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Technology, demand, and productivity: What an industry model tells us about business cycles

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ABSTRACT

In this paper, we study the relative importance of demand and technology shocks in generating business cycle fluctuations, both at the aggregate level and at the level of individual industries. We construct a New Keynesian DSGE model that is highly disaggregated at the industry level with an input-output network structure. Measured productivity in the model fluctuates in response to both technology and demand shocks due to endogenous factor utilization. We estimate the model by the simulated method of moments using U.S. industry data from 1960 to 2005.

We find that the aggregate technology shock has zero variance. Exogenous shocks to technology are necessary for our model to fit the data, but these shocks are exclusively industry-specific, uncorrelated across industries. The bulk of the aggregate fluctuations, including those in aggregate measured productivity, are explained through shocks to aggregate demand. This shock structure is supported by a host of information from the disaggregate data.

Our second finding is that about half of the decrease in the cyclicity of measured productivity in the U.S. after the mid-1980s can be explained by the reduction in the importance of demand shocks, in line with the narrative of the *great moderation*.

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1. Introduction

What type of shocks are driving business cycles? Contemporary workhorse DSGE models often feature a wide variety of shocks, the importance of which might vary over time. For many of the commonly used types of these shocks, there are prevailing controversies about whether they can be interpreted as structural sources of economic fluctuations, see for example [Chari et al. \(2009\)](#). In contrast, many models in the theoretical literature are still built on the assumption that business cycles are driven solely by technological changes. The plausibility of aggregate technology shocks, i.e., changes in factor productivity affecting the whole economy, has long been disputed in the macroeconomic literature, see e.g. [Summers \(1986\)](#), [Francis and Ramey \(2005\)](#).

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Technological changes at the level of narrowly defined industries appear more plausible and are easier to identify because they tend to be larger and therefore less likely to be dominated by mismeasurement. Thus, a strand of literature has emerged that studies whether independent shocks at various levels of disaggregation can explain the aggregate fluctuations. Focusing mostly on the mechanisms that propagate idiosyncratic shocks across the economy within the RBC framework, the conclusion so far is that only a part of the fluctuations in aggregate productivity can be attributed to independent industry-level shocks.

In this paper, we study the role of the different types of shocks in generating business cycle fluctuations in the U.S. in a New Keynesian DSGE model, building on the growing literature on multi-industry business cycle models. We find that, although exogenous shocks to technology are necessary for our model to fit the data, these shocks are exclusively industry-specific. The variance of the aggregate technology shock is zero. The model replicates the observed fluctuations of aggregate and industry variables, as well as the co-movement patterns across industry-level variables. The majority of the aggregate fluctuations, including those in aggregate measured productivity, are explained through the shocks to aggregate demand. On the other hand, idiosyncratic industry-specific technology and demand shocks are the dominant drivers of fluctuations at the industry level. Industry-specific shocks to technology are necessary to explain the strong fluctuations of measured industry productivity. Moreover, they also contribute a significant part to the volatility of measured productivity at the aggregate level.

Our model has the following key characteristics: First, the production of goods is highly disaggregated, composed of 77 industries connected through the input-output network. Second, the economy is driven by technology and demand-side shocks at both the aggregate and the industry level. Third, endogenous factor utilization allows non-technology shocks to generate changes in measured productivity. Fourth, there are nominal rigidities at the firm level, in line with the New Keynesian literature. The nominal rigidities are important because the price mechanism is central for the propagation of shocks via the input-output network. For example, an increase in industry productivity only leads to higher industry output if the prices reflect the change in productivity.

While the model features a detailed industry structure, it only includes four types of shocks, less than a typical medium-sized DSGE model. At the aggregate level, our model features one demand side shock and one productivity shock. Additionally, each industry is affected by its own idiosyncratic shock to demand and productivity. We show that this parsimonious shock structure delivers a very good fit of the model along many dimensions at the aggregate and industry level.

The model can generate the observed fluctuations in aggregate productivity without aggregate technology shocks through the combination of two elements. First, the contribution of industry-level shocks to aggregate productivity, and second, endogenous fluctuations arising from variable factor utilization (effort) and increasing returns to scale (fixed costs). Factor utilization allows non-technology shocks to affect measured productivity, which sets our model apart from the existing literature on multi-industry macroeconomic models.

Our results are compatible with recent evidence that the bulk of aggregate macroeconomic fluctuations is driven by one type of shock that has the characteristics of a demand shock, see [Angeletos et al. \(2020\)](#) and [Andrle et al. \(2017\)](#). We support these findings by using industry-level evidence, which brings in a host of information that is useful for the identification of shocks. We find that, considering aggregate data only, it is difficult to distinguish a model with aggregate technology shocks from a model that relies on endogenous productivity fluctuations. However, we show that these models have quite different implications for the industry-level variables. One important piece of industry-level evidence is the co-movement of the variables, especially measured productivity, across industries. Moreover, the models differ in their implications for the size of fluctuations of industry variables relative to aggregate variables and for the cyclicity of measured productivity.

Our second finding is that about a half of the decrease in the cyclicity of measured productivity in the U.S. in the period after 1984 can be explained by a reduction in the importance of demand shocks, in line with the narrative of the *great moderation*. We refer to the empirical observation that the procyclicality of measured productivity in the U.S. has to a large extent disappeared in the period after 1984, see [Stiroh \(2009\)](#), [Galí and Gambetti \(2009\)](#), and [Fernald and Wang \(2016\)](#). Several authors, for example [Galí and Gambetti \(2009\)](#) and [Barnichon \(2010\)](#), have suggested that the great moderation period after 1984 was characterised by a different composition of shocks, especially stressing the lower volatility of shocks to aggregate demand, or muted effects of these shocks on the economy. Thus, we assume a lower volatility of the shocks to aggregate demand for the period after 1984, keeping the rest of parameters the same. The correlation between aggregate measured TFP and hours decreases from 0.49 to 0.11, corresponding to 50% of the change observed in the data. Importantly, our model is able to generate the decrease in the procyclicality of the aggregate measured productivity without generating counterfactual changes at the industry level.

The idea that industry-specific technology shocks might add up to sizeable technology shocks in the aggregate goes back at least to [Long and Plosser \(1983\)](#) and has attracted renewed attention in recent years. [Horvath \(1998\)](#), [Horvath \(2000\)](#), [Acemoglu et al. \(2012\)](#), and [Acemoglu et al. \(2017\)](#) point out that idiosyncratic shocks might propagate between industries due to asymmetric input-output linkages and thus affect the aggregate fluctuations more strongly than the law of large numbers would predict. Following the idea of industry-level shocks propagated through the input-output network, several authors have attempted to quantify the relative importance of both industry-specific and aggregate shocks for the macroeconomic fluctuations. [Foerster et al. \(2011\)](#) use factor analysis to decompose the industrial production series into the aggregate and idiosyncratic components and adjust the results for the contribution of the input-output network. In the framework of an RBC model with technology shocks only, they estimate that industry-specific shocks are responsible for 20% to 50% of the aggregate fluctuations, depending on the sample period (industry specific shocks are more important in the pe-

riod after the mid-1980s). [Holly and Petrella \(2012\)](#) utilize an industry-level VAR model of U.S. manufacturing and identify the industry-specific shocks to productivity using the long-run restrictions at the industry level. Their estimates are broadly in line with the results of our paper in that they find a very limited role of aggregate shocks to technology, while industry-level shocks to technology play an important role.

[Atalay \(2017\)](#) and [vom Lehn and Winberry \(2021\)](#) are closely related to the present paper, although both feature RBC models with supply side shocks only. [Atalay \(2017\)](#) estimates a structural industry-level model with a generalized production function. He shows that the elasticities of substitution between production factors, between intermediate inputs from different industries and between the consumption of industry-level goods are important determinants of how strongly shocks propagate between industries. He identifies low elasticities between industry goods in the production function which suggest strong complementarity between intermediate inputs. As a result, industry-specific shocks account for at least half of the variation of the aggregate output, and the share can be even higher depending on other model parameters.

To the best of our knowledge, [vom Lehn and Winberry \(2021\)](#) is the only paper which also examines the vanishing cyclicity of productivity in the U.S. in the mid-1980s using the industry approach. They find that the industries which act as suppliers of the investment goods are important drivers of aggregate fluctuations and that idiosyncratic shocks to these industries generate countercyclical movement in aggregate measured productivity. Since the relative importance of the shocks to these industries has increased in the recent decades, their model generates the decrease in the cyclicity of productivity. This explanation is complementary to ours as their model abstracts from demand-side shocks. The vanishing cyclicity of productivity in [vom Lehn and Winberry \(2021\)](#) relies on the assumption of decreasing returns to scale, which is not present in our model.

Lastly, this paper is also related to the recent literature that studies the propagation of shocks in industry-level New Keynesian models. The models in this literature are closely related to ours, but the papers have a different focus, concentrating mostly on the heterogeneity of industry-level inflation and transmission of monetary policy shocks. [Bouakez et al. \(2014\)](#), [Pasten et al. \(2017\)](#) and [Pasten et al. \(2020\)](#) point out the importance of heterogeneous price rigidity across industries, amplified through the input-output linkages. [Smets et al. \(2019\)](#) estimate a New Keynesian model using Bayesian techniques and find that the input-output linkages are the major source of heterogeneous inflation patterns across industries and that industry-level shocks contribute to aggregate inflation volatility.

The rest of the paper is structured as follows. We introduce the multi-industry New Keynesian general equilibrium model in [Section 2](#). We describe the data sources and the calibration strategy in [Section 3](#). [Section 4](#) presents and discusses the results. Finally, [Section 5](#) concludes.

2. Model

This section presents the New Keynesian DSGE model with production disaggregated at the industry level, featuring 77 industries which are linked via the input-output network. Because we model each industry individually, the model features a large number of variables (1641 variables in total). We solve the model by linearization around the deterministic steady state.

2.1. Industries

Production in the model economy is organized into I different industries, indexed by $i = 1, \dots, I$. The output of each industry has three potential purposes: it is used as a *consumption good* (cf. [Section 2.2](#)), in the production of *investment goods* ([Section 2.4](#)), or as an *intermediate input* in the production of firm output ([Section 2.3](#)).

Each industry consists of a continuum of monopolistically competitive firms represented by the unit interval. The differentiated firm goods aggregate to industry output according to

$$y_{i,t} = \left(\int_0^1 y_{ki,t}^{\frac{\sigma_i-1}{\sigma_i}} dk \right)^{\frac{\sigma_i}{\sigma_i-1}}, \quad (1)$$

where $y_{ki,t}$ denotes the output produced by an individual firm k in industry i and $\sigma_i > 0$ is the elasticity of substitution between the firm goods. [Eq. \(1\)](#) implies isoelastic demand for goods of firm k :

$$y_{ki,t} = \left(\frac{p_{ki,t}}{p_{i,t}} \right)^{-\sigma_i} y_{i,t}, \quad (2)$$

where $p_{ki,t}$ is the price set by firm k , and $p_{i,t}$ is the price index of industry i , given by

$$p_{i,t} = \left(\int_0^1 p_{ki,t}^{1-\sigma_i} dk \right)^{\frac{1}{1-\sigma_i}}. \quad (3)$$

2.2. Households

The economy is populated by a continuum of infinitely-lived representative households. Households provide labor input, consume goods, save in the form of bonds and capital, and receive all firm profits. The objective of the representative

household is to maximize

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(C_t - \chi \bar{C}_t) - \frac{N_t^{1+1/\sigma_U}}{1 + 1/\sigma_U} \right], \tag{4}$$

where C_t are units of a bundle of consumed goods and the term $\chi \bar{C}_t$ represents consumption habits that are assumed to be external to the individual household, $\bar{C}_t = C_{t-1}$. N_t is an index of the labor services provided to various industries and σ_U is the corresponding elasticity of the total labor supply. The consumption bundle is a composite of differentiated industry goods

$$C_t = \left(\sum_{i=1}^I v_{i,t}^{\frac{1}{\sigma_C}} c_{i,t}^{\frac{\sigma_C-1}{\sigma_C}} \right)^{\frac{\sigma_C}{\sigma_C-1}}, \tag{5}$$

where $c_{i,t}$ is the amount of industry i good that is used for consumption, $v_{i,t}$ is the weight of that good in the consumption basket and $\sigma_C > 0$ is the elasticity of substitution between the industry goods. The weights are subject to exogenous variation over time, which we interpret as *shocks to relative industry demand*, specified in more detail in Section 2.7. The price P_t of a unit of the consumption bundle is defined so as to satisfy

$$P_t C_t = \sum_{i=1}^I p_{i,t}^{NOM} c_{i,t}, \tag{6}$$

where $p_{i,t}^{NOM}$ is the nominal price of industry good i . Expressing industry prices relative to the price of the consumption bundle, $p_{i,t} = p_{i,t}^{NOM}/P_t$, the isoelastic demand function for goods of industry i is given by

$$c_{i,t} = v_{i,t} p_{i,t}^{-\sigma_C} C_t. \tag{7}$$

The utility function (4) states that households draw negative utility from providing the index of labor services N_t to various industries. The labor supply index is given by

$$N_t = \left(\sum_{i=1}^I \eta_i g(h_{i,t}, e_{i,t})^{\frac{\sigma_N+1}{\sigma_N}} \right)^{\frac{\sigma_N}{\sigma_N+1}}. \tag{8}$$

The disutility depends on the number of differentiated hours $h_{i,t}$, as well as the effort $e_{i,t}$ exerted by the workers in each industry. We assume that workers' effort is a measure of performance that is observed and remunerated by firms, but not observed in the data. Similar to Horvath (2000) and Bouakez et al. (2014), household preferences over working in different industries are given by the weight parameters η_i and the elasticity parameter $\sigma_N > 0$. The latter determines how elastically the industry labor supply allocation reacts to changes in industry wages. For σ_N approaching infinity, labor inputs in various industries are perfect substitutes as far as the household is concerned. For $\sigma_N < \infty$, households prefer to diversify their labor input, thus the labor input is not perfectly mobile across industries. This specification allows for industry-specific wages in our representative household framework.

Finally, the function g describes household preferences over supplying units of hours and effort. Utility is decreasing in both hours and effort supplied to each industry according to

$$g(h_{i,t}, e_{i,t}) = \left(h_{i,t} + \Lambda_i \frac{e_{i,t}^{\sigma_e}}{\sigma_e} \right)^{\frac{1+\sigma_e}{\sigma_e}}, \tag{9}$$

where the parameter $\sigma_e \geq 0$ determines the elasticity with which households adjust the supply of effort, relative to hours, and $\Lambda_i \geq 0$ is an industry-specific weight parameter. Notice that g is jointly convex in hours and effort. The total labor input available to the firms in industry i is the product of hours and effort,

$$l_{i,t} = e_{i,t} h_{i,t}. \tag{10}$$

Firms pay the wage $w_{i,t}$ per unit of labor service $l_{i,t}$ and the household can choose hours and effort optimally, such that the disutility of providing labor services $l_{i,t}$ is minimized, cf. Barnichon (2010). Household first order conditions imply

$$e_{i,t} = \Lambda_i^{-\frac{1}{\sigma_e}} h_{i,t}^{\frac{1}{\sigma_e}}. \tag{11}$$

Hence, there is a monotone relationship between hours and effort. In comparison to hours, effort fluctuates less when the parameter σ_e is higher.

With all prices expressed in terms of the consumption bundle, the budget constraint of the household is given by

$$\left(\sum_{i=1}^I w_{i,t} l_{i,t} \right) + r_t^k K_{t-1} + T_t + r_t^b B_{t-1} = C_t + P_t^X X_t + B_t, \tag{12}$$

where the $w_{i,t}$ are real industry-specific wages per unit of labor input, K_t is capital stock at the end of period t , r_t^k is gross real return on capital, T_t are aggregate firm profits, X_t is gross investment and P_t^X is the real price of the investment good.

Besides physical capital, the household can also save in the form of a one-period riskless bond, B_t . The bond yields the real return

$$r_t^b = D_{t-1} \frac{R_{t-1}}{\pi_t}, \tag{13}$$

where the nominal interest rate R_t is set by the monetary authority, and π_t is consumer price inflation. We interpret the exogenous disturbance term D_t as the aggregate demand shock. The shock represents a wedge between the nominal interest rate set by the monetary authority and the interest rate available to the household. This type of demand shock is fairly common in the contemporary DSGE literature. For example, in [Smets and Wouters \(2007\)](#) it is referred to as the *risk premium shock*.

2.3. Firms

In each industry, firms act under monopolistic competition and produce goods using capital and labor services as well as intermediate inputs. Firms maximize the expected discounted value of their future profits. All firms in an industry have access to the same technology and are the same ex ante. Therefore, in order to simplify the formulas, we omit firm indices in the following firm-level equations. The gross output of a firm in industry i follows

$$y_{i,t} = A_t z_{i,t} \left[\mu_{i,K} \frac{1}{\sigma_y} k_{i,t}^{\frac{\sigma_y-1}{\sigma_y}} + \mu_{i,L} \frac{1}{\sigma_y} l_{i,t}^{\frac{\sigma_y-1}{\sigma_y}} + \mu_{i,M} \frac{1}{\sigma_y} M_{i,t}^{\frac{\sigma_y-1}{\sigma_y}} \right]^{\frac{\sigma_y}{\sigma_y-1}} - \Phi_i, \tag{14}$$

where A_t is an exogenous stochastic aggregate technology process that affects all industries. In contrast, $z_{i,t}$ is a technology process that only affects firms in industry i . The production factors capital $k_{i,t}$, labor $l_{i,t}$, and intermediate inputs $M_{i,t}$ are combined with elasticity of substitution $\sigma_y > 0$. The weights $\mu_{i,\{K,L,M\}}$ determine the relative importance of the production factors. The intermediate input composite $M_{i,t}$ consists of industry goods combined with the CES technology

$$M_{i,t} = \left(\sum_{j=1}^I \alpha_{ji} \frac{1}{\sigma_M} m_{ji,t}^{\frac{\sigma_M-1}{\sigma_M}} \right)^{\frac{\sigma_M}{\sigma_M-1}}, \tag{15}$$

where $m_{ji,t}$ denotes the intermediate good from industry j that a firm in industry i uses to produce its output. The parameter $\sigma_M > 0$ is the elasticity of substitution between intermediate inputs from different industries. The weights $\alpha_{ji} \geq 0$ determine the relative importance of intermediate inputs from various industries.

In order to produce, firms in industry i must pay a fixed cost $\Phi_i \geq 0$ expressed in units of output. Because of the fixed cost, the firms face increasing returns to scale in net output and changes in demand generate changes in measured productivity. Next to endogenous factor utilization, fixed costs are the second reason why changes in measured productivity are different from exogenous technological changes.

The firms are subject to nominal price rigidities of the Calvo-type. Since the firms in industry i are ex ante identical, they all choose the same optimal price $p_{i,t}^*$ in case they adjust the price in period t . Substituting into [Eq. \(3\)](#), the price index of the industry i good evolves according to

$$p_{i,t} = \left[\theta_i \left(\frac{p_{i,t-1}}{\pi_t} \right)^{1-\sigma_i} + (1-\theta_i) p_{i,t}^{*1-\sigma_i} \right]^{\frac{1}{1-\sigma_i}}, \tag{16}$$

where $\theta_i \in [0, 1]$ is the probability that a firm is not able to adjust the price in period t . As discussed amongst others in [Bouakez et al. \(2014\)](#), the degree of price stickiness is likely to differ across industries. However, the identification of the price rigidity parameter at the industry level is difficult. Therefore, we use the same degree of price stickiness across all industries in the baseline calibration, and check for robustness using the parameters θ_i identified by [Bouakez et al. \(2014\)](#).

The problem of a representative firm at time t is to choose the amount of capital, labor, intermediate inputs, and the price of its good (if possible to adjust) in order to maximize the value of expected future profits. In nominal terms, the dynamic price-setting problem of the firms is to maximize

$$E_t \sum_{s=0}^{\infty} \theta_i^s Q_{t,t+s} [y_{i,t+s|t} p_{i,t}^{NOM} - C_{i,t+s|t}], \tag{17}$$

where $p_{i,t}^{NOM}$ is the nominal price set at time t and $y_{i,t+s|t}$ is period $t+s$ demand for goods of a firm in industry i that was last setting its prices in period t . $Q_{t,t+s}$ is the nominal stochastic discount factor between periods t and $t+s$, defined as

$$Q_{t,t+s} = \beta^s \frac{\lambda_{t+s} P_t}{\lambda_t P_{t+s}}, \tag{18}$$

where λ_t denotes the marginal utility of consumption at period t . $C_{i,t+s|t}$ are the nominal costs of producing output $y_{i,t+s|t}$. Apart from the fixed costs, the production is constant returns to scale. Thus, we can express the nominal costs in terms of the real marginal costs $RM C_{i,t}$ as

$$C_{i,t+s|t} = P_{t+s} RM C_{i,t+s} (y_{i,t+s|t} + \Phi_i), \tag{19}$$

where the real marginal costs are given by

$$RMC_{i,t} = \frac{1}{A_t Z_{i,t}} \left(\mu_{i,K} r_t^k 1^{-\sigma_y} + \mu_{i,L} w_{i,t} 1^{-\sigma_y} + \mu_{i,M} P_{i,t}^M 1^{-\sigma_y} \right)^{\frac{1}{1-\sigma_y}} \quad (20)$$

In the absence of nominal rigidities, profit maximization of the firms implies a price markup of $1/(\sigma_l - 1)$ over the marginal costs.

2.4. Investment and capital

Investment into physical capital requires a specialized investment good. The quantity of investment good units X_t is given by

$$X_t = \left(\sum_{i=1}^I \xi_i^{\frac{1}{\sigma_X}} x_{i,t}^{\frac{\sigma_X-1}{\sigma_X}} \right)^{\frac{\sigma_X}{\sigma_X-1}}, \quad (21)$$

where $x_{i,t}$ is the amount of industry i good that is used in the production of the investment good, ξ_i gives the weight of industry i good in production, and the parameter $\sigma_X > 0$ is the elasticity of substitution between industry goods. The demand for the good of industry i is isoelastic, given by

$$x_{i,t} = \xi_i \left(\frac{P_{i,t}}{P_t^X} \right)^{-\sigma_X} X_t. \quad (22)$$

The price of the investment good (relative to consumption) follows from the relative prices of the industry goods as

$$P_t^X = \left(\sum_{i=1}^I \xi_i P_{i,t} 1^{-\sigma_X} \right)^{\frac{1}{1-\sigma_X}}. \quad (23)$$

Capital is subject to adjustment costs formulated as in Hayashi (1982). The costs are quadratic in investment intensity ι_t , defined by

$$X_t = \iota_t K_{t-1}. \quad (24)$$

The aggregate capital stock evolves according to

$$K_t = (1 - \delta) K_{t-1} + \phi(\iota_t) K_{t-1}, \quad (25)$$

where δ is the rate of capital depreciation and the adjustment cost function $\phi(\iota_t)$ is given by

$$\phi(\iota_t) = \iota_t - \frac{(\iota_t - \delta)^2}{\kappa \delta}. \quad (26)$$

The parameter κ determines the strength of the adjustment costs. While the aggregate capital stock in the model is rigid, there are no frictions to capital mobility across industries.

2.5. Monetary policy

Monetary policy follows a simple interest rate rule,

$$R_t = R^* + \gamma_r (R_{t-1} - R^*) + (1 - \gamma_r) \gamma_\pi (\pi_t - \pi^*). \quad (27)$$

Parameters R^* and π^* are the desired policy targets. Parameter $\gamma_r \geq 0$ determines the rigidity of the interest rate rule of the monetary authority and $\gamma_\pi > 1$ is the Taylor parameter that governs the strength with which the monetary authority reacts to the fluctuations of inflation.

2.6. Market clearing

All markets clear in equilibrium. In particular, for each industry good j , the total production equals the amount of good j used in the production of final good, investment good, and intermediate inputs to production in all industries

$$y_{j,t} = c_{j,t} + x_{j,t} + \sum_{i=1}^I m_{ji,t}. \quad (28)$$

2.7. Exogenous shocks

There are four types of exogenous structural shocks in our model. Two aggregate processes drive the aggregate technology A_t and the risk premium wedge D_t . Two types of industry-specific processes drive the industry technology $z_{i,t}$ and the demand for industry goods $v_{i,t}$.

- Aggregate technology follows an AR(1) process

$$\log(A_t) = \rho^A \log(A_{t-1}) + \epsilon_t^A, \quad \epsilon_t^A \sim \mathcal{N}(0, \sigma_A^2) \quad (29)$$

- The risk premium shock (aggregate demand) follows

$$\log(D_t) = \rho^D \log(D_{t-1}) + \epsilon_t^D, \quad \epsilon_t^D \sim \mathcal{N}(0, \sigma_D^2) \quad (30)$$

- The technology of industry i follows

$$\log(z_{i,t}) = \rho^z \log(z_{i,t-1}) + \epsilon_{i,t}^z, \quad \epsilon_{i,t}^z \sim \mathcal{N}(0, \sigma_{z,i}^2) \quad (31)$$

- The relative demand for goods of industry i is normalized such that $\sum_{i=1}^I v_{i,t} = 1$ in each period, implying that the shocks do not affect the aggregate price level up to a first order approximation. We assume that the relative demand of industry i is given by $v_{i,t} = \tilde{v}_{i,t} / \sum_{i=1}^I \tilde{v}_{i,t}$, where the exogenous shocks $\tilde{v}_{i,t}$ follow

$$\log\left(\frac{\tilde{v}_{i,t}}{v_i}\right) = \rho^v \log\left(\frac{\tilde{v}_{i,t-1}}{v_i}\right) + \epsilon_{i,t}^v, \quad \epsilon_{i,t}^v \sim \mathcal{N}(0, \sigma_{v,i}^2). \quad (32)$$

Since these four types of shocks play a central role in our analysis, let us briefly discuss their interpretation. We view the aggregate demand shock in the form of the risk premium wedge as a proxy for a variety of demand-side shocks. Demand-side shocks are typically characterized as disturbances that generate a positive correlation between aggregate consumption, investment, output, interest rates, and the price level. The risk premium wedge shares these characteristics and is similar in effect to several other shocks standard in the literature, such as monetary policy shocks, discount factor shocks, financial intermediation shocks, and others.

We model the technology process for individual industries as a combination of independent industry technology shocks z_i and a common aggregate technology shock A . In fact, the correlations between the technology processes across different industries might have a much more general structure. However, it is not possible to identify the general variance-covariance matrix using the short data series that we have available.¹

The (positive) demand shock to industry i is modelled as a shift in relative demand, such that for a given level of prices, consumers prefer to consume more of good i at the expense of the goods of other industries. As a consequence, the relative price of this good tends to rise, contrary to the industry-level technology shock.² Notice that we treat industry-level demand shocks differently from industry technology shocks. Industry technology shocks are independent across industries and thereby can contribute to aggregate fluctuations. In contrast, shifts in relative demand only have a very limited effect on aggregate variables, as their effect on the aggregate prices is neutralised. While we find this specification intuitive and plausible, we also consider the alternative case of independent industry demand shocks as a robustness check, see Appendix C. The results for the alternative specification are similar to the baseline. The main difference is that industry-level demand shocks account for some of the aggregate fluctuations, about 16% for hours, and 19% for value added, while the variance attributed to the aggregate demand shock is reduced by about the same amount. The alternative specification does not change the result that the variance of the aggregate technology shock is zero.

2.8. Measurement errors

Hours in the model are subject to measurement errors. It is widely recognized that measuring hours worked is difficult, as it relies on survey information or administrative data, both of which are connected to well known issues, see e.g. [Heathcote et al. \(2014\)](#), [Blundell et al. \(2016\)](#). Moreover, adding measurement errors also helps to bring the model closer to the data. Our model is parsimonious in terms of the number of shocks, and as a consequence tends to generate too strong co-movement between variables. Measurement error shocks systematically reduce the correlations in the model, bringing them closer to the data.

In line with how we specified the four types of structural shocks, the measurement error shock also has an aggregate and an industry-specific component. We assume that measured hours in each industry follow

$$\log(h_{i,t}^m) = \log(h_{i,t}) + \epsilon_{i,t}^{ME} + \epsilon_t^{aME}, \quad (33)$$

¹ The estimated correlation matrix from a collection of T data points of n variables has rank smaller than or equal to $T - 1$. We work with 77 industries and the sample is 46 years, 25 in the pre-1984 subperiod.

² In the data, the increased demand might be a consequence of an increase in the quality of good i , in the case this is not correctly accounted for by the statistical office. Since our model cannot distinguish between shifts in preferences and unaccounted quality improvements, it would identify both cases as demand shocks.

where $\epsilon_{i,t}^{ME}$ is the idiosyncratic industry-level measurement error and ϵ_t^{aME} is the aggregate measurement error. We assume that measurement error shocks are independent normally distributed. Notice that, by affecting measured hours, the measurement errors indirectly affect measured labor productivity and measured total factor productivity as well.

2.9. Transmission of shocks between industries

The channels of transmission of the industry-specific shocks between industries in our model are similar to the mechanisms described in the existing literature, apart from some modifications that arise due to the nominal rigidity. The mechanisms are based on Eq. (20), which expresses the real marginal costs of an optimizing firm, and Eq. (7), which expresses the optimal demand for consumption of industry i good given its price.

The responses of the firms in industry i to shocks in their own industry are straightforward: a positive shock to technology drives down the real marginal costs, pushing down the prices of industry i 's goods. A positive shock to demand in industry i increases the output of that industry, which creates an upward pressure on the prices of the industry's inputs and, subsequently, output. However, the price effect is relatively small, as the movement of production factors across industries in our model is relatively flexible. Even after a demand shock, measured productivity increases, due to the endogenous labor utilization and fixed costs.

A positive shock to technology in an upstream industry j , which provides either intermediate inputs or investment goods to sector i , decreases the real marginal costs in sector i , creating a negative pressure on its prices and boosting the output. Thus, output and measured productivity in sector i co-move with sector j . This channel has been thoroughly studied in the literature. In the New Keynesian model with price rigidities, the mechanism is dampened in comparison to the RBC setup where all prices adjust instantly. In contrast, a positive shock to demand in the upstream industry j has an adverse effect on industry i . As prices of industry j good increase with higher demand, industry i also faces higher input prices. Thus, its output and productivity fall.

Transmission of the shocks also happens in the opposite direction, from downstream industries upwards. A positive shock to demand in the downstream industry k , which buys intermediate inputs or investment goods from industry i , increases industry k 's demand for production factors, effectively increasing the demand for goods of upstream industry i as well. Thus, the demand shock generates a positive co-movement between industries k and i . For a positive technology shock in downstream industry k , on the other hand, the effect on industry i is ambiguous in the short run. Due to rigid prices, the demand for goods of industry k is quasi-fixed in the short run. Thus, the demand for production factors in industry k falls on impact, suppressing output and productivity in industry i . Later, as more and more firms in industry k are able to adjust their prices, the demand for industry k good grows, with the demand for industry i good also recovering.

3. Data and calibration

3.1. Data sources

The primary data source is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson, 2008). The data set provides annual information on capital, labor, and intermediate inputs and outputs of the U.S. economy between 1960 and 2005, disaggregated into 88 industries. The data set is unique in that it provides complete industry input-use tables, including the corresponding price data for each year within the sample period, which allow us to calibrate the substitution elasticities in production technology and household preferences. Additionally, we supplement the data set with the information from the BEA capital-flow table and the BEA input-use table (BEA, 1992a; BEA, 1992b) to calibrate industry weights in investment and final consumption, respectively.

We focus on the private business sector which consists of 77 industries. We use the standard bottom-up KLEMS methodology in order to construct the aggregate series from the industry-level data, see for example Timmer et al. (2007). The list of the industries, as well as the details describing the data series are provided in appendix B.

3.2. Measures of productivity

Our model features a factor utilization margin, which is not observed in the data, fixed costs of production, firm profits and measurement errors. As a consequence, the standard Solow residual measures used in productivity accounting deviate from the exogenous technology processes in the model. At firm level, the Solow residuals following the KLEMS methodology are given by

$$TFP_{i,t}^m = \hat{y}_{i,t} - s_{i,t}^K \hat{k}_{i,t} - s_{i,t}^L \hat{h}_{i,t} - s_{i,t}^M \hat{M}_{i,t}, \quad (34)$$

where s^X denotes the cost share of input X in gross output and hats denote growth rates of variables. We refer to residual TFP^m as the *measured productivity*. On the other hand, the firm-level exogenous *technology* can be expressed in our model as

$$TFP_{i,t} = \hat{A}_t + \hat{z}_{i,t} = \frac{y_{i,t}}{y_{i,t} + \Phi_i} \left[\hat{y}_{i,t} - \mu_{i,t} (s_{i,t}^K \hat{k}_{i,t} - s_{i,t}^L (\hat{h}_{i,t} + \hat{e}_{i,t}) - s_{i,t}^M \hat{M}_{i,t}) \right], \quad (35)$$

where Φ_i is the fixed cost and $\mu_{i,t}$ is the effective markup over the marginal costs. Expressions on the right hand side of Eqs. (34) and (35) are only equal if the fixed costs are zero, prices are perfectly competitive, worker effort is constant over time and hours are measured precisely.

While we can easily distinguish the two measures of productivity in the model, it is very difficult to identify the true technology process $TFP_{i,t}$ in the data: The effective markup $\mu_{i,t}$, fixed costs Φ_i , and workers effort $e_{i,t}$ are not observable. Both inputs and output are subject to measurement issues. Moreover, the data set reports the remuneration of production factors, but the capital share is pinned down as the residual. Therefore, firm profits are included in the reported capital shares $s_{i,t}^K$.

At the aggregate level, we construct the growth rates of measured productivity in line with most of the literature, using aggregate measures of inputs and output³

$$\hat{TFP}_t^m = \hat{VA}_t - s_t^K \hat{K}_t - s_t^L \hat{H}_t^m, \quad (36)$$

where VA_t is aggregate value added, s^K and s^L denote the cost share of capital resp. labor in value added, K_t is the aggregate capital and H_t^m are the aggregate measured hours. When comparing the data with the model-generated series, we compute measured productivity in the same way in both cases, using Eqs. (34) and (36).

One should recognize that measures of productivity based on Solow residuals may reflect unobserved fluctuations in production inputs other than effort, most importantly composition effects and changes in capital utilization. The data set is to some extent adjusted for variation in labor and capital composition. The measure of labor input reported in the data set is effective hours, defined as total hours adjusted for the composition of workforce, taking into account workers' education, age, and gender.

3.3. Calibration

We formulate the model at quarterly frequency and aggregate the simulated series to annual frequency in order to compare the model to our annual data. The baseline calibration aims to reflect the U.S. economy over the period 1960–1983. We provide additional details on the calibration procedure in Appendix B and robustness checks in Appendix C.

Where possible and appropriate, we set the model parameters to standard values from the literature. The discount rate β is set such that the implied interest rate is 4% annually. The annual capital depreciation rate δ is 10%. The capital adjustment cost parameter κ is calibrated such that the volatility of investment generated by the model is about 3.3 times higher compared to output, in line with the empirical evidence. The elasticity of substitution between firm goods within the same industry σ_i is set to imply a 10% markup, which is within the standard range. We calibrate the fixed costs Φ_i such that firms make zero profits in steady state. In the baseline calibration, the price stickiness θ_i is set to 0.75 in each industry, implying that firms adjust their prices once a year on average. The consumption habit parameter χ is set to 0.5, towards the lower end in the DSGE literature.

We set the Taylor rule parameters to $\gamma_\pi = 1.5$ and $\gamma_r = 0.8$, which is standard in the New Keynesian literature. However, for the pre-1984 period, this requires some justification. Estimates of the monetary policy parameters for the sample period until 1979 typically find a γ_π well below 1, see for example Clarida et al. (2000). Such a value of γ_π implies indeterminacy of the solution and cannot be handled within our solution framework. In contrast, the first years of the Volcker period (1979–1984) were characterized by a very strong interest rate reaction. Rather than trying to replicate this pattern, we stick to the conventional value of $\gamma_\pi = 1.5$ in our baseline calibration. We derive an alternative calibration with $\gamma_\pi = 1.16$ in the context of comparing the subperiods pre- and post-1984, cf. Section 3.3.3. Although much closer to the indeterminacy region, it turns out that the recalibration has a negligible effect along the dimensions that we focus on.

The parameters of the model describing the industry-level structure of the economy are all chosen to match long-run averages in the data. In the production function, each of the intermediate input weights α_{ji} is set to match the long-run average cost share of intermediate inputs from industry j to industry i in the Jorgenson data set. The industry-specific factor weights $\mu_{i,K}$, $\mu_{i,L}$, and $\mu_{i,M}$ are set to match the industry i 's cost shares of capital, labor, and intermediate inputs, again using the long-run averages from the Jorgenson data set. The investment good composition weights ξ_i are set to match the cost shares of investment from the 1992 BEA capital-flow table. As the model only features one type of investment, we use the average composition across all industries to calibrate weights ξ_i . Regarding the household preferences, the consumption composition weights v_i are set to match the cost shares of consumption from the 1992 BEA input-use table. The industry-specific preference parameters for supplying labor across different industries η_i are set such that in steady state, the allocation of hours across industries matches the long-run average industry composition in the data, conditional on average industry wages, cf. the intra-temporal labor supply first order condition (A.13) in the appendix.

The combination of the labor input elasticity σ_U and the effort elasticity parameter σ_e determines the wage elasticity of hours comparable to the standard Frisch elasticity in aggregate macroeconomic models. The parameter σ_U is calibrated conditional on σ_e , such that the implied Frisch elasticity is 0.5, within the range considered in the literature.

The remaining parameters of the model consist of the substitution elasticities in the production process, consumption, and labor supply (σ_y , σ_M , σ_X , σ_C , σ_N and σ_e), the variances of the shocks to technology (σ_A^2 and $\sigma_{z,i}^2$), to demand (σ_D^2

³ Our measure of aggregate TFP is value added-based, not gross output-based. The difference between the two measures only affects the scaling of the productivity series.

Table 1
Calibration summary, baseline specification.

Parameter	Symbol	Value	Target/Source
Elasticities			
Intra-industry substitution	σ_I	11	10% markup
Production factors substitution	σ_y	0.39	price elasticity of production factors
Intermediate inputs substitution	σ_M	0.75	price elasticity of intermediate inputs
Consumption good substitution	σ_C	0.38	price elasticity of industry gross output
Investment good substitution	σ_X	0.38	equals σ_C
Total labor input	σ_U	1.1	Frisch elasticity 0.5
Industry labor input substitution	σ_N	7.9	mean volatility of industry hours
Effort	σ_e	1.9	correlation agg. productivity and hours
Cost shares			
Production factor weights	$\mu_{i,x}$		cost shares Jorgenson database, average
Intermediate inputs weights	α_{ji}		cost shares Jorgenson database, average
Consumption bundle weights	v_i		1992 BEA input-use table
Investment good weights	ξ_i		1992 BEA capital flow table
Fixed costs	Φ_i		zero profits in steady state
Shock processes			
Aggregate technology, volatility	σ_A	0.000	SMM objective
Industry technology, mean volatility	$\sigma_{z,i}$	0.019	SMM objective
Aggregate demand, volatility	σ_D	0.0017	SMM objective
Industry demand, mean volatility	$\sigma_{v,i}$	0.162	SMM objective
Agg. measurement error, volatility	σ_{aME}	0.012	20% variance of agg. measured hours
Ind. measurement error, mean volatility	$\sigma_{ME,i}$	0.028	25% variance of ind. measured hours
Autocorrelation, structural shocks	ρ^x	0.95	standard
Other			
Discount factor	β	0.96	standard (annual)
Capital depreciation	δ	10%	standard (annual)
Consumption habit	χ	0.5	standard
Taylor parameter	γ_τ	1.5	standard
Taylor rule smoothing	γ_r	0.8	standard
Adjustment cost capital	κ	20	relative volatility of investment
Price stickiness	θ_i	0.75	standard
Industry weight labor disutility	η_i		industry hours/wages in steady state
Effort weight in labor disutility	Δ_i		normalization effort in steady state

and $\sigma_{v,i}^2$), and of the measurement errors. Out of these parameters, the elasticities σ_y , σ_M are calibrated directly to match specific data targets, see the discussion below. The rest of the parameters are calibrated using indirect inference, within a two-step procedure which targets a relevant set of moments in the data. In the inner loop of the procedure, we determine the variances of all shocks conditional on the elasticity parameters. The variances of the measurement error shocks are calibrated to generate an ex-ante given share of aggregate and industry fluctuations. The variances of the structural shocks are estimated using simulated method of moments. In the outer loop, the elasticities σ_X , σ_C , σ_N and σ_e are calibrated such that they jointly match a set of three moments and one additional identifying assumption, see Section 3.3.2 for further details.

Comparatively little attention has been given to estimating the elasticities of substitution between factor inputs and between industry goods in the macroeconomic literature in recent decades, although they influence the way in which the economy responds to the various types of shocks, cf. Atalay (2017). Since the model elasticities are the same across all industries, we have a relatively small set of parameters that we estimate using a large number of industry-level time series in the outer loop. We choose the method of moments over maximum likelihood methods, because it allows a better interpretation of which data features determine the values of the individual parameters. Table 1 shows an overview of the model parameters and calibration targets.

3.3.1. Elasticities: identifying moments

We calibrate the production function parameters σ_y and σ_M directly from the estimated elasticity of the corresponding input shares to the changes in the relative prices. For the elasticity of substitution between production factors σ_y , the first order condition (A.26) in Appendix A implies that for each model industry i ,

$$d \ln \left(\frac{M_{i,t} P_{i,t}^M}{l_{i,t} w_{i,t}} \right) = (\sigma_y - 1) d \ln \left(\frac{w_{i,t}}{P_{i,t}^M} \right). \quad (37)$$

We use the industry-level information about prices and volumes from the Jorgenson data set and regress the changes in the cost shares (left-hand side of Eq. (37)) on the changes in the relative prices (right-hand side) industry by industry. We use the average across the I industry coefficients to pin down the value of σ_y . For the elasticity of substitution between intermediate inputs from various industries σ_M , we use the same approach based on the first order condition for the optimal

Table 2

Relative standard deviations of variables generated by each type of the shock separately.

	Data	Industry shocks		Aggregate shocks	
		technology	demand	technology	demand
$\sigma(T\hat{P}^m)/\sigma(\hat{V}A)$	0.62	0.89	×	0.93	0.48
$\sigma(\hat{H}^m)/\sigma(\hat{V}A)$	0.83	0.26	×	0.12	0.76
$\bar{\sigma}(\hat{f}p_i^m)/\bar{\sigma}(\hat{y}_i)$	0.50	1.87	0.19	0.60	0.19
$\bar{\sigma}(\hat{y}_i)/\sigma(\hat{Y})$	1.96	1.87	15.2	1.16	1.13
$\bar{\sigma}(\hat{f}p_i^m)/\sigma(T\hat{P}^m)$	1.86	3.11	14.0	0.53	0.62

Notes: The first column shows the ratios of standard deviations measured in the data while columns 2 to 5 show the corresponding ratios generated by each type of shock in the model. For industry variables, $\bar{\sigma}(\cdot)$ denotes average across industry standard deviations. All variables are expressed in growth rates.

composition of intermediate inputs (A.20). We compute the regression coefficient for each pair of non-zero intermediate inputs supplied into each production industry i . We use the average across all estimates to pin down the value of σ_M .

There are no model equations that directly map the remaining elasticity parameters σ_C , σ_X , σ_N and σ_e to the available data. Thus, these parameters are calibrated simultaneously in the outer loop of the calibration procedure using a set of three targets and one additional identifying assumption. However, each of the targeted moments identifies one of the parameters in an intuitive way. The parameters σ_C and σ_X both influence the reaction of the industry output shares to the changes in relative prices. As we do not have any information that distinguishes the impact of the two elasticities, we assume σ_C and σ_X are equal. We target the average sensitivity of the relative industry output shares to relative prices, computed as the average regression coefficient across industry pairs.

The elasticity of substitution between working in different industries σ_N influences the volatility of industry-level hours. We use the mean volatility of industry hours relative to the volatility of aggregate hours as the second target in the outer loop. The resulting value of $\sigma_N = 7.9$ implies high mobility of labour force across industries.

One of the essential elements of our model is the endogenous factor utilization. The elasticity of unobservable effort relative to hours is determined by parameter σ_e . A more elastic effort implies that measured productivity fluctuates more with hours and, everything else equal, the two variables are more correlated.⁴ Thus, we identify σ_e by targeting the correlation between aggregate hours and measured productivity in the pre-1984 period. This is the only aggregate correlation that we target in the calibration procedure. The value of $\sigma_e = 1.9$ implies that for a one percent increase in hours worked, the effective labor input increases by roughly 1.5%, which is consistent with the existing literature. Basu et al. (2006) estimate that, including the factor utilization, a one percent increase in measured hours is associated with an increase of effective labor between 2.1% (nondurable manufacturing) and 0.64% (non-manufacturing industries).

3.3.2. Shock variances

The main exercise of this paper is the estimation of variances of the exogenous shocks and their contribution to business cycle fluctuations. We jointly estimate the variances of the two aggregate shocks (σ_A^2 and σ_D^2) and two times I industry-specific shocks ($\sigma_{z,i}^2$ and $\sigma_{v,i}^2$) using the generalized simulated method of moments. We use three aggregate and $2 \times I$ industry-level variances in the SMM objective function. At the aggregate level, we target the variances of aggregate measured productivity, value added and hours. At the industry level, we target the variance of industry measured productivity and of industry gross output.⁵ The resulting variances are the solution of a quadratic problem with inequality constraints, as all variances must be greater or equal to zero. The detailed description of the SMM objective function is provided in Appendix B.

In order to provide some intuition on which data features identify the composition of the shocks in the model, we simulate the model four times, each time allowing for shocks of only one type. Table 2 displays the relative standard deviations for the set of variables that enter the SMM objective. The first column shows the data, while columns 2 to 5 report model simulations, each column generated by only one type of shock.⁶

The main insight from Table 2 is that the different types of shocks generate different sets of second moments, such that the variances of the shocks are well identified. The relative importance of aggregate versus industry shocks is identified because the industry shocks generate higher volatilities of industry-level variables compared to the aggregate variables. This is not true for the aggregate shocks, cf. the last two rows of Table 2. The volatility of the aggregate demand shock relative to technology shocks is pinned down by (each of) the first two rows of Table 2. The first line shows that technology shocks, both on the aggregate and the industry level, generate fluctuations in aggregate measured productivity of almost the same

⁴ See Molnárová (2020) for a detailed discussion.

⁵ Notice that we do not include the variance of industry-level hours. The choice of the elasticity parameter σ_N in the outer loop pins down their average variance.

⁶ In the case of industry shocks, we keep the variances of shocks across industries the same as in our baseline calibration.

size as that of aggregate value added, while the aggregate demand shock generates much smaller relative fluctuations. The second line displays the relative standard deviation of aggregate hours. In this case it is the demand shocks that generate large fluctuations, while technology shocks do very little.⁷ Thus, in order to match the relative volatilities of the aggregate variables, the model clearly needs aggregate demand shocks. Subsequently, as the relative size of aggregate demand shocks is determined by the relative volatilities of the aggregate variables, the information in the last two rows pins down the weight of the aggregate shock to technology relative to the industry-specific shocks. Lastly, the relative importance of the two industry-level shocks follows from the relative size of industry-level fluctuations in measured productivity and output, which is shown in the third row. Besides the three relative shock variances determined by the information in Table 2, the absolute size of fluctuations is pinned down by the size of the fluctuations in the data.

One should point out that for industry variables, Table 2 displays average standard deviations across all industries. In fact, we estimate the industry shock variances separately for each industry. Nevertheless, the identification logic described above works analogously for each industry individually. Due to the over-identification in the SMM procedure and the non-negativity constraint on variances, the targets are not matched precisely.

The variances of the measurement errors are calibrated to generate given shares of aggregate and industry measured hours, for discussion see e.g. Boivin and Giannoni (2006), Justiniano et al. (2013). The measurement errors are set to explain 20% of the variance of the aggregate hours and 25% of the variance of the industry hours. The measurement error shocks are not essential for our main results, namely that there are no aggregate technology shocks and that the cyclicity of aggregate measured productivity decreases with smaller aggregate demand shocks. However, omitting the measurement error increases the co-movement between variables above what we observe in the data, see the robustness checks in Appendix C.

3.3.3. Alternative calibrations for the comparison of pre- and post-1984 period

Several authors, for example Barnichon (2010) and Galí and Gambetti (2009), have suggested that the great moderation period was characterised by a different composition of shocks, especially stressing the smaller shocks to aggregate demand, or muted effects of these shocks on the economy. Therefore, in our second exercise we investigate the implications of the diminished role of demand shocks in the context of our model, in particular with respect to the cyclicity of measured productivity.

Aggregate demand shocks may have become less important after the mid-1980s either because they became smaller (good luck hypothesis), or because monetary policy became more successful in counteracting their effects (good policy). In our model, like in most other New Keynesian models, active monetary policy is a very effective tool to counteract demand shocks and it is difficult to distinguish between good luck and good policy. Therefore, we do not try to identify the decrease in the volatility of the aggregate demand shocks, but rather perform the comparison between sample periods under two alternative assumptions.

In the main exercise, which we analyse in detail below, we assume that monetary policy is the same in both subperiods, but the variance of the aggregate demand shock is lower in the post-1984 period. To isolate the effect of the smaller demand shocks, we keep the rest of the parameters the same as in the baseline calibration, including the variances of the other shocks. In order to pin down the variance of the aggregate demand shock after 1984, we notice that the shock composition in the model has strong implications for the correlation between the aggregate hours and value added. Decreasing the volatility of the aggregate demand shock reduces the correlation. We choose this moment to discipline the exercise and decrease the variance of the shock such that the implied reduction in the correlation between the aggregate hours and value added is 17 percentage points, which equals the reduction between the pre- and post-1984 samples in the data. Using this criterion, the shock volatility σ_D decreases by around 40%, in line with the change identified in the existing literature, see Barnichon (2010). As a further evidence that this decrease in volatility of the aggregate demand shock is reasonable, we observe that the alternative calibration generates a reduction in the standard deviation of value added from the pre-1984 value of 0.026 to the post-1984 value of 0.017, which is very close to the data.

Alternatively, to examine the good policy hypothesis, we attribute all the change between periods to a change in the monetary policy rule, specifically the Taylor parameter γ_π . For the post-1984 period we keep the exact same specification as in the main exercise described above, because the standard parameter value $\gamma_\pi = 1.5$ is widely accepted for this period. For the pre-1984 period, instead of changing the standard deviation of the aggregate demand shock, we alter the value of γ_π so as to again match the pre-1984 correlation of hours and value added. This leads to an alternative calibration for the pre-1984 period, with a lower variance of the aggregate demand shock and a lower Taylor parameter $\gamma_\pi = 1.16$. This parameter value is much closer to the indeterminacy region, and conforms to the view of a less active monetary policy rule in the earlier subperiod. It turns out that the recalibration has a negligible effect along the dimensions that we focus on in this paper. Over the range of parameters that we consider, there is a near-equivalence between a calibration with a high variance of the aggregate demand shock and relatively active monetary policy (high γ_π), and one with low variance and relatively low γ_π . The main difference lies in the variance of the nominal interest rate which is smaller with more active monetary policy. Therefore, in the next sections we only report the results for the decreased variance of the aggregate demand shock.

⁷ The weak response of hours to tech shocks is typical for New Keynesian models, see e.g. Galí (1999).

Table 3

Comparison of selected second moments in the model and in the data, growth rates of aggregate variables.

Aggregate variables: second moments									
	Standard deviation			Correlation			Correlation		
	relative to value added*			with value added			with measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Baseline calibration									
Value added	0.027	(0.00)	0.026	1.00	(0.00)	1.00	0.85	(0.06)	0.87
Gross output	1.17	(0.05)	1.32	0.98	(0.00)	0.98	0.80	(0.08)	0.82
Measured TFP	0.62	(0.03)	0.59	0.85	(0.06)	0.87	1.00	(0.00)	1.00
Hours	0.83	(0.07)	0.81	0.86	(0.03)	0.83	0.49	(0.12)	0.49
Intermediate inputs	1.37	(0.09)	1.68	0.95	(0.01)	0.95	0.74	(0.08)	0.77
Inflation	0.93	(0.08)	1.01	0.14	(0.17)	0.92	-0.11	(0.24)	0.72
Labor productivity	0.51	(0.05)	0.54	0.56	(0.13)	0.58	0.89	(0.03)	0.88
Int. inputs per hour	0.77	(0.05)	1.04	0.76	(0.03)	0.88	0.80	(0.03)	0.87
Investment	-	-	3.29	-	-	0.97	-	-	0.83
Consumption	-	-	0.35	-	-	0.66	-	-	0.64
True TFP	-	-	0.27	-	-	0.18	-	-	0.40
Post-1984 calibration									
Value added	0.016	(0.00)	0.017	1.00	(0.00)	1.00	0.47	(0.18)	0.80
Gross output	1.20	(0.13)	1.25	0.90	(0.02)	0.96	0.26	(0.23)	0.71
Measured TFP	0.72	(0.07)	0.72	0.47	(0.18)	0.79	1.00	(0.00)	1.00
Hours	1.25	(0.20)	0.87	0.70	(0.04)	0.66	-0.26	(0.16)	0.11
Intermediate inputs	1.62	(0.25)	1.58	0.74	(0.07)	0.89	0.07	(0.23)	0.61
Inflation	1.51	(0.19)	0.93	0.11	(0.08)	0.82	0.05	(0.22)	0.51
Labor productivity	0.90	(0.13)	0.77	0.14	(0.17)	0.53	0.89	(0.01)	0.92
Int. inputs per hour	1.08	(0.12)	1.10	0.29	(0.17)	0.74	0.41	(0.10)	0.79
Investment	-	-	3.18	-	-	0.95	-	-	0.73
Consumption	-	-	0.44	-	-	0.66	-	-	0.62
True TFP	-	-	0.40	-	-	0.40	-	-	0.59

Notes: Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. The values that are targeted in the calibration procedure are marked in bold. Bootstrapped standard errors (SE). *Except of standard deviation of value added.

4. Results

4.1. Model fit

In this section we show that the baseline calibration of the model fits the data very well in many dimensions. Tables 3–5 compare sets of second moments in the data and in the model simulations. All moments are computed for the growth rates of variables. The top panel of each table displays the results for the baseline calibration and compares them to the data for pre-1984 period. The bottom panels show the results for the post-1984 period, which we discuss in Section 4.5.

The top panel of Table 3 displays standard deviations of aggregate variables relative to aggregate value added (GDP), as well as their correlations with value added and with measured productivity. Our model provides a good match for all aggregate moments, with one notable exception. The model generates highly procyclical inflation, i.e., a strong Phillips curve characteristic for New Keynesian models. In contrast, inflation is basically acyclical in the data, which contain the stagflation period of the 1970s.

Table 4 summarizes the same information at the industry level. As the second moments vary across industries both in the model and in the data, we report weighted averages. The top panel of Table 4 shows that the model fit is satisfactory at the industry level as well. Average correlations of the industry variables with value added and measured productivity are well in line with the data for all variables. Average relative standard deviations are close to their data counterparts, once again with one exception. The volatility of prices at the industry level is substantially higher in the data than in the model. The possible explanations are that the model is missing pricing (markup) shocks, or that it does not reflect the measurement error in price data. The alternative version of the model with flexible prices, which we discuss in Section 4.4, demonstrates that the low volatility of industry prices is not just a consequence of price rigidity in the model. Despite of the low volatility, the negative correlation between relative prices and value added at the industry level is an important confirmation that the model features a reasonable ratio of demand and supply-side shocks at the industry level.

Lastly, Table 5 documents the co-movement between industries. For each industry-level variable we compute a correlation between each pair of industries. The table reports the unweighted mean of these 2926 pairwise correlations. The model does a good job in matching the average cross-industry correlations of most variables. The co-movement in the intermediate inputs used by the industries is slightly exaggerated. As a consequence, gross output across industries also co-moves more than in the data.

Table 4

Comparison of selected second moments in the model and in the data, growth rates of industry variables.

Industry variables: averages across second moments									
	Standard deviation			Correlation			Correlation		
	relative to value added*			with value added			with measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Baseline calibration									
Value added	0.088	(0.01)	0.074	1.00	(0.00)	1.00	0.78	(0.01)	0.81
Gross output	0.71	(0.00)	0.84	0.84	(0.01)	0.88	0.57	(0.01)	0.55
Measured TFP	0.36	(0.01)	0.38	0.78	(0.01)	0.81	1.00	(0.00)	1.00
Hours	0.56	(0.02)	0.60	0.38	(0.02)	0.46	-0.02	(0.03)	-0.06
Intermediate inputs	0.83	(0.01)	0.92	0.35	(0.04)	0.58	0.14	(0.02)	0.18
Prices	0.66	(0.03)	0.25	-0.33	(0.01)	-0.36	-0.43	(0.02)	-0.54
Input prices	0.33	(0.04)	0.11	-0.13	(0.02)	-0.15	-0.16	(0.02)	-0.21
Labor productivity	0.95	(0.04)	0.86	0.72	(0.01)	0.72	0.84	(0.01)	0.94
Int. inputs per hour	0.73	(0.02)	0.52	0.17	(0.04)	0.48	0.22	(0.04)	0.38
True TFP	-	-	0.36	-	-	0.44	-	-	0.73
Post-1984 calibration									
Value added	0.097	(0.01)	0.070	1.00	(0.00)	1.00	0.76	(0.03)	0.79
Gross output	0.47	(0.00)	0.79	0.84	(0.00)	0.87	0.53	(0.03)	0.51
Measured TFP	0.30	(0.01)	0.40	0.76	(0.03)	0.79	1.00	(0.00)	1.00
Hours	0.43	(0.01)	0.59	0.28	(0.02)	0.36	-0.23	(0.04)	-0.20
Intermediate inputs	0.58	(0.03)	0.84	0.43	(0.01)	0.50	0.12	(0.03)	0.06
Prices	0.83	(0.19)	0.26	-0.41	(0.01)	-0.38	-0.46	(0.01)	-0.54
Input prices	0.25	(0.03)	0.11	-0.10	(0.03)	-0.14	-0.11	(0.04)	-0.20
Labor productivity	1.03	(0.13)	0.91	0.68	(0.03)	0.73	0.90	(0.01)	0.95
Int. inputs per hour	0.52	(0.02)	0.47	0.20	(0.02)	0.37	0.34	(0.02)	0.33
True TFP	-	-	0.38	-	-	0.49	-	-	0.75

Notes: Reported numbers are averages (weighted by industry output) across industry moments. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. The values that are targeted in the calibration procedure are displayed in bold. Bootstrapped standard errors (SE). *Except of standard deviation of value added.

Table 5

Comparison of average cross-industry correlations in the model and in the data, growth rates of industry variables.

Cross-industry correlations			
	Data	(SE)	Model
Baseline calibration			
Value added	0.14	(0.009)	0.13
Gross output	0.22	(0.015)	0.30
Measured TFP	0.05	(0.008)	0.07
Hours	0.20	(0.011)	0.20
Intermediate inputs	0.19	(0.035)	0.36
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.21
Labor productivity	0.02	(0.006)	0.04
True TFP	-	-	0.00
Post-1984 calibration			
Value added	0.11	(0.011)	0.07
Gross output	0.19	(0.011)	0.18
Measured TFP	0.06	(0.009)	0.04
Hours	0.25	(0.047)	0.12
Intermediate inputs	0.22	(0.020)	0.20
Output price	0.18	(0.037)	0.01
Input price	0.29	(0.055)	0.21
Labor productivity	0.07	(0.012)	0.04
True TFP	-	-	0.00

Notes: Reported numbers are simple averages across pairwise industry correlations. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. Bootstrapped standard errors (SE).

Table 6
Variance decomposition of selected model variables, baseline calibration.

	Variance Decomposition				
	Aggregate shocks		Industry shocks		Measurement error
	technology	demand	technology	demand	
Industry variables					
Value added	0.00	0.18	0.28	0.54	0.00
Gross output	0.00	0.35	0.05	0.60	0.00
Measured TFP	0.00	0.07	0.75	0.11	0.07
Hours	0.00	0.22	0.13	0.40	0.25
Intermediate inputs	0.00	0.42	0.14	0.44	0.00
Output price	0.00	0.05	0.94	0.01	0.00
Input price	0.00	0.05	0.94	0.01	0.00
Labor productivity	0.00	0.05	0.65	0.18	0.12
True TFP	0.00	0.00	1.00	0.00	0.00
Aggregate variables					
Value added	0.00	0.88	0.12	0.00	0.00
Gross output	0.00	0.95	0.04	0.01	0.00
Measured TFP	0.00	0.59	0.26	0.00	0.15
Hours	0.00	0.78	0.02	0.00	0.20
Intermediate inputs	0.00	0.96	0.02	0.02	0.00
Inflation	0.00	0.99	0.01	0.00	0.00
Labor productivity	0.00	0.20	0.35	0.00	0.45
Investment	0.00	0.92	0.08	0.00	0.00
Consumption	0.00	0.50	0.45	0.05	0.00
True TFP	0.00	0.01	0.99	0.00	0.00

Of the many results reported in Tables 3 to 5, we want to highlight several aspects. First, the correlations of all real aggregate variables with value added and with measured productivity are in line with the data. Moreover, the correlations of industry variables with industry value added and measured productivity are also matched well. Second, the model fits well the relative standard deviations of the variables. Noticeably, the model replicates the fact that gross output fluctuates more than value added at the aggregate level, but less than value added at the industry level, see the discussion in Section 4.4. Third, the model does a good job in matching the average cross-industry correlations of most variables, although we do not target any of them. In particular, the average cross-industry correlations of measured productivity and of labor productivity are small, although significantly different from zero. In the next section we show that all technology shocks in the model are idiosyncratic industry-level shocks, and the positive correlation is generated by the aggregate demand shocks through endogenous effort and, to a smaller extent, due to increasing returns to scale.

4.2. What shocks are driving business cycle fluctuations?

Table 6 shows the variance decomposition of selected model variables. The most striking observation is that our model implies zero role for aggregate technology shocks. Technology shocks are present in the model, but all of them are industry-specific.

The top panel of Table 6 displays the decomposition for the industry-level variables. Not surprisingly, for all industry-level variables, the majority of the fluctuations is explained by the industry-specific shocks: industry demand shocks explain about a half of the fluctuations of industry-level value added and production inputs (capital, hours, intermediate inputs). On the other hand, shocks to technology are especially important for measured productivity and prices. Due to the high flexibility of factors across industries, industry relative prices react very little to an increased demand for the industry good.

The bottom panel of Table 6 displays the variance decomposition for the aggregate variables. In this case, the effect of the industry-specific shocks is considerably smaller. The industry demand shocks do not contribute to aggregate fluctuations by construction, and industry shocks to technology wash out to a large extent. The majority of the fluctuations of the aggregate variables, including measured TFP, is explained by aggregate shocks to demand, due to endogenous effort and returns to scale, as we described in the previous sections. Fluctuations in hours are driven almost exclusively by demand shocks, but observed hours are by assumption also subject to sizeable measurement errors.

To the best of our knowledge, we are the first ones to attribute zero role to the aggregate technology shock in this class of models.⁸ The reason why the existing literature assigned a big part of the fluctuations to the aggregate component of the technology shocks is that it is hard to generate the co-movement in measured productivity observed in the data from independent industry-level shocks only. Even though the average correlation of 0.05 in Table 5 appears small, the aggregate

⁸ Atalay (2017) analyses the importance of the industry-specific shocks with respect to a large range of model parameters. He finds that for some combinations of parameters, idiosyncratic industry-specific shocks can explain all the aggregate fluctuations. In his "benchmark" calibration, aggregate technology shocks still play a significant role.

Table 7

Distributions of within-industry and cross-industry correlations. Data, model population distribution, and (average) sample distributions.

Distribution of within-industry and cross-industry correlations					
	Average correlation		Standard deviation of the distribution		
	Data	Model	Data	Model sampling	Model population
Within-industry correlations					
$\text{corr}(va_i, tfp_i^m)$	0.76	0.80	0.24	0.11	0.07
$\text{corr}(h_i^m, tfp_i^m)$	-0.03	-0.14	0.33	0.37	0.32
Cross-industry correlations					
Value added	0.14	0.13	0.29	0.25	0.15
Gross output	0.22	0.30	0.28	0.27	0.20
Measured TFP	0.05	0.07	0.27	0.22	0.07
Hours	0.20	0.20	0.29	0.23	0.12

All averages are computed as simple means, all variables are in growth rates.

component necessary to generate the co-movement turns out to be powerful enough to explain a major part of the aggregate fluctuations.⁹ This is also true in our model. However, the co-movement between industry measured productivity can in our model also arise from aggregate demand shocks.

Digging a bit deeper, we can describe how the individual mechanisms in our model alter the previous results. On the one hand, our model includes features that further reduce the role of industry technology shocks in comparison to the previous literature. First, the model includes industry demand shocks which explain a substantial part of the fluctuations at the industry level. Second, prices in the model are rigid, which suppresses the transmission of shocks across industries, cf. [Section 2.9](#). Both features imply that an even larger part of aggregate productivity fluctuations remains to be explained by aggregate shocks. However, in contrast to the literature, we do not assume that these aggregate shocks must be technology shocks. [Table 3](#) shows that the standard deviation of aggregate “true” technology, arising purely from technology shocks, is indeed less than half of the standard deviation of measured TFP. The rest is generated by the changes in aggregate demand.

4.3. Moments within and across industries

Given the importance of the industry-level moments for the identification of shocks in our model, we test whether the model generates a realistic distribution of these moments across industries. Therefore, we complement the industry-level averages reported in [Tables 4](#) and [5](#) with the information about their variability across industries. Since we target the variances of output and measured productivity for each individual industry in the calibration procedure, they closely match the data. The correlations between industry-level variables within and across industries are not targeted and serve as an additional validity check of the model.

[Table 7](#) summarizes the distribution of the industry-level correlation coefficients in the data and generated by the model. The correlations in our data set display a large variation across industries, resp. industry pairs. Since the standard deviations of the correlations in the data are affected by sampling errors, we compare them with the average standard deviation of the distributions generated in a large number of “short” model simulations, cf. column *model sampling*. The number of periods in each of the short simulations is the same as in the data.

Comparison of columns 3 and 4 in [Table 7](#) shows that the model generates the variation in within- and cross-industry correlations that is comparable with the data. The only exception is the industry-level correlation between value added and measured TFP, which the model underestimates due to a small number of strong outliers in the data, see also [Figs. C.1](#) and [C.2](#) in [Appendix C](#). The last column of [Table 7](#) shows that accounting for the sampling error is important. If we replace the large number of the short model simulations by one long simulation, the sampling error in the model disappears and the volatility of the distributions is smaller. The distributions generated by the model lend further credibility to our results. Despite a lot of symmetry imposed on the model industries, such as identical substitution elasticities and degree of price rigidity, the model generates a realistic level of industry-level heterogeneity.

4.4. Discussion of alternative modelling choices

To make the main mechanisms behind the results more transparent, and to provide an intuition about which aspects of the data identify the model, we compare our baseline calibration against two alternative model specifications which we consider the most relevant. First, endogenous effort explains most of the aggregate fluctuations in measured productivity, and thereby “crowds out” the aggregate technology shocks from our model. Therefore, we recalibrate a version of the model with constant effort and point out the dimensions in which this version does not fit the data. Second, we calibrate a version

⁹ We illustrate this point with a simple analytical example in [appendix E](#).

Table 8

Comparison of moments across various model specifications.

Alternative model specifications: aggregate variables				
	Data	Baseline	Constant effort	Flexible prices
Standard deviation relative to value added				
Value added	1.00	1.00	1.00	1.00
Gross output	1.17	1.32	1.03	0.80
Measured TFP	0.62	0.59	0.76	0.69
Hours	0.83	0.81	0.83	0.51
Intermediate inputs	1.37	1.68	1.19	0.60
Correlation with measured TFP				
Value added	0.85	0.87	0.82	0.96
Gross output	0.80	0.82	0.61	0.96
Measured TFP	1.00	1.00	1.00	1.00
Hours	0.49	0.49	0.07	0.65
Intermediate inputs	0.74	0.77	0.35	0.92

Table 9

Comparison of moments across various model specifications. Industry variables (weighted average across industries).

Alternative model specifications: industry variables				
	Data	Baseline	Constant effort	Flexible prices
Standard deviation relative to value added				
Value added	1.00	1.00	1.00	1.00
Gross output	0.71	0.84	0.79	0.67
Measured TFP	0.36	0.38	0.35	0.34
Hours	0.56	0.60	0.77	0.57
Intermediate inputs	0.83	0.92	0.81	0.56
Prices	0.66	0.25	0.21	0.34
Labor productivity	0.95	0.86	0.82	0.84
Int. inputs per hour	0.73	0.52	0.30	0.25
Correlation with measured TFP				
Value added	0.78	0.81	0.69	0.78
Gross output	0.57	0.55	0.39	0.62
Measured TFP	1.00	1.00	1.00	1.00
Hours	-0.02	-0.06	-0.23	-0.07
Intermediate inputs	0.14	0.18	-0.04	0.18
Prices	-0.43	-0.54	-0.54	-0.65
Labor productivity	0.84	0.94	0.96	0.97
Int. inputs per hour	0.22	0.38	0.41	0.45
Cross-industry correlation				
Value added	0.14	0.13	0.15	0.19
Gross output	0.22	0.30	0.24	0.20
Measured TFP	0.05	0.07	0.13	0.18
Hours	0.20	0.20	0.15	0.09
Intermediate inputs	0.19	0.36	0.25	0.13
Prices	0.07	0.01	0.01	0.01
Labor productivity	0.02	0.04	0.13	0.16
Int. inputs per hour	0.07	0.40	0.35	0.28

of the model with perfectly flexible prices, which is more comparable to the RBC-style industry-level models in the literature. For each alternative, we recalibrate the variances of all shocks. Tables 8 and 9 summarize the most important results. Detailed results for the two alternative versions of the model are available in Appendix C.

Column 3 of Tables 8 and 9 presents the results for the alternative model with constant effort. Apart from the shock variances, all the structural parameters are kept the same as in the baseline. In the absence of endogenous effort, our model assigns a substantial role to aggregate technology shocks, which explain 75% of the variance of aggregate measured TFP. However, aggregate technology shocks contribute very little to the fluctuations of aggregate hours, which are explained by demand shocks.

This calibration of the model fails to match the data in several important ways. Most obviously, the model grossly overestimates the average cross-industry correlation of both measured TFP and of labor productivity. Aggregate technology shocks generate almost as much co-movement in measured productivity as in value added, at odds with the data: the cross-industry correlation of measured TFP increases to 0.13, compared to 0.05 in the data. Second, the model is not able to generate a positive correlation between aggregate hours and measured productivity. Both in New Keynesian models and empirically,

technology shocks are associated with a small, and often negative, response of labor input, see the rich literature starting from Galí (1999). For similar reasons, the alternative calibration also fails to generate the strong positive correlation of intermediate inputs with measured productivity. Third, the volatility of aggregate gross output falls to about the same level as that of aggregate value added, while in the data it is substantially larger. We conclude that the empirical performance of the model deteriorates in several dimensions if we try to explain the movements in productivity by technology shocks rather than factor utilization.

The second alternative that we consider is the case of flexible prices. The baseline calibration follows the New Keynesian literature and assumes a price rigidity parameter θ_i equal to 0.75 in all industries. Variation of the parameter value within the range usually assumed in the literature does not substantially change our conclusions. However, with perfectly flexible prices (case $\theta_i = 0$) the model results are independent of nominal variables. Therefore, the aggregate demand shock generates zero fluctuations. To give the model a better chance to fit the data, we eliminate additional rigidities in the model by setting the labor supply elasticity to infinity, decreasing the capital adjustment costs, and eliminating the consumption habit and the measurement error on hours. The last column of Tables 8 and 9 presents the results for the model with flexible prices. Industry technology shocks explain a bigger part of the aggregate fluctuations, because their propagation across the input-output network is stronger. Again, aggregate technology shocks are important. The performance of the model worsens along the same dimensions as in the case of constant effort, and by a wider margin. The cross-industry correlations of productivity measures are too high, basically the same as those of value added and gross output. On the other hand, the cross-industry co-movement of hours is too low. The correlation of aggregate measured productivity with hours is too high, as hours now follow a typical positive RBC response to technology shocks. Moreover, in this case the model is not able to generate a sufficiently high response of aggregate hours. Aggregate gross output fluctuates much less than GDP, contrary to the data. The relative prices at the industry level still fluctuate substantially less than in the data, but now their correlation with industry measured productivity is also too negative.

The discussion of the alternative models highlights the importance of the industry-level information. The version of the model with no aggregate technology shocks is strongly supported by the low cross-industry correlation of measured productivity compared to output and hours, and by the fact that aggregate gross output fluctuates more than value added. The importance of the relative variance of gross output for identification of demand versus technology shocks requires some further explanation. Technology shocks tend to make aggregate value added react more strongly, in percentage terms, than gross output: if the elasticity of substitution between labor and intermediate inputs is lower than unity, and the labor input response to a technology shock is not too strong, then intermediate inputs change proportionally less than gross output. Therefore, value added reacts proportionally more than gross output. This is not the case for demand shocks, which generate a comparatively stronger reaction of production factors. This mechanism explains why at the industry level, where technology shocks are dominating, gross output fluctuates less than value added. At the aggregate level, where demand shocks are dominant, gross output fluctuates more. We provide a simple analytical illustration in Appendix D.

A further industry-level statistic that speaks in favour of endogenous effort is the ratio of intermediate inputs per hour worked. The ratio is fluctuating in all three model variants because the relative price of labor and intermediate inputs is changing in response to the shocks. However, there is a further mechanism in the case of endogenous effort: cost minimization determines the ratio of intermediate inputs to *effective* labor input, given factor prices. With flexible effort, effective labor input fluctuates more than hours, making intermediate inputs per hour more volatile. This explains why the ratio of intermediate inputs per hour worked in the baseline model fluctuates more than in the two alternatives. The comparison in Table 9 shows that the average standard deviation of the ratio of intermediate inputs per hour at the industry level is 0.73 in the data, 0.52 in the baseline model, 0.30 in the model with constant effort, and 0.25 in the model with flexible prices, supporting the baseline calibration.

4.5. Changes in business cycle co-movement after 1984

A growing strand of literature tries to explain the changes in the business cycle fluctuations in the U.S. in the mid-1980s, in particular the vanishing cyclicity of measured productivity. Molnárová (2020) shows that industry evidence provides important information for assessing the plausibility of the proposed explanations. A number of the mechanisms proposed in the literature imply that the changes in cyclicity should be equally visible at the industry and the aggregate level, which is not the case in the data. In this section, we investigate to what extent our model is able to explain the changes in the mid-1980s taking into account both aggregate and industry-level evidence.

The bottom panels of Tables 3 – 5 show data moments and simulation results for the post-1984 period. A comparison of the industry data moments (Tables 4 and 5) for periods before and after 1984 shows that many of the business cycle statistics are remarkably stable between the two sub-samples. While the absolute size of the fluctuations is smaller in the post-1984 period, most of the relative volatilities and correlations do not change much. However, in line with the existing literature, we find that there are some important differences between the aggregate data moments in the periods pre- and post-1984 (Table 3):

- The absolute size of the aggregate fluctuations is smaller in the post-1984 period.

- The correlation between aggregate measured productivity and hours decreased from 0.49 to -0.26, the correlation with output decreased from 0.85 to 0.47, the change for measured labor productivity being similarly strong. Other correlations reported in the table also decreased in the post 1984-period, although the differences are much smaller.
- Standard deviations of aggregate factor inputs, labor and intermediate inputs increased relative to the standard deviation of value added.
- The ratio of intermediate inputs over hours at the aggregate level became less correlated with output and productivity.

Several authors have suggested that the great moderation period after 1984 was characterised by a different composition of shocks, especially stressing the lower volatility of shocks to aggregate demand, or muted effects of these shocks on the economy, see e.g. [Barnichon \(2010\)](#) and [Galí and Gambetti \(2009\)](#). To investigate the implications of such change for the cyclicity of measured productivity, we decrease the volatility of the aggregate demand shock σ_D in our model by around 40%, see [Section 3.3.3](#). We keep the rest of the parameters, including the variances of industry shocks, the same as in the baseline.¹⁰

The bottom panels of [Tables 3](#) and [4](#) show the second moments of the model variables under this calibration and compare them to the data in the post-1984 period. The single change in the shock volatilities generates a significant part of the vanishing cyclicity of labor productivity observed in the aggregate data. In the model, the correlation between aggregate measured TFP and hours decreases to 0.11, which corresponds to 50% of the observed change. The correlation between measured TFP and output decreases from 0.87 to 0.79, which corresponds to 19% of the observed change. At the same time, the correlation between measured TFP and value added at the industry level stayed on average almost unchanged both in the data and in the model. The average correlation between the industry measured TFP and hours in the data decreased moderately from -0.02 to -0.23, while the model generates around 65% of the decrease, from -0.06 to -0.20.

To summarize, the calibration with the reduced variance of the aggregate demand shock replicates the post-1984 decrease in the volatility of aggregate output and productivity, and it generates a significant part of the decrease in the procyclicality of measured aggregate productivity, without generating a counterfactual decrease in procyclicality of productivity at the industry level. Looking at a larger set of moments, however, there are several dimensions along which this calibration is less successful. In particular, the correlation of aggregate measured productivity with output and intermediate inputs has decreased significantly more in the data than in the model.

5. Concluding remarks

In this paper, we have developed a highly disaggregated DSGE model with input-output linkages between industries. We use this framework to study the relative importance of technology and demand shocks, both at the aggregate and industry level. We find that there are no aggregate technology shocks. All the variation in observed productivity can be explained by two components: idiosyncratic technology shocks at the industry level and endogenous variations in factor utilization, driven by shocks to aggregate demand. Considering only aggregate empirical evidence, it would be difficult to distinguish between a model with endogenous effort and a model with aggregate technology shocks. However, we show that the model with endogenous effort matches the industry-level evidence much better than the model with aggregate technology shocks. There is a small but highly important co-movement of measured productivity across industries, which points towards the presence of an aggregate component. The co-movement pattern is explained well in our model with endogenous fluctuations in effort, caused by the aggregate shocks to demand, while it is exaggerated in the model with aggregate technology shocks.

Our results support a Keynesian view of business cycles in the sense that aggregate demand shocks are the main driver of aggregate fluctuations. They explain 78% of the fluctuations in aggregate hours, with the remaining part being attributed to measurement errors. This is in line with recent evidence in [Angeletos et al. \(2020\)](#) and [Andrle et al. \(2017\)](#). Since we model the aggregate demand shock as a risk premium wedge affecting the inter-temporal substitution, we also see our results as consistent with [Hall \(2017\)](#), who shows that fluctuations in employment are primarily driven by changes in financial discount factors. Our estimates attach an important role to endogenous effort, in line with [Fernald and Wang \(2016\)](#), who find that the procyclicality of measured productivity is mostly due to endogenous factor utilization.

We have also explored to what extent our model can account for the change in the cyclicity of productivity after the mid-1980s. We find that a reduction in the importance of aggregate demand shocks, compatible with the great moderation narrative, explains a substantial part of the reduction in correlations between aggregate measured productivity and labor input. However, it explains only a small part of the change of some other moments, such as correlation between aggregate productivity and output. Clearly, there are other aspects of the changes in the great moderation period which our model does not take into account. While we cannot fully account for the change in the cyclical properties of productivity after 1984, our results support the view that the vanishing cyclicity of measured productivity should not be interpreted as a reduced role of technology shocks. In fact, technology shocks have never been a major driver in the procyclicality of measured productivity in the first place.

¹⁰ As discussed in [Section 3.3](#), we come to the same results when we model the great moderation as a change in monetary policy rather than a change in the composition of shocks.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at [10.1016/j.jedc.2021.104272](https://doi.org/10.1016/j.jedc.2021.104272)

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