Sectoral Phillips Curves and the Aggregate Phillips Curve*

Jean Imbs† Eric Jondeau‡ Florian Pelgrin§

May 11, 2011

Abstract

Sector-level Phillips curves are estimated in French data. There is considerable heterogeneity across sectors, with vastly different estimates of the backward looking component of inflation and the duration of nominal rigidities. A multi-sector model of inflation dynamics is calibrated on the basis of these sectoral estimates. Aggregate inflation, simulated on the basis of heterogeneous sectors, displays comparable dynamics to actual data. A comparison is drawn between the policy trade-offs implied by a Phillips curve based on macroeconomic estimates, vs. one based on a model with heterogeneous sectors. The difference is sizeable.

JEL Classification Code: E31, E52, E60

Keywords: New Keynesian Phillips Curve, Heterogeneity, Inflation Persistence, Marginal Costs.

*We are grateful to audiences at the ECB/CEPR conference on Wage and Labour Cost Dynamics (December 2006), ESSIM 2006, the 2006 meetings of the Society of Computational Economics, the 2006 meetings of the Society for Economic Dynamics, the 2006 Dynare conference, the joint seminar of the National Bank of Belgium, Université Catholique de Louvain, Université Libre de Bruxelles and Katholieke Universiteit Leuven, and especially to Klaus Adams, Carlos Carvalho, Marco Del Negro, David López-Salido and Rafael Wouters for insightful discussions. Thanks are also due to Alexander Wolman and an anonymous referee, who helped us sharpen considerably the paper's point. Stephane Gregoir was kind enough to give us access to French data. The paper was partly written while Imbs was a Resident Scholar at the Research Department of the International Monetary Fund. Financial support from the National Center of Competence in Research "Financial Valuation and Risk Management" is gratefully acknowledged. The National Centers of Competence in Research (NCCR) are a research instrument of the Swiss National Science Foundation. All errors are our own.

†(Corresponding author) Paris School of Economics and CEPR. Postal address: Paris School of Economics, 106 Boulevard de l'Hopital, 75013 Paris, France. Email: Jean.Imbs@parisschoolofeconomics.eu

‡Faculty of Business and Economics, University of Lausanne, and Swiss Finance Institute. Postal address: University of Lausanne, CH–1015 Lausanne, Switzerland. Email: Eric.Jondeau@unil.ch

§Faculty of Business and Economics, University of Lausanne and CIRANO. Postal address: University of Lausanne, CH–1015 Lausanne, Switzerland. Email: Florian.Pelgrin@unil.ch

1 Introduction

The frequency of price adjustments varies across economic activities. This is one of the main conclusions of the European Inflation Persistence Network (IPN) that collects information on prices at a microeconomic level, for a cross-section of European countries. The duration of nominal rigidities varies across countries, but even more from one sector to the next. For instance, Altissimo et al. (2006) document the price of food changes on average every four months in Italy, but the price of capital goods remains on average unchanged for about 20 months. Similar heterogeneity appears to prevail in all countries covered by the IPN, as well as in the US, as documented by Bils and Klenow (2004) or Nakamura and Steinsson (2008a).

We use French data to estimate sectoral Phillips curves, as implied by a disaggregated version of Galí and Gertler (1999). The implied sector specific estimates are documented across the 16 sectors with French data. The focus is on the dynamics of sectoral inflation, the significance of properly measured marginal costs, and the implied duration of nominal rigidities.

Sector-level Phillips curves are well supported by French data. Prices respond to observed marginal costs, and are significantly forward looking. On average, the proportion of backward looking behavior is around 30%, as compared with 40% in the aggregate. The estimated reduced form coefficient on marginal costs is substantially larger at the sector level, and significant in most cases. The difference matters in an economic sense. Ceteris paribus, a larger role for marginal costs in driving prices corresponds to shorter nominal rigidities. Sectoral estimates imply nominal rigidities in the vicinity of two quarters, as opposed to a little less than one year in the aggregate.

There is extensive sectoral heterogeneity. Across the 16 French sectors with data, the backward looking component of inflation ranges between 0 and 0.5, the reduced form coefficient on marginal costs takes values between 0 and 2, and the duration of nominal rigidities ranges between one quarter and almost two years. The frequency of price changes implied by our sectoral estimates maps well with existing studies on French data, both at the sector and the macroeconomic level. In particular, aggregate data imply conventional estimates of the aggregate Phillips curve. There is in fact nothing special about the data here.[1]

A multi-sector model of the macroeconomy is then calibrated on the basis of our sectoral estimates. The model is simulated to obtain a series for aggregate inflation. A conventional model of the Phillips curve is estimated on the thus generated synthetic series. The measure of aggregate inflation simulated on the basis of our sectoral estimates shares most of the properties of directly observed inflation. Just like in conventional macroeconomic estimates of the Phillips curve, there is a sizeable backward looking component and relatively long lasting nominal rigidities. This happens even though aggregate inflation is simulated on the basis of sector-level parameters.

Is such heterogeneity relevant for the conduct of monetary policy? Policy frontiers in the Taylor (2001) tradition are computed for two cases based on the multi-sector model. In the first case, a frontier is generated from the (incorrect) aggregate Phillips curve estimated on simulated data from the multi-sector model. It is compared with the true frontier based on the multi-sector model. In the former instance, aggregate inflation is given by an aggregate Phillips curve; in the latter, it is given by a GDP-weighted average of the heterogeneous inflation processes implied by the estimated sectoral Phillips curves. The conventional aggregate estimates of the Phillips curve imply a substantially less favorable policy frontier than the multi-sector model. For given volatilities of inflation and the nominal interest rate, a multi-sector economy with calibrated heterogeneous sectoral inflation dynamics implies a volatility of the output gap one-third to one-half of what conventional aggregate estimates suggest. This happens because, on average, sectoral inflation is less inherently persistent, prices are more responsive to cost shocks, and nominal rigidities less long lasting.

The paper takes seriously the micro-foundations of the New Keynesian Phillips curve. The structural coefficients obtained in the estimation of sectoral Phillips curves are re-

[1] For more details on sectoral estimates, see Imbs et al. (2008).

flective of firms' pricing decisions. There is large heterogeneity across sectors, at least in French data. Such heterogeneity is liable to result in a mis-specified aggregate Phillips curve, with potentially large policy implications. Ignoring heterogeneity and using a Phillips curve model based on aggregate data leads to a markedly different policy frontier than the one implied by a multi-sector model calibrated to incorporate observed sectoral heterogeneity.

Many others have taken interest in the aggregate consequences of heterogeneous pricing. Carvalho (2006) introduces heterogeneous price stickiness in an otherwise conventional purely forward-looking model. He shows the response of the economy to monetary shocks gains in persistence, as price changes are staggered according to their heterogeneous frequencies. He also derives analytically a generalized Phillips curve accounting for heterogeneity. Interestingly, Sheedy (2007) contends heterogeneity may have the opposite effect on inflation persistence, as the first cohort of firms that change their prices in response to a monetary shock is likely to reverse its initial decision once the opportunity arises again and the shock has dissipated. Justiniano et al. (2006) construct a multi-sector model where sectoral prices adjust frequently, as suggested by the microeconomic evidence, but measured aggregate prices change more sluggishly because of input-output linkages.

All these papers approach the question of pricing heterogeneity from a theoretical standpoint. In some cases, their results are complementary to ours as they add a theoretical backbone to our empirical conclusions. But they also differ in a number of important ways. Here, sectoral versions of conventional Phillips curves are *estimated*, and the implied aggregate inflation series is *simulated*. Aggregation is in fact of the simplest kind, since sectoral price indices are averaged up to the aggregate using observed GDP weights. Here therefore, it is the *empirical* consequences of heterogeneity that are explored. There is no analytical derivation of the true aggregate process implied by sectoral heterogeneity. Instead, a conventional Phillips curve is forced on the aggregate data, rather than the augmented version suggested by Carvalho (2006). The differences this omission implies are then examined.[2] Since our aggregate framework is entirely standard, conventional policy analysis can be conducted. The policy trade-off between inflation and the output gap is in fact substantially altered by the existence of sectoral heterogeneity.[3]

It is also possible to address the question of heterogeneity from an empirical standpoint, even when it is not directly observable. Zaffaroni (2004) and Altissimo et al. (2009) propose to do so. They derive aggregate inflation dynamics under assumptions on the specific (but unobserved) processes followed by sectoral prices. Both papers apply insights on the effects of cross-sectional aggregation of heterogeneous processes that were first introduced by Robinson (1978) and Granger (1980).

The rest of the paper is organized as follows. Section 2 reviews the derivation of an expression for a sectoral Phillips Curve allowing for nominal rigidities and backward looking pricing that are sector specific. Our data and our estimator are then introduced. The estimation accounts for aggregate influences on sectoral prices in as general a manner as possible. Results follow, with a comparison of the sectoral estimates and those implied by the aggregated data. In Section 3, sector-specific results are used to calibrate a multi-sector model of the macroeconomy. The Section describes the model and the simulation method to obtain a synthetic series on aggregate inflation. The paper closes with the policy frontiers implied by the aggregate and sectoral dynamics of inflation.

[2] Heterogeneity is but one example of a potential source of mis-specification. For instance, Dotsey (2002) shows a significant coefficient on lagged inflation obtains if the econometric specification imposes Calvo pricing, whereas the real underlying model is based on staggered contracts in the Taylor fashion.

[3] There are many other instances of monetary models with sectoral heterogeneity, but they are less directly relevant to what is done here. Erceg and Levin (2002) allow for sectoral differences in demand characteristics, focusing on differences between durable and non-durables goods. Aoki (2001), Benigno (2004) and Huang and Liu (2004) analyze the implications of sectoral heterogeneity for the design of monetary policy. Dixon and Kara (2005) study the impact of heterogeneity in the context of Taylor-type staggered wage setting. Bouakez et al. (2009) construct and calibrate a model with heterogenous production sectors, and show substantial heterogeneity across sectors in the degree of sectoral sensitivity to monetary policy shocks. Nakamura and Steinsson (2008b) develop a similar argument with added input-output linkages. Álvarez et al. (2005) analyze the impact of heterogeneity under a variety of different assumptions on price-setting behavior.

2 Sectoral Phillips Curves

An expression for a sectoral Phillips Curve is first derived, as implied by Galí and Gertler (1999). Price dynamics in each sector are assumed to respond only to the dynamics of marginal costs there. This is unlikely to happen in reality. Sectoral prices or costs can be related through input-output production linkages for instance, or because factor markets are integrated at the aggregate level. The empirics are careful to allow for sectoral disturbances that are potentially correlated across activities. They are general enough to incorporate the cross-sectoral interdependences that are absent from the model, but potentially present in the data.

2.1 A Sectoral Phillips Curve

For each sector $j = 1, ..., J$, a New Keynesian Phillips is derived, where the magnitude of backward looking behavior and price stickiness are sector specific. The Phillips curves are obtained combining ingredients from Sbordone (2001), Woodford (2003) and Galí and Gertler (1999). There is a continuum of firms on a unit interval, indexed by i in sector j, producing differentiated goods. With monopolistic competition, demand for product i in sector j takes the form

$$Y_{ij,t} = \left(\frac{P_{ij,t}}{P_{j,t}}\right)^{-\eta} Y_{j,t}, \tag{1}$$

where $P_{ij,t}/P_{j,t}$ is the relative price of firm i's production of good j, $\eta > 1$ denotes the elasticity of substitution across varieties and $Y_{j,t}$ is defined as

$$Y_{j,t} = \left[\int_0^1 Y_{ij,t}^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}}. \tag{2}$$

Each firm produces a differentiated good according to the production technology

$$Y_{ij,t} = Z_{j,t}\ H_{ij,t}^{1-a_j}, \tag{3}$$

where $Z_{j,t}$ denotes (sector specific) technology, $H_{ij,t}$ are hours worked and $1 - a_j$ is the share of labor in industry j's value added.

Price setting decisions are governed by the Calvo (1983) mechanism. In each period, firms face a constant probability $1 - \alpha_j$ of being able to re-optimize their price. When they optimize, firms choose their price $P^*_{ij,t}$ to solve

$$\max_{P^*_{ij,t}} E_t \sum_{k=0}^{\infty} (\beta\alpha_j)^k \left[Y_{ij,t,t+k}\ P^*_{ij,t} - \Psi(Y_{ij,t,t+k})\right], \tag{4}$$

subject to the demand for good i. β is the subjective discount factor and $\Psi(Y_{ij,t,t+k})$ denotes total nominal costs. $Y_{ij,t,t+k}$ is real output at date $t + k$ for the firms that changed their price at t. Optimality implies

$$\sum_{k=0}^{\infty} (\beta\alpha_j)^k E_t \left[Y_{ij,t,t+k}\left(P^*_{ij,t} - \frac{\eta}{\eta - 1} S_{ij,t,t+k} P_{ij,t+k}\right)\right] = 0, \tag{5}$$

where $S_{ij,t,t+k} = \Psi'(Y_{ij,t,t+k})/P_{ij,t+k}$ denotes *real* marginal costs.

Define a steady state where $P_{ij,t+k} = P_{ij,t}$, $P_{t+k} = P_t$, $P^*_{ij,t} = P_{ij,t+k} = P_{ij}$, $Y_{ij,t,t+k} = Y_{ij}$ and $S_{ij,t,t+k} = S_j = \frac{\eta-1}{\eta}$.[4] A Taylor expansion of equation (1) around that steady state gives

$$\hat{p}^*_{ij,t} = (1 - \beta\alpha_j) \sum_{k=0}^{\infty} (\beta\alpha_j)^k E_t \left[(\hat{s}_{ij,t,t+k} + \hat{p}_{ij,t+k})\right], \tag{6}$$

with $\hat{s}_{ij,t,t+k} = s_{ij,t,t+k} - s_j$ and $\hat{p}_{ij,t+k} = p_{ij,t+k} - \hat{p}_{ij}$.

2.1.1 Marginal costs

There is a discrepancy between real marginal costs at the firm level $S_{ij,t+k}$, and their sector average across firms, $S^{avg}_{j,t+k}$. We only observe the latter. Sbordone (2001) and Galí

[4]Our (unfiltered) data is not consistent with a zero inflation steady state. This is a recurrent problem in the literature. An alternative to filtering the data is to construct a monetary model where trend inflation is allowed for, an avenue followed among others by Ascari (2004).

et al. (2001) establish the following relation

$$S_{ij,t,t+k} = \frac{W_{j,t+k}}{P_{j,t+k}} \frac{\partial H_{ij,t,t+k}}{\partial Y_{ij,t,t+k}} = \left(Y_{ij,t,t+k}\right)^{\frac{a_j}{1-a_j}} \frac{1}{1-a_j} \frac{W_{j,t+k}}{P_{t+k}} Z_{j,t+k}^{-\frac{1}{1-a_j}} \equiv \left(Y_{ij,t,t+k}\right)^{\frac{a_j}{1-a_j}} \tilde{S}_{j,t+k}, \tag{7}$$

where $W_{j,t}$ are the nominal wages in sector j, and $\tilde{S}_{j,t+k}$ is *not* firm specific. Moreover, sectoral average real marginal costs are given by

$$S_{j,t+k}^{avg} = \left(Y_{j,t,t+k}\right)^{\frac{a_j}{1-a_j}} \tilde{S}_{j,t+k}, \tag{8}$$

and ultimately,

$$S_{ij,t,t+k} = \left(\frac{Y_{ij,t,t+k}}{Y_{j,t+k}}\right)^{\frac{a_j}{1-a_j}} S_{j,t+k}^{avg} = \left(\frac{P_{ij,t}^{*}}{P_{j,t+k}}\right)^{-\frac{\eta a_j}{1-a_j}} S_{j,t+k}^{avg}. \tag{9}$$

This implies that real marginal costs vary across firms only if optimal pricing does. In the absence of any firm-specific shock, all firms that are allowed to re-optimize their price at date t select the same optimal price, which ensures a symmetric equilibrium across firms in each sector. As a result firm indices are omitted from now on. In deviations from the steady state, marginal costs follow

$$\hat{s}_{j,t,t+k} = \hat{s}_{j,t+k}^{avg} - \frac{\eta a_j}{1-a_j} \left(\hat{p}_{j,t}^{*} - \hat{p}_{j,t+k}\right).. \tag{10}$$

2.1.2 Price indices

Because of price rigidities, the sectoral (log) price level at time t is given by

$$\hat{p}_{j,t} = \alpha_j \, \hat{p}_{j,t-1} + (1-\alpha_j) \, \hat{p}_{j,t}^{*}. \tag{11}$$

Galí and Gertler (1999) introduce purely backward looking firms, assumed to obey a rule of thumb whereby the price in period t depends only on information dated $t-1$ or earlier. A proportion ω_j of the firms that are allowed to adjust their prices do so in a purely backward looking manner. By definition, newly set prices are given by

$$\hat{p}^{*}_{j,t} = \omega_j \hat{p}^{b}_{j,t} + (1-\omega_j)\,\hat{p}^{f}_{j,t}, \tag{12}$$

where p^{b}_{jt} (p^{f}_{jt}) denote the price set by backward (forward) looking firms. Forward looking firms choose prices optimally according to equation (6). Backward looking firms merely adjust for inflation the prices they set the last time they could, i.e.

$$\hat{p}^{b}_{j,t} = \hat{p}^{*}_{j,t-1} + \hat{\pi}_{j,t-1}. \tag{13}$$

As is well known, equations (6) and (10)-(13) combine to imply a (linearized) hybrid Phillips curve:

$$\hat{\pi}_{j,t} = \frac{\omega_j}{\phi_j}\ \hat{\pi}_{j,t-1} + \frac{\beta\alpha_j}{\phi_j}\ E_t\hat{\pi}_{j,t+1} + \frac{(1-\omega_j)(1-\alpha_j)(1-\beta\alpha_j)}{\phi_j} h_j\ \hat{s}^{avg}_{j,t}. \tag{14}$$

With $\phi_j = \alpha_j + \omega_j\left[1-\alpha_j(1-\beta)\right]$ and $h_j = 1/\left(1+\frac{\eta a_j}{1-a_j}\right)$, equation (14) implements the correction derived in equation (10). Hatted variables denote deviations from the no inflation steady state. To economize on notation, define $\lambda^b_j = \frac{\omega_j}{\phi_j}$, $\lambda^f_j = \frac{\beta\alpha_j}{\phi_j}$ and $\theta_j = \frac{(1-\omega_j)(1-\alpha_j)(1-\beta\alpha_j)}{\phi_j}$. A cost-push shock $\tilde{\varepsilon}^{\pi}_{j,t}$ is introduced, which may embed measurement error. Following Woodford (2003), the shock is directly inserted in the reduced form expression.[5] The Phillips Curve can be rewritten in its well known hybrid form

$$\hat{\pi}_{j,t} = \lambda^b_j\ \hat{\pi}_{j,t-1} + \lambda^f_j\ E_t\hat{\pi}_{j,t+1} + \theta_j\ h_j\hat{s}^{avg}_{j,t} + \tilde{\varepsilon}^{\pi}_{j,t}. \tag{15}$$

The industry level Phillips curve does not include any reference to an aggregate variable, nor indeed to any relative prices. At face value, this may seem a contradiction relative to the findings in Aoki (2001), Benigno (2004) or Carlstrom et al. (2006). But all these authors use versions of the New Keynesian Phillips curve that refer to the output gap as a measure of economic activity. In contrast, here marginal costs enter directly.

[5] See equation (4.38) page 451 and following.

Relative prices are effectively subsumed in our definition of $\hat{s}_{j,t}^{avg}$. This follows directly from Woodford (2003).[6]

2.2 Data

Data are constructed by INSEE, the French statistical institute. They are observed quarterly from 1978:1 to 2005:3, with information on output, prices, wages and employment for sixteen sectors of the French economy, comprising all activities. Coverage includes agriculture, manufacturing (six sectors) and services (nine sectors).[7] For each industry, the inflation rate is computed as the quarter-on-quarter growth rate of the value-added deflator.[8] A sector-specific measure of marginal costs is computed following Sbordone (2001) or Galí et al. (2001). $\hat{s}_{j,t}^{avg}$ is the (logarithm) deviation of the sector share of labor income in value added from its sample mean. We apply the sector specific correction implied by h_j. From its definition, the correction is computed on the basis of the observed industry share of labor in production a_j, and a value for η corresponding to a level of markups calibrated at ten percent.[9]

These data are coarse. A partition of all economic activities in 16 sectors entails plenty of aggregation. Short of alternative data sources, however, there is simply nothing better available. In fact, these French data are already remarkable in that they provide *quarterly* information on prices, quantities, and labor market outcomes covering all French economic activities, and using the same sector definitions. It is quite difficult to obtain similar information of homogeneous quality for any country, including the United States. For instance, Leith and Malley (2007) estimate sectoral Phillips curves in US sectors, but on the basis of re-constructed data. The fact our data are still the result of some

[6] This is developed in the Appendix B.7 to Chapter 3, and in particular in equation B.33 on page 668.

[7] The sectors are "Agriculture", "Food Manufacturing", "Consumption Goods", "Car Industry", "Equipment Goods", "Intermediary Goods", "Energy", "Construction", "Trade", "Transportation", "Financial Activities", "Real Estate", "Business Services", "Personal Services", "Education and Health Services", and "Government".

[8] Firms' pricing decisions presumably concern the price of gross output rather than value added. The two are probably different in the data, even though they are not in our theory. Unfortunately, no data on gross output prices are available for France at the level of disaggregation we focus on.

[9] This follows directly from Sbordone (2001) or Galí et al. (2001). The latter in particular argue that different markup values do not alter any of their results (in footnote 24). We checked that using a unique, aggregate measure of a_j does not change any of our results either.

aggregation is not necessarily crucial. The consequences of heterogeneity (in pricing behavior) are investigated across the 16 sectors with data. There may well be further heterogeneity within each one of these sectors. It is however likely to be of second order importance relative to the paper's main point.

Table 1 presents some summary statistics. The Table reports average inflation and average growth in real marginal costs, their serial correlations, and their contemporaneous cross-correlation, at both industry and aggregate levels. There is extensive heterogeneity across sectors in both average measures. Annual inflation ranges between 0.2% and 5.5%, and the average annual growth in real marginal costs ranges between -3.6% and 0.1%. There is also heterogeneity in the serial correlation in inflation, and the cross-correlation between $s_{j,t}$ and $\pi_{j,t}$. In contrast marginal costs are consistently highly serially correlated. In all subsequent estimations, industry-specific means are subtracted from each series. Filtering the data instead implies virtually identical results.

Table 1 also reveals that aggregate inflation and real marginal costs are highly serially correlated, and covary to a large extent. The covariance between aggregates is in fact larger than *any* of its sectoral equivalents. Such a discrepancy exemplifies the possibility that a Phillips curve estimated on aggregate data implies drastically different policy choices than an average of sectoral data would. Figure 1 confirms visually the two variables track each other closely over time, as they should given the existing empirical support for aggregate Phillips curves.

2.3 Estimation Method

The conventional estimators that have often been used on aggregate inflation series are implemented on equation (15). In the body of the text, a data generating process is assumed for marginal costs, following Fuhrer and Moore (1995), Sbordone (2001) or Kurmann (2007). With such assumption, future expected inflation can be solved out of the Phillips curve. And the obtained model can be brought to the data directly using a Maximum Likelihood (ML) approach. By assumption, marginal costs follow an autoregressive process of order two, which is validated in our sectoral data. The full model of sectoral inflation rests on the following system

$$\begin{aligned} \hat{\pi}_{j,t} &= \lambda_j^b \ \hat{\pi}_{j,t-1} + \lambda_j^f \ E_t \hat{\pi}_{j,t+1} + \theta_j \ h_j \hat{s}_{j,t}^{avg} + \tilde{\varepsilon}_{j,t}^{\pi} \\ \hat{s}_{j,t}^{avg} &= \rho_{1j} \ \hat{s}_{j,t-1}^{avg} + \rho_{2j} \ \hat{s}_{j,t-2}^{avg} + u_{j,t}, \end{aligned} \tag{16}$$

where $u_{j,t}$ denotes an independent and identically distributed shock to real marginal costs in sector j, $|\rho_{2j}| < 1$, $\rho_{1j} + \rho_{2j} < 1$, $\rho_{2j} - \rho_{1j} < 1$, $\sigma^2_{\tilde{\varepsilon}_j^{\pi}} = E(\tilde{\varepsilon}_{j,t}^{\pi 2})$, and $\sigma^2_{u_j} = E(u^2_{j,t})$. An appendix shows the dynamics of sectoral inflation can then be rewritten[10]

$$\hat{\pi}_{j,t} = \delta_{1j} \hat{\pi}_{j,t-1} + \phi_{1j} h_j \hat{s}_{j,t}^{avg} + \phi_{2j} h_j \hat{s}_{j,t-1}^{avg} + \varepsilon_{j,t}^{\pi}, \tag{17}$$

where δ_{1j}, ϕ_{1j}, and ϕ_{2j} are defined in the Appendix, and $\varepsilon_{j,t}^{\pi}$ is an appropriate transformation of $\tilde{\varepsilon}_{j,t}^{\pi}$.

It is eminently likely that shocks to sectoral inflation or marginal costs can be correlated across sectors. With factor markets that are integrated at the country level for instance, shocks to marginal costs are correlated across sectors, and $E[u_{i,t} u_{j,t}] = \sigma_{u_i u_j} \neq 0$. The same would obtain in the presence of input-output linkages, which presumably exist in the data, but not in the model we estimate in equation (17). By the same token, in the presence of aggregate shocks, cost push shocks will correlate across sectors so that $E[\varepsilon_{i,t}^{\pi} \varepsilon_{j,t}^{\pi}] = \sigma_{\varepsilon_i \varepsilon_j} \neq 0$. Finally, the shocks to marginal costs $u_{j,t}$ have no unique structural interpretation. So it is possible they in fact correlate with $\varepsilon_{j,t}^{\pi}$. They would for instance in response to technological developments that affect both the marginal cost of production and firms' market power. We therefore also assume $E[\varepsilon_{i,t}^{\pi} u_{j,t}] = \sigma_{\varepsilon_i u_j} \neq 0$.

[10]All appendices are available directly from the Journal's website as supplementary materials. This includes codes and the data used in the paper.

A SURE correction is implemented to account for all three cross-sector interdependencies. In the ML case, stacking all sectors implies sectoral dynamics given by

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_J \end{pmatrix} = \begin{pmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & X_J \end{pmatrix} \begin{pmatrix} \Lambda_1 \\ \Lambda_2 \\ \vdots \\ \Lambda_J \end{pmatrix} + \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_J \end{pmatrix}, \tag{18}$$

where $Y_j = \begin{pmatrix} \hat{\pi}_j \\ \hat{s}_j \end{pmatrix}$, $X_j = \begin{pmatrix} \hat{\pi}_{j,-1} & h_j\hat{s}_j & h_j\hat{s}_{j,-1} & 0 & 0 \\ 0 & 0 & 0 & h_j\hat{s}_{j,-1} & h_j\hat{s}_{j,-2} \end{pmatrix}$, $v_j = \begin{pmatrix} \varepsilon_j^{\pi} \\ u_j \end{pmatrix}$, $\hat{\pi}_j = (\hat{\pi}_{j,t})$, $\hat{\pi}_{j,-1} = (\hat{\pi}_{j,t-1})$, $\hat{s}_j = (\hat{s}_{j,t})$, $\hat{s}_{j,-k} = (\hat{s}_{j,t-k})$, and $\Lambda_j = (\delta_{1j}, \phi_{1j}, \phi_{2j}, \rho_{1j}, \rho_{2j})'$. The stacked disturbances v_j have a covariance matrix Ω which standard maximum likelihood techniques can account for.

The SURE correction requires the estimation of a large-dimensional covariance matrix, which may affect the finite-sample properties of the estimators. For robustness, an alternative estimator proposed by Pesaran (2006) is implemented, that introduces a correction technique to account for unobserved common factors potentially correlated with sector-specific regressors. The sector-specific estimations are filtered by means of cross-section averages, which allow for unobserved common factors. The approach is particularly appealing because of its simplicity. It merely requires the addition of an auxiliary regressor, given by the cross-sectional average of the regressors, which suffices to filter the common correlated effect (CCE) out. An appendix describes the implementation of the CCE estimator for our purposes. The results presented later correspond to the CCE estimator, and also to a conventional Generalized Method of Moments (GMM) estimator implemented on sectoral data.

Neither SURE, nor CCE are quite the same as constructing a model of linkages between sectors, either via an explicit input-output structure, or with general equilibrium effects working for instance via integrated factor markets at country level. Recent papers by Carvalho (2006), Sheedy (2007) or Justiniano et al. (2006) have chosen to account for heterogeneity in theoretical models, and so have made progress down that route. However, their empirical implications are not always tractable. In contrast, the SURE approach is sufficiently general that our estimates of sectoral Phillips curves are in fact consistent with a broad range of theoretical reasons for cross-sector interdependencies.

2.4 Results

Sector-specific estimates are first presented, correcting or not for common factors across sectors. The results implied by aggregated data follow.

2.4.1 Industry Estimates

Industry-level estimates of the New Keynesian Phillips curve are obtained on the basis of a ML approach. Marginal costs are at the industry level are assumed to follow an autoregressive process of order two. The resulting reduced form equation is estimated. Several results stand out.

First, the measured dynamics of sectoral marginal costs are well characterized by autoregressive processes of order two.[11] The fit is tight in all cases, with R^2 above 0.80 in thirteen of the sixteen sectors. The lowest value occurs in "Energy", with a value of 0.43. Second, Table 2 suggests inflation dynamics at the industry level are consistent with the New Keynesian framework. The results correspond to simple ML implemented on each sector individually. Estimates of ϕ_1 or ϕ_2 are significant in ten of the sixteen sectors, so that marginal costs affect significantly the pricing decisions of firms. The estimates also display substantial heterogeneity across sectors. The coefficients corresponding to the reduced form Phillips curve given in equation (15) confirm large differences in the extent of backward looking behavior, with values of λ^b ranging from zero to around a half. The heterogeneity carries through to sector-level estimates of the structural parameters. We obtain values for α_j between zero and virtually one, with vastly different implied

[11] An Appendix reports our measure of real marginal costs, along with the fitted values implied by the estimated autoregressive process. The results are also available in Imbs et al. (2008).

durations. They range from less than one quarter in Food, to around one quarter in Agriculture, Energy or Transportation, to more than two years in Cars. On the whole, duration is found to take high values in virtually all service industries - although the point estimates are not always significant or well defined.

Fisher tests were implemented to investigate coefficient equality across sectors. On the basis of the industry-level estimates in Table 2, there is overwhelming rejection of the homogeneity assumption across all parameters δ, ϕ_i, and ρ_i. Unreported results summarize the empirical plausibility of purely forward looking Phillips curves in our 16 sectors. The fit worsens sizeably. Most regressors, especially marginal costs, become insignificant in virtually all cases. And the model's ability to predict observed inflation rates becomes mediocre at best.

Figure 2 plots observed inflation for each industry against the path predicted by the estimated Phillips curve in that sector. The fit is poor for "Food Manufacturing", "Equipment Goods", and "Business Services", but tight for the other thirteen industries, with R^2 above 0.25. In fact, both series are virtually identical for eight of our sectors. For instance, R^2 are above 0.75 in "Trade", "Education and Health Services", "Real Estate", and " Government".

A technical appendix reports the results corresponding to a GMM estimation of equation (15), using lagged inflation, lagged marginal costs and lagged wage inflation as instruments for future expected inflation. Similar heterogeneity is uncovered: the backward looking coefficient ranges from zero in "Food" or "Energy" to 0.5 in "Finance" or "Real Estate". The implied durations are around 1.3 quarters for "Agriculture" and "Food", slightly higher in manufactures, with a point estimate of 4.6 quarters in "Car", and even higher in services, with durations around 3 quarters in "Education and Health", "Business" and "Real Estate".

The results in Table 2 correspond to sector-by-sector estimations of a Phillips curve. The approach ignores the possibility that sectoral prices may be related in the macroeconomy. But there is no reason to expect the same from actual sectoral data. Tables

3 presents results augmented with a SURE correction. The approach is general enough to account for common macroeconomic shocks, cross-sector linkages or indeed anything that would engender influences on sectoral prices or marginal costs that are contemporaneously correlated across industries. Our conclusions are largely unchanged: marginal costs are significant in half of the industries, and they are persistent. The proportion of backward looking behavior ranges between zero and a half, with low values in "Food" or "Energy", and high values in "Agriculture" or "Education and Health". Relative to Table 2, the Fisher test rejects homogeneity at even higher confidence levels. Like in Table 2, the implied durations are lowest for "Food" and "Agriculture", higher in manufactures, and highest in services. The technical appendix reports the corresponding sectoral estimates implied by the CCE correction. Heterogeneity still prevails, with a similar ranking of sectors.[12]

Table 4 offers a direct comparison of our sectoral estimates of the duration of nominal rigidities in France with the literature. The comparison draws on contributions by Gautier (2008), Vermeulen et al. (2007), Baudry et al. (2007, 2009) and Loupias and Ricart (2005). All these papers have made use of highly disaggregated French price data to identify the observed frequency of price changes, and infer the corresponding duration of nominal rigidities. Several caveats are in order. First, the mapping with our sectoral classification is far from perfect. In particular, there is little price information for services. For most service sectors, therefore, only the durations based on (our) Phillips curve estimates are available. Second, we use Producer Prices, whereas most of the papers using French data focus on Consumer Prices, with the exception of Gautier (2008) and Vermeulen et al. (2007). Third, the time periods are different. Our data go back to 1978 and stop in 2005. Gautier (2008) uses data from 1994 to 2005, and Baudry et al. (2007) from 1994 to 2003. These limitations notwithstanding, Table 4 suggests a reasonably close mapping between our structural estimates and the micro-evidence gathered for France in

[12]The CCE and SURE are only implemented on the ML version of the model. GMM requires an instrument set, which is potentially different across sectors. This renders the SURE approach unpalatable. As for the CCE correction, nothing is known about its asymptotic properties when implemented on a GMM estimator.

the literature. For instance, in manufacturing longest durations are estimated for cars and equipment goods, as individual price data imply. Duration levels are virtually identical for food manufacturing, transportation, and education and health services. Given the vast differences involved in obtaining these estimates, such relative concordance is remarkable.

Panel A of Table 5 reports the characteristics of a representative average sector as implied by our data. The reduced form estimates of δ, ϕ_i, and ρ_i from Tables 2 and 3 are averaged to infer the corresponding structural parameters. A simple average of sector specific estimates is in fact exactly equivalent to what the Mean Group heterogeneous estimator introduced by Pesaran and Smith (1995) implies. Table 5 suggests the representative sector of our French data displays nominal rigidities that last around 2 quarters, consistent with most microeconomic studies in the literature. The average proportion of backward looking firms ranges between 25 and 30 percent.

2.4.2 Aggregate Estimates

Our data are aggregated using GDP weights to obtain series for aggregate inflation and marginal costs. We implement both a ML and a GMM estimator on the resulting data. The aggregate Phillips curve can be written as

$$\hat{\pi}_t = \lambda^b \ \hat{\pi}_{t-1} + \lambda^f \ E_t \hat{\pi}_{t+1} + \theta \ h \hat{s}_t^{avg} + \tilde{\varepsilon}_t^{\pi}, \tag{19}$$

where h is a corrective term accounting for staggered pricing decisions, given by an average of h_j across sectors. Following the standard in this literature, equation (19) is estimated using a GMM estimator, with expected inflation instrumented by lagged inflation, lagged marginal costs, and lagged wage inflation.

Assuming aggregate marginal costs continue to follow an autoregressive process of order two, with coefficients ρ_1 and ρ_2, equation (19) implies the reduced form

$$\hat{\pi}_t = \delta_1 \hat{\pi}_{t-1} + \phi_1 h \hat{s}_t^{avg} + \phi_2 h \hat{s}_{t-1}^{avg} + \varepsilon_t^{\pi}, \tag{20}$$

where

$$\phi_1 = \frac{\theta}{\Delta\delta_2\lambda^f},\ \phi_2 = \phi_1\frac{\rho_2}{\delta_2},$$
$$\Delta = 1-\frac{\rho_1}{\delta_2}-\frac{\rho_2}{\delta_2^2},$$
$$\delta_1 = \frac{1-\sqrt{1-4\lambda^f\lambda^b}}{2\lambda^f} \quad \text{and} \quad \delta_2 = \frac{1+\sqrt{1-4\lambda^f\lambda^b}}{2\lambda^f}.$$

Equation (20) is estimated using ML techniques. Panel B of Table 5 reports our results.

The proportion of backward looking firms, λ_b, is 0.35 with GMM, and 0.40 with ML. The coefficient θ on aggregate marginal costs, in turn, is weakly significant, 0.08 with GMM and 0.04 with ML. These values stand in stark contrast with the estimates obtained at the sectoral level. Panel A points to an average close to 0.30, four to eight times larger.

The duration of nominal rigidities implied by aggregate French data is above three quarters, and not significantly different from one year. This is close to the estimates obtained by Benigno and López-Salido (2006) who estimate a duration of nominal rigidities across European countries. In their Table 1 (page 596), they present estimates for France close to one year in two of three estimates - rising to 11 quarters when more instruments are included in the GMM estimation. For the Euro area as a whole, Galí et al. (2001) report a duration estimate of 4.7 quarters in their Table 2. Our estimate of the duration of nominal rigidities in aggregate French data is therefore slightly below conventional results in the literature.

Nominal rigidities in the representative sector are close to two quarters, which is consistent with estimates based on disaggregated data. The very same data, when aggregated and constrained to fit a conventional New Keynesian Phillips curve, imply significantly longer nominal rigidities. This suggests heterogeneity in the pricing behavior of firms is a key driving force behind the interpretation of aggregate inflation dynamics.

3 The Aggregate Phillips Curve

This Section investigates the policy relevance of heterogeneity. A multi-sector general equilibrium model of the macroeconomy is calibrated and simulated using our (structural) sectoral estimates. Conventional policy analysis is then performed on the resulting synthetic aggregate inflation measure. The Section closes with implications for stabilization policy.

3.1 Simulation and Calibration

Our purpose is to simulate a synthetic series for aggregate inflation, implied by a multi-sector model calibrated with our sectoral results. The sector-level Phillips curves are given by equations (2)-(6), which are calibrated directly using the structural estimates of α_j and ω_j from Section 2. Rather than imposing specific dynamics for sectoral marginal costs $s_{j,t}$, and use the corresponding reduced form autoregressive coefficients obtained earlier, we go the structural route and introduce aggregate production, Y_t. Preferences are given by

$$U\left(C_t, \mathcal{H}_t, H_{ij,t}\right) = \left[\frac{1}{1-\sigma}\left(C_t - \gamma \mathcal{H}_t\right)^{1-\sigma} - \frac{1}{1+\varphi}\sum_{j=1}^{n}\int_0^1 \left(H_{ij,t}\right)^{1+\varphi} di\right]\exp\left(\varepsilon_t^y\right). \quad (21)$$

Preferences display external habit formation, with the habit stock $\mathcal{H}_t$ equal to the level of aggregate consumption in $t-1$. $\sigma > 0$, $\varphi > 0$ and $0 \leq \gamma < 1$ have conventional interpretations. ε_t^y is a demand shock, which follows an autoregressive process of order one

$$\varepsilon_t^y = \rho^y \varepsilon_{t-1}^y + \nu_t^y, \quad (22)$$

with $\mid \rho^y \mid < 1$ and ν_t^y is white noise with variance σ_y^2. Following Carvalho (2006), consumers allocate their labor across all firms and sectors.

With goods market clearing, the intratemporal labor-leisure choice implies

$$\frac{W_{ij,t}}{P_t} = H_{ij,t}^{\varphi} \left(C_t - \gamma C_{t-1} \right)^{\sigma}, \tag{23}$$

where P_t denotes the aggregate price level. Using the definition of real wages and the sector production function, Woodford (2003) obtains an expression for (log-linearized) average real marginal costs $\hat{s}_{j,t}^{avg}$,

$$\hat{s}_{j,t}^{avg} = \left(\frac{\varphi + a_j}{1 - a_j} + \frac{\sigma}{1 - \gamma} \right) \hat{y}_t^* - \frac{\gamma \sigma}{1 - \gamma} \hat{y}_{t-1}^* - \frac{1 + \varphi}{1 - a_j} \hat{z}_{j,t}, \tag{24}$$

where hatted variables are computed in deviation from the steady state, $\hat{y}_t^*$ denotes $\hat{y}_t + \eta \left(\hat{p}_t - \hat{p}_{j,t} \right)$, $\hat{y}_t$ is the output gap defined in equation (27), and $\hat{z}_{j,t}$ is a sectoral productivity shock, which follows an autoregressive process of order one given by

$$\hat{z}_{j,t} = \rho_j^z \hat{z}_{j,t-1} + \nu_{j,t}^z \tag{25}$$

with $\mid \rho_j^z \mid < 1$ and $\nu_{j,t}^z$ is white noise with variance $\sigma_{j,z}^2$. Since our purpose is now a calibration, rather than an estimation, we put structure on the shocks that perturb the multi-sector model. In particular, under our assumptions on the production function, sectoral productivity shocks are directly observable. Their persistence and variance properties can readily be calibrated from our sectoral data.

On the basis of the system formed by equations (6), (10)-(13) and (24)-(25), sectoral inflation can be simulated as a function of relative sectoral prices and the aggregate output gap.[13] The model is closed in the most conventional manner possible, following Woodford (2003). The intertemporal Euler equation is

$$\frac{1}{\beta} E_t \left(\frac{1 + \pi_{t+1}}{1 + i_t} \right) = E_t \left(\frac{\left(C_{t+1} - \gamma C_t \right)^{-\sigma} \exp \left(\varepsilon_{t+1}^y \right)}{\left(C_t - \gamma C_{t-1} \right)^{-\sigma} \exp \left(\varepsilon_t^y \right)} \right). \tag{26}$$

[13] We also experimented with an aggregative model of sectoral inflation simulated on the basis of the AR(2) estimates for $s_{j,t}$ obtained in the empirical section of the paper. Even though this approach is not structural, the end results were virtually identical.

In log-linearized form, and combined with goods market clearing, this can be rewritten into a standard hybrid IS curve

$$\hat{y}_t = \frac{\gamma}{1+\gamma}\hat{y}_{t-1} + \frac{1}{1+\gamma}E_t\hat{y}_{t+1} - \frac{1-\gamma}{(1+\gamma)\,\sigma}(\hat{\imath}_t - E_t\hat{\pi}_{t+1}) + \kappa\varepsilon_t^y, \tag{27}$$

with $\kappa = \frac{(1-\rho^y)(1-\gamma)}{(1+\gamma)\sigma}$, and i_t denotes the nominal interest rate. As usual, the demand side of the economy pins down the dynamics of the output gap.

Finally, monetary policy follows an augmented Taylor rule with interest rate smoothing, given by

$$\hat{\imath}_t = \rho\hat{\imath}_{t-1} + (1-\rho)\left(\varphi_\pi\hat{\pi}_t + \varphi_y\hat{y}_t\right) + \varepsilon_t^i, \tag{28}$$

where ε_t^i is a monetary policy shock, which follows an autoregressive process of order one

$$\varepsilon_t^i = \rho^i\varepsilon_{t-1}^i + \nu_t^i, \tag{29}$$

with $\mid \rho^i \mid < 1$ and ν_t^i is white noise with variance σ_i^2. Monetary policy pins down the dynamics of the nominal interest rate.

Section 2 presented an aggregate Phillips curve estimated on the basis of GDP-weighted aggregates of sectoral inflation rates and marginal costs. This weighting scheme is reproduced in the model. Each sector is calibrated using the estimates for α_j and ω_j given in in Table 3, i.e. by the SURE approach. Aggregation in the model is similar to the treatment of the data: sectoral inflation rates are simply added up using GDP weights. We can do that because the model is calibrated on the basis of sectoral estimates arising from the SURE approach.

The system formed by equations (6), (10)-(13), (22), (24)-(25) and (27)-(29) is simulated. Sectoral Solow residuals are calibrated following Burnside et al. (1996). The correcting terms h_j and a_j, along with the GDP weights used in aggregation are identical to Section 2, as are the elasticity of substitution η (set at 11) and the subjective discount factor $\beta = 0.99$. The remaining parameters are aggregate and are chosen on the basis of existing estimations of an aggregate New Keynesian model for France.[14]

The model is simulated $2,000$ times. Sector inflation and marginal costs are collected at each repetition. Each simulation gives rise to aggregate series for inflation and marginal costs, which can then be used to estimate an aggregate Phillips curve. Note this can be performed using either a ML approach or a GMM estimator. The mean reduced form estimates of the Phillips curve, averaged across $2,000$ repetitions, are then reported, along with the corresponding structural parameters. Using medians instead does not affect our conclusions.

3.2 Results and Implications for Stabilization Policy

Panel C of Table 5 reports Phillips curve estimates implied by simulated aggregate series. Results are presented corresponding to the usual estimations implemented on aggregate data. First, the ML approach, which rests on an assumed data generating process for marginal costs. We verify the dynamics of our synthetic series for marginal costs do indeed follow an autoregressive process of order two, as they do in the raw data. Second, GMM is implemented.

The aggregate New Keynesian Phillips curves obtained in Table 5 are standard. The proportion of backward looking firms is estimated to range between 30 and 40 percent. The coefficients on marginal cost are relatively small in magnitude, and correspond to a duration for nominal rigidities between 3 and 4 quarters. In addition, the reduced form estimates of the process followed by aggregate marginal costs correspond to an AR(2).

Most importantly, the estimates in the third panel of Table 5 are strikingly close to what is implied by aggregate data. Interestingly, both ML and GMM estimators imply similar coefficients whether they are implemented on the synthetic series or on actual data, with no significant differences in estimates across reduced form and quasi-reduced

[14] In particular, following Jondeau and Sahuc (2008) the parameter values are: $\sigma = 2$, $\gamma = 0.5$, $\phi = 0.6$, $\rho^i = 0.603$, $\sigma_i^2 = 0.005^2$, $\rho^y = 0.2$, $\sigma_y^2 = 0.1^2$, $\rho = 0.90$, $\varphi_\pi = 1.5$, and $\varphi_y = 0.5$.

form coefficients. The estimate of λ^b equals 0.415 when a ML approach is imposed on simulated data, as against 0.402 when it is imposed on the raw data. The duration implied by ML on the simulated data is 3.29 quarters, while it is 3.43 quarters in the aggregate data. The durations implied by GMM are slightly smaller, 2.73 on simulated inflation, and 3.16 on the actual aggregate series.

In other words, a simulated aggregation of sector-specific price dynamics reproduces the dynamics implied by the aggregated data. And this happens even though sector-specific dynamics are consistent with microeconomic evidence, whereas aggregate dynamics are not. These results indicate that the aggregation of heterogeneous sectors plays a large part in explaining the difficulty in rationalizing aggregate inflation dynamics. Aggregate inflation implies rather long nominal rigidities, difficult to map with observable data. But that should not be puzzling: it is merely an artefact of heterogeneity across sectors.

This establishes the econometric importance of sector-level heterogeneity. A natural next question is to evaluate the policy relevance of the discrepancy. In particular, we can compare the policy trade-offs implied by observed aggregate inflation dynamics, with what would happen in a multi-sector model, characterized by the heterogeneous dynamics at sector level.

Following Taylor (2001), a policy frontier is computed solving the following program

$$\underset{\rho,\varphi_\pi,\varphi_y}{\text{Min}} \qquad \lambda V\left(\pi_t\right) + \left(1-\lambda\right) V(y_t)\,, \tag{30}$$

subject to the constraint that $V(\Delta i_t) \leq \tilde{\kappa}$, $\Delta i_t = i_t - i_{t-1}$. The operator $V(.)$ denotes a variance, and $\lambda \in [0,1]$ captures the relative weight of inflation and output volatilities in the policymaker's objective function.[15] The program is solved using the general equilibrium described by equations (19), (22) and (27)-(29), along with the aggregate analogue

[15] Alternatively, the computation was performed with an objective function where $V(\Delta i_t)$ entered directly. Our conclusions remained unchanged.

of equation (24), given by

$$\hat{s}_t^{avg} = \left(\frac{\varphi + a}{1-a} + \frac{\sigma}{1-\gamma} \right) \hat{y}_t - \frac{\gamma\sigma}{1-\gamma} \hat{y}_{t-1} - \frac{1+\varphi}{1-a} \hat{z}_t$$

where $\hat{z}_t$ is an aggregate productivity shock, calibrated from aggregate data.

The sole difference between the two models pertains to the modeling of aggregate inflation. In one case, it is given by a standard Phillips curve, calibrated to aggregate data as in Section 3.1. In the other, it is implied by the sectoral dynamics aggregated synthetically in our calibrated multi-sector model.[16] Importantly, the New Keynesian Phillips curve functional form is not imposed on aggregate inflation; rather, its moments are collected from our multi-sector simulation.

For each value of λ, the minimization identifies the optimal values for ρ, φ_π and φ_y in the policy rule, and the implied volatilities of $V(\pi_t)$ and $V(y_t)$ given that the volatility in interest rates must stay below $\tilde{\kappa}$. Then letting λ vary traces a frontier in the $[V(\pi_t), V(y_t)]$ space that captures optimal policy in the precise -yet limited- sense of the minimal volatility afforded by the considered type of Taylor rule. In other words, the approach pinpoints the lowest possible values for the volatilities of inflation and output that can be reached for all λ given an upper bound to the volatility of the policy instrument. In practice, the starting value is $\lambda = 0$, and it is changed it by increments of 0.005. $\tilde{\kappa}$ is set at 0.01.

Within this setup, the following question is asked. Given the calibration choices in Section 3.1, how much do minimal volatilities change when we use estimates for λ^b, λ^f, and θ that correspond to aggregate data, or when we feed simulated aggregate inflation as implied by our multi-sector model? The two policy frontiers are reported in Figure 3. The estimates corresponding to simulated inflation imply lower values for $V(y_t)$ at all values of inflation volatility. For all values of λ, the policy frontiers implied by heterogeneous

[16] Each sectoral inflation process is subjected to an inflation shock measured as a residual. The residual between fitted sectoral inflation (as implied by our sectoral Phillips curves) and it observed counterpart is computed. The volatility of the residual is used to calibrate (the volatility of) sectoral inflation shocks, $\epsilon^{\pi}_{j,t}$. The one sector model, in turn, is calibrated using the volatility in residual aggregate inflation, defined as the difference between actual and predicted aggregate inflation.

sectors lie substantially below the one implied by aggregate estimates of the Phillips curve. For given values of the volatility in inflation and the nominal interest rate, policy can deliver a volatility of the output gap that is up to twice smaller than what is implied by aggregate estimates. These are substantial differences. Heterogeneity does matter in a policy sense.

4 Conclusion

Thanks to detailed French data observed at the sector level, it is possible to estimate sector-level Phillips curves. The estimates are obtained using conventional econometric approaches, and allowing for the possibility that prices and marginal costs are correlated across industries. On average at the sector level, prices respond significantly to marginal costs and are forward looking. The implied duration of nominal rigidities is around two quarters. There is considerable heterogeneity around these averages, which maps well with estimates obtained directly from microeconomic French price data.

Once aggregated, our data imply inflation dynamics and New Keynesian Phillips curve estimates that are in agreement with the conventional macroeconomic literature. Heterogeneity does therefore explain the discrepancy between micro- and macro-studies of price setting behavior. The difficulty in rationalizing the dynamics of aggregate inflation can simply originate in the aggregation of heterogeneous sectoral dynamics.

This establishes the econometric importance of heterogeneity in French data. Aggregation also matters in a policy sense. A standard calibration of a monetary economy is implemented. It shows sectoral estimates imply policies that can deliver volatilities in the output gap and in inflation that are half as big as what is implied by aggregate data.

Our results are based on French data, and so it is difficult to ascertain their generality. To our knowledge, similar datasets do not exist elsewhere, that include quarterly measures of prices and real marginal costs using the same sectoral definition. Given the current interest in disaggregated price dynamics, it is our hope the present exercise provides but a first step on the way. Whether our quantitative results continue to be true elsewhere is an open question.

References

Altissimo,F., Ehrmann, M., Smets, F., 2006. Inflation persistence and price-setting behaviour in the euro area a summary of the IPN evidence. Occasional Paper Series 46, European Central Bank.

Altissimo, F., Mojon, B., Zaffaroni, P., 2009. Can aggregation explain the persistence of inflation? Journal of Monetary Economics 56,231-241.

Álvarez, L.J., Burriel, P., Hernando, I., 2009. Do decreasing hazard functions for price changes make any sense? ECB Working Paper Series No. 461.

Aoki, K., 2001. Optimal monetary policy responses to relative-price changes. Journal of Monetary Economics 48, 55-80.

Ascari, G., 2004. Staggered prices and trend inflation: some nuisances. Review of Economic dynamics 7, 642-667.

Baudry, L., Le Bihan, H., Sevestre, P., Tarrieu, S., 2009. La rigidité des prix en France : Les enseignements des relevés de prix à la consommation. Economie et Statistique 386, 37-57.

Baudry, L., Le Bihan, H., Sevestre, P., Tarrieu, S., 2007. What do thirteen million price records have to say about consumer price rigidity? Oxford Bulletin of Economics and Statistics 69, 139-183.

Benigno, P., 2004. Optimal monetary policy in a currency area. Journal of International Economics 63, 293-320.

Benigno, P., López-Salido, D., 2006. Inflation persistence and optimal monetary policy in the Euro area. Journal of Money, Credit, and Banking 38, 587–614.

Bils, M., Klenow, P., 2004. Some evidence on the importance of sticky prices. Journal of Political Economy 112, 947-985.

Bouakez, H., Cardia, E., Ruge-Murcia, F.J., 2009. The transmission of monetary policy in a multi-sector economy. International Economic Review 50, 1243-1266.

Burnside, C., Eichenbaum, M., Rebelo, S., 1996. Sectoral Solow residuals. European Economic Review 40, 861-869.

Calvo, G., 2003. Staggered prices in a utility-maximizing framework. Journal of Monetary Economics 12, 383-398.

Carlstrom, C.T., Fuerst, T.S., Ghironi, F., Hernández, K., 2006. Relative price dynamics and the aggregate economy. Mimeo.

Carvalho, C., 2006. Heterogeneity in price stickiness and the real effects of monetary shocks. Frontier of Macroeconomics 2, 1-56.

Dixon, H., Kara, E., 2005. Persistence and nominal inertia in a generalized Taylor economy: How longer contracts dominate shorter contracts. ECB Working Paper Series No. 489.

Dotsey, M., 2002. Pitfalls in interpreting tests of backward-looking pricing in New Keynesian models. Economic Quarterly - Federal Reserve Bank of Richmond, Winter.

Erceg, C.J. , Levin, A.T., 2002. Optimal monetary policy with durable and non-durable goods. ECB Working Paper Series No. 179.

Fuhrer, J.C., Moore, G.R., 1995. Inflation persistence. Quarterly Journal of Economics 110, 127-160.

Galí, J., Gertler, M., 1999. Inflation dynamics: A structural econometric analysis. Journal of Monetary Economics 44, 195-222.

Galí, J., Gertler, M., López-Salido, D., 2001. European inflation dynamics. European Economic Review 45, 1237-1270.

Gautier, E., 2008. The behaviour of producer prices: some evidence from the French PPI micro data. Empirical economics, 301-332.

Granger, C.W.J., 1980. Long memory relationships and the aggregation of dynamic models. Journal of Econometrics 14, 227-238.

Huang, K.X.D., Liu, Z., 2004. Input output structure and nominal rigidity: The persistence problem revisited. Macroeconomic Dynamics 8, 188-206.

Imbs, J., Jondeau, E., Pelgrin, F., 2008. Aggregating Phillips curves. CEPR Discussion Paper No 6184.

Jondeau, E., Sahuc, J.G., 2008. Optimal monetary policy in an estimated DSGE model of the Euro area with cross-country heterogeneity. International Journal of Central Banking 4, 23-72.

Justiniano, A., Kumhof, M., Ravenna, F., 2006. Multi-sectoral cascading and price dynamics - A bayesian econometric evaluation. Mimeo.

Kurmann, A., 2007. VAR-based estimation of Euler equations with an application to new Keynesian pricing. Journal of Economic Dynamics and Control 31, 767-796.

Leith, C., Malley, J., 2007. A sectoral analysis of price-setting behaviour in US manufacturing industries. Review of Economics and Statistics 89, 335-342.

Loupias, C., Ricart, R., 2005. Une synthèse des résultats d'enquêtes sur la formation des prix des entreprises en France et dans la zone Euro. Bulletin de la Banque de France 141.

Nakamura, E., Steinsson, J., 2008a. Five facts about prices: A reevaluation of menu cost models. Quarterly Journal of Economics 123, 1415-1464.

Nakamura, E., Steinsson, J., 2008b. Monetary non-neutrality in a multi-sector menu cost model. Mimeo.

Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica 74, 967-1012.

Pesaran, M.H., Smith, R., 1995. Estimation of long-run relationships from dynamic heterogenous panels. Journal of Econometrics 68, 79-114.

Robinson, P.M., 1978. Statistical inference for a random coefficient autoregressive model, Scandinavian. Journal of Statistics 5, 163-168.

Sbordone, A., 2001. Prices and unit labor costs: A new test of price stickiness. Journal of Monetary Economics 49, 265-292.

Sheedy, K., 2007. Inflation persistence when price stickiness differs between industries. Centre of Economic Performance Discussion Paper 838.

Taylor, J.B., 2001. Monetary policy rules. In: Taylor, J. B. (Ed), NBER Business Cycles Series 31.

Vermeulen, P. Dias, P., Doosche, M., Gautier, E., Hernando, I., Sabbatini, R., Stahl, H., 2007. Price setting in the euro area: Some stylized facts from individual producer price. Banque de France Working Paper 164.

Woodford, M., 2003. Interest and prices. Princeton University Press.

Zaffaroni, P., 2004. Contemporaneous aggregation of linear dynamic models in large economies. Journal of Econometrics 120, 75-102.

Table 1: Summary statistics

Industry	Weights	$\bar{\pi}$	$\bar{s}$	$corr(\pi_{t-1}, \pi_t)$	$corr(s_{t-1}, s_t)$	$corr(\pi_t, s_t)$
Aggregate	100.00	3.996	−0.095	0.921	0.984	0.887
Agriculture	2.92	1.255	−0.276	0.782	0.977	−0.247
Food Mfg	2.33	3.477	−0.102	−0.075	0.778	−0.320
Cons. Goods	3.02	2.639	−0.087	0.620	0.939	0.367
Car	0.96	3.293	−3.616	0.291	0.981	0.198
Equip. Goods	2.96	0.237	−0.128	0.041	0.915	−0.412
Inter. Goods	5.72	2.788	−1.007	0.725	0.988	0.600
Energy	2.18	5.393	−0.934	−0.281	0.683	−0.449
Construction	6.67	4.889	−0.327	0.511	0.977	0.389
Trade	10.57	4.241	−0.253	0.760	0.974	0.662
Transportation	3.76	2.935	−0.112	0.027	0.777	0.034
Finance	5.01	3.366	−0.410	0.600	0.971	0.143
Real Estate	11.82	5.023	−0.272	0.864	0.983	−0.683
Business Serv.	14.19	3.635	−0.021	−0.290	0.946	−0.362
Personal Serv.	5.75	5.486	0.062	0.758	0.961	−0.707
Educ. & Health	13.94	5.542	−0.261	0.933	0.986	0.848
Govt.	8.21	4.419	−0.050	0.954	0.917	0.484

Note: Descriptive statistics (average inflation, average growth in real marginal costs, serial correlations, and contemporaneous cross-correlation) are reported at both industry and aggregate levels using quarterly French data from 1978:1 to 2005:3. Inflation rate is computed as quarter-on-quarter growth rate of the value-added deflator. Real marginal cost is defined as the (logarithm) deviation of the sector share of labor income in value added from its sample mean.

Table 2: Sectoral Phillips Curves

Industries	Agr.	Food	Cons.	Car	Equip.	Interm.	Energy	Const.	Trade	Transp.	Fin.	R. Estate	Business	Pers. Serv.	Educ. & Health	Govt
	Reduced Form - Equation (17)															
δ_1	0.776*** (0.061)	0.518*** (0.084)	0.611*** (0.073)	0.296*** (0.077)	0.148* (0.079)	0.501*** (0.065)	0.081 (0.114)	0.504*** (0.070)	0.531*** (0.065)	0.050 (0.084)	0.576*** (0.066)	0.845*** (0.057)	0.001 (0.076)	0.771*** (0.059)	0.718*** (0.061)	0.930*** (0.028)
ϕ_1	14.632 (10.64)	13.131*** (3.947)	1.502*** (0.550)	0.229*** (0.074)	0.001 (0.003)	0.766*** (0.174)	21.201* (11.81)	1.963*** (0.628)	2.299*** (0.465)	5.457*** (1.546)	3.391*** (1.035)	0.006 (0.269)	0.001 (0.004)	0.001 (0.001)	0.695*** (0.216)	0.039 (0.062)
ϕ_2	−10.75 (7.899)	−3.481*** (1.094)	0.038 (0.127)	−0.063** (0.029)	0.001 (0.001)	−0.134** (0.064)	−1.686 (2.172)	−0.421* (0.226)	−0.587** (0.238)	0.478 (0.390)	−1.912*** (0.618)	−0.004 (0.186)	0.001 (0.001)	−0.001 (0.002)	0.136** (0.069)	0.008 (0.013)
ρ_1	1.709*** (0.059)	0.916*** (0.086)	0.914*** (0.088)	1.249*** (0.078)	0.584*** (0.084)	1.155*** (0.078)	0.708*** (0.080)	1.194*** (0.083)	1.219*** (0.081)	0.704*** (0.083)	1.525*** (0.060)	1.661*** (0.069)	0.866*** (0.078)	1.128*** (0.094)	0.767*** (0.101)	0.733*** (0.096)
ρ_2	−0.758*** (0.057)	−0.270*** (0.043)	0.026 (0.087)	−0.277*** (0.077)	0.010 (0.078)	−0.177*** (0.076)	−0.080 (0.069)	−0.217*** (0.082)	−0.255*** (0.079)	0.089 (0.077)	−0.573*** (0.055)	−0.698*** (0.068)	0.021 (0.071)	−0.201** (0.093)	0.199** (0.099)	0.207** (0.096)
	Reduced Form - Equation (15)															
λ^b	0.442*** (0.021)	0.343*** (0.038)	0.382*** (0.029)	0.229*** (0.046)	0.129** (0.061)	0.335*** (0.029)	0.075 (0.098)	0.336*** (0.032)	0.349*** (0.028)	0.048 (0.076)	0.368*** (0.027)	0.461*** (0.018)	0.001 (0.076)	0.437*** (0.019)	0.421*** (0.022)	0.488*** (0.010)
λ^f	0.554*** (0.021)	0.650*** (0.038)	0.615*** (0.029)	0.765*** (0.046)	0.863*** (0.061)	0.661*** (0.029)	0.915*** (0.098)	0.659*** (0.032)	0.647*** (0.028)	0.943*** (0.076)	0.628*** (0.028)	0.539*** (0.018)	0.989 (0.076)	0.562*** (0.019)	0.578*** (0.022)	0.511*** (0.010)
θ	0.469 (0.412)	3.145*** (1.382)	0.071 (0.049)	0.006 (0.005)	0.001 (0.004)	0.017* (0.010)	7.417 (5.239)	0.043 (0.036)	0.069* (0.040)	1.124* (0.602)	0.116* (0.069)	0.001 (0.006)	0.001 (0.001)	0.001 (0.001)	0.021*** (0.009)	0.002 (0.003)
	Structural Estimates															
ω	0.281*** (0.094)	0.075*** (0.022)	0.401*** (0.070)	0.268*** (0.046)	0.148* (0.089)	0.411*** (0.060)	0.008 (0.009)	0.369*** (0.067)	0.358*** (0.057)	0.018 (0.029)	0.345*** (0.051)	0.819 (0.678)	0.001 (0.001)	0.770*** (0.159)	0.547*** (0.058)	0.823*** (0.082)
α	0.357*** (0.131)	0.142*** (0.047)	0.652*** (0.086)	0.904*** (0.039)	0.999*** (0.281)	0.820*** (0.049)	0.100* (0.061)	0.730*** (0.089)	0.672*** (0.074)	0.352*** (0.061)	0.596*** (0.085)	0.968 (0.843)	0.999*** (0.266)	0.999*** (0.198)	0.757*** (0.035)	0.872*** (0.074)
Duration	1.554*** (0.316)	0.166*** (0.065)	2.871*** (0.705)	10.429** (4.217)	-	5.557*** (1.523)	1.111*** (0.078)	3.709*** (1.230)	3.049*** (0.683)	1.542*** (0.217)	2.472*** (0.519)	31.21 (82.12)	–	–	4.122*** (0.590)	7.812* (4.503)

Note: Standard deviation in parentheses. Marginal costs follow an autoregressive process of order two. The estimates are obtained using a Maximum Likelihood procedure. The structural estimates are inferred from reduced form coefficients using a Delta method.

Table 3: Sectoral Phillips Curves in SURE

Industries	Agr.	Food	Cons.	Car	Equip.	Interm.	Energy	Const.	Trade	Transp.	Fin.	R. Estate	Business	Pers. Serv.	Educ. & Health	Govt
	Reduced Form - Equation (18)															
δ_1	0.693***	0.338***	0.464***	0.203***	0.197***	0.385***	0.001	0.432***	0.579***	0.004	0.549***	0.678***	0.082	0.468***	0.728***	0.748***
	(0.063)	(0.091)	(0.040)	(0.074)	(0.072)	(0.061)	(0.068)	(0.069)	(0.067)	(0.079)	(0.062)	(0.065)	(0.073)	(0.079)	(0.051)	(0.052)
ϕ_1	24.363**	8.406***	1.974**	0.319**	0.439	0.982**	0.001	0.484	3.687***	4.808*	3.120**	0.001	0.001	0.001	0.615	0.264**
	(9.639)	(3.087)	(0.760)	(0.126)	(0.347)	(0.362)	(0.072)	(0.726)	(0.810)	(2.673)	(1.279)	(0.056)	(0.021)	(0.011)	(0.367)	(0.104)
ϕ_2	−15.364**	−1.618*	−0.200	−0.074*	0.030	−0.085	−0.001	−0.129	−1.236***	0.055	−1.795**	−0.001	−0.001	−0.001	−0.227	-0.066
	(6.239)	(0.915)	(0.199)	(0.039)	(0.031)	(0.071)	(0.005)	(0.197)	(0.388)	(0.289)	(0.737)	(0.038)	(0.001)	(0.003)	(0.165)	(0.045)
ρ_1	1.570***	0.911***	0.969***	1.115***	0.827***	1.005***	0.979***	1.234***	1.206***	0.629***	1.518***	1.622***	0.984***	1.106***	1.307***	1.227***
	(0.049)	(0.078)	(0.082)	(0.070)	(0.070)	(0.072)	(0.071)	(0.076)	(0.069)	(0.111)	(0.051)	(0.056)	(0.073)	(0.093)	(0.098)	(0.093)
ρ_2	−0.648***	−0.195***	−0.102	−0.233***	0.069	−0.088	−0.065	−0.269***	−0.341***	0.012	−0.584***	−0.681***	−0.045	−0.240**	−0.376***	−0.255**
	(0.048)	(0.059)	(0.082)	(0.067)	(0.067)	(0.067)	(0.064)	(0.073)	(0.060)	(0.060)	(0.043)	(0.054)	(0.068)	(0.091)	(0.096)	(0.101)
	Reduced Form - Equation (15)															
λ^b	0.414***	0.254***	0.318***	0.169***	0.165***	0.279***	0.001	0.303***	0.369***	0.003	0.356***	0.406***	0.076	0.320***	0.424***	0.430***
	(0.023)	(0.052)	(0.055)	(0.051)	(0.050)	(0.032)	(0.069)	(0.034)	(0.028)	(0.079)	(0.026)	(0.023)	(0.062)	(0.037)	(0.017)	(0.017)
λ^f	0.581***	0.740***	0.677***	0.824***	0.828***	0.716***	0.989***	0.693***	0.626***	0.987***	0.639***	0.592***	0.916***	0.676***	0.573***	0.568***
	(0.023)	(0.051)	(0.039)	(0.050)	(0.049)	(0.031)	(0.067)	(0.033)	(0.027)	(0.078)	(0.026)	(0.024)	(0.061)	(0.036)	(0.017)	(0.017)
θ	1.249**	1.839*	0.196*	0.033*	0.042	0.066*	0.001	0.015	0.341**	1.752	0.145*	0.001	0.001	0.001	0.028	0.006
	(0.620)	(1.013)	(0.058)	(0.018)	(0.045)	(0.038)	(0.007)	(0.029)	(0.132)	(1.410)	(0.082)	(0.002)	(0.001)	(0.001)	(0.022)	(0.006)
	Structural Estimates															
ω	0.164***	0.076***	0.254***	0.164***	0.155***	0.272***	0.001	0.362***	0.256***	0.001	0.315***	0.677	0.082	0.468***	0.534***	0.639***
	(0.044)	(0.022)	(0.055)	(0.057)	(0.054)	(0.048)	(0.068)	(0.078)	(0.039)	(0.023)	(0.047)	(0.593)	(0.073)	(0.136)	(0.068)	(0.068)
α	0.232***	0.226***	0.545***	0.807***	0.788***	0.705***	0.999*	0.838***	0.439***	0.289**	0.571***	0.999	0.999***	0.999***	0.729***	0.851***
	(0.067)	(0.083)	(0.089)	(0.050)	(0.104)	(0.065)	(0.567)	(0.142)	(0.062)	(0.122)	(0.094)	(0.887)	(0.171)	(0.240)	(0.080)	(0.068)
Duration	1.302***	1.291***	2.198***	5.191**	4.705**	3.394***	–	6.161	1.782***	1.406***	2.329***	–	–	–	3.689***	6.725**
	(0.113)	(0.139)	(0.433)	(1.356)	(2.293)	(0.752)		(5..373)	(0.196)	(0.241)	(0.510)				(1.094)	(3.093)

Note: Standard deviation in parentheses. Marginal costs follow an autoregressive process of order two. The estimates are obtained using a Maximum Likelihood procedure implemented on a system of sectoral equations using the SURE procedure. The structural estimates are inferred from reduced form coefficients using a Delta method.

Table 4: A comparison of price duration (in quarters) with other French studies

		Producer prices*		Consumer prices**
		Gautier (2008)	Imbs et al.	Baudry et al. (2006, 2007)
Agriculture		-	1.301	-
Manufacturing				
	Food manufacturing	1.100	1.291	1.375
	Consumption goods	-	2.198	-
	Car industry*	2.350	5.191	1.375
	Equipment goods	2.980	4.705	-
	Intermediary goods	1.850	3.394	-
	Energy	0.550	-	0.350
Services		-	-	3.630
	Construction	-	-	-
	Trade	-	1.782	-
	Transportation	-	1.406	1.53
	Financial activities	-	2.329	-
	Real estate	-	-	1.980
	Business services	3.630	-	-
	Personal services	-	-	-
	Education and health services	-	3.689	[3.2;4]
	Government	-	6.725	-

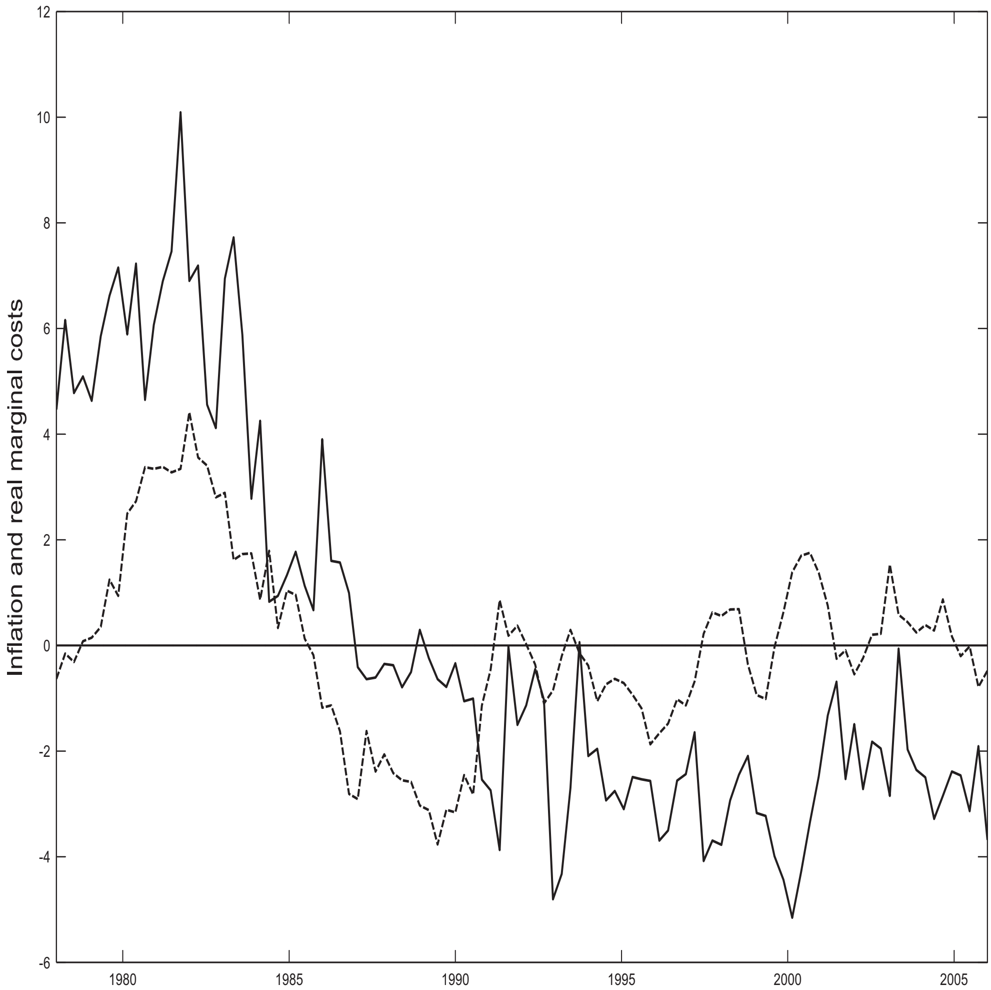
Notes: * Producer prices are in Gautier (2008) and the ECB survey (Vermeulen et al., 2007). Similar evidence is found in Loupias and Ricart (2005). Duration are taken from Table 4 of Gautier (2008), which reports the frequency of price change and the implied price duration. Gautier (2008) does not report ”car industry” (respectively, ”equipment goods”) but rather ”durable consumer goods” (respectively, ”Non-food, non-durables”). The sample period is different from ours. In Gautier (2008), the period is 1994-2005.
** Consumer price data are in Baudry et al. (2007). Average price duration is taken from Table 4 (Baudry et al., 2007). Data for the ”service industry” are taken from Baudry et al. (2007) using the COICOP category (Baudry et al., 2009, Table 7). The COICOP category goes as follows: 01 Food and non-alcoholic beverage, 02 Alcoholic bev. and tobacco, 03. Clothing and footwear, 04. Housing, water, electricity, etc 05. Furnishings, household equipment, 06. Health, 07. Transportation, 08. communication, 09 recreation and culture, 10 Education, 11 Restaurants and hotels, 12. Other goods and services In the case of Education and health services, the value of each corresponding COICIP category is reported, i.e. [12.8;16]. The sample period is different from ours. In Baudry et al. (2007), the sample period is 1994-2003.

Table 5: Single Equation Phillips Curves

	Panel A		Panel B		Panel C	
	Representative Sector		Aggregate Data		Simulated Aggregates	
	ML	ML / SURE	ML	GMM	ML	GMM
			Reduced Form			
δ_1	0.491	0.409	0.666***		0.701***	
			(0.064)		(0.024)	
ϕ_1	4.076	3.091	1.514***		1.561***	
			(0.424)		(0.603)	
ϕ_2	−1.148	−1.294	0.006		0.086	
			(0.146)		(0.063)	
ρ_1	1.082	1.138	0.969***		0.917***	
			(0.098)		(0.025)	
ρ_2	−0.185	−0.253	0.004		0.056***	
			(0.099)		(0.009)	
			Quasi Reduced Form			
λ^b	0.331	0.292	0.402***	0.351***	0.415	0.299***
			(0.024)	(0.064)		(0.031)
λ^f	0.664	0.703	0.595***	0.645***	0.582	0.697***
			(0.024)	(0.065)		(0.038)
θ	0.313	0.271	0.039*	0.080*	0.041	0.110***
			(0.022)	(0.042)		(0.034)
			Structural Estimates			
ω	0.231	0.209	0.475***	0.368***	0.491	0.270
			(0.064)	(0.037)		
α	0.469	0.508	0.708***	0.684***	0.695	0.635
			(0.059)	(0.097)		
Duration	1.882	2.031	3.430***	3.165***	3.289	2.732
			(0.690)	(0.094)		

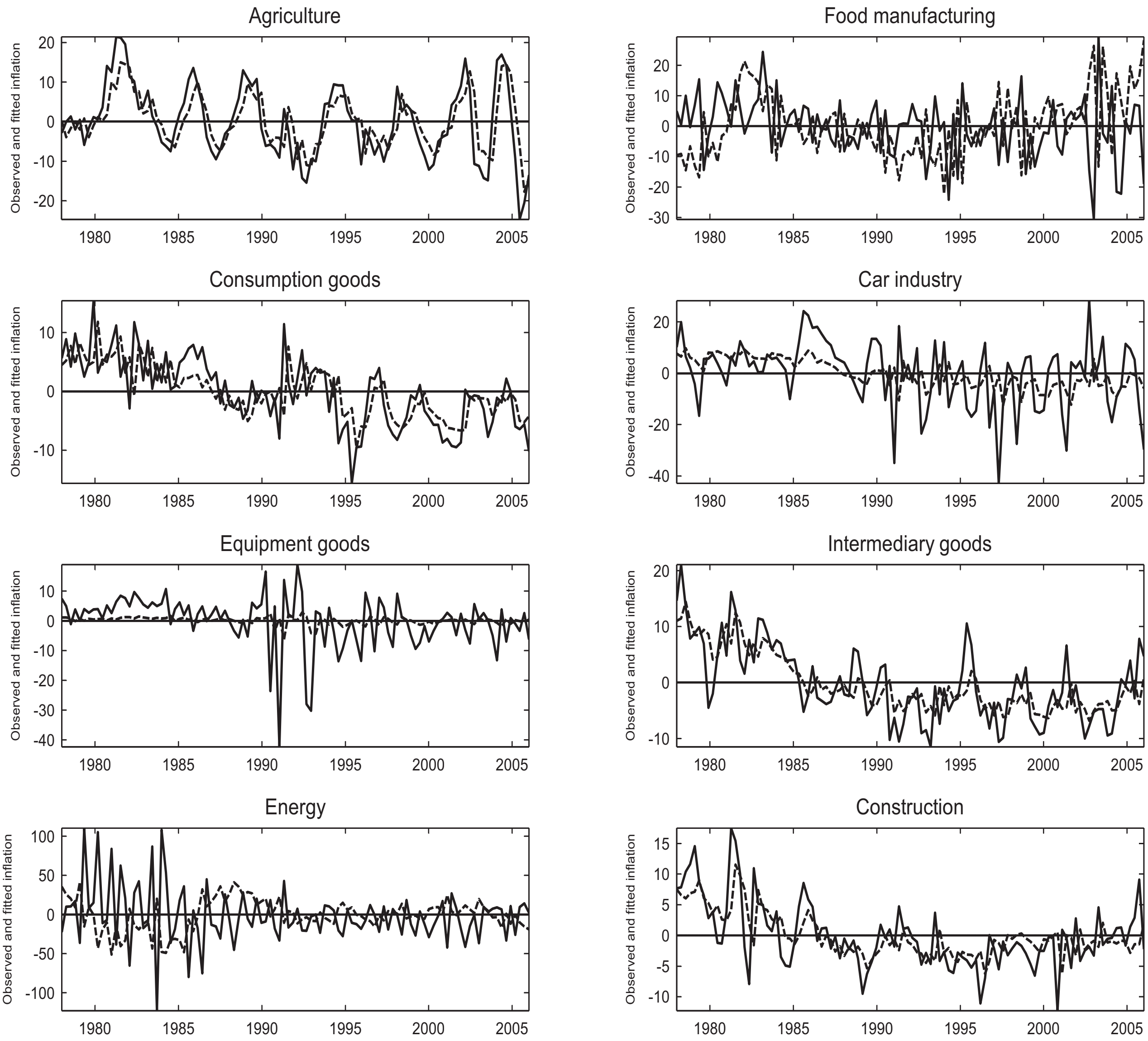
Note: "Representative Sector" corresponds to the simple average of the reduced form parameters δ_1, ϕ_1, ϕ_2, ρ_1 and ρ_2 corresponding to Tables 2 and 3. The parameters from equation (15) and the structural estimates are inferred on the basis of these averages. ML-SURE uses the individual estimates from Table 3. "Aggregate Data" reports ML and GMM estimates of the Phillips Curve on the basis of aggregated data. GMM makes use of lagged aggregate inflation, lagged marginal costs and lagged wage inflation as instruments for expected inflation. "Simulated Aggregates" reports Phillips curve estimates obtained from the simulation of a multi-sector model. Mean absolute deviations are reported between brackets. GMM uses the individual estimates from Appendix 4.

Figure 1: Aggregate Inflation and Marginal Costs (unfiltered)



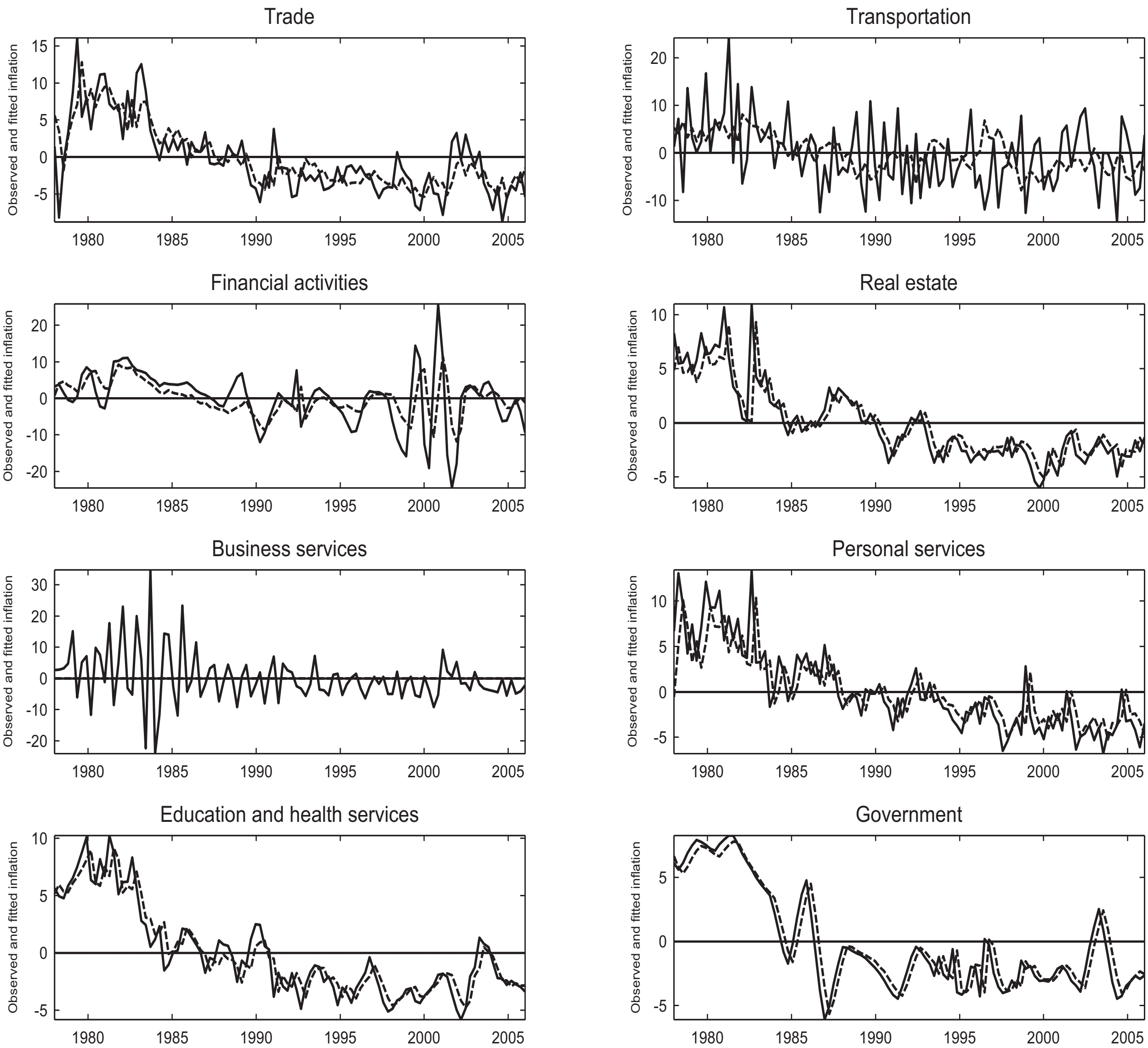
Note: The plain line denotes inflation and the dotted line the observed marginal cost.

Figure 2: Industry Phillips Curves



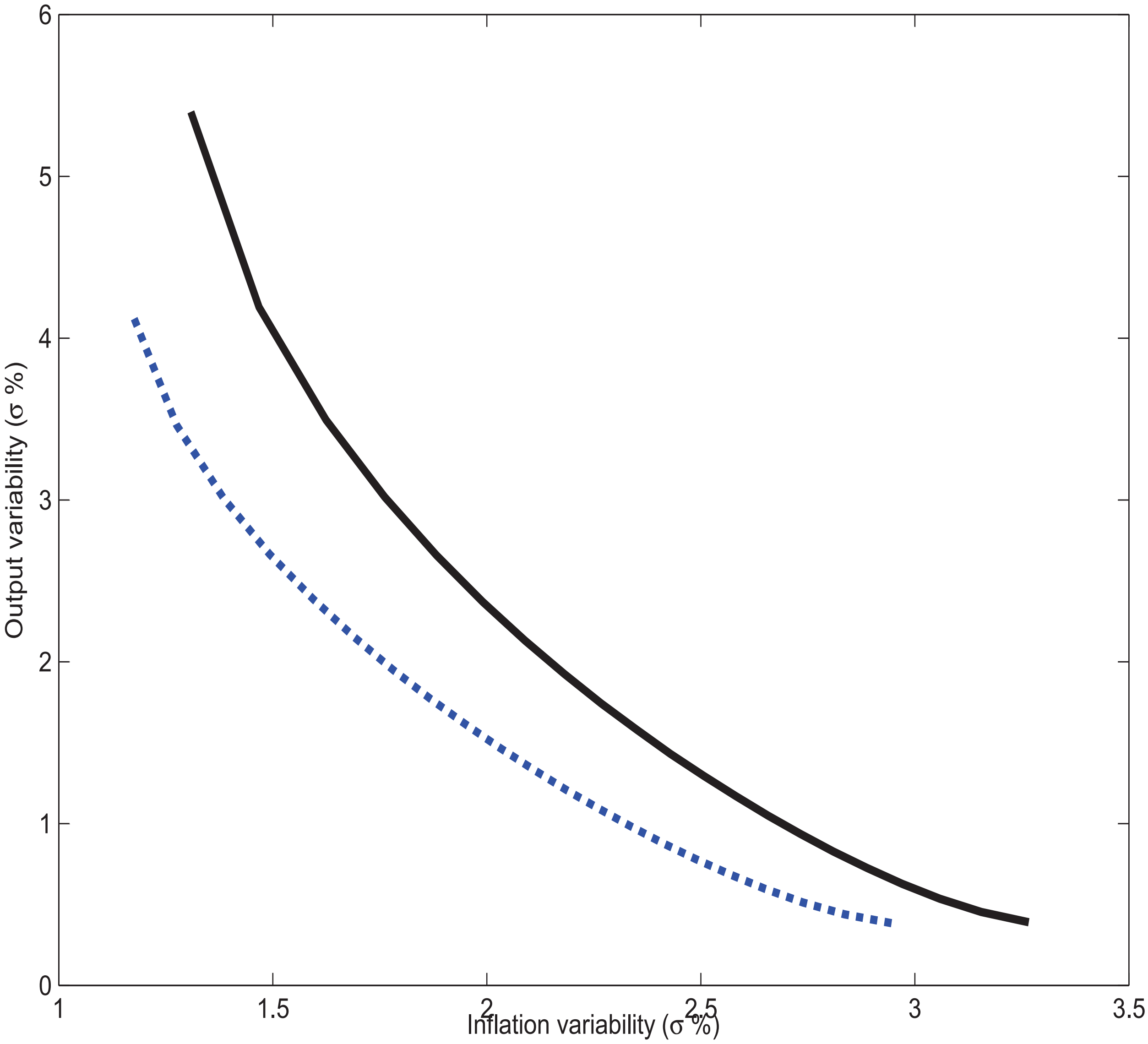
Note: The plain line denotes observed inflation and the dotted line is fitted inflation.

Figure 2 (continued): Industry Phillips Curves



Note: The plain line denotes observed inflation and the dotted line is fitted inflation.

Figure 3: Policy Frontiers



Note: The plain line denotes the policy frontier implied by the aggregate model. The dotted line is the policy frontier implied by the multi-sector model.