ft} + \eta_{ft}, \tag{15}$$

where $\eta_{ft} := p_{ft} - p^{o}_{ft}$ denotes the cointegration error, and $p^{o}_{ft}$ depends on marginal cost and competitors prices as in equation (8).

Under the Calvo framework, the conditional expectation of the observed price given the information set at time $t$ is given by:[18]

$$\mathbb{E}\{p_{ft}|p^{o}_{ft}, p_{ft-1}\} = (1-\theta)p^{o}_{ft} + \theta p_{ft-1}.$$

Defining the projection error $v_{ft} := p_{ft} - \mathbb{E}\{p_{ft}|p^{o}_{ft}, p_{ft-1}\}$ and rearranging the above equation, we obtain the following error-correction specification:

$$\Delta p_{ft} = (1-\theta)\Delta p^{o}_{ft} - (1-\theta)\eta_{ft-1} + v_{ft}, \tag{16}$$

The first term, $\Delta p^{o}_{ft}$, captures variation in reset prices due to supply and demand shocks. The second term, $\eta_{ft-1} = p_{ft-1} - p^{o}_{ft-1}$, is the error-correction term (Engle and Granger 1987), which controls for persistent deviations of prices and reset prices from their long-run cointegrating relation. In an environment with nominal rigidities, failing to account for the error correction term would lead to biased estimates. The reason is that $\eta_{ft}$ does not average out in the short run unless prices are fully flexible (i.e., $\theta = 0$), leading to persistent fluctuations of the price gap $(p^{o}_{ft} - p_{ft})$ around its long-run average.[19]

It is useful to draw a connection between the dynamic model above and its static counterpart. Taking the limit of (16) as $\theta$ goes to zero, we have that $\eta_{ft} \longrightarrow v_{ft}$

[18] In Appendix D we discuss how, under certain circumstances, this framework can be applied to the case of state-dependent pricing.

[19] Combining the cointegrating relation in (15) and the error correction in (16), we obtain that the cointegration error satisfies an ARMA process, $\eta_{ft} = \theta\eta_{ft-1} - \theta\Delta p^{o}_{ft} + v_{ft}$, with autocorrelation coefficient given by the degree of nominal rigidities.

and we recover the long-run model:

$$\Delta p_{ft} = \Delta p^{o}_{ft} + \Delta \eta_{ft},$$

which is the time-differenced counterpart of the cointegrating relation in (15). Amiti et al. (2019) use this framework and annual data, where it can be argued that $\theta \cong 0$, to estimate the pass-through elasticities.[20]

## 4.2 Identification

Starting from the error-correction equation (16), we use equation (8) to replace for $p^{o}_{ft}$, substitute expected values with realized values, and introduce an expectational error $e_{ft}$, obtaining the following population regression:

$$p_{ft} = (1-\theta)\left((1-\Omega)((mc^{n}_{ft})^{\infty} + \mu_f) + \Omega(p^{-f}_{it})^{\infty}\right) + \theta p_{ft-1} + \varepsilon_{ft}, \tag{17}$$

where we used the notation $(mc^{n}_{ft})^{\infty}$ and $(p^{-f}_{it})^{\infty}$ to denote the discounted present value of marginal cost and competitors' prices, respectively.[21] The composite residual is given by:

$$\varepsilon_{ft} := v_{ft} + (1-\theta)(1-\beta\theta)e_{ft} + (1-\theta)u_{ft},$$

where $u_{ft}$ captures the firm's demand shock that enters the reset price as in equation (8). Under rational expectations, the expectation error $e_{ft}$ is mean zero and uncorrelated with the regressors. Deviations from the rational expectation benchmark do not pose a threat to identification as long as our instruments for marginal costs and competitors' prices are orthogonal to the (possibly non-zero mean) $e_{ft}$. Finally, note that, given our empirical measure of nominal marginal costs, the residuals of our empirical model will also include the present discounted value of SR-RTS.

Equation (17) is a dynamic pass-through regression linking short-run fluctuations in the firm's marginal cost and competitors' prices to the current price. The firm's lagged price serves the same purpose as the error correction term, entering the empirical specification as a predetermined regressor that controls for

---

[20] Formally, $\theta \cong 0$ is a necessary condition for the orthogonality of the static model to hold: $Cov(\Delta p^{o}_{ft}, \Delta\eta_{ft}) = -\theta Var(\Delta p^{o}_{ft}) + Cov(\Delta p^{o}_{ft}, v_{ft}) = 0$.

[21] Specifically, $(x_t)^{T} := (1-\beta\theta)\sum_{\tau=0}^{T-1}(\beta\theta)^{\tau}x_{t+\tau} + (\beta\theta)^{T}x_{t+T}$ denote the discounted present values of $x_t = \{mc^{n}_{ft}, p^{-f}_{it}\}$ up to time $T$.

short-run price dynamics. Identification requires the orthogonality between the composite error term $\varepsilon_{ft}$ and a set of instrumental variables, described below.

**Baseline model.** To construct the sample analog of the population regression (17), we calibrate the discount factor $\beta = 0.99$, a standard value at the quarterly frequency, and truncate present values after $T = 8$ quarters, which is a sufficiently distant period to ensure that the discount factor $(\beta\theta)^{\tau}$ is approximately zero for $\tau > T$. We obtain the following dynamic pass-through regression:

$$p_{ft} = (1-\theta)\left((1-\Omega)(mc_{ft}^{n})^{8} + \Omega(p_{it}^{-f})^{8}\right) + \theta p_{ft-1} + \alpha_f + \alpha_{s\times t} + \varepsilon_{ft}. \quad \text{(Model A)}$$

The use of micro data allows us to include a set of granular fixed effects that address several identification issues that typically complicate the identification of the NKPC with aggregate data. The sector-by-time fixed effects ($\alpha_{s\times t}$) serve several purposes: First, they allow us to extend the theoretical framework to incorporate sector-specific trends or time-varying steady states of the variables in the data. Second, they address the concerns related to shifts in long-term inflation expectations discussed in Hazell et al. (2022). Third, they soak up demand shocks common across firms within a sector, which would generate a spurious correlation between marginal cost and prices due to general equilibrium effects. The firm fixed effects ($\alpha_f$) absorb variation in steady-state markups and in the unobserved component of marginal costs, to the extent that SR-RTS are firm-specific but time invariant (e.g., as with Cobb-Douglas). These fixed effects also account for the normalization of the price level (footnote 15).

As explained in the previous section, the firm's lagged price enters the empirical specification as a control for short-run price dynamics with coefficient $\theta$. On the one hand, imposing this theoretical restriction tightens the inference of the structural parameters. On the other, one might be concerned that the lagged price is an endogenous variable to the extent that *idiosyncratic* demand shocks are persistent, even after controlling for sector-time fixed effects. To address this concern, we estimate the following unrestricted variant of Model A:

$$p_{ft} = (1-\theta)\left((1-\Omega)(mc_{ft}^{n})^{8} + \Omega(p_{it}^{-f})^{8}\right) + \zeta p_{ft-1} + \alpha_f + \alpha_{s\times t} + \varepsilon_{ft}. \quad \text{(Model A Unrestricted)}$$

The model above allows for a coefficient in front of $p_{f-1}$, which could possibly differ from $\theta$. Importantly, while the estimate of $\zeta$ might in principle be biased, the estimates of the other parameters remain consistent since the identification of $\theta$ and $\Omega$ relies solely on variation in the instruments for marginal cost and competitors' prices.

**Instruments.** We estimate Model A and Model A Unrestricted via Generalized Method of Moments (GMM). The moment conditions take the form $\mathbb{E}\{Z_{ft} \cdot \varepsilon_{ft}\} = 0$, where the vector $Z_{ft}$ denotes a set of instruments that address potential endogeneity and measurement issues of marginal costs and competitors' prices.[22]

*Marginal cost*—A valid instrument for marginal cost needs to address a number of concerns. To begin with, our measure of marginal cost is subject to measurement error, which can result in attenuation bias. Moreover, for several reasons, marginal cost is likely to be endogenous. First, when firms operate with non-constant SR-RTS, marginal cost varies with the level of production, which is affected by demand shocks. Second, SR-RTS might themselves vary with the scale of production (e.g., with CES production technologies), which could introduce omitted variable bias. Finally, even if SR-RTS are constant, endogeneity may arise if input supply curves are locally upward sloping.

We leverage our micro data to construct an instrument suitable for addressing these concerns. We construct a firm-level total factor productivity index ($a_{ft}$) using information on firm-level physical output and input demands (labor, capital, and intermediate inputs). In logs:

$$a_{ft} = y_{ft} - f(l_{ft}, k_{ft}, m_{ft}),$$

where $f(\cdot)$ denotes the firm's production function. Variation in this index captures changes in technical efficiency (TFPQ, using Foster et al. 2008 terminology), which is a fundamental component of firms' marginal cost, as noted in equation (5). Importantly, unlike commonly used revenue-based productivity measures (TFPR),

[22]The GMM estimation procedure follows the two-step approach. To ensure that our estimates are representative from a macroeconomic standpoint, we weight observations using their Törnqvist weight, $\bar{s}_{ft}$, thereby ensuring that each firm is assigned the same weight as in the construction of aggregate price indexes. We cluster standard errors at the sector level to account for the potential correlation of error terms across firms in similar businesses.

changes in technical efficiency are not confounded by movements in output prices.

We recover the firm's productivity index, $a_{ft}$, as a residual from a gross-output production function estimation. As explained in Appendix C, we follow the estimation strategy developed in Lenzu et al. (2023). For our baseline instrument, we parameterized firms' technologies assuming a Cobb-Douglas production function with elasticities estimated separately for each sector.[23] To avert the possibility of correlated measurement errors in productivity and price indexes, we lag our instrument by four quarters.

The identifying assumption is that, conditional on the set of firm and sector-by-time fixed effects included in our model, the persistent component of total factor productivity has explanatory power over current marginal costs (i.e., the instrument is strong) but is orthogonal to idiosyncratic demand shocks and the scale of production (i.e., the instrument is valid). We provide statistical evidence consistent with these identifying assumptions in the section below.

*Competitors' price index*—Competitors' prices are also measured with error and, perhaps more importantly, they are jointly determined with a firm's own price and thus correlate with the firm's demand shocks that enter the error term. To address these, we construct two instruments for $p_{it}^{-f}$ that leverage variation in international trade prices, building on the ones developed in Amiti et al. (2019).

Denote by $\mathcal{F}_{ki}^{\star}$ the set of international competitors of firm $f \in \mathcal{F}_i$ that operate in country $k$ and industry $i$. The first instrument, denoted by $p_{it}^{\star EU}$, is a shifter of the price of Euro area international competitors. We use the Comext dataset from Eurostat to compute the (sales-weighted) average log price of goods in industry $i$ that a given Euro-area country, $k$, charges to different export destinations around the world.[24] We exclude Belgium as well as all other Euro-area countries from the list of export destinations to make sure that variation in the instrument does not pick up demand shocks that are correlated across Belgium and other neighboring countries. We compute an index by averaging across all competitors $j$ from EU

[23] We explore alternative parametrizations in the robustness section.

[24] Following Amiti et al. (2019) we consider the following set of EU countries $k \in$ {Austria, Germany, Spain, Finland, France, Greece, Ireland, Italy, Netherlands, and Portugal}.

countries:

$$\Delta p_{it}^{\star EU} = \sum_{k \in EU} \sum_{j \in \mathcal{F}_{ki}^{\star}} w_{jt} \cdot \Delta \bar{p}_{kit}^{-B},$$

where the weight $w_{jt}$ is obtained by normalizing the Törnqvist weight in formula (13) by the market share of EU competitors in industry $i$ in Belgium: $w_{jt} := \bar{s}_{jt}^{-f} \cdot (\sum_{k \in EU} \sum_{j \in \mathcal{F}_{ki}^{\star}} \bar{s}_{jt}^{-f})/(\sum_{k} \sum_{j \in \mathcal{F}_{ki}^{\star}} \bar{s}_{jt}^{-f})$. Finally, we concatenate $\Delta p_{it}^{\star EU}$ to obtain the instrument (in levels), $p_{it}^{\star EU}$. The rationale for this instrument is that the average price charged by international competitors outside the EU correlates with their marginal cost of production but not with demand shocks in Belgium.

The second instrument, denoted by $p_{it}^{\star F}$, is a shifter of the price of non-EU competitors that leverages variation in bilateral exchange rates ($\Delta e_{kt}$) between the currency used by country $k$ and the Euro:

$$\Delta p_{it}^{\star F} = \sum_{k \notin EU} \sum_{j \in \mathcal{F}_{ki}^{\star}} w_{jt} \cdot \Delta e_{kt},$$

where the weight $w_{jt}$ is now scaled by the market share of non-EU competitors: $w_{jt} := \bar{s}_{jt}^{-f} \cdot (\sum_{k \notin EU} \sum_{j \in \mathcal{F}_{ki}^{\star}} \bar{s}_{jt}^{-f})/(\sum_{k} \sum_{j \in \mathcal{F}_{ki}^{\star}} \bar{s}_{jt}^{-f})$. As before, we concatenate $\Delta p_{it}^{\star F}$ to obtain the instrument $p_{it}^{\star F}$ in levels. Here, the exclusion restriction requires that non-EU exchange rates are orthogonal to domestic demand shocks.

# 5 Estimation results

**Baseline estimates.** Column (1) in Table 2 presents the estimates of our baseline model. We begin by assessing the power of our instruments. In Panel a, we regress the present values of marginal cost and competitors' prices on the set of instruments, essentially producing what would be the first-stage regressions of a linear two-stage least squares model. As we can see, all coefficients have the expected signs and are statistically significant. The high values of the Cragg-Donald and Kleibergen-Paap F-statistics indicate that we can confidently reject the hypothesis of weak instruments at standard confidence levels. Additionally, the low test statistics for the Hansen-Sargan over-identification test indicate that our instruments also satisfy the exclusion restrictions required by the moment conditions.

Column (1) in Panel b reports the structural estimates for the degrees of nominal and real rigidities obtained by estimating Model A via GMM. Our estimates indicate a substantial degree of price stickiness. We find a precisely estimated value of $\theta = 0.702$. Through the lens of a Calvo model, this implies that, on average, prices remain fixed for approximately three to four quarters.[25] These estimates are remarkably consistent with the frequency of price adjustments measured by Nakamura and Steinsson (2008) from US PPI data and with those obtained from Belgian PPI data.

Our estimates also reveal an economically meaningful role of strategic complementarities in the pass-through of shocks. The estimate of $\Omega$ is 0.556 and is precisely estimated. This estimate aligns with the one obtained by Amiti et al. (2019) in a long-run model with flexible prices, indicating that the pass-through from marginal costs and from competitors' prices are roughly of the same magnitude. However, it is important to emphasize how, in an environment with sticky prices and forward-looking pricing behavior, the short-run pass-through of marginal costs depends on both the degree of strategic complementarities and nominal rigidities. Specifically, the elasticity of a firm's own price to a permanent shock to marginal cost is given by $\frac{\partial p_{ft}}{\partial mc_{ft}^{n}} = (1 - \Omega)(1 - \theta)$, which is approximately equal to 0.135 at the estimated parameter values.

Overall, these results highlight the benefits of estimating the slope using micro data, which overcomes the endogeneity and lack of instrument power commonly encountered with aggregate time-series data (Mavroeidis et al. 2014).

**Unrestricted estimates.** Column (2) in Panel b of Table 2 presents the estimates of the unrestricted version of model A, which addresses concerns related to the endogeneity of $p_{ft-1}$. We find that estimates of both $\theta = 0.705$ and $\Omega = 0.545$ (and therefore the NKPC slope) are almost identical to those obtained from the restricted model in Column (1). Additionally, the estimated coefficient on lagged prices is $\zeta = 0.707$. We cannot reject the null hypothesis that $\zeta = \theta$ with a p-value of 0.96. These results show that the estimates from the baseline model are robust to the possibility that $p_{ft-1}$ is endogenous and also lend strong empirical support

[25] In Appendix D we show that, under certain reasonable conditions, our estimates of nominal rigidity remain valid in an environment with state-dependent pricing (e.g. menu cost models).

**Table 2:** Estimation results

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Model A Baseline* | *Model A Unrestricted* | *Model B* | *Model C* |
| *Panel a: First stage* | | | | |
| Dep. Var. → | $(mc^n_{ft})^8$ | $(p^{-f}_{it})^8$ | $(mc^n_{ft})^8$ | $mc^n_{ft}$ |
| $TPFQ_{ft-4}$ | -0.125 | 0.039 | -0.108 | -0.258 |
| | (0.023) | (0.022) | (0.025) | (0.033) |
| $p^{\star EU}_{ft}$ | 0.215 | 0.525 | | |
| | (0.181) | (0.181) | | |
| $p^{\star F}_{ft}$ | 0.225 | 0.530 | | |
| | (0.181) | (0.189) | | |
| $p_{ft-1}$ | 0.244 | 0.124 | 0.270 | 0.324 |
| | (0.035) | (0.030) | (0.027) | (0.026) |
| *Panel b: Structural estimates* | | | | |
| $\theta$ | 0.708 | 0.705 | 0.680 | 0.710 |
| | (0.014) | (0.069) | (0.025) | (0.019) |
| $\Omega$ | 0.572 | 0.545 | 0.512 | 0.427 |
| | (0.056) | (0.058) | (0.144) | (0.170) |
| $\zeta$ | | 0.707 | | |
| | | (0.020) | | |
| $\rho^{mc}$ | | | | 0.749 |
| | | | | (0.092) |
| *Panel c: Slope of the Phillips curve* | | | | |
| $\lambda$ | 0.053 | 0.058 | 0.075 | 0.070 |
| | (0.008) | (0.029) | (0.035) | (0.031) |
| *Test statistics* | | | | |
| Cragg-Donald $F$ | 907.773 | 908.301 | 1695.906 | 5632.374 |
| Kleibergen-Paap $F$ | 75.868 | 75.504 | 107.770 | 101.894 |
| Hansen-Sargan $J$ | 3.747 | 4.279 | 0.707 | 0.1995 |
| $H_0 : \theta = \zeta$ p-val | | 0.963 | | |
| Firm FE | y | y | y | y |
| Sector × time FE | y | y | | |
| Industry × time FE | | | y | y |

*Notes.* Panel a reports the estimates of linear regressions of marginal costs and competitors' prices on the exogenous instruments and controls. Standard errors of the first stage (in parenthesis) are block-bootstrapped to account for estimation error in the estimates needed to construct the present values. Panels b and c report the estimates of the structural parameters and slope of the NKPC ($\lambda$), respectively. GMM robust standard errors are clustered at the sector level.

to the restrictions imposed by the economic theory.

**The slope of the primitive NKPC.** Using the structural parameters estimates, we recover the slope of the marginal cost-based NKPC, presented in Panel c. We find an economically meaningful relation between fluctuations in marginal costs and aggregate inflation dynamics. The estimated slope from our baseline model is $\lambda = 0.053$, precisely estimated and statistically different from zero. It is slightly higher for the unconstrained model, reaching 0.058.

These estimates stand in contrast with the available estimates of the NKPC slope featuring the output gap or unemployment as a measure of real economic activity. These estimates typically display a magnitude that is two and a half to ten times smaller than ours. For instance, Rotemberg and Woodford (1997) and Hazell et al. (2022) find a $\kappa$ of 0.024 and 0.006, respectively, for US data. In Section 7, we return to this comparison and provide empirical evidence that helps reconcile why inflation appears to be much more responsive to marginal cost fluctuations than to changes in output or unemployment.

## 5.1 Robustness analysis

We now evaluate the robustness of our findings and address possible concerns with our identification strategy. We then consider the possibility that the economy might display aggregate non-constant returns to scale and discuss its implications for the NKPC slope.

**Measurement of competitors' prices.** The first concern we address is related to a possible mismeasurement of the competitors' price index. Our baseline measure assumes that the set of competitors corresponds to all other firms operating in the same four-digit industry. However, some relevant competitors might operate outside the industry perimeter. To address this concern, we include a set of industry-by-time fixed effects, which absorb the present value of competitors' prices without prior assumptions on the relevant price index.[26]

[26] Over 90% of the variation in each firm's competitor price index occurs at the industry-year level since the vast majority of firms are small compared to their industry.

Similar to the sector-by-time fixed effects used earlier, these narrower fixed effects also control for trends. In this way, we obtain the following empirical model:

$$p_{ft} = (1-\theta)(1-\Omega)(mc^n_{ft})^8 + \theta p_{ft-1} + \alpha_f + \alpha_{i\times t} + \varepsilon_{ft}, \qquad \text{(Model B)}$$

where $\alpha_{i\times t}$ is an industry-by-time fixed effect. Column (B) presents the first-stage regression estimates, structural parameter estimates, and the implied NKPC slope (corresponding to Panels a, b, and c, respectively). Both the estimated degree of price stickiness and strategic complementarities are close to their baseline values and precisely estimated. The implied slope of the Phillips curve is somewhat higher ($\lambda = 0.075$), suggesting an even stronger pass-through of marginal costs to prices in this case.

**Measurement of present values.** A valuable feature of both Model A and B is that they do not impose stringent constraints on how firms form expectations about the dynamics of future marginal costs and industry prices. The flip side of this flexibility is that the estimating equations are data demanding and highly nonlinear; $\theta$ enters the estimating equation both as a coefficient in front of the present values and lagged prices as well as in the construction of the discounted present values. To address this concern, we assume that marginal cost, in deviations from its industry trend, follows a first-order auto-regressive process with persistence parameter $\rho < \frac{1}{\beta\theta}$. This allows us to estimate the following system of linear equations:

$$\begin{aligned} p_{ft} &= \Psi^{mc} \cdot mc^n_{ft} + \theta p_{ft-1} + \alpha_f + \alpha_{i\times t} + \varepsilon_{ft}, \\ mc^n_{ft} &= \rho mc^n_{ft-1} + \alpha_f + \alpha_{i\times t} + \epsilon^{mc}_{ft} \end{aligned} \qquad \text{(Model C)}$$

where $\Psi^{mc} := (1-\theta)(1-\Omega)\frac{1-\beta\theta}{1-\beta\theta\rho}$ measures the pass-through of of transitory shocks to marginal costs into prices, accounting for the persistence of such shocks. Column (4) presents the estimation results. These estimates are in line with the ones obtained from the nonlinear GMM specifications, but even more precisely estimated. As with model B, the implied slope of the Phillips curve is somewhat higher than in the baseline. These results also imply a price elasticity to a transitory increase in marginal cost, $\Psi^{mc}$, of approximately 0.01.

**Capacity utilization.** Our TFP instrument for marginal cost does not account for variable capacity utilization, as the intensity of input usage is not directly observable in the data. If demand-driven variation in (lagged) capacity utilization moves current marginal cost, one might worry that, by not adjusting our measure of TFP for utilization, our instrument (lagged TFP) could correlate with demand via the utilization channel. In Appendix E, we provide evidence suggesting that this is unlikely the case.

We gather supplementary data from the Business Survey administered by the National Bank of Belgium. The survey covers a subset of firms in our sample, asking them to report the percentage of their production capacity utilized in any given quarter. In this subsample, we demonstrate that lagged capacity utilization has no predictability for current marginal cost in two ways. First, we regress capacity utilization (lagged four quarters, as our instrument) on $mc^n_{ft}$. We find a small and statistically insignificant elasticity (estimate 0.011, SE 0.052). Second, we estimate the first-stage regression for marginal cost, including lagged capacity utilization in the instrument set. We again find a small and statistically insignificant coefficient (estimate 0.036, SE 0.025).

As an additional validation exercise, we construct an alternative productivity instrument adjusting inputs for capacity utilization. This requires predicting capacity utilization when it is not directly observable, as we discuss in the Appendix. The estimates of the parameters and slope are essentially unchanged relative to those reported in Table 2.

**Alternative production functions.** Our baseline TFP instrument is constructed assuming a Cobb-Douglas functional form to describe firms' production technologies, allowing heterogeneity in production function parameters across sectors. Although standard, this assumption rules out within-sector heterogeneity in production technologies that may affect measured TFP. As a robustness exercise, we construct an alternative productivity index assuming Translog production functions, which allows the production function elasticities (and therefore returns to scale) to vary across firms and over time. We show that our baseline estimates are essentially the same if we use this alternative TFP measure as an instrument for marginal cost. We also show that the estimates are robust to controlling for the estimated firm-specific and time-varying returns to scale. The results are reported in Appendix E.

**Macroeconomic complementarities.** We derived the aggregates of our model under the assumption of constant SR-RTS on average. In Appendix A.2 we consider the more general case with time-invariant, but possibly decreasing aggregate SR-RTS. We show that the NKPC slope can be expressed as:

$$\lambda = \frac{(1-\theta)(1-\beta\theta)}{\theta}(1-\Omega)\Theta,$$

where the additional term $\Theta := \frac{1}{1+\gamma\nu(1-\Omega)}$ captures the role of macroeconomic complementarities that stem from decreasing returns. Here $\nu$ is a parameter inversely related to the average of SR-RTS; $\gamma$ denotes the elasticity of substitution across goods within industries.[27] Therefore, if the economy exhibits aggregate decreasing (increasing) returns to scale, firms' price adjustments in response to changes in economic activity would be more modest (amplified), resulting in a flatter (steeper) slope of the Phillips curve (see, e.g., Galí 2015). In Appendix C we present estimates of returns to scale for different sectors which suggest that SR-RTS to scale are close to unity at both the sector level and in the aggregate. Given these estimates and a reasonable calibration of $\gamma$, we obtain a value of $\Theta = 0.94$.[28] Thus macroeconomic complementarities imply a very modest reduction of the NKPC slope, which is well within the confidence bounds of our baseline estimates.

# 6 Aggregate inflation dynamics

In this section, we assess the capacity of our estimated model to capture the aggregate times series of inflation for the Belgian manufacturing sector.

To derive an expression for aggregate inflation, we use the equation for the price index (equation 9) and the equation for the reset price (equation 10). We

[27] See Appendix A.2 for derivations.

[28] The sectoral estimates range from 0.93 to 0.98, while the aggregate returns to scale are estimated to be approximately 0.96. This implies a value of $\nu$ of approximately 0.04. Calibrating $\gamma$ to 4 to obtain a gross aggregate steady-state markup between 1.3 and 1.4, and using our estimate of $\Omega = 0.55$, we obtain a value of $\Theta = 0.94$.

then close the model by assuming that nominal marginal cost follows a random walk with drift.[29] We therefore obtain the following reduced-form expression for quarterly inflation (see Appendix A.3 for derivations):

$$\pi_t = \tilde{\lambda}\left(mc_t^n - p_{t-1}\right) + \alpha + \theta u_t, \tag{18}$$

where $\alpha$ captures trend inflation and $u_t$ is the aggregate cost-push shock. The reduced-form slope $\tilde{\lambda} = 0.22$ is a functional equation in $\theta$, $\Omega$, and $\beta$. It captures the contemporaneous pass-through of aggregate real marginal cost to inflation taking into account the persistence of cost shocks.

According to equation (18), quarterly inflation increases with current nominal marginal cost scaled by the lagged price level, consistent with the theory presented earlier. As before, the sensitivity of inflation depends on the primitive pricing parameters, $\theta$ and $\Omega$. We combine lags of equation (18) to derive an expression in terms of year-over-year inflation, which depends on a four-quarter moving average of nominal marginal cost scaled by the price level:

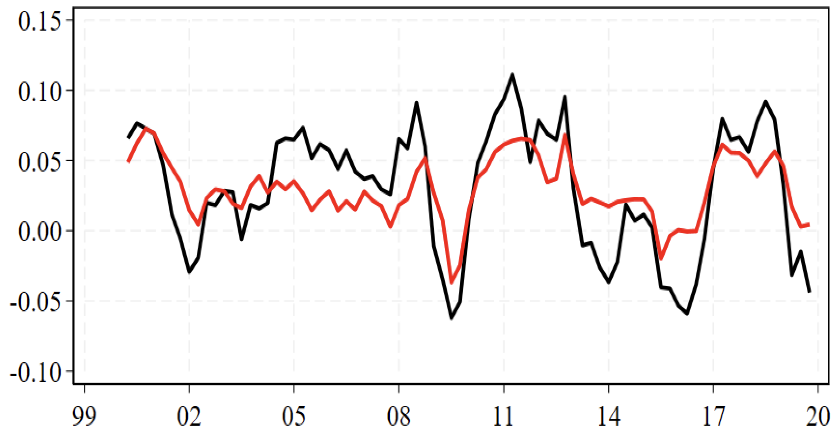
$$\pi_t^{\text{y-y}} = \sum_{\tau=0}^{3} \tilde{\lambda}(1-\tilde{\lambda})^{\tau}(mc_{t-\tau}^n - p_{t-4}) + \alpha^{\text{y-y}}. \tag{19}$$

The black line in Figure 1 plots year-over-year producer-price inflation for the Belgian manufacturing sector from PRODCOM. The red line in Figure 1 depicts the model-implied inflation series. The difference between the black and red lines is the component of inflation due to the cost-push shock, $u_t$.

As we can see, this parsimonious model effectively tracks the broad swings in Belgian manufacturing inflation over our sample period. It accounts for nearly seventy percent of the variation in inflation ($R^2 = 0.68$) with a correlation coefficient of 0.8. it is particularly noteworthy that the model captures the drop in inflation during the 2008 financial crisis and the sharp run-up in 2016 followed by

[29] This assumption is consistent with the empirical evidence. To show this, we first construct aggregate marginal cost, $mc_t^n$, as a weighted average (with Törnqvist weights) of firm marginal costs $mc_{ft}^n$. Then, we regress $mc_t^n$ on its one-quarter lag, instrumenting the latter with a two-quarter lag to reduce downward bias due to measurement error. We find that the estimated autoregressive coefficient is $\hat{\rho}^{mc} = 0.987$ (0.015), with Newey-West standard errors in brackets. Additionally, the Dickey-Fuller test does not reject the null hypothesis of unit root with $Z = -1.639$ and p-value $= 0.463$. Notice that this estimate is different, although consistent, from those in Table 2, as those estimates should be interpreted as the persistence of deviations from trend due to the inclusion of time fixed effects.

**Figure 1:** Aggregate inflation dynamics




*Notes.* This figure compares the inflation dynamics in the data to the model-implied one. The black line represents manufacturing PPI inflation in the data. The red line is the model-implied manufacturing PPI inflation constructed as in equation (19).

a subsequent decline. Additionally, the model successfully captures the consistent decline in inflation from 2011 to 2016, although it does not fully capture the amplitude.

Note that, within our framework, unobservable cost-push shocks account for a much smaller fraction of inflation volatility than is typically found in the quantitative literature.[30] In addition, we purposely chose to compare the data against the simplest possible framework. For instance, we did not account for other factors that could further rationalize inflation dynamics, such as lag-dependence in inflation, deviations from rational expectations, or imperfect information (see, e.g., Galí and Gertler 1999, Jørgensen and Lansing 2023, Gabaix 2020). Incorporating these forces in future research may further enhance our understanding of the relationship between inflation dynamics and real economic activity.

# 7 Reconciliation with the conventional NKPC

In this section, we reconcile our high slope estimates for the marginal cost-based curve with the low estimates of the conventional formulation. Following the literature, we make assumptions that allow us to establish a log-linear relationship

[30] For example, in Primiceri et al. (2006), cost-push shocks arising from variation in the desired price and wage markups account for about 70 percent of the volatility of inflation.

between marginal costs, prices, and the output gap at the firm level. Under these assumptions, the output-based Phillips curve slope ($\kappa$) is the product of the marginal cost-based slope ($\lambda$) and the output elasticity of marginal cost ($\sigma^y$):

$$\kappa = \lambda \cdot \sigma^y.$$

We then develop two different identification approaches to estimate $\sigma^y$ from micro-level data and retrieve $\kappa$. Consistent with the literature, we find a low output-based slope, which is explained for by a low elasticity of marginal cost to changes in output.

## 7.1 Marginal cost and the output gap at the firm level

To begin, we derive a log-linear relation between firm-level marginal cost and the output gap, similar to the one typically assumed at the aggregate level to obtain the conventional formulation of the Phillips curve. In doing so, we allow for general equilibrium effects that affect firms' costs through the impact of labor demand on wages (see e.g., Galí 2015).

In particular, we assume real wages are determined in general equilibrium at the industry level. Accordingly, we can express firm-level log real marginal cost, $mc_{ft}$, as a function of the industry real wage, $w_{it} - p_t$, and firm-level marginal product of labor, $mpn_{ft}$:

$$mc_{ft} = (w_{it} - p_t) - mpn_{ft}$$

Next, as in the benchmark NK model, we assume that industry real wages are flexible and increasing in current industry output, $y_{it}$. In addition, the firm marginal product of labor depends inversely on firm output, $y_{ft}$, and positively on firm productivity, $z_{ft}$, where the latter may contain both an aggregate and an idiosyncratic component:

$$mc_{ft} = \sigma^w y_{it} + z_{ft} + \nu y_{ft}.$$

In the equation above, $\sigma^w$ denotes the elasticity of real wages with respect to industry output. The presence of industry output captures general the equilibrium feedback of aggregate demand on firms' marginal cost. We assume that labor supply is industry-specific, which implies that $\sigma^w$ is independent of whether industry output is driven by aggregate or industry-specific shocks. We also assumed, for simplicity, that SR-RTS ($\nu$) are homogeneous across firms and time-invariant.

Without loss of generality, we can write log firm output as the sum of log industry output and idiosyncratic supply ($\epsilon^s_{ft}$) and demand ($\epsilon^d_t$) shocks:

$$y_{ft} = y_{it} + \epsilon^s_{ft} + \epsilon^d_{ft}.$$

The supply and demand shocks are linear, respectively, in the idiosyncratic component of the productivity factor, $z_{ft}$, and in the firm demand shifter, $\varphi_{ft}$, respectively.

Finally, we define the natural levels of industry and firm output, $y^*_{it}$ and $y^*_{ft}$. As is conventional, we define $y^*_{it}$ as the equilibrium level of output under flexible prices and wages, where the desired markup is constant. The natural level, $y^*_{ft}$, is similarly defined, also taking into account idiosyncratic supply shocks:

$$y^*_{ft} := y^*_{it} + \epsilon^s_{ft}.$$

Under these assumptions, we can express the deviation of real firm marginal cost from steady state, $\widehat{mc}_{ft}$, as a constant-elasticity function of firm-level output gap:

$$\widehat{mc}_{ft} = \sigma^y (y_{ft} - y^*_{ft}) - \sigma^w \epsilon^d_{ft}, \tag{20}$$

where the coefficient $\sigma^y := \sigma^w + \nu$ represents the elasticity of marginal cost with respect to the output gap. The error term $\sigma^w \epsilon^d_{ft}$ accounts for the fact that wages depend on the industry component of firm demand, but not the idiosyncratic component.

To derive a pricing equation in terms of output that allows us to identify $\sigma^y$ and therefore $\kappa$, we rearrange equation (20) and substitute for $mc^n_{ft}$ into from Section 4.2. As in Model C, we then postulate that nominal output and the competitors' price index, in deviations from their trends, follow first-order autoregressive processes. This leads to an empirical model that directly relates firm-level prices and output:

$$p_{ft} = \Psi^y \cdot \sigma^y y^n_{ft} + \Psi^p p^{-f}_{it} + \theta p_{ft-1} + \alpha_f + \alpha_{s\times t} + \varepsilon^p_{ft}, \tag{Model D}$$

where the coefficients $\Psi^y$ and $\Psi^p$ depend on the persistence of shocks:

$$\Psi^y := (1-\theta)(1-\Omega)\frac{1-\beta\theta}{1-\beta\theta\rho^y} \quad \text{and} \quad \Psi^p := (1-\theta)\Omega\frac{1-\beta\theta}{1-\beta\theta\rho^p}.$$

The error term $\varepsilon^p_{ft} := (1-\sigma^w)\varepsilon^d_{ft} - \sigma^y y^*_{ft}$ depends on the idiosyncratic demand shock and the (unobservable) natural level of output.

A complementary way to identify $\sigma^y$ is to rewrite equation (20) in terms of nominal marginal cost. Then, taking first differences, we obtain:

$$\Delta mc^n_{ft} = \sigma^y \Delta y^n_{ft} + \alpha_f + \alpha_{s\times t} + \varepsilon^{mc}_{ft}, \qquad \text{(Model E)}$$

where the price level is absorbed into the sector-by-time fixed effects and the error term $\varepsilon^{mc}_{ft} := -\sigma^w \Delta\epsilon^d_{ft} - \sigma^y \Delta y^*_{ft}$. Unlike Model D, which directly maps into the dynamic pass-through framework developed in section 4.2, Model E allows us to directly estimate the elasticity of interest from contemporaneous changes of marginal cost and output.

## 7.2 Identification of $\sigma^y$ and $\kappa$

We take Model D and Model E to the data to identify the elasticity $\sigma^y$ and thereby recover the slope of the output-based NKPC, $\kappa$. To do so, we use firms' nominal value added (revenues minus costs of intermediate inputs) as a measure of firm-level nominal output, $y^n_{ft}$. The identification of $\sigma^y$ requires us to isolate variation in $y^n_{ft}$ that is orthogonal to both the firm-level natural level of output and idiosyncratic demand shocks, as both enter the error terms $\varepsilon^{mc}_{ft}$ and $\varepsilon^p_{ft}$.

To tackle this issue, we follow the literature that estimates output and unemployment gap-based NKPCs by exploiting shifts in aggregate demand.[31] We recover industry sensitivities to high-frequency monetary policy shocks. We then construct a Bartik-style instrument to improve the power of the aggregate shocks while also allowing us to include sector-by-time fixed effects to control for higher-level movements in demand.

For each industry $i$, we estimate the sensitivity to an aggregate demand shock by projecting firm-level nominal value-added output on the monetary policy

[31] See Barnichon and Mesters (2020), McLeay and Tenreyro (2020), and Hazell et al. (2022) for recent examples.

**Table 3:** Estimates of the output-based slope

| | (1) | (2) |
|---|---|---|
| | *Model D* | *Model E* |
| *Panel a: Structural estimates* | | |
| $\sigma^y$ | 0.402 | 0.111 |
| | (0.099) | (0.026) |
| $\rho^y$ | 0.876 | |
| | (0.038) | |
| $\rho^p$ | 0.912 | |
| | (0.005) | |
| *Panel b: Slope of the output-based Phillips curve* | | |
| $\kappa$ | 0.021 | 0.006 |
| | (0.005) | (0.001) |
| *Test statistics* | | |
| Cragg-Donald $F$ | 191.276 | 482.438 |
| Kleibergen-Paap $F$ | 23.299 | 62.194 |
| Firm FE | y | y |
| Sector $\times$ time FE | y | y |

*Notes.* This table presents the empirical estimates of models D and E. The output-based NKPC slope, $\kappa$, is obtained as the product of the estimate of $\sigma^y$ and the estimate of $\lambda$ from Model A. All models are estimated using the complete sample. Robust standard errors (reported in parenthesis) are clustered at the industry-by-time level.

shock.[32] We lag the shock to reflect its delayed effect on real activity, which peaks at four quarters:

$$y^n_{ft} = \alpha_f + \psi_i MS_{t-4} + \epsilon^m_{ft},$$

We then obtain our demand-side instrument by interacting the aggregate money shock with the estimated sensitivity,

$$y^{IV}_{ft} := \hat{\psi}_i \cdot MS_{t-4}.$$

This shifter is orthogonal to both aggregate and idiosyncratic supply shocks as well as idiosyncratic demand shocks. However, it picks up movements in firms'

[32]Monetary policy shocks are constructed following Gürkaynak et al. (2005) as the log change in the price of overnight index swaps within a narrow window around ECB monetary policy announcements. The time series of aggregate money shocks are taken from Altavilla et al. (2019).

output due to general equilibrium effects as it captures common demand shocks at the industry level. Moreover, unlike the aggregate monetary policy surprises, it is a powerful instrument as it leverages variation in the high-frequency surprises interacted with the cross-industry response to these shocks.

We estimate Models D and E via GMM. For Model D, we calibrate $\theta$ and $\Omega$ to our baseline estimates. We then estimate the pass-through equation jointly with the AR(1) dynamics for output and competitors' prices. Table 3 presents the resulting estimates for the output elasticity of marginal cost and the implied estimates for the slope of the output-based Phillips curve. For model D, we find a value of $\sigma^y = 0.402$ and $\kappa = 0.021$. For model E, we find even smaller estimates, $\sigma^y = 0.111$ and $\kappa = 0.006$.

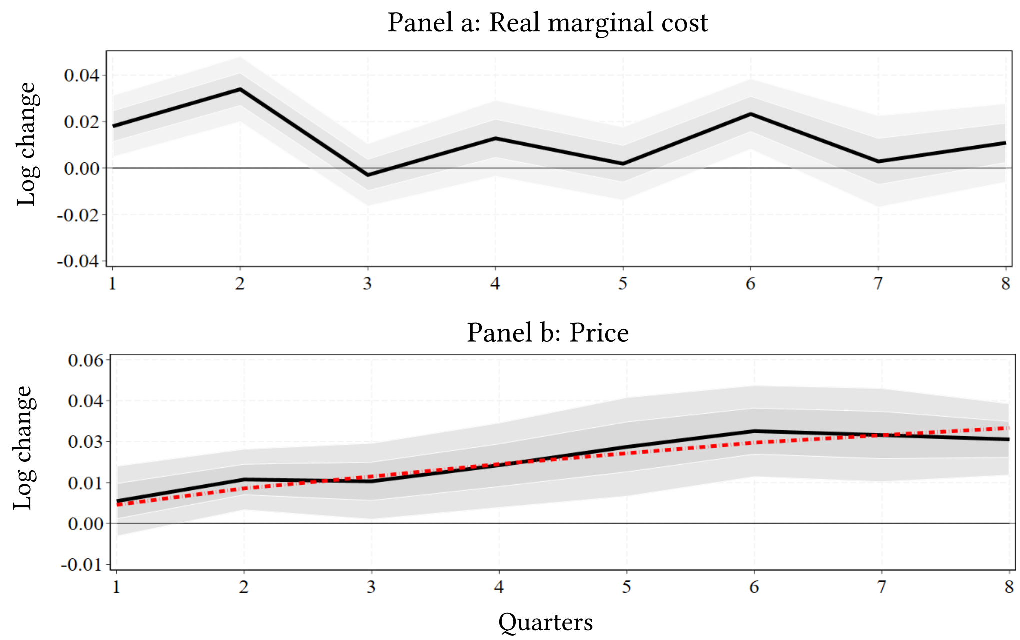
The low sensitivity of marginal cost to movements in output is consistent, for example, with a high degree of wage rigidity and an economy not operating too close to full capacity. These low estimates of $\kappa$ corroborate the findings in previous literature, which concludes that the slope of the output-based and unemployment-based NKPC appears to be flat. Indeed, our point estimates overlap closely with those in Rotemberg and Woodford (1997) and Hazell et al. (2022) who find slope coefficients of 0.024 and 0.006.

In sum, our analysis suggests that the pass-through from marginal costs to prices is high, as the micro-estimates indicate, but the flatness of the conventional NKPC is likely due to a low sensitivity of marginal cost to output. These considerations call for further theoretical and empirical work to elucidate the relationship between output and marginal cost, especially considering the possibility that the elasticity connecting the two could be time-varying and possibly nonlinear.

# 8 Tracing the effect of supply shocks on inflation

In this section, we study the pass-through of identified supply shocks to inflation. This exercise serves two purposes: it illustrates the advantage of a marginal cost-based Phillips curve for characterizing the transmission of supply shocks to inflation; it also provides an alternative estimate of the NKPC slope via

**Figure 2:** Dynamic effects of oil shocks




*Notes.* This figure shows the impulse response function (IRF) of real marginal cost and price level to aggregate oil shocks estimated via local linear projections. The dark (light) gray shaded areas are 68 (95) percent confidence bands obtained from Newey-West standard errors with four quarters of correlation. The red line represents the model-based IRF of prices, calculated by feeding the path of real marginal cost into a New Keynesian model featuring a cost-based NKPC.

impulse-response matching (e.g. Barnichon and Mesters 2020), validating the one obtained from our micro-level pass-though models.

**Tracing the effect of supply shocks.** The discussion in the previous section highlighted that it is challenging to assess the impact of such shocks on inflation using the output-based NKPC curve, without relying on a fully specified macroeconomic model to derive the natural level of output. The cost-based NKPC curve does not suffer from this. The impact of supply shocks on marginal cost is measurable, which implies that the cost-based NKPC can be used to quantify the pass-through of supply shocks to inflation.

We consider oil shocks as prototype supply shocks. Following Känzig (2021), we measure oil shocks as unexpected movements in oil price futures the day after OPEC meetings and estimate the empirical IRFs of aggregate real marginal cost and price level to these identified shocks via local linear projections:

$$x_{ft+h} - x_{ft-1} = a_f + b_h^x OS_{t-1} + \epsilon_{ft+h}$$

for $x \in \{mc^r, p\}$ and $h = 1, ..., 8$ quarters. We normalize the oil shock so that $b_1$ represents the effect on impact of a one-standard deviation shock to oil prices (a 15.7 percent increase in Brent crude oil price). As in our pass-through regressions, observations are weighted using Törnqvist sales-weights.

The estimates are reported in Figure 2. On average, firms' real marginal costs rise by 2–2.5 percent during the first two quarters in response to a one-standard-deviation shock to oil prices, before gradually returning to their pre-shock level (panel a). The oil shock also has significant effect on firms' prices (panel b, black line). Consistent with the presence of nominal rigidities, the price response is delayed but persistent, peaking at a 3 percent increase after six quarters.

**Estimation via impulse-response matching.** These empirical results allow us to validate our estimate of the slope of the NKPC. We feed the path of real marginal cost shocks (with perfect foresight) to an NK model featuring a cost-based Phillips curve. We then estimate the slope of the NKPC by minimizing the distance between the empirical impulse responses of prices, $\{\hat{b}_h^p\}_{h=1}^8$, and the corresponding model's impulse-responses of prices, $\{g_h^p(\lambda)\}_{h=1}^8$:

$$\lambda^{IRF} = \arg\min_{\lambda} \, (\hat{\boldsymbol{b}}^p - \boldsymbol{g}^p(\lambda))' \, W \, (\hat{\boldsymbol{b}}^p - \boldsymbol{g}^p(\lambda)),$$

where the weighting matrix $W$ is a diagonal matrix whose elements are the reciprocal of the variances of empirical IRFs estimates. Standard errors are calculated using the delta method (Mertens and Ravn 2011).

The model accurately reflects the dynamic effects of the shocks on the price level, both in terms of magnitude and persistence (Figure 2 panel b, red dotted line). The model's impulse-responses consistently lie within the confidence bands of those estimated in the data. Importantly, the slope of the cost-based NKPC that allows us to match the IRFs is $\lambda^{IRF} = 0.050$ (SE 0.004), which is nearly identical to the estimate obtained from the pass-through model ($\hat{\lambda} = 0.053$).

# 9 Concluding remarks

We use disaggregated data to identify the slope of the primitive form of the New Keynesian Phillips curve, which features marginal cost as a relevant measure of economic activity. We observe a high pass-through of marginal cost into prices, as evidenced by both the micro data and the marginal cost-based Phillips curve's ability to track aggregate inflation dynamics. We have also shown that a low elasticity of marginal cost to output can reconcile the low sensitivity of aggregate inflation to output (or employment) with the high pass-through of marginal cost.

The ability of the marginal cost-based NKPC to capture inflation dynamics should not be of narrow interest. Indeed, most quantitative macroeconomic (DSGE) models feature some form of wage rigidity to fit the data, which requires the cost-based formulation of the Phillips curve to capture the transmission of shocks into prices. See, e.g., Chapter 6 in Galí (2015) and the reference therein. Our analysis suggests, however, that there is room for improvements in different directions.

We start with the measure of marginal cost. DSGE models typically feature labor as the only variable input. However, accounting for intermediates costs is pivotal to the success of our empirical measure, as intermediates represent both the largest and most volatile component of production costs. To this point, research has shown that intermediate goods price shocks were among the most important drivers of the recent inflation surge (e.g., Di Giovanni et al. 2022). Developing models that incorporate how intermediates factor into firms' costs is an active and important direction for future research (see, e.g., Rubbo 2023).

Secondly, further research is needed to understand the primitive drivers of the elasticity of marginal cost with respect to output and how it may evolve over time. We show that this elasticity is low in normal times. However, it might have increased recently as the economy reached full capacity, possibly contributing to the inflation surge (e.g., Benigno and Eggertsson 2023).

Finally, the elasticity of inflation with respect to marginal cost depends on the frequency of price adjustment. Our evidence suggests this frequency was stable in the pre-pandemic period, leading to a stable elasticity as in Calvo. However, recent data indicates that frequency varied substantially throughout the inflation cycle, calling for the use of state-dependent pricing when large shocks hit.

## References


Altavilla, C., L. Brugnolini, R. S. Gürkaynak, R. Motto, and G. Ragusa (2019): "Measuring euro area monetary policy," *Journal of Monetary Economics*, 108, 162–179.

Amiti, M., O. Itskhoki, and J. Konings (2019): "International shocks, variable markups, and domestic prices," *The Review of Economic Studies*, 86, 2356–2402.

Atkeson, A. and A. Burstein (2008): "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 98, 1998–2031.

Barnichon, R. and G. Mesters (2020): "Identifying modern macro equations with old shocks," *The Quarterly Journal of Economics*, 135, 2255–2298.

Basu, S. (1995): "Intermediate Goods and Business Cycles: Implications for Productivity and Welfare," *American Economic Review*, 85, 512.

Benigno, P. and G. B. Eggertsson (2023): "It's baaack: The surge in inflation in the 2020s and the return of the non-linear phillips curve," Tech. rep., National Bureau of Economic Research.

Beraja, M., E. Hurst, and J. Ospina (2019): "The aggregate implications of regional business cycles," *Econometrica*, 87, 1789–1833.

Calvo, G. A. (1983): "Staggered prices in a utility-maximizing framework," *Journal of Monetary Economics*, 12, 383–398.

Di Giovanni, J., Á. Kalemli-Özcan, A. Silva, and M. A. Yildirim (2022): "Global supply chain pressures, international trade, and inflation," Tech. rep., National Bureau of Economic Research.

Engle, R. F. and C. W. Granger (1987): "Co-integration and error correction: representation, estimation, and testing," *Econometrica: journal of the Econometric Society*, 251–276.

Foster, L., J. Haltiwanger, and C. Syverson (2008): "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?" *American Economic Review*, 98, 394–425.

Gabaix, X. (2020): "A behavioral New Keynesian model," *American Economic Review*, 110, 2271–2327.

Galí, J. (2015): *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*, Princeton University Press.

Galí, J. and M. Gertler (1999): "Inflation dynamics: A structural econometric analysis," *Journal of Monetary Economics*, 44, 195–222.

Goldberg, P. K. and F. Verboven (2001): "The evolution of price dispersion in the European car market," *The Review of Economic Studies*, 68, 811–848.

Gürkaynak, R. S., B. P. Sack, and E. T. Swanson (2005): "Do actions speak louder than words? The response of asset prices to monetary policy actions and statements," *International Journal of Central Banking*, 1, 55–93.

Hazell, J., J. Herreno, E. Nakamura, and J. Steinsson (2022): "The slope of the Phillips Curve: evidence from US states," *The Quarterly Journal of Economics*, 137, 1299–1344.

Hooper, P., F. S. Mishkin, and A. Sufi (2020): "Prospects for inflation in a high pressure economy: Is the Phillips curve dead or is it just hibernating?" *Research in Economics*, 74, 26–62.

Hottman, C. J., S. J. Redding, and D. E. Weinstein (2016): "Quantifying the sources of firm heterogeneity," *The Quarterly Journal of Economics*, 131, 1291–1364.

Jørgensen, P. L. and K. J. Lansing (2023): "Anchored inflation expectations and the slope of the phillips curve," in *Federal Reserve Bank of San Francisco Working Paper 2019-27*.

Känzig, D. R. (2021): "The macroeconomic effects of oil supply news: Evidence from OPEC announcements," *American Economic Review*, 111, 1092–1125.

Kimball, M. S. (1995): "The quantitative analytics of the basic neomonetarist model," *Journal of Money, Credit, and Banking*, 27, 1241–1277.

Lenzu, S., D. Rivers, and J. Tielens (2023): "Financial Shocks, Productivity, and Prices," *Working paper*.

Mavroeidis, S., M. Plagborg-Møller, and J. H. Stock (2014): "Empirical evidence on inflation expectations in the New Keynesian Phillips Curve," *American Economic Journal: Journal of Economic Literature*, 52, 124–188.

McLeay, M. and S. Tenreyro (2020): "Optimal inflation and the identification of the Phillips curve," *NBER Macroeconomics Annual*, 34, 199–255.

Mertens, K. and M. O. Ravn (2011): "Understanding the aggregate effects of anticipated and unanticipated tax policy shocks," *Review of Economic dynamics*, 14, 27–54.

Nakamura, E. and J. Steinsson (2008): "Five facts about prices: A reevaluation of menu cost models," *The Quarterly Journal of Economics*, 123, 1415–1464.

Nakamura, E. and D. Zerom (2010): "Accounting for incomplete pass-through," *The Review of Economic Studies*, 77, 1192–1230.

Primiceri, G., E. Schaumburg, and A. Tambalotti (2006): "Intertemporal disturbances," *NBER Working Paper No. 12243*.

Rotemberg, J. J. and M. Woodford (1997): "An optimization-based econometric framework for the evaluation of monetary policy," *NBER Macroeconomics Annual*, 12, 297–346.

Rubbo, E. (2023): "Networks, Phillips curves, and monetary policy," *Econometrica*, 91, 1417–1455.

Sbordone, A. M. (2002): "Prices and unit labor costs: a new test of price stickiness," *Journal of Monetary Economics*, 49, 265–292.

Wang, O. and I. Werning (2022): "Dynamic oligopoly and price stickiness," *American Economic Review*, 112, 2815–49.

Woodford, M. (2011): *Interest and Prices: Foundations of a Theory of Monetary Policy*, Princeton University Press.

# Anatomy of the Phillips Curve: Micro Evidence and Macro Implications

L. Gagliardone M. Gertler S. Lenzu J. Tielens

Appendix for Online Publication

## A Derivations

This section provides additional information and derivations of the key equations presented in Section 2. We begin by showing how the markup function in the paper maps to the markup functions under two prominent frameworks featuring imperfect competition. We then present the aggregation steps followed to derive the Phillips curve.

### A.1 Derivation of markup function

**Dynamic oligopoly with nested CES preferences**

Assume that there is a continuum of industries (indexed by $i$) and a finite number of firms $N$ within each industry. Each firm is indexed by $f$ (or $j$). Within each industry, firms compete à la Bertrand. In this environment, the price indexes for each industry $P_{it}$ and the aggregate price index $P_t$ are defined, respectively, as:

$$P_{it} := \left( \frac{1}{N} \sum_{f=1}^{N} (\varphi_{fit} P_{fit})^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \; ; \; P_t := \left( \int_{i \in I} (\varphi_{it} P_{it})^{1-\sigma} di \right)^{\frac{1}{1-\sigma}},$$

where $\varphi_{fit}$ is a firm-specific relative demand shifter (firm appeal), and $\varphi_{it}$ is an industry-specific demand shifter (relative across industries). In what follows, the subscript $i$ is dropped when redundant and we normalize the steady-state price level to simplify the notation. The demand function for firm $f \in \mathcal{F}_i$ takes a nested CES form, with the elasticity of substitution across industries $\sigma > 1$ and the elasticity of substitution within industries $\gamma > \sigma$:

$$\mathcal{D}_{ft+\tau} = \left(\frac{\varphi_{ft+\tau}P^o_{ft}}{\varphi_{it+\tau}P_{it+\tau}}\right)^{-\gamma}\left(\frac{\varphi_{it+\tau}P_{it+\tau}}{P_{t+\tau}}\right)^{-\sigma} Y_{t+\tau}. \tag{A.1}$$

Firms internalize the dynamic effect of their choices on the industry price index and on industry demand. Therefore, the residual elasticity of demand faced by firm $f$ takes the following form:

$$\epsilon_{ft+\tau} := -\frac{\partial \ln \mathcal{D}_{ft+\tau}}{\partial \ln P^o_{ft}} = \gamma - (\gamma - \sigma)\frac{\partial p_{it+\tau}}{\partial p^o_{ft}}. \tag{A.2}$$

We can further characterize the derivative above. First, the price index of competitors of firm $f$ is defined as:

$$P^{-f}_{it} := \left(\frac{1}{N-1}\sum_{j\neq f}^{N-1}(\varphi_{jit}P_{jit})^{1-\gamma}\right)^{\frac{1}{1-\gamma}}.$$

It follows that $P^{1-\gamma}_{it} = \frac{N-1}{N}\left(P^{-f}_{it}\right)^{1-\gamma} + \frac{1}{N}\left(\varphi_{ft}P^o_{ft}\right)^{1-\gamma}$. Next, we can express the derivative of the price index in period $t+\tau$ with respect to the firms' reset price in period $t$ as follows:

$$\frac{\partial P_{it+\tau}}{\partial P^o_{ft}} = P^{\gamma}_{it+\tau}\left[\left(\frac{N-1}{N}\right)(P^{-f}_{it+\tau})^{-\gamma}\frac{\partial P^{-f}_{it+\tau}}{\partial P^o_{ft}} + \left(\frac{1}{N}\right)(\varphi_{ft})^{1-\gamma}(P^o_{ft})^{-\gamma}\right].$$

Multiplying both sides by $\frac{P^o_{ft}}{P_{it+\tau}}$, and defining the competitors' reaction function $\zeta_{ft+\tau} := \frac{\partial p^{-f}_{it+\tau}}{\partial p^o_{ft}}$, we obtain:

$$\begin{aligned}\frac{\partial p_{it+\tau}}{\partial p^o_{ft}} &= \zeta_{ft+\tau}\left(\frac{N-1}{N}\right)\left(\frac{P^{-f}_{it+\tau}}{P_{it+\tau}}\right)^{1-\gamma} + \frac{1}{N}\left(\frac{\varphi_{ft+\tau}P^o_{ft}}{P_{it+\tau}}\right)^{1-\gamma}\\ &= \zeta_{ft+\tau}(1-s_{ft+\tau}) + s_{ft+\tau},\end{aligned}$$

where $s_{ft+\tau} := \frac{1}{N}\frac{P^o_{ft}\mathcal{D}_{ft+\tau}}{P_{it}Y_{it+\tau}} = \frac{1}{N}\left(\frac{\varphi_{ft+\tau}P^o_{ft}}{P_{it+\tau}}\right)^{1-\gamma}$ denotes the within-industry revenue share of firm $f$, and $Y_{it+\tau} := \varphi^{\gamma-\sigma}_{it+\tau}\left(\frac{P_{it+\tau}}{P_{t+\tau}}\right)^{-\sigma} Y_{t+\tau}$ is the industry demand. Replacing the expression for $\frac{\partial p_{it+\tau}}{\partial p^o_{ft}}$ into equation (A.2), we find that the within-industry elasticity of demand faced by firm $f$ is given by:

$$\epsilon_{ft+\tau} = \gamma - (\gamma - \sigma)\left[\zeta_{ft+\tau}(1-s_{ft+\tau}) + s_{ft+\tau}\right]. \tag{A.3}$$

The intuition behind this expression is straightforward. The stronger the reaction of competitors to a firm's price change—captured by $\zeta_{ft+\tau}$—the lower the residual elasticity of demand. A low residual elasticity of demand, in turn, implies that the firm can sustain a higher markup in equilibrium. This result mirrors the one in the dynamic oligopoly environment in Wang and Werning (2022) and it nests a number of static environments featuring imperfectly competitive firms. In a static oligopoly, $\epsilon_{ft+\tau} = 0$ for $\tau > 0$. In Atkeson and Burstein (2008) static Nash oligopoly, $\epsilon_{ft+\tau} = 0$ for $\tau > 0$ and $\zeta_{ft+\tau} = 0$ for all $\tau$s. Under monopolistic competition, $N \to \infty$, which implies $\zeta_{ft+\tau} \to 0$ and $s_{ft+\tau} \to 0$.

We now use this result to derive the expression for the log-linearized desired markup in equation (7) in the paper. As is standard, we log-linearize around a symmetric Nash steady state (Atkeson and Burstein, 2008).[33] Log-linearizing the elasticity in (A.3) around the steady state, we obtain the steady state residual demand elasticity:

$$\epsilon = \gamma - (\gamma - \sigma)\frac{1}{N},$$

which corresponds to the expression in Atkeson and Burstein (2008). In this model, the desired markup is given by the Lerner index $\mu_{ft+\tau} := \ln(\epsilon_{ft+\tau}/(\epsilon_{ft+\tau} - 1))$. Log-linearizing this expression and substituting the expression for steady-state residual demand elasticity, we obtain the expression for the log-linearized desired markup (in deviation from steady state) in equation (7):

$$\mu_{ft+\tau} - \mu_f = -\Gamma\left(p^o_{ft} - p^{-f}_{it+\tau}\right) + u^{\mu}_{ft+\tau},$$

where $\mu_f = \mu$ for all $f$s in the symmetric steady state, $\Gamma := \frac{(\gamma-\sigma)(\gamma-1)}{\epsilon(\epsilon-1)}\frac{N-1}{N} > 0$

[33]The symmetry assumption is standard in the literature (e.g., Midrigan (2011) and Alvarez and Lippi (2014)), which eases the notation but is largely immaterial for our estimation purposes. Relaxing this assumption would imply firm-specific steady-state demand elasticities, $\epsilon_f$. In this case, the estimates of the parameters of our pricing equations should be interpreted as average across firms. The assumption of Nash steady state, also standard in the literature, implies that $\zeta_{j,\tau} = 0$ in the steady state for all $j$s and $\tau$s. This comes with some loss of generality, but two points can be made. First, as shown by Wang and Werning (2022), one can write a "behavioral" model with the weaker assumption that $\mathbb{E}\{\zeta_{j,\tau}\} = 0$ for all $j$s and $\tau$s, which delivers, under specific values for the elasticities $\sigma$ and $\gamma$, a pass-through of shocks to marginal cost into prices qualitatively similar to that produced by the Nash model. Second, these considerations also apply to our empirical analysis, as we directly estimate the parameters ($\Gamma$, in particular) rather than the underlying elasticities.

denotes the markup elasticity with respect to prices, and:

$$u^{\mu}_{ft} := -\frac{(\gamma-\sigma)(\gamma-1)}{\epsilon(\epsilon-1)}\ln\varphi_{ft} + \frac{\gamma-\sigma}{\epsilon(\epsilon-1)}\frac{N-1}{N}\zeta_{ft}, \tag{A.4}$$

captures residual variation in the markup that depends on the demand shifters and changes in the slope of competitors' reaction function.

Finally, using these expressions, we can show how to obtain the pricing equation (8). Log-linearizing the industry price index and ignoring constants, we obtain:

$$p_{it} = \frac{N-1}{N}p^{-f}_{it} + \frac{1}{N}(\ln\varphi_{ft} + p^{o}_{ft}).$$

Substituting in equation (6) for the markup and rearranging, we obtain:

$$p^{o}_{ft} = (1-\beta\theta)\mathbb{E}_t\left\{\sum_{\tau=0}^{\infty}(\beta\theta)^{\tau}\left((1-\Omega)(mc^{n}_{ft+\tau}+\mu_f) + \Omega p^{-f}_{it+\tau} + (1-\Omega)u^{\mu}_{ft+\tau}\right)\right\}, \tag{A.5}$$

where, as in the paper, $\Omega := \frac{\Gamma}{1+\Gamma}$. This parameter denotes the relative weight on the price index of competitors ($p^{-f}_{it}$) and captures the importance of strategic complementarities. When $\Omega$ is close to one, firms are not strategic and only look at their marginal cost when resetting prices. In particular, $\Omega \to 0$ as $N \to \infty$, which is the monopolistic competition case. The error term in equation (8) is:

$$u_{ft} := (1-\beta\theta)(1-\Omega)\mathbb{E}_t\left\{\sum_{\tau=0}^{\infty}(\beta\theta)^{\tau}u^{\mu}_{ft+\tau}\right\}, \tag{A.6}$$

which is therefore a firm-specific shock that depends on the expectation of future demand shifters.

### Monopolistic competition with Kimball preferences

Assume that the industry output $Y_{it}$ is produced by a unitary measure of perfectly competitive firms using a bundle of differentiated intermediate inputs $Y_{ft}$, $f \in i$. The bundle of inputs is assembled into final goods using the Kimball aggregator:[34]

$$\int_0^1 \Upsilon\left(\frac{Y_{ft}}{Y_{it}}\right)df = 1,$$

where $\Upsilon(\cdot)$ is strictly increasing, strictly concave, and satisfies $\Upsilon(1) = 1$.

Taking as given the industry demand $Y_{it}$, each firm minimizes costs subject

[34] For simplicity we now abstract from taste shocks.

to the aggregate constraint:

$$\min_{Y_{ft}} \int_0^1 P_{ft} Y_{ft} df \qquad \text{s.t.} \quad \int_0^1 \Upsilon\left(\frac{Y_{ft}}{Y_{it}}\right) df = 1.$$

Denoting by $\psi$ the Lagrange multiplier of the constraint, the first-order condition of the problem is:

$$P_{ft} = \psi \Upsilon'\left(\frac{Y_{ft}}{Y_{it}}\right)\frac{1}{Y_{it}} \tag{A.7}$$

Define implicitly the industry price index $P_{it}$ as:

$$\int_0^1 \phi\left(\Upsilon'(1)\frac{P_{ft}}{P_{it}}\right) df = 1$$

where $\phi := \Upsilon \circ (\Upsilon')^{-1}$. Evaluating the first-order condition (A.7) at symmetric prices, $P_{ft} = P_{it}$, we get $\psi = \frac{P_{it}Y_{it}}{\Upsilon'(1)}$. Replacing for $\psi$, we recover the demand function:

$$\frac{P_{ft}}{P_{it}} = \frac{1}{\Upsilon'(1)}\Upsilon'\left(\frac{Y_{ft}}{Y_{it}}\right). \tag{A.8}$$

Therefore, the demand function faced by firms when resetting prices is:

$$\mathcal{D}_{ft+\tau} = \left[(\Upsilon')^{-1}\left(\Upsilon'(1)\frac{P^o_{ft}}{P_{it+\tau}}\right)\right]\left(\frac{P_{it+\tau}}{P_{t+\tau}}\right)^{-\sigma} Y_{t+\tau}$$

Taking logs of equation (A.1) and differentiating, we obtain the following expression for the residual elasticity of demand:

$$\epsilon_{ft+\tau} := -\frac{\partial \ln \mathcal{D}_{ft+\tau}}{\partial \ln P^o_{ft}} = -\frac{\Upsilon'\left(\frac{Y_{ft+\tau}}{Y_{it+\tau}}\right)}{\Upsilon''\left(\frac{Y_{ft+\tau}}{Y_{it+\tau}}\right)\cdot\left(\frac{Y_{ft+\tau}}{Y_{it+\tau}}\right)} \tag{A.9}$$

We now use this result to derive the expression for the log-linearized desired markup in equation (7) in the paper, under monopolistic competition with Kimball preferences. As above, for ease of exposition, we focus on the symmetric steady state. Denote the steady-state residual demand elasticity by $\epsilon = -\frac{\Upsilon'(1)}{\Upsilon''(1)}$. Then the derivative of the residual demand elasticity $\epsilon_{ft+\tau}$ in (A.9) with respect to $\frac{Y_{ft+\tau}}{Y_{it+\tau}}$, evaluated at the steady state, is given by:

$$\epsilon' = \frac{\Upsilon'(1)\left(\Upsilon'''(1) + \Upsilon''(1)\right) - \left(\Upsilon''(1)\right)^2}{\left(\Upsilon''(1)\right)^2} \leq 0. \tag{A.10}$$

The equation above holds with equality if the elasticity is constant (e.g., under CES preferences). Also in this model, the desired markup is given by the Lerner index.

Log-linearizing the Lerner index around the steady state and using equation (A.10), we have that, up to a first-order approximation, the log-markup (in deviation from the steady state) is equal to:

$$\mu_{ft+\tau} - \mu_f = \frac{\epsilon'}{\epsilon(\epsilon - 1)} \left( y_{ft+\tau} - y_{it+\tau} \right)$$

Finally, log-linearizing the demand function (A.1) and using it to replace the log difference in output, we obtain:

$$\mu_{ft+\tau} - \mu_f = -\Gamma \left( p^o_{ft} - p_{it+\tau} \right)$$

where, in the case of Kimball preferences, the sensitivity of the markup to the relative price is given by $\Gamma := \frac{\epsilon'}{\epsilon(\epsilon-1)} \frac{1}{\Upsilon''(1)}$.

Notice that, because there there is a continuum of firms within an industry, we have that $p_{it+\tau} = p^{-f}_{it+\tau}$ without loss of generality. Substituting into the pricing equation (6) and and rearranging leads to the expression equation (7) in the paper.

Finally, following the same steps as the previous section, we obtain $\Omega := \frac{\Gamma}{1+\Gamma}$ and the corresponding mapping to the pricing equation in (8).

## A.2 Aggregation and the Phillips Curve

Suppose $N < \infty$ and order firms in each industry from 1 to $N$.[35, 36] The aggregate price index (in log-linear terms) is:

$$p_t = \int_{i \in I} \left( \frac{1}{N} \sum_{f=1}^{N} p_{fit} \right) di,$$

(In the paper, we dropped the industry subscript for ease of notation.) Denote by $A^\star_{ft}$ for $f \in \{1, \ldots, N\}$ the set of industries in which the $f$-th firm can adjust. The price index can then be rewritten as:

$$p_t = \frac{1}{N} \sum_{f=1}^{N} \left( \int_{i \in I/A^\star_{ft}} p_{fit-1} di + \int_{i \in A^\star_{ft}} p^o_{fit} di \right),$$

[35] Notice that the same argument goes through with minor modifications but heavier notation for $N_i \neq N$ for a non-zero measure of industries. In general, heterogeneity of the parameters can be accommodated by repeating the same argument for each group of homogeneous industries with non-zero measure and then taking weighted averages of different industries. See for example Wang and Werning (2022), Appendix C2.

[36] Letting $N \to \infty$, all results hold under Kimball preferences.

where we are using the fact that firms that cannot adjust set their price to their $t-1$ level, whereas firms that can adjust their price set it to their optimal reset price.

Since $A^{\star}_{ft}$ has measure $1-\theta$, and the identity of firms that adjust is an i.i.d. draw from the total population of firms, using the law of large numbers for each $f=\{1,\ldots,N\}$ across industries we have that:[37]

$$\frac{1}{N}\sum_{f=1}^{N}\int_{i\in I/A^{\star}_{ft}} p_{fit-1}di = \theta\int_{i\in I}\left(\frac{1}{N}\sum_{f=1}^{N}p_{fit-1}\right)di = \theta p_{t-1}$$

and

$$\frac{1}{N}\sum_{f=1}^{N}\int_{i\in A^{\star}_{ft}} p^{o}_{fit}di = (1-\theta)\int_{i\in I}\left(\frac{1}{N}\sum_{f=1}^{N}p^{o}_{fit}\right)di.$$

Defining $p^{o}_{t} := \int_{i\in I}\left(\frac{1}{N}\sum_{f=1}^{N}p^{o}_{fit}\right)di$ as the average reset price in the economy, we obtain:

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

which is equation (9) in the paper.[38]

Next, we replace the aggregate reset price, $p^{o}_{t}$, with an expression that depends on aggregate marginal costs and prices. Using the definition of firm-level marginal cost in equation (5), and allowing for arbitrary aggregate returns to scale ($\nu \lesseqqgtr 0$), we obtain the following expression for the logarithm of firm-level nominal marginal cost:

$$mc^{n}_{fit} = c_{it} + a_{fit} + \nu y_{fit}.$$

The average marginal cost in the industry is $mc^{n}_{it} := \frac{1}{N}\sum_{f=1}^{N}mc^{n}_{fit}$, implying:

$$mc^{n}_{it} = c_{it} + a_{it} + \nu y_{it}.$$

Combining the two equations above and subtracting the (log) industry price index from both sides, we obtain an expression that relates real marginal costs to cost

[37] The i.i.d. assumption implies that: $\int_{i\in B\subseteq[0,1]} p_{fit}di = Pr(B)\int_{i\in I}p_{fit}di$. Notice also that $\int_{i\in[0,1]}\left(\frac{1}{N}\sum_{f=1}^{N}p^{-f}_{it}\right)di = \int_{i\in[0,1]}\left(\frac{1}{N}\sum_{f=1}^{N}\left[\frac{N}{N-1}p_{it} - \frac{1}{N-1}p_{fit}\right]\right)di = p_t$.

[38] Notice that $p_t = \theta p_{t-1} + (1-\theta)p^{o}_{t}$ holds with Kimball preferences as well up to a first-order approximation around the symmetric steady state.

shifters and output:

$$mc_{fit} = mc_{it} + (a_{fit} - a_{it}) + \nu(y_{fit} - y_{it}).$$

We use the demand function to express the log output deviation, $y_{fit} - y_{it}$, in terms of log prices. In the case of CES preferences (see equation (A.1)), we obtain:

$$mc_{fit} = mc_{it} + (a_{fit} - a_{it}) - \gamma\nu(p^o_{fit} - p_{it}) - \gamma\nu \ln \varphi_{fit},$$

where $\gamma$ denotes the within-industry elasticity of substitution.[39]

We then proceed with the following steps: we first manipulate equation (A.5) to express the reset price in recursive form, then decompose firm-level nominal marginal cost into firm-level real marginal cost and the industry price index prices, and finally use equation (A.2) to replace for firm-level real marginal cost:

$$\begin{aligned} p^o_{fit} &= (1-\beta\theta)\left((1-\Omega)(mc^n_{fit} + \mu_f) + \Omega p^{-f}_{it} + (1-\Omega)u^\mu_{fit}\right) + \beta\theta\mathbb{E}_t p^o_{fit+1} \\ &= (1-\beta\theta)\Theta\left((1-\Omega)\widehat{mc}_{it} + \Omega p^{-f}_{it} + (1-\Omega)(1+\gamma\nu)p_{it} + (1-\Omega)u^\mu_{fit}\right) \\ &\quad + \beta\theta\mathbb{E}_t p^o_{fit+1} + (1-\beta\theta)\Theta(1-\Omega)\left(a_{fit} - a_{it} - \gamma\nu\ln\varphi_{fit}\right), \end{aligned}$$

where $\Theta := \frac{1}{1+\gamma\nu(1-\Omega)}$ captures macroeconomic complementarities due to aggregate returns to scale in production.

Finally, averaging across firms and industries, we have that the aggregate reset price is given by:

$$p^o_t = (1-\beta\theta)\left((1-\Omega)\Theta\widehat{mc}_t + p_t\right) + \beta\theta\mathbb{E}_t p^o_{t+1} + \frac{\theta}{1-\theta}u_t,$$

where $u_t := \frac{(1-\theta)(1-\beta\theta)}{\theta}(1 - \Omega)\Theta\int_{i\in I}\left(\frac{1}{N}\sum_{f=1}^N u^\mu_{fit}\right)di$ is an aggregate cost-push shock and $\left(a_{fit} - a_{it} + \gamma\nu\ln\varphi_{fit}\right)$ is such that $\int_{i\in I}\left(\frac{1}{N}\sum_{f=1}^N(a_{fit} - a_{it} + \gamma\nu\ln\varphi_{fit})\right)di = 0$. This follows from the i.i.d. assumption on price adjustments, which implies that the average productivity of resetting firms coincides with the unconditional average.

Subtracting $p_t$ from both sides and using the log-linearized price index, we

[39] A similar expression holds under monopolistic competition with Kimball preferences. In this case, $\gamma$ is replaced with the corresponding elasticity of relative output to relative prices, $1/\Upsilon''(1)$.

obtain:

$$p_t^o - p_t = (1-\beta\theta)(1-\Omega)\Theta\widehat{mc}_t + \beta\theta(\mathbb{E}_t p_{t+1}^o - p_t) + \frac{\theta}{1-\theta}u_t$$
$$\Rightarrow \frac{\theta}{1-\theta}\pi_t = (1-\beta\theta)(1-\Omega)\Theta\widehat{mc}_t + \beta\theta\mathbb{E}_t\left(\frac{\theta}{1-\theta}\pi_{t+1} + \pi_{t+1}\right) + \frac{\theta}{1-\theta}u_t$$

Rearranging one obtains the marginal cost-based Phillips curve:

$$\pi_t = \lambda\Theta\,\widehat{mc}_t + \beta\mathbb{E}_t\pi_{t+1} + u_t$$

where $\lambda := \frac{(1-\theta)(1-\beta\theta)}{\theta}(1-\Omega)$ is the slope. The equation above highlights that macroeconomic complementarities also mediate the pass-through of marginal cost to prices via $\Theta$. Under the assumption of constant aggregate returns to scale, we have that $\Theta = 1$, and the Phillips curve simplifies to equation (11). This condition is exactly met when $\nu = 0$, but also when $\Omega = 1$.

## A.3 Derivations of inflation dynamics

Ignoring the intercept, the system of equations is given by:

$$\begin{aligned} p_t^o &= (1-\beta\theta)((1-\Omega)mc_t^n + \Omega p_t) + \beta\theta\mathbb{E}_t p_{t+1}^o + \frac{\theta}{1-\theta}u_t, \\ p_t &= (1-\theta)p_t^o + \theta p_{t-1}, \\ mc_t^n &= mc_{t-1}^n + \varepsilon_t^{mc}. \end{aligned} \tag{A.11}$$

We guess and verify using the method of undetermined coefficients that the solution is of the form:

$$\begin{aligned} p_t^o &= \Xi(mc_{t-1}^n + \varepsilon_t^{mc}) + (1-\Xi)p_{t-1} + \frac{\theta}{1-\theta}u_t, \\ p_t &= \tilde{\lambda}(mc_{t-1}^n + \varepsilon_t^{mc}) + (1-\tilde{\lambda})p_{t-1} + \theta u_t, \end{aligned}$$

where $\Xi$ and $\tilde{\lambda}$ are the coefficients to be determined. Plugging the guessed solution into the system gives the following restrictions on the parameters:

$$\begin{aligned} \Xi &= (1-\beta\theta)(1-\Omega+\Omega\tilde{\lambda}) + \beta\theta(\Xi + (1-\Xi)\tilde{\lambda}), \\ \tilde{\lambda} &= (1-\theta)\Xi. \end{aligned}$$

We select the solution of system (A.11) characterized by having exactly one eigenvalue larger than one in modulus. This gives the following values for the parameters in terms of primitives:

$$\Xi = \frac{\beta\theta(2-\Omega(1-\theta)-\theta)+\Omega(1-\theta)-1}{2\beta(1-\theta)\theta}$$
$$+\frac{\sqrt{(-\Omega(1-\theta)(1-\beta\theta)-\beta(2-\theta)\theta+1)^2+4\beta(1-\Omega)(1-\theta)\theta(1-\beta\theta)}}{2\beta(1-\theta)\theta},$$
$$\tilde{\lambda} = (1-\theta)\Xi.$$

Rearranging the guessed solution for $p_t = \tilde{\lambda} mc_t^n + (1-\tilde{\lambda})p_{t-1} + \theta u_t$ and adding back the intercept, we obtain equation (18). Using our structural estimates, $\theta = 0.7$ and $\Omega = 0.52$ (median values across the different models in Table 2), we obtain that the aggregate pass-through coefficient $\tilde{\lambda} = 0.22$.

# B Data and Measurement

## B.1 Data sources and data cleaning

In this section, we describe the various administrative sources used to assemble our micro-level data

We use information from PRODCOM to compute the quarterly change in product- and firm-level prices and to define the boundaries of markets (industries) in which firms compete. PRODCOM is a large-scale survey commissioned by Eurostat and administered in Belgium by the national statistical office. The survey is designed to cover at least 90% of domestic production value within each manufacturing industry (4-digit NACE codes) by surveying all firms operating in the country with (a) a minimum of 20 employees or (b) total revenue above 4.5 million euros (European Commission 2014). Firms are required to disclose, on a monthly basis, product-specific physical quantities (e.g., volume, kg., $m^2$, etc.) of production sold and the value of production sold (in euros) for all their manufacturing products. Products are defined in PRODCOM by an 8-digit PC code (e.g., 10.83.11.30 is "Decaffeinated coffee, not roasted", 10.83.11.50 is "Roasted coffee, not decaffeinated", and 10.83.11.70 is "Roasted decaffeinated coffee"). Industries are defined by the first four digits of the product codes (e.g., 10.83 is "Processing of tea and coffee"). Sectors are defined by the first two digits of the product codes (e.g., AC is "Manufacture of food products, beverages, and tobacco products"). The sector definitions follow the NACE Rev.2 classification. For the most part, the industry definition also follows Rev.2. The only exceptions are industries under NACE Rev.1 (i.e., before 2008) that do not directly map into a NACE Rev.2 industry; these are assigned a fictitious, unique 4-digit industry code.

In the raw data, there are approximately $4,000$ product headings distributed across 13 manufacturing sectors. The PC product codes have been revised several times between 1999 and 2019, with a substantial overhaul in 2008. We use the conversion tables provided by Eurostat and firm-specific information on firms' product baskets to harmonize the 8-digit product codes across consecutive quarters and harmonize 4-digit industry codes over time.[40] In most cases, the conversion tables provide a unique mapping of the 8-digit product codes across consecutive years. In a limited number of cases, the mapping is many-to-one, one-to-many, or many-to-many. The many-to-one mapping is straightforward, while the one-to-many and many-to-many mappings could be problematic. We are able to handle most of these cases using information on the basket of products produced by each firm.[41] In a limited number of cases (less than 0.1% of the sample), we do not have sufficient information to resolve the uncertainty regarding the mapping. We drop these observations from the sample. Table A.1 reports the list of manufacturing sectors and their 2-digit PC codes.

We aggregate monthly information at the quarterly level and construct product-level prices (unit values) by dividing product-level sales by product-level quantities sold. As explained in the paper, we are interested in domestic prices, i.e., prices charged by producers in Belgium. PRODCOM does not require firms to separately report production and sales to domestic and international customers. Therefore, we recover domestic values and quantities sold by combining information from PRODCOM with data on firms' product-level exports (quantities and sales) available through Belgian Customs (for extra-EU trade)

[40]The official conversion tables are available at `https://ec.europa.eu/eurostat/ramon`. The harmonization of the industry code essentially consists of harmonizing the NACE Rev.1 industry, used before 2008, to the NACE Rev.2 industry codes, used from 2008.

[41]For example, consider a case where the official mapping indicates that product 11.11.11.11 in year $t$ could map to either 22.22.22.21 or 22.22.22.22 in year $t+1$. Suppose two firms, $f_1$ and $f_2$, report in period $t$ sales of product 11.11.11.11 in year $t$. If $f_1$ reports *only* sales of 22.22.22.21 and $f_2$ *only* reports sales of 22.22.22.22 in year $t+1$ we infer that we should map 11.11.11.11 to 22.22.22.21 for the former and 11.11.11.11 to 22.22.22.22 for the latter.

and the Intrastat Inquiry (for intra-EU trade).[42] We use the official conversion tables provided by Eurostat to map the CN product code classification used in the international trade data to the PRODCOM product code classification.[43] In most cases, the CN-to-PC conversion involves either a one-to-one or many-to-one mapping, which poses no issues. We drop observations that involve one-to-many and many-to-many mappings. These account for less than 5% of the observations and production value.

We apply the following filters and data manipulations to the PRODCOM data set. First, we retain firms' observations in a given quarter only if there was positive production reported for at least one product in that quarter. This avoids large jumps in quarterly values due to non-reporting for some months by certain firms. In the rare cases when a firm reports positive values but quantities are missing, we impute the quantity sold from the average value-to-quantity ratio in the months where both values and quantities are reported. Second, we require firms to file VAT declarations and Social Security declarations (as explained below); these two data sources are needed to measure firms' marginal costs.

The second important use of international trade data is to obtain information on international competitors selling manufacturing products in Belgium. For each domestic firm, the merged Customs-Intrastat data reports the quantity purchased (in kg) and sales (converted to euros) of different manufacturing products (about 10,000 distinct CN product headings) purchased by Belgian firms from each foreign country. As is standard when dealing with customs data, we define a foreign competitor as a foreign country-domestic buyer pair. For each foreign competitor, we aggregate the product-level sales and quantity sold at the quarterly level (the reporting is monthly in the raw data) and compute quarterly prices (unit values) by taking the ratio of the two.[44]

[42]In constructing our measure of domestic sales, we address issues related to carry-along trade, which might overstate the amount of production by firms that import products destined for immediate sales.

[43]The first six digits of the CN product classification codes correspond to the World HS classification system.

[44]Some CN codes change over time (although to a lesser extent than PC codes). We use the official conversion tables, available on the Eurostat website, to map CN product codes across consecutive years. We make adjustments only if the code change is one-to-one between two years. We do not account for changes in PC codes that involve splitting into multiple codes or multiple PC codes combining into one code. Effectively, these changes in the PC codes are treated as if new

We leverage data from two administrative sources to measure firms' total production (turnover) and variable production costs on a quarterly basis. Belgian firms file VAT declarations to the tax authority that contain information on the total sales of the enterprise as well as information on purchases of raw materials and other goods and services that entail VAT-liable transactions, including domestic and international transactions. The coverage of the VAT declarations is almost universal, with a limited number of exceptions that affect the reporting of sole proprietorships and self-employed individuals, and therefore mostly do not apply to the firms surveyed by PRODCOM.[45] We obtain information on employment and labor costs (wage bill) from the Social Security declarations filed quarterly by each Belgian firm with the Department of Social Security of Belgium.

We sum firm-quarter level expenses on intermediates and labor to obtain a measure of total variable costs, which we use to construct firms' marginal costs. We multiply these costs by the ratio of total manufacturing sales (from PRODCOM) to total sales (from the VAT declarations) to adjust for the fact that some firms also have production outside manufacturing.[46]

Finally, we apply the following data-cleaning steps to address missing values and outliers. (i) We focus on manufacturing industries defined by the NACE Rev.2 2-digit codes 15–36, dropping from our sample all product headings that correspond to mining and quarrying, and all product codes corresponding to industrial services. (ii) We drop observations referring to firms whose sales from manufacturing products (as measured in PRODCOM) are lower than seventy percent of total firm-level sales (as reported in the VAT declarations). This ensures that our sample includes firms whose real activity is primarily, if not entirely,

---

products are generated.

[45]Enterprises file their VAT declarations online, either monthly or quarterly, depending on certain size-based thresholds. Smaller enterprises (turnover <$2.5M euros excl. VAT) can choose to file either monthly or quarterly. Larger enterprises file monthly. In the case of multiple plants or establishments under one VAT identifier, the declaration is filed as a single document for that VAT identifier. We aggregate all monthly declarations to the quarterly level. At this reporting frequency, VAT declarations tend to reflect the sales of output produced in the previous quarter. For this reason, we use one-quarter leads in VAT declarations to construct the measure of firm-level value added used in the regressions discussed in Section 7.

[46]As mentioned below, we conservatively drop observations referring to firms whose manufacturing sales are less than seventy percent of total sales. In the remaining sample, the ratio has a mean of 0.94 and a median of 0.97, confirming PRODCOM's extensive coverage.

in manufacturing. (iii) As is standard, we exclude firms that operate in the "Coke and refined petroleum products" sector and the "Pharmaceuticals, medicinal chemical, and botanical products" sector, whose output prices are frequently privately bargained or determined in international markets. We also exclude firms operating in the "Other manufacturing and repair and installation of machinery and equipment" sector, a residual grouping consisting of firms producing diverse and varied products for which it is difficult to define an appropriate set of competitors. (iv) We keep only observations for which we are able to compute product-level price indexes, the corresponding quantity indexes, competitors' price indexes, and marginal costs. (v) We drop observations for which the quarter-to-quarter change of either the firm-level price index or marginal costs is greater than 100% in absolute value. (vi) Finally, for each firm-industry pair that enters our dataset discontinuously, we keep only the longest continuous time spell. This ensures that each time series used in the estimation has no gaps, which would otherwise force us to interpolate by making assumptions about prices and marginal costs when the data is not recorded.

**Table A.1:** List of manufacturing sectors

| Sector | Sector definition | NACE Rev.2 2-digits codes |
|---|---|---|
| CA | Food products, beverages and tobacco products | 10–12 |
| CB | Textiles, apparel, leather and related products | 13–15 |
| CC | Wood and paper products, and printing | 16–18 |
| CE | Chemicals and chemical products | 20 |
| CG | Rubber and plastics products, and other non-metallic mineral products | 22–23 |
| CH | Basic metals and fabricated metal products, except machinery and equipment | 24–25 |
| CI | Computer, electronic and optical products | 26 |
| CJ | Electrical equipment | 27 |
| CK | Machinery and equipment n.e.c. | 28 |
| CL | Transport equipment | 29–30 |

*Notes.* This table reports the list of manufacturing sectors in our sample and the corresponding 2-digit NACE Rev.2 codes.

## B.2 Construction of price indexes

We construct a set of indexes that capture price changes in manufacturing goods at various levels of aggregation (firm-industry, firm, industry, individual manufacturing sector, and whole manufacturing sector).

**Firm-industry price index.** The main variable of interest is the price of domestically sold manufacturing products at the firm-industry level, $P_{ft}$, for both domestic and foreign producers. We construct this variable using information on price changes at the most disaggregated level allowed by the data.

Due to repeated product code revisions, a consistent 8-digit product code taxonomy does not exist across the entire sample period.[47] Therefore, we compute the sequence of price changes across consecutive time periods ($t$ and $t+1$) by mapping the product codes at $t+1$ to their corresponding codes at $t$, aggregating them at the firm-industry level, and recovering the time series of the firm-industry price index (in levels) by concatenating quarterly price changes.

Specifically, denote by $\mathcal{P}_{ft}$ the set of products manufactured by firm $f$ and by $P_{pt}$ the price (unit value) of a given product $p \in \mathcal{P}_{ft}$. We first compute the gross price change for each product, $P_{pt}/P_{pt-1}$. In doing so, we appropriately account for any changes in product codes and drop product-level observations with abnormally large price jumps in a given quarter ($P_{pt}/P_{pt-1} > 3$ or $P_{pt}/P_{pt-1} < 1/3$). We then construct the Törnqvist index, which measures the firm-industry price change:

$$P_{ft}/P_{ft-1} = \prod_{p \in \mathcal{P}_{ft}} (P_{pt}/P_{pt-1})^{\bar{s}_{pt}}, \tag{A.12}$$

where $\bar{s}_{pt}$ is a Törnqvist weight computed as the average of the sale shares between $t$ and $t-1$: $\bar{s}_{pt} := \frac{s_{pt}+s_{pt-1}}{2}$.[48] Finally, we use the sequence of quarterly price changes to construct the time series of firm-industry prices (in levels):

$$P_{ft} = P_{f0} \prod_{\tau = t_f^0 + 1}^{t} \left( P_{f\tau}/P_{f\tau-1} \right), \tag{A.13}$$

[47] See Appendix B.1 for additional information on the data.

[48] his index accounts for the presence of multi-product firms by averaging across products produced by the same firm in a given industry. The Törnqvist weights, $\bar{s}_{pt}$, give larger weights to those products that account for a larger share of the firm's turnover.

where $t_f^0$ denotes the first quarter when $f$ appears in our data, and $P_{f0}$ is the price level in that quarter. We normalize $P_{f0}$ to one for all firm-industry pairs $f$ in our dataset. As discussed in the paper, this normalization is immaterial for our empirical analysis, as any level effects are absorbed by the firm-industry fixed effects included in all our empirical specifications.

**Firm price index.** As discussed in the paper, the vast majority of firms in our data operate in only one (4-digit) industry, implying that the firm-industry price index, $P_{ft}$, and the firm price index, $\bar{P}_{ft}$, coincide. However, in a limited number of cases, it becomes necessary to construct a firm's price index that aggregates across different firm-industry price indexes. In doing this, we construct the firm-level price index $\bar{P}_{ft}$ following a method similar to the one described above. Specifically, we construct a Törnqvist index that aggregates across price changes of the individual (4-digit) industry bundles $i \in I_f$ produced by firm $f$ in quarter $t$: $\bar{P}_{ft}/\bar{P}_{ft-1} = \prod_{i \in I_f} (P_{fit}/P_{fit-1})^{\bar{s}_{fit}}$ , with Törnqvist weights defined as $\bar{s}_{fit} := (s_{fit} + s_{fit-1})/2$, where $s_{fit}$ is the share of sales of industry $i$ in the firms' total sales (across manufacturing industries). We then concatenate the quarterly price changes above to obtain the price index $\bar{P}_{ft}$, normalizing the level of the price index to one in the first quarter when the firm first appears in our dataset. Note that for single-industry firms the price index $\bar{P}_{ft}$ coincides with the firm-industry price index $P_{fit}$ in (A.13).

**Competitors price index.** Using a similar approach, we construct the competitors' price index for each domestic firm. We start by computing quarterly price changes: $P_{it}^{-f}/P_{it-1}^{-f} = \prod_{k \in \mathcal{F}_i/f} (P_{kt}/P_{kt-1})^{\bar{s}_{kt}^{-f}}$, with $\bar{s}_{kt}^{-f} := \frac{1}{2}\left(\frac{s_{kt}}{1-s_{ft}} + \frac{s_{kt-1}}{1-s_{ft-1}}\right)$ denoting a Törnqvist weight constructed by averaging the residual revenue share of competitors in the industry at time $t$ (net of firm $f$ revenues) with that at time $t-1$. We then concatenate the changes, normalizing the level of the price index in the first period to one. Also, in this case, the normalization is immaterial for estimation purposes as our empirical model always includes firm fixed effects. Note that the set of domestic competitors for each Belgian producer, denoted in the paper by $\mathcal{F}_i$, includes not only other Belgian manufacturers operating in the same industry but also foreign manufacturers that belong to the same industry and sell to Belgian customers.

**Industry, sector, and aggregate price index.** We construct the industry-level, sector-level, and aggregate (manufacturing) price indexes by aggregating quarterly firm-level price changes. The formula to construct the percentage change in these price indexes is analogous to the one in (A.12), where now the Törnqvist weights assigned to each firm-industry price change, $P_{ft}/P_{ft-1}$, capture the (weighted) average market shares of the firm in its own industry, sector, or manufacturing, respectively. Once again, the level of the indexes is constructed by concatenating changes and normalizing the level of the price index to one for the first observation in the time series.

# C Estimation of firm-level productivity

Consider the following log-production function: $y_{ft} = a_{ft} + f(l_{ft}, k_{ft}, m_{ft})$. Here, $y_{ft}$ denotes firm-level output (physical quantity) produced by firm $f$ in period $t$. $f(\cdot)$ denotes the log-gross output production function, which is an aggregator of labor ($l_{ft}$), capital ($k_{ft}$), and intermediate inputs ($m_{ft}$). The object of interest is the firm's total factor productivity, $a_{ft}$, which is a measure of technical efficiency in production (TFPQ).

We recover a quarterly measure of firms' TFPQ following the structural approach in Lenzu et al. (2023). We construct a firm-level quantity index by deflating firm-level sales by the firm-level price index: $Y_{ft} = \frac{(PY)_{ft}}{\bar{P}_{ft}}$. We measure labor services using the total quarterly wage bill from the Social Security dataset and intermediate costs using the quarterly expenses in materials and services reported in firms' VAT declarations. We construct a quarterly measure of capital services following the perpetual inventory method, using data on quarterly investments in fixed tangible assets from firms' VAT declarations. We deflate labor, capital, and intermediate inputs using the corresponding industry-level deflators.

We assume firms' technologies can be approximated by a Cobb-Douglas production function, with input elasticities $\gamma^l, \gamma^m, \gamma^k$. We estimate sector-specific $\gamma$s via production function estimation for each sector and obtain our TFPQ measure as a residual:[49]

$$a_{ft} = y_{ft} - \hat{\gamma}^l \cdot l_{ft} - \hat{\gamma}^k \cdot k_{ft} - \hat{\gamma}^m \cdot m_{ft}. \tag{A.14}$$

Table A.2 presents the estimates of the output elasticities and returns to scale for individual manufacturing sectors and for the aggregate economy.[50] The latter is the average of the sectoral estimates. Short-run returns to scale (SR-RTS) are the sum of the elasticities of variable inputs (labor and intermediates). Consistent with the findings in previous studies (see, e.g., Gandhi et al. (2020) and the references therein), our estimates indicate returns to scale in the ballpark of unity for most sectors and, therefore, in the aggregate.

**Table A.2:** Estimates of output elasticities and returns to scale

| | Output elasticities | | | Returns to scale | |
|---|---|---|---|---|---|
| Sector | Labor ($\gamma^l$) | Intermediates ($\gamma^m$) | Capital ($\gamma^k$) | Short-run ($\gamma^l + \gamma^m$) | Long-run ($\gamma^l + \gamma^m + \gamma^k$) |
| CA | 0.214 | 0.026 | 0.752 | 0.966 | 0.992 |
| CB | 0.200 | 0.028 | 0.764 | 0.964 | 0.992 |
| CC | 0.230 | 0.033 | 0.731 | 0.960 | 0.994 |
| CE | 0.217 | 0.039 | 0.720 | 0.937 | 0.976 |
| CG | 0.219 | 0.008 | 0.768 | 0.987 | 0.996 |
| CH | 0.188 | 0.028 | 0.776 | 0.963 | 0.991 |
| CJ | 0.177 | 0.036 | 0.782 | 0.960 | 0.996 |
| CK | 0.247 | 0.054 | 0.684 | 0.932 | 0.986 |
| CL | 0.243 | 0.036 | 0.725 | 0.968 | 1.004 |
| Aggregate | 0.212 | 0.026 | 0.753 | 0.965 | 0.992 |

*Notes.* This table reports the production function estimates for different sectors (average of within-sector estimates across different 2-digit industries). The three columns report the estimated output elasticities of labor, intermediate inputs, and capital. The last two columns report the short-run and long-run returns to scale. Each row refers to a different manufacturing sector. The last row is the average of the sectoral estimates.

[49] The details of the estimation routine are provided in Lenzu et al. (2023).

[50] Due to its small sample size, we are unable to perform the production function estimation for a handful of observations in the sector "Computer, electronic and optical products" (CI). For this sector, the elasticities are recovered as an average of the elasticities of the sectors "Basic metals and fabricated metal products" (CH) and "Electrical equipment" (CJ). We verified that excluding this sector from our analysis has no implications for our results.

# D State dependent pricing

Our baseline framework presumes that firm pricing behavior is time dependent à la Calvo. With menu costs, the degree of nominal rigidity may differ from the frequency of price adjustment due to selection in price setting, as we elaborate shortly. Under certain reasonable conditions, we argue that our firm-level pricing regressions correctly identify the degree of nominal rigidity, and therefore our estimates of the slope of the Phillips curve remain valid.

In the conventional menu cost framework, the fixed cost of adjustment gives rise to an endogenous inaction region around the reset price, bounded by "Ss bands." As a result, price adjustments can be broken down into two components: shifts in the reset price given the adjustment frequency (the intensive margin) and shifts in the adjustment frequencies that correspond to shifts in the Ss bands (the extensive margin). As discussed by Caballero and Engel (2007), the extensive margin gives rise to a selection effect, wherein firms farthest away from their reset price are more likely to adjust. The selection effect implies that, for a given price adjustment frequency, there will be greater price flexibility in the menu cost framework compared to the corresponding Calvo setup, which features only intensive margin adjustments.

Despite these differences, Auclert et al. (2022) argues that, when aggregate shocks are not too large, there exists an approximate observational equivalence between models with Calvo rigidities and canonical models with menu costs (Golosov and Lucas 2007; Nakamura and Steinsson 2010).[51] In particular, a Calvo model calibrated with a "fictitious" degree of nominal rigidities $\tilde{\theta}$ serves as a good approximation of canonical menu cost models calibrated using the frequency of price adjustments in the data $(1-\theta)$.[52] In particular, when the equivalence result

[51]The authors show that, up to a first-order approximation of the price response, one can derive two "virtual hazard rates" (i.e., fictitious probabilities of keeping the price fixed between any two consecutive periods) that exactly replicate both the intensive and extensive margins of adjustments. It follows that, quantitatively, an average of the two virtual hazard rates can be used to calibrate a time-dependent model so that the aggregate response of the price level is similar to that of a menu cost model. Moreover, the average virtual hazard rate is approximately flat for a wide range of calibrations, which implies that the adjustment probability declines geometrically.

[52]See also Gertler and Leahy (2008) for conditions under which an exact equivalence result holds.

holds, we can express the conditional expectation of a firm's price change as:

$$\mathbb{E}\{p_{ft} - p_{ft-1} | \mathcal{I}_t\} \approx \underbrace{(1-\theta)(p^o_{ft} - p_{ft-1})}_{\text{Calvo term}} + \underbrace{(\theta - \tilde{\theta})(p^o_{ft} - p_{ft-1})}_{\text{Selection term}}, \tag{A.15}$$

The selection term captures the fact that adjusting firms are not a random sample of the population but are exactly those whose reset price is farthest from their price in the previous period. Rearranging equation (A.15) leads to a population regression equivalent to equation (4.1) in Section 4.1, but with $\tilde{\theta}$ replacing $\theta$:

$$\mathbb{E}\{p_{ft} | p^o_{ft}, p_{ft-1}\} \approx (1-\tilde{\theta}) p^o_{ft} + \tilde{\theta} p_{ft-1}. \tag{A.16}$$

Next, combining equation (A.16) with the expression for the optimal reset price in (8) leads to the following generalized Phillips curve under menu costs:

$$\pi_t \approx \tilde{\lambda}\, \widehat{mc}_t + \beta\, \mathbb{E}_t\{\pi_{t+1}\} + u_t, \qquad \text{where} \quad \tilde{\lambda} := \frac{(1-\tilde{\theta})(1-\beta\tilde{\theta})}{\tilde{\theta}}(1-\Omega).$$

Note that this generalized slope takes the same form as under Calvo, but with $\tilde{\theta}$ replacing $\theta$. Since $\tilde{\theta} \leq \theta$ due to selection, the slope is steeper. Therefore, when the approximate equivalence holds, our empirical methodology remains valid because it correctly identifies the degree of nominal rigidities and hence the slope of the generalized Phillips curve.

Finally, we calculate the average frequency of price changes using PPI micro data and obtain an estimate for $(1-\theta) = 0.32$. As this number closely matches our estimates of $\tilde{\theta} \approx 0.7$, selection does not appear to play a major role in our sample. This is further confirmed by evidence on the observed kurtosis of price changes (Alvarez et al. 2016). Using PPI data, we calculate the kurtosis to be 5.4, which is in line with the kurtosis produced by standard Calvo models (around 6) and larger than canonical menu cost models (between 1 and 3).

# E Robustness exercises

This section reports the estimates of a battery of robustness tests discussed in Section 5.1.

**Table A.3:** Robustness exercises

| | CU K | CU K&L | Translog | Translog w/ SR-RST control | $mc^n$ w/ SR-RTS |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\theta$ | 0.708 | 0.708 | 0.708 | 0.705 | 0.709 |
| | (0.014) | (0.014) | (0.014) | (0.013) | (0.014) |
| $\Omega$ | 0.572 | 0.569 | 0.537 | 0.503 | 0.542 |
| | (0.057) | (0.057) | (0.051) | (0.053) | (0.052) |
| $\lambda$ | 0.053 | 0.053 | 0.057 | 0.063 | 0.056 |
| | (0.008) | (0.008) | (0.006) | (0.004) | (0.006) |
| Cragg-Donald $F$ | 896.791 | 859.950 | 805.265 | 775.705 | 805.888 |
| Kleibergen-Paap $F$ | 71.433 | 74.241 | 50.787 | 46.184 | 51.005 |
| Hansen-Sargan $J$ | 3.748 | 3.812 | 4.204 | 3.347 | 4.467 |

*Notes.* The table reports various robustness tests on the validity of our instruments. All regressions build on our baseline specification, Model A. In Columns (1) and (2), we adjust our productivity instrument to account for variable capacity utilization in capital and in both capital and labor. In Columns (3)–(5), we replace our baseline TFP instrument with one that assumes Translog production functions, we include firm-time varying SR-RTS in the control set, and account for firm-time varying SR-RTS in the construction of our measure of nominal marginal cost.

**Capacity utilization.** We assess whether our instrument might pick up variation in demand shocks through unmeasured capacity utilization. Toward this purpose, we gather supplementary data on capacity utilization from the Business Survey administered by the National Bank of Belgium. The survey covers a subset of our data, asking firms to report the percentage of their production capacity utilized in any given quarter. After matching the Business Survey to our final regression sample, we are able to gather information on capacity utilization for 485 firms and $18,422$ firm-industry-quarter observations.

On the matched subsample, we test the explanatory power of lagged capacity utilization on current marginal cost in two ways. First, we regress the four-quarter lag of utilization (same timing as our instrument) and fixed effects on $mc^n_{ft}$. We find a small and statistically insignificant elasticity (estimate 0.011, SE 0.052). Second, we estimate the first-stage regression for marginal cost, including lagged capacity utilization in the regress set. We again find a small, statistically insignificant coefficient (estimate 0.036, SE 0.025).

As an additional robustness exercise, we construct a version of the TFP instrument that tries to correct for variability in capacity utilization. Because information on capacity utilization is available only for a relatively small subset of our dataset, we estimate the following predictive regressions to impute firm-level capacity when it is not observable. First, for firms for which we observe information capacity utilization for at least some periods, we impute the missing values using information on the firms' capital-to-labor ratio, intermediates-to-labor ratio, intermediates-to-sales ratio, current and past investments in physical assets, percentage change in the firm's sales, percentage change in the firm's wage bill, firm fixed effects, and industry fixed effects:

$$\begin{aligned}\widehat{CU}_{ft} = &\underbrace{\beta_1}_{-0.042}(K_{ft}/WL_{ft}) + \underbrace{\beta_2}_{0.091}\left(P^M M_{ft}/WL_{ft}\right) + \underbrace{\beta_3}_{-0.045}(PM_{ft}/PQ_{ft}) + \\ &\underbrace{\beta_4}_{0.004}\left(\ln Invest_{ft}\right) + \underbrace{\beta_5}_{0.006}\left(\ln Invest_{ft-1}\right) + \underbrace{\beta_6}_{0.006}(\Delta \ln PQ_{ft}) + \\ &\underbrace{\beta_7}_{0.059}(\Delta \ln WL_{it}) + \iota_f + \iota_{it}.\end{aligned}$$

Second, for firms that never appear in the Business Survey sample, we impute capacity utilization using information on the firms' capital-to-labor ratio, intermediates-to-labor ratio, intermediates-to-sales ratio, current and past investments in physical assets, percentage change in industry sales, percentage change in the firm's sales, percentage change in the firm's wage bill, a second-order polynomial in the firm's age, and industry-by-calendar quarter fixed effects:

$$\begin{aligned}\widehat{CU}_{ft} = &\underbrace{\beta_1}_{-0.018}(K_{ft}/WL_{ft}) + \underbrace{\beta_2}_{0.050}\left(P^M M_{ft}/WL_{ft}\right) + \underbrace{\beta_3}_{-0.043}(PM_{ft}/PQ_{ft}) + \\ &\underbrace{\beta_4}_{0.007}\left(\ln Invest_{ft}\right) + \underbrace{\beta_5}_{0.006}\left(\ln Invest_{ft-1}\right) + \underbrace{\beta_7}_{}(\Delta \ln PQ_{it}) + \\ &\underbrace{\beta_6}_{0.018}(\Delta \ln PQ_{ft}) + \underset{0.010}{+}\underbrace{\beta_9}_{0.065}(\Delta \ln WL_{ft}) + \underbrace{\beta_9}_{0.001}(age_{ft}) + \underbrace{\beta_{10}}_{-0.001}\left(age^2_{ft}\right) + \iota_{qi}.\end{aligned}$$

We then construct alternative TFP instruments by adjusting either capital or both capital and labor for capacity utilization.[53] We re-estimate our baseline model (Model A) using these instruments and report the results in Table A.3. In Column (1), the TFP instrument is constructed by adjusting only the firm's capital stock; in Column (2), both capital and labor are adjusted. In both cases, the regressions pass the weak instrument and overidentification tests with test statistics similar to those of our baseline specification. More importantly, the estimates of the pass-through coefficients and NKPC slope are essentially unaffected, suggesting that fluctuations in demand picked up by unobserved capacity utilization are unlikely to pose a threat to identification.

**Alternative production functions.** We construct an alternative productivity index by modeling firms' technologies with a Translog production function:

$$a_{ft} = y_{ft} - \sum_{x=l,k,m} \hat{a}_x \cdot x_{ft} - \sum_{x=l,k,m} \sum_{x'=l,k,m} \hat{a}_{xx'}/2 \cdot x_{ft} x'_{ft}$$

We estimate the production function parameters separately for each sector following the estimation procedure in Lenzu et al. (2023). We then recover firm-time specific input elasticities, $\hat{\gamma}^x_{ft} = \hat{a}_x + \hat{a}_{xx'}/2 \cdot x'_{ft} + \hat{a}_{xx'} \cdot x_{ft}$, which provide us with an estimate of firm-time specific SR-RTS = $\hat{\gamma}^l_{ft} + \hat{\gamma}^m_{ft}$.

In Column (3) of Table A.3, we replace the Cobb-Douglas TFP index used in our baseline model with the Translog TFP index. In Column (4), we estimate our baseline model including the logarithm of the four-quarters lagged SR-RTS as a control in the regression. In Column (5), we directly account for variation in SR-RTS in the construction of our measure of nominal marginal cost, $MC^n_{ft} = AVC^{(1+\hat{\nu}_{ft})}_{ft}$, where $\hat{\nu}_{ft} = (\hat{\gamma}^l_{ft} + \hat{\gamma}^m_{ft})^{-1} - 1$. Across all these robustness exercises, the estimates of the pass-through coefficients and the implied NKPC slope are largely consistent with those obtained from our baseline model in both magnitude and statistical significance.

[53] The capital- and capital-labor adjusted TFPQ measures are constructed using (A.14) but scaling the capital and labor as follows: $k^{CU}_{ft} = \ln(\widehat{CU}_{ft} \cdot K_{ft})$ and $l^{CU}_{ft} = \ln(\widehat{CU}_{ft} \cdot L_{ft})$.

# References


Alvarez, F., H. Le Bihan, and F. Lippi (2016): "The real effects of monetary shocks in sticky price models: a sufficient statistic approach," *American Economic Review*, 106, 2817–2851.

Alvarez, F. and F. Lippi (2014): "Price setting with menu cost for multiproduct firms," *Econometrica*, 82, 89–135.

Atkeson, A. and A. Burstein (2008): "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 98, 1998–2031.

Auclert, A., R. D. Rigato, M. Rognlie, and L. Straub (2022): "New Pricing Models, Same Old Phillips Curves?" Tech. rep., National Bureau of Economic Research.

Caballero, R. J. and E. M. Engel (2007): "Price stickiness in Ss models: New interpretations of old results," *Journal of Monetary Economics*, 54, 100–121.

European Commission (2014): "Quality Report on PRODCOM 2014 Annual Data," PRODCOM Working Group.

Gandhi, A., S. Navarro, and D. A. Rivers (2020): "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, 128, 2973–3016.

Gertler, M. and J. Leahy (2008): "A Phillips curve with an Ss foundation," *Journal of Political Economy*, 116, 533–572.

Golosov, M. and R. E. Lucas (2007): "Menu costs and Phillips curves," *Journal of Political Economy*, 115, 171–199.

Lenzu, S., D. Rivers, and J. Tielens (2023): "Financial Shocks, Productivity, and Prices," *Working paper.*

Midrigan, V. (2011): "Menu costs, multiproduct firms, and aggregate fluctuations," *Econometrica*, 79, 1139–1180.

——— (2010): "Monetary non-neutrality in a multisector menu cost model," *The Quarterly Journal of Economics*, 125, 961–1013.

Wang, O. and I. Werning (2022): "Dynamic oligopoly and price stickiness," *American Economic Review*, 112, 2815–49.