



Income dispersion and counter-cyclical markups[☆]

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ARTICLE INFO

Article history:

Received 22 October 2008

Received in revised form

18 June 2009

Accepted 23 June 2009

Available online 30 June 2009

JEL classification:

E32

E25

Keywords:

Business cycles

Markups

Income dispersion

ABSTRACT

Recent advances in measuring cyclical changes in the income distribution raise new questions: How might these distributional changes affect the business cycle itself? We show how counter-cyclical income dispersion can generate counter-cyclical markups in the goods market, without any preference shocks or price-setting frictions. In recessions, idiosyncratic labor productivity shocks raise income dispersion, lower the price elasticity of demand, and increase imperfectly competitive firms' optimal markups. The calibrated model explains not only many cyclical features of markups, but also cyclical and long-run patterns of standard business cycle aggregates.

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1. Introduction

A long line of empirical research suggests that prices vary less over the business cycle than marginal costs. In other words, markups are counter-cyclical. The question is why. We argue that the cross-sectional dispersion of earnings might play a role. In recessions, when earnings are more dispersed, buyers' willingness to pay is also more dispersed. If sellers reduce prices in recessions, they attract few additional buyers (the small shaded area in the left panel of Fig. 1). This low elasticity makes the marginal benefit of lowering prices smaller and induces firms to keep prices high. Therefore when dispersion is high, prices stay high but profits are low. In contrast, in booms when dispersion is low, sellers who reduce prices attract many additional buyers (the larger shaded area in the right panel of Fig. 1). Therefore in booms, sellers keep prices low but earn high profits.

While there have been many previous explanations for counter-cyclical markups, our mechanism has two strengths: it is based on observables and it can be embedded in a simple dynamic equilibrium model.¹ The observable variable is

[☆] We thank George Alessandria, David Backus, Mark Bilts, Mark Gertler, Carlos Garriga, Aubhik Khan, John Leahy, Emi Nakamura, Nick Souleles, Harald Uhlig, Lawrence Uren, Stijn Van Nieuwerburgh, Pierre-Olivier Weill, Michael Woodford, Randy Wright, and seminar participants at Columbia, Tokyo, Princeton, UCLA, NYU, FRB Philadelphia, Rochester, Iowa, Oslo, Melbourne and the 2008 Washington University in St Louis conference on money, credit and policy, the 2007 New York area monetary policy meetings, 2007 AEA and 2006 SED meetings for helpful comments. We especially thank Jeff Campbell, Nick Bloom and two anonymous referees whose detailed suggestions greatly improved the paper. Laura Veldkamp also thanks Princeton University for their hospitality and financial support through the Kenen fellowship.

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¹ Seminal papers on counter-cyclical markups are Rotemberg and Saloner (1986) and Bilts (1989). For a review, see Rotemberg and Woodford (1999). Recent work on the related phenomenon of real price rigidity includes Nakamura and Steinsson (2006) and Menzio (2007).

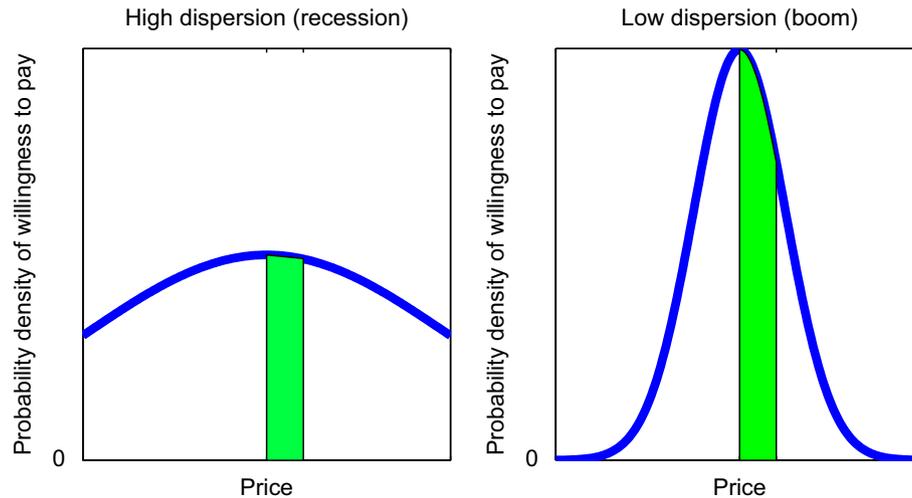


Fig. 1. Lowering price is more beneficial when dispersion is low. The shaded area represents the increase in the probability of trade from lowering the price, by an amount equal to the width of the shaded area. This higher probability, times the expected gains from trade, is the marginal benefit to reducing the price. In our model, willingness to pay is based on household earnings.

earnings dispersion. Embedding the earnings process estimated by Storesletten et al. (2004) in a production economy allows us to compare the model's predictions to business cycle aggregates. In particular, our mechanism delivers realistic pro-cyclical profit shares, a feature of the data that many models struggle with.

To illustrate our mechanism, Section 2 analyzes a static version of the model. There is a competitive sector where price equals marginal cost and an imperfectly competitive sector where prices are marked up. In both sectors, the only input is effective labor. Households choose how much to work and how much of each good to buy. Income dispersion arises because some households are more productive. The main result is that more dispersed idiosyncratic productivity results in higher markups and higher prices.

Theory alone cannot tell us if the variation in earnings dispersion is a plausible source of counter-cyclical markups. The problem is that changes in aggregate productivity are a force for pro-cyclical markups. Therefore Section 3 calibrates and simulates a dynamic version of the model. For reasonable parameter values, the earnings dispersion effect dominates the productivity effect. Since measured dispersion is counter-cyclical, markups are as well. Their correlation with GDP is almost as negative as in the data. The resulting prices look inflexible because they fluctuate less than marginal cost. Yet, there are no price-setting frictions.

One reason economists pay attention to counter-cyclical markups is because they can amplify the effects of other business cycle shocks. In this model, when aggregate productivity is low, high markups keep prices from falling much. Higher prices mean fewer goods are sold, amplifying the effect of the productivity shock. In our quantitative results, the effect of the productivity shock is amplified sevenfold relative to a standard real business cycle model. Section 3.5 compares the model's predictions for GDP, employment, real wages, and profits to their empirical counterparts. Importantly, the model's ability to explain markups does not come at the cost of undermining its ability to match macroeconomic aggregates.

To keep heterogeneous earnings tractable, our model abstracts from important issues in the literature on income heterogeneity in macroeconomics, such as risk sharing and capital accumulation (Krusell and Smith, 1998; Rios-Rull, 1996; Krueger and Perri, 2005). In Section 3.7 we show that our main results hold up if we re-calibrate idiosyncratic productivity to the level of consumption dispersion documented in Krueger and Perri (2005). Omitting capital hurts the performance of the model by making aggregates too correlated with GDP.

Other mechanisms can generate counter-cyclical markups. One possibility is that sticky prices and pro-cyclical marginal costs make the difference between price and cost, the markup, counter-cyclical. The problem with this explanation is that, without additional frictions, it implies counter-cyclical firm profits, strongly at odds with the data. Similarly, while firm entry and exit change the degree of market competition and thus the markup (Jaimovich and Floetotto, 2008), free entry implies zero profits. Our model delivers realistic pro-cyclical profits. Booms are times when markups are low but volume is high enough to compensate. Comin and Gertler (2006) reverse the causality: they use shocks to markups as a source of business cycles. Three closely related models also produce a cyclical elasticity of demand due to changing production technology (Kimball, 1995), changing demand composition (Gali, 1994), or changes in product variety (Bilbiie et al., 2006).

To argue that earnings dispersion is part of the reason for price variation, we look for other evidence that long-run changes and cross-sectional differences in earnings dispersion are correlated with differences in prices and profit shares as predicted by the model. Section 4 shows that the observed increase in earnings dispersion is consistent with the observed slowdown in real wage growth and the accompanying increase in profit shares. Section 4.2 documents additional facts from the empirical pricing literature that when the customer base has more dispersed earnings, prices tend to be higher.

Our model takes counter-cyclical earnings dispersion as given.² But this raises an obvious question: Why does earnings dispersion rise in a recession? One explanation is job destruction in recessions (Caballero and Hammour, 1994). Rampini (2004) argues that entrepreneurs' incentives change in recessions, making firm outcomes and owners' earnings riskier. Cooley et al. (2004) and Lustig and Van Nieuwerburgh (2005) argue that low collateral values inhibit risk sharing in recessions. Any of these explanations could be merged with our mechanism to produce a model driven by productivity shocks alone.

2. An illustrative static model

Households: There is a continuum of households indexed by i with identical preferences over a numeraire consumption good c_i , labor supply n_i and a continuum of products x_{ij} indexed by $j \in [0, 1]$,

$$U_i = \log(c_i) - \theta n_i + v \int_0^1 x_{ij} dj, \quad \theta, v > 0. \quad (1)$$

Let w_i denote a household's idiosyncratic effective labor productivity and let p_j denote the price of good j , both in terms of the numeraire. The budget constraint for household i is

$$c_i + \int_0^1 p_j x_{ij} dj \leq w_i n_i + \pi, \quad (2)$$

where π denotes lump-sum profits paid out by firms.

Each of the x -goods is indivisible. A household either buys an x -good or not, $x_{ij} \in \{0, 1\}$. This assumption simplifies the aggregation. The online supplementary appendix³ shows that our main results go through if the x -goods are perfectly divisible and households can consume any $x_{ij} \geq 0$ in their budget set.

Firms and market structure: The economy consists of a continuum of island locations. At each location is one firm that produces the x -good (a monopolist) and a large number of identical perfectly competitive firms that produce the numeraire c -good. Each island receives an IID random assignment of a unit mass of households drawn from the population. Each household supplies labor to a competitive labor market on its island. Producers of x - and c -goods hire that labor. Both types of goods are produced by a technology that transforms effective labor 1-for-1 into final products. Since the aggregate supply of effective labor on an island is $\int_0^1 w_i n_i di$ the labor market clears on island j when

$$\int_0^1 c_i di + \int_0^1 x_{ij} di = \int_0^1 w_i n_i di. \quad (3)$$

The monopolist producer of an x -good on island j chooses its price to maximize profits π_j . Profits are price p_j times the quantity sold at that price $x(p_j)$ less cost:

$$\pi_j = (p_j - 1)x(p_j). \quad (4)$$

Since the competitive firms make zero profits, aggregate profits are $\pi := \int_0^1 \pi_j dj$. Each household gets an equal share of these aggregate profits.⁴

Notice that which island a household is assigned to is immaterial since the x -goods are perfect substitutes to households. Islands are identical, the only role they play in the analysis is in ensuring that each x -good producer is a (local) monopolist.

Earnings dispersion: Heterogeneous effective labor productivity is the source of earnings dispersion. The distribution of productivity is summarized by its mean $z > 0$ and a measure of dispersion $\sigma > 0$. Let $w_i = z + \sigma \varepsilon_i$ where ε_i has mean zero and is IID in the population with probability density $f(\varepsilon)$ and cumulative distribution $F(\varepsilon)$ on support $[\underline{\varepsilon}, \bar{\varepsilon}]$. Also let $\underline{\varepsilon} > -z/\sigma$ so that $w_i > 0$ for all i and that:

Assumption 1. The hazard $h(\varepsilon) := f(\varepsilon)/(1 - F(\varepsilon))$ is monotone increasing on $(\underline{\varepsilon}, \bar{\varepsilon})$.

As discussed by Bagnoli and Bergstrom (2005), this is equivalent to assuming that the survival function $1 - F(\varepsilon)$ is log-concave⁵ on $(\underline{\varepsilon}, \bar{\varepsilon})$.

² This is the general consensus in the literature, as exemplified by Storesletten et al. (2004). This finding is bolstered by related work showing that the cross-industry dispersion of firm productivity growth also rises in recessions (Bloom et al., 2009). Since firm productivity growth translates into both higher profits and higher wages for workers (Van Reenen, 1996), it is likely to be a source of higher earnings dispersion in recessions. Barlevy and Tsiddon (2006) come to an opposite conclusion because they consider the reduction in inequality in the years following the great depression.

³ The appendix can be found online in the supplemental materials section of the journal's website and from the authors' webpages.

⁴ These profits are available to a household in time to be used as income for c and x purchases. One interpretation of this is that households are able to make some consumption purchases on credit backed by the (deterministic) profit income they will receive and then subsequently repay their creditors when the profit income is paid out by firms.

⁵ That is, $\log(1 - F(\varepsilon))$ is concave. A sufficient condition for $1 - F(\varepsilon)$ to be log-concave is for the density $f(\varepsilon)$ to be log-concave. Examples of distributions with log-concave densities include the uniform, normal, exponential, logistic, extreme value and members of the gamma and beta families. Linear transformations of log-concave distributions are also log-concave.

Equilibrium: An equilibrium in this economy is: (i) a set of consumption choices c_i and x_{ij} and labor supply choices n_i for each household that maximize utility (1) subject to the budget constraint (2), (ii) a price p_j for the monopolist x -good producer on each island j that maximizes profit (4) taking as given the demand for the firm's product such that (iii) the markets for c -goods, x -goods, and labor (3) all clear on each island j .

Results: Optimal consumption of the x -goods follows a cutoff rule, household i buys the x -good on island j if the additional utility it provides exceeds the price p_j times the household's Lagrange multiplier on (2), i.e., if $v \geq p_j \lambda_i$. The first-order condition for labor supply tells us that $\lambda_i = \theta/w_i$. Combining these two expressions yields the household's demand for the x -good:

$$x_{ij} = \begin{cases} 1 & \text{if } w_i \geq \frac{\theta}{v} p_j, \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

The fraction of households who buy a differentiated product is just the probability that each household has a labor productivity higher than the cutoff value, so the demand curve facing an x -good producer is

$$x(p_j) := \int_0^1 x_{ij} di = \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \mathbb{1} \left\{ \varepsilon_i \geq \frac{\theta p_j / v - z}{\sigma} \right\} f(\varepsilon_i) d\varepsilon_i = 1 - F \left(\frac{\theta p_j / v - z}{\sigma} \right). \quad (6)$$

Differentiating the profit function (4) with respect to p_j yields the first-order condition characterizing the profit-maximizing price:

$$p_j + \frac{x(p_j)}{x'(p_j)} = 1. \quad (7)$$

The left-hand side is the firm's marginal revenue, the right-hand side its constant marginal cost. Using the expression for the demand curve (6) and rearranging gives

$$p_j - 1 = \frac{1 - F \left(\frac{\theta p_j / v - z}{\sigma} \right) v \sigma}{f \left(\frac{\theta p_j / v - z}{\sigma} \right) \theta} = \frac{1}{h \left(\frac{\theta p_j / v - z}{\sigma} \right) \theta}, \quad (8)$$

where $h(\varepsilon) := f(\varepsilon)/(1 - F(\varepsilon))$ is the hazard rate of the distribution of idiosyncratic labor productivity. By assumption, $h(\varepsilon)$ is monotone increasing. Therefore the right-hand side of (8) is monotone decreasing in p_j , while the left-hand side is monotone increasing in p_j . The unique intersection of the two curves determines the optimal price set on island j . In a symmetric equilibrium this price is the same on every island, $p_j = p$ for all j .

Our interest here is in how the optimal markup varies with the parameters of the distribution of idiosyncratic labor productivity z, σ . Since marginal cost is constant and normalized to 1, the optimal markup is equal to the optimal price.

Proposition 1. *The optimal markup $m(z, \sigma)$ is increasing in aggregate productivity z and increasing in dispersion σ .*

The formal proof is in the online supplementary appendix. To get intuition for this result, it is instructive to use (6) to calculate the elasticity of demand:

$$\epsilon(p_j) := - \frac{x'(p_j) p_j}{x(p_j)} = 1 + h \left(\frac{\theta p_j / v - z}{\sigma} \right) \frac{\theta}{v \sigma}.$$

Both an increase in aggregate productivity z and an increase in dispersion σ reduce the elasticity of demand. When the elasticity of demand falls, lower prices generate few additional sales so the optimal markup and price rise.

Example. Proposition 1 holds for any distribution of idiosyncratic productivity $f(\varepsilon)$ with a (weakly) increasing hazard. To illustrate the economics a little further, it is worth looking at a special case that can be solved explicitly. Let ε_i be IID uniform on $[-1, +1]$ so that w_i is IID uniform on $[z - \sigma, z + \sigma]$ with constant density $1/2\sigma$. Then demand for x -goods on island j is linear in the price:

$$x(p_j) = \int_{\theta p_j / v}^{z + \sigma} \frac{1}{2\sigma} dw_i = \frac{z + \sigma}{2\sigma} - \frac{\theta / v}{2\sigma} p_j.$$

This demand curve implies the optimal markup as a function of the parameters of the distribution of idiosyncratic labor productivity:

$$m(z, \sigma) = 1 + \frac{1}{2} \left(\frac{z + \sigma}{\theta / v} - 1 \right).$$

Firms only produce if they earn non-negative profits, which is when $m(z, \sigma) \geq 1$. To ensure this, we assume that marginal cost is sufficiently low: $1 \leq (z + \sigma)v/\theta$. If this assumption were violated, no firm would produce.

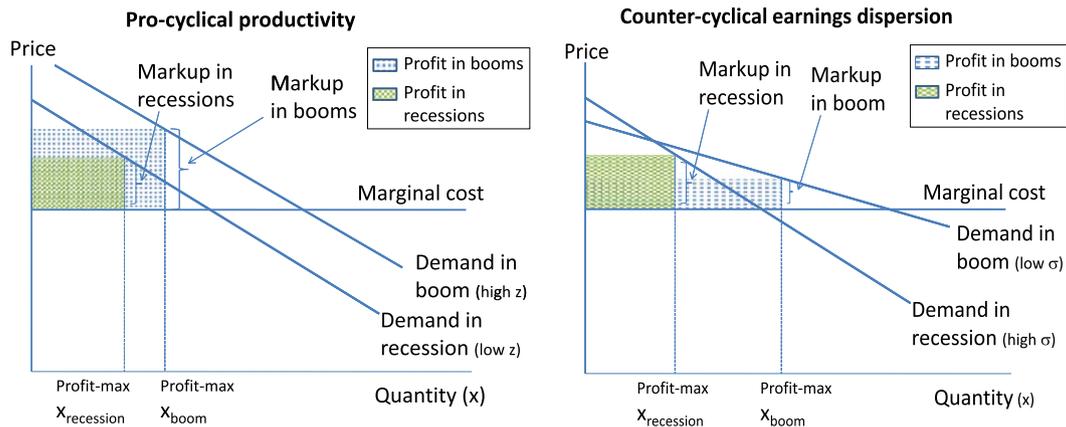


Fig. 2. Changes in aggregate productivity and dispersion. The effects of changes in aggregate productivity z (left) and changes in earnings dispersion σ (right) on prices, markups, quantity sold, and firm profits in the x sector.

The elasticity of demand at the optimal price is

$$\epsilon(z, \sigma) = \frac{\frac{z + \sigma}{\theta/\nu} + 1}{\frac{z + \sigma}{\theta/\nu} - 1}.$$

This elasticity is decreasing in both aggregate productivity and dispersion. An increase in aggregate productivity z shifts out and steepens the firm's marginal revenue curve, this leads to higher sales of x -goods and higher markups and prices as the firm uses its monopoly power to capture a share of the higher surplus generated by the additional demand. By contrast, an increase in dispersion σ shifts in but also steepens the firm's marginal revenue curve so that sales of x -goods fall but markups and prices rise.

Fig. 2 illustrates how changes in productivity and dispersion change the aggregate demand curve and the resulting equilibrium prices, markups, quantities and profits. As in Proposition 1, either higher z or σ increase markups and prices but higher z causes higher x -good sales while higher σ causes lower x -good sales. Profits can rise in booms because the increase in volume more than compensates for the loss in profits from lower markups.⁶ This effect can be seen in the right panel of Fig. 2 where the lightly shaded rectangle has a larger area than the darker square. While profits rise with income dispersion in this example, in general, the relationship depends on parameter values.

Alternative specifications: One concern with these results is whether they extend to other assumptions about demand. The online supplementary appendix shows that our results also hold with two alternative specifications. First, we show analytically that if the x -good is perfectly divisible, then Proposition 1 still holds. Second, we solve numerically a version of our model with a discrete-choice random-coefficients demand system like that of Berry et al. (1995), commonly used in the industrial organization literature. In this specification, households can choose only one of the $j \in [0, 1]$ varieties of x -goods and producers compete on price.⁷ If, as in our benchmark model, households have the 'outside option' of turning down all of the varieties to simply consume more c -good, then an increase in earnings dispersion raises markups, as in Proposition 1. But if households do not have this outside option, our mechanism breaks down.

Counter-cyclical markups? If business cycles involved only changes in productivity, then our mechanism predicts that markups would be pro-cyclical, an increase in z would increase markups. But in the data, earnings dispersion is counter-cyclical, suggesting σ falls when z rises. Can this offsetting force be strong enough to explain counter-cyclical markups? To answer this, Section 3 builds a dynamic quantitative model.

3. A dynamic quantitative model

Our dynamic model departs from the static model in four ways. First, aggregate productivity z and dispersion σ fluctuate. Second, idiosyncratic labor productivity has a realistic lognormal distribution.⁸ Third, marginal cost is variable

⁶ This tension between markups and volume is pervasive in markets with imperfect competition. For example, Campbell and Hopenhayn (2005) document, in a cross-section of retail trade in US cities, that larger markets have more competition, lower markups and higher volume, as in our model.

⁷ That is, producers of the differentiated x -goods engage in a form of monopolistic competition (Anderson et al., 1992). This suggests that the absence of competition between x -good producers in our benchmark model is also inessential for our main results.

⁸ The lognormal distribution does not have an increasing hazard function and so is not covered by Assumption 1. The assumption of an increasing hazard function is sufficient but not necessary for an increase in dispersion to increase markups. More details available on request.

instead of constant, so that firm profit shares are realistic. Fourth, richer preferences deliver a more realistic wealth effect on labor supply.

In the model, profits rise in booms. With a strong wealth effect on labor, cyclical profits can make labor counter-cyclical. Although other models encounter this problem, it is particularly acute here because imperfect competition in x -goods makes profits larger and more volatile. The dynamic model has ‘GHH’ preferences (Greenwood et al., 1988) that eliminate the wealth effect on labor supply to deliver more realistic labor fluctuations.

To keep the model computationally tractable, the model abstracts from capital and other assets. Since households have no opportunity to share risk or smooth consumption, this assumption could distort our results. To gauge the effects of this distortion, in Section 3.7 the model is re-calibrated to match consumption data, which incorporates the effect of financial income, savings and transfers.

Our dynamic model is not intended to be a full model of business cycle fluctuations. Rather, it shows that with realistic parameters, our dispersion mechanism can generate counter-cyclical markups, the magnitude of the markup fluctuation is not trivial, and that including the mechanism does not undermine the model’s ability to match standard macroeconomic aggregates.

3.1. Model setup

Individuals have GHH preferences over the numeraire consumption good c_i and labor n_i and get additive utility from the x_{ij} goods:

$$U_i = \log\left(c_i - \theta \frac{n_i^{1+\gamma}}{1+\gamma}\right) + v \int_0^1 x_{ij} dj,$$

which they maximize subject to their budget constraint (2), as above.

The log of aggregate productivity is an AR(1) process:

$$\log(z_t) = (1 - \rho) \log(\bar{z}) + \rho \log(z_{t-1}) + \varepsilon_{zt}, \quad \varepsilon_{zt} \sim \mathcal{N}(0, \sigma_z^2). \tag{9}$$

Idiosyncratic labor productivity is lognormal, $\log(w_{it}) = \log(z_t) + \varepsilon_{it}$ where $\varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. Our model of idiosyncratic productivity follows Storesletten et al. (2004) who estimate an earnings process with persistent and transitory shocks. Let

$$\begin{aligned} \varepsilon_{it} &= \xi_{it} + u_{it}, \quad u_{it} \sim \mathcal{N}(0, \sigma_u^2), \\ \xi_{it} &= \rho_\xi \xi_{it-1} + \eta_{it}, \quad \eta_{it} \sim \mathcal{N}(0, \sigma_{\eta,t}^2). \end{aligned} \tag{10}$$

The key feature of the earnings process is that $\sigma_{\eta,t}^2$ increases when GDP is below its long-run mean, specifically $\sigma_{\eta,t}^2 = \sigma_B^2$ if $y_t \geq \bar{y}$ and $\sigma_{\eta,t}^2 = \sigma_R^2$ if $y_t < \bar{y}$, where $\sigma_B^2 < \sigma_R^2$, y_t is GDP, as defined in Eq. (12), and \bar{y} is its long-run mean.

Putting these elements together, our stochastic process for dispersion σ_t is given by

$$\sigma_t^2 = \rho_\xi^2 \sigma_{t-1}^2 + (1 - \rho_\xi^2) \sigma_u^2 + \begin{cases} \sigma_B^2 & \text{if } y_t \geq \bar{y}, \\ \sigma_R^2 & \text{if } y_t < \bar{y}. \end{cases}$$

Finally, x -good firms have variable marginal costs. They transform effective labor into x -goods with a standard Cobb–Douglas technology, $x = n^\alpha$ with $0 < \alpha < 1$. Aggregate effective labor is $\int_0^1 w_i n_i di$ and the labor market clears on island j when $\int_0^1 c_i di + \int_0^1 x_{ij}^{1/\alpha} di = \int_0^1 w_i n_i di$. Profits for firm j are

$$\pi_j = p_j x(p_j) - x(p_j)^{1/\alpha}, \tag{11}$$

with variable marginal cost $x(p_j)^{(1-\alpha)/\alpha}$ where $x(p_j)$ is the firm’s aggregate demand curve.

Measuring GDP in the model: Total value-added in the model is given by

$$y := \int_0^1 c_i di + \int_0^1 \int_0^1 p_j x_{ij} dj di. \tag{12}$$

GDP varies both because of changes in the production of each good and because of changes in the relative price of x -goods and c -goods.

3.2. Model solution

The first-order condition for labor choice tells us that labor depends only on the wage and on preference parameters:

$$n_i = \left(\frac{w_i}{\theta}\right)^{1/\gamma}. \tag{13}$$

This simple relationship, devoid of any wealth effect, is what GHH preferences are designed to deliver. These preferences also simplify our calibration procedure: they imply log earnings are proportional to log idiosyncratic productivity and so it

Table 1

Parameters and the moment of the data each parameter matches.

Parameter			Calibration target	
Utility weight on leisure	θ	15	Steady state hours	0.33
Concavity of production	α	0.24	Steady state labor share	0.67
Utility weight on x -goods	ν	100	Steady state x -sector markup	1.23
Mean of productivity	\bar{z}	7.7	Steady state aggregate markup	1.10
Inverse labor supply elasticity	γ	0.6	Measured elasticity (GHH)	1.67
Productivity innovation std. dev.	σ_z	0.0032	Output std. dev.	0.017
Productivity autocorrelation	ρ	0.80	Output autocorrelation	0.80
Transitory earnings std. dev.	σ_u	0.024	STY estimate (annual)	0.065
Persistent earnings std. dev. $y > \bar{y}$	σ_B	0.012	STY estimate (annual)	0.032
Persistent earnings std. dev. $y < \bar{y}$	σ_R	0.020	STY estimate (annual)	0.054
Earnings autocorrelation	ρ_ξ	0.988	STY estimate (annual)	0.952

The parameters of the model and our calibration targets. All are for a quarterly frequency except for the parameter estimates for the cyclical properties of the earnings distribution from Storesletten et al. (2004) which are at an annual frequency. The online supplementary appendix derives the steady state moments of the model and details our transformation of the Storesletten et al. (2004) parameters from annual to quarterly.

is straightforward to match the empirical earnings distribution by a corresponding exogenous idiosyncratic productivity distribution. But GHH preferences complicate the model's solution because the cutoff rule for x -good demand is no longer linear in the wage. While household i still buys a unit of x_j if $\nu \geq p_j \lambda_i$, the Lagrange multiplier on their budget constraint is now $\lambda_i = (c_i - \theta n_i^{1+\gamma}/1 + \gamma)^{-1}$. To derive the demand for x -goods, use (2) and (13) to substitute out c_i and n_i in the λ_i formula. Then, substitute λ_i into the cutoff rule at the indifference point ($p_j = \nu/\lambda_i$). This delivers a critical wage $\hat{w}(p_j)$ such that any household with wage higher than this threshold buys the good. Thus the aggregate demand curve facing the x -good producer on island j is $x(p_j) = \Pr[w_i \geq \hat{w}(p_j)]$.

Firms' prices are chosen to maximize profit (11) taking the aggregate demand curve as given. The first-order condition for profit maximization equates marginal revenue and marginal cost,

$$p_j + \frac{x(p_j)}{x'(p_j)} = \frac{1}{\alpha} x(p_j)^{(1-\alpha)/\alpha}.$$

The set of equations that determine a solution to the model can no longer be solved in closed form. The online supplementary appendix details the fixed point problem solved in the following numerical exercises.

3.3. Calibration

Table 1 lists all parameters and their calibrated values. The utility weight on leisure θ matches 33% of time spent working in steady state and the concavity of the x -sector technology α matches an aggregate labor share of 67%, both standard business cycle calibration targets. The calibrated α differs from the typical value of 0.67 because in this two-sector model, the degree of diminishing returns to labor in one of the sectors is not equivalent to the aggregate labor share. The supplementary appendix explores model results with higher and lower α 's. The second moments of the productivity process match the persistence and standard deviation of output as reported in Stock and Watson (1999).

Markups in the x -sector are defined as price divided by marginal cost. Estimates of markups vary widely, depending on the sector of the economy being measured. At the very high end, Berry et al. (1995) and Nevo (2001) document markups of 27–45% for automobiles and branded cereals. For the macroeconomy as a whole, Chari et al. (2000) argue for a markup more like 10%. Since the competitive c -sector has zero markup, the markup for the economy as a whole is the x -sector markup times the x -sector expenditure share, which is about 40%. Our calibration uses the mean of productivity and the utility weight on x -goods (which determines the x -good expenditure share) to determine both an x -sector markup and an aggregate markup. To be conservative, we use an x -sector markup of 23%, a bit lower than the highest markups documented in the industrial organization literature for very differentiated products, and an aggregate markup of 10%.

The relationship between earnings dispersion and output is not something that can be manipulated directly: both earnings and GDP are endogenous variables. Our idiosyncratic labor productivity process is chosen to fit the earnings data. Because log labor supply is proportional to log productivity (Eq. (13)), productivity dispersion and hourly wage dispersion both have the same correlation with log output. Because an individual's labor supply is positively correlated with their productivity, total earnings $w_i n_i$ have higher dispersion than productivity, by a factor of $(1 + \gamma)/\gamma = 1.60/0.60 = 2.67$. Therefore, our idiosyncratic productivity parameters are the STY estimates, transformed from annual to quarterly, divided by 2.67. The online supplementary appendix gives further details.

To determine whether the economy is in the high or low dispersion state (σ_B or σ_R), we first simulate the model in one state and then check whether GDP is higher or lower than its steady-state level. If realized GDP is inconsistent with the

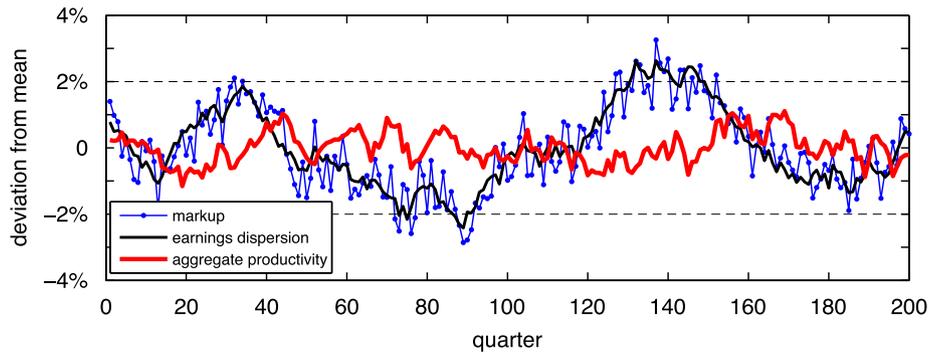


Fig. 3. Simulated markups, earnings dispersion and productivity. A typical realization of markups, earnings dispersion σ_t , and aggregate productivity z_t from a simulation of the benchmark model. Each variable is expressed as a percentage deviation from its unconditional mean. Each period is a quarter of a year.

dispersion state, we re-simulate with the correct dispersion parameter. The resulting correlations of dispersion and log GDP are quite accurate: -0.29 in the model and -0.30 in the data.⁹

Issues in measuring dispersion: Storesletten et al. (2004)'s estimates have been controversial, because of the difficulty in identifying transitory and permanent shocks. Guvenen (2009) and others argue that, because of unmeasured permanent differences in earnings profiles, the persistence of earnings shocks is overestimated. While this distinction is crucial in a consumption-savings problem, it is not relevant for our model, which has no savings. Whether earnings dispersion is persistent because each person gets persistent shocks or because new workers with more dispersed characteristics enter the sample—this does not matter to our seller who sets the price facing a distribution of willingness to pay. Thus both sides in this debate hold views consistent with our model's predictions.

3.4. Results: counter-cyclical markups

Recessions are times when firms pursue low-volume, high-margin sales strategies. To compare our simulated model to data, our aggregate statistics include activity in both the x and c sectors. The correlation of log markups and log GDP is -0.19 in the model, compared to -0.27 in the data (Rotemberg and Woodford, 1999). The standard deviation of log markups is 0.29 times the standard deviation of log GDP, compared to 0.36 in the data. Thus, markups are counter-cyclical and smoother than GDP, as in the data. In contrast, in a perfectly competitive market, the markup would always be zero. Fig. 3 illustrates a simulated time-series of markups.

In the data, counter-cyclical markups have been documented by and Rotemberg and Woodford (1999) using three different methods, by Murphy et al. (1989) using input and output prices, by Chevalier et al. (2003) with supermarket data, by Portier (1995) with French data and by Bils (1987) inferring firms' marginal costs. Besides their negative correlation with output, the other salient cyclical feature of markups is that they lag output. Fig. 4 shows that the model's markup is negatively correlated as a lagging variable, but turns to positively correlated when it leads, just as in the data. The difference is that the model's markup must lead by five quarters, rather than two quarters, to achieve a positive correlation.

The reason that the model's markups are lagging is that the earnings dispersion process is highly persistent. In low-productivity periods, it is the shocks to the persistent component of earnings that become more volatile (Eq. (10)). As these high-volatility shocks continue to arrive, the earnings distribution fans out. When productivity picks up and shocks become less volatile, there is enormous dispersion in the persistent component of earnings. It takes many periods of low-volatility shocks for the earnings distribution to become less dispersed. Since markups are driven by earnings dispersion, which is a lagging variable, markups are lagging as well. This feature of the model is similar to Bilbiie et al. (2006). In their setting, a large fixed cost causes firms to delay entry. Since markups depend on how many firms enter, markups lag the cycle.

3.5. Does the model match standard business cycle moments?

Our explanation for counter-cyclical markups is not useful if it implies counter-factual fluctuations in macroeconomic aggregates. Of course, there are some facts that our model cannot speak to because of its simplicity. For example, consumption cannot be compared to output because, without savings, the two are identical. But our model does have

⁹ A simpler alternative procedure is to link σ_B or σ_R to productivity. Because productivity is exogenous, this would eliminate the need for an iterative procedure. However, this both increases the distance between the model and STY's estimates and results in less counter-cyclical dispersion, which hurts the model's performance. This distinction becomes an issue because GDP and productivity are not so tightly linked in this model as they are in more standard business cycle models.

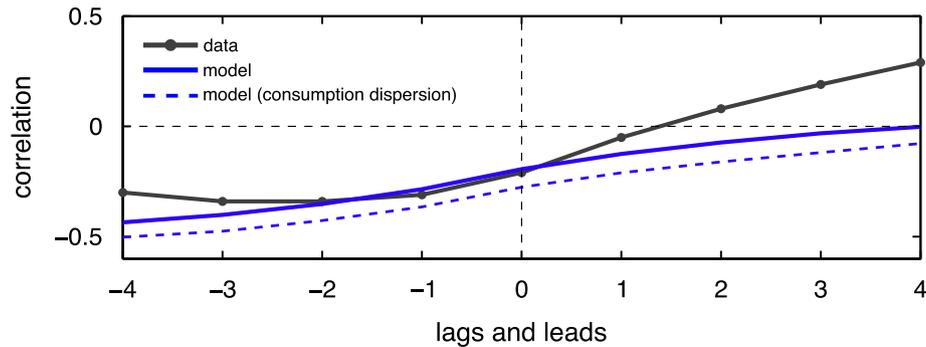


Fig. 4. Leads and lags of markup–GDP correlations. Entries are the simple correlation of $\log(\text{markup}_t)$ with $\log(y_{t+k})$ for $k = -4, -3, \dots, 0, \dots, 3, 4$ quarters. Positive k numbers indicate leads and negative k numbers indicate lags. As with all model moments, the cross-correlation function shown here results from averaging over many simulations. See the online supplementary appendix for further details. The leads and lags from the data are from Rotemberg and Woodford (1999) (their Table 2, column 2) and are for the postwar US at a quarterly frequency. Their markup is estimated using the labor share in the non-financial corporate business sector and an elasticity of non-overhead labor of -0.4 .

Table 2

Second moments of aggregate variables in model and postwar quarterly US data.

	Relative std. dev.	Correlation
<i>Model variable</i>		
Profit share	0.82	0.81
Labor	0.49	0.96
Real wages	0.28	0.22
<i>Data variable</i>		
Profit share	0.80	0.22 (0.37)
Labor (employment)	0.84 (0.82)	0.81 (0.89)
Labor (hours)	0.97 (0.98)	0.88 (0.92)
Real wages	0.39 (0.36)	0.16 (0.25)*
<i>King and Rebelo (1999)</i>		
Profit share	0.00	0.00
Labor	0.48	0.97
Real wages	0.54	0.98

Relative standard deviations are the standard deviation of the variable in logs divided by the standard deviation of log GDP. Similarly correlations are of the variable in logs with log GDP. Unless otherwise noted below, statistics for postwar quarterly US data are from Stock and Watson (1999). Labor and wage numbers in parentheses are from Cooley and Prescott (1995). The real wage correlation marked with an asterisk (*) is from Rotemberg and Woodford (1999). All profit share statistics are derived from the labor share statistics in Gomme and Greenwood (1995). The second correlation, in parentheses, is from the Bureau of Economic Analysis's National Income and Product Accounts (NIPA) data. The NIPA-based measures count all proprietors' earnings as profits, although it is part profit and part labor compensation. The correlation without parentheses does not count proprietor's earnings. For comparison, the table also shows the results from a standard real business cycle model (King and Rebelo, 1999).

implications for fluctuations in labor, profits and the real wage. In the model the real wage is calculated as the price of labor relative to the expenditure-weighted price index of x - and c -goods.

Table 2 compares the model aggregates to data. An important result is that the profit share is pro-cyclical (although too pro-cyclical). Pro-cyclical profits distinguish this model from sticky price theories, models with free entry or standard business cycle models such as King and Rebelo (1999). The reason that profits are pro-cyclical, despite markups being lower in booms, is that more of the x -goods are being purchased. Since x -good firms earn profits and c -good firms do not, the shift in demand raises the aggregate profit share. The fraction of expenditure on x -goods averages 40.7% in booms and 39.9% in recessions, so the overall extent of expenditure-switching between sectors is modest. Labor and real wages do slightly less well, but not worse than a standard real business cycle model. Without a capital stock in the model, wages, labor and output are more driven by changes in productivity. This makes their correlations with output too high.

Amplification of business cycle fluctuations: Understanding counter-cyclical markups is important for business cycle research because the resulting prices are less flexible (less volatile) and price rigidity amplifies the effects of productivity shocks on output. In our model, prices are only 2/3rds as volatile as they would be in a standard competitive economy where price equals marginal cost. If our prices were more flexible, they would fall further in recessions so that more x -goods would be sold. From Table 2, it appears as though our model explains no more of macrovolatility than the standard model. But the similarity is misleading. Recall that our aggregate productivity process was calibrated to match the volatility

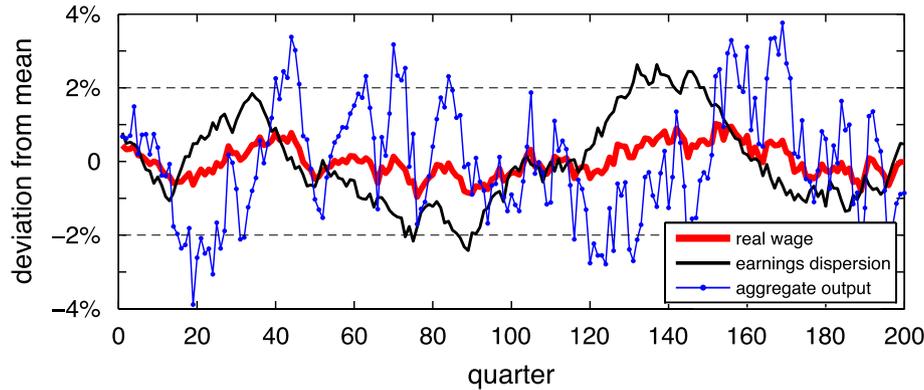


Fig. 5. Real wages, earnings dispersion and GDP in the simulated model. A typical realization of real wages, earnings dispersion σ_t , and aggregate output y_t from a simulation of the benchmark model. Each variable is expressed as a percentage deviation from its unconditional mean. Each period is a quarter of a year. Real wages are measured as the price of labor relative to the expenditure-weighted price index of x - and c -goods.

of GDP. Our calibrated shocks are 1/7th as volatile as those in King and Rebelo (1999).¹⁰ Because our model's recessions are deeper, using the King and Rebelo (1999) productivity process would make our business cycles many times more volatile.

Fig. 5 illustrates the behavior of real wages and GDP. It has two features that look familiar. First, real wages look like the mirror image of markups. The intuition for this is that wages are the main component of marginal costs and so wages relative to the x -good price behave like the reciprocal of the markup. Furthermore, both real wages and markups are closely correlated with dispersion. Rotemberg and Woodford (1999) argue that many empirical measures of markups are functions of the inverse real wage. The fact that simulated real wages are pro-cyclical means that this alternative measure of the model's markups is counter-cyclical as well. Second, the measure of GDP looks quite similar to productivity, plotted in Fig. 3. This tells us that, although dispersion has an effect, GDP is still primarily driven by aggregate productivity shocks.

3.6. Benchmark economies

Our results are driven by the earnings dispersion mechanism, not the preferences or the two-sector structure. Both the presence of earnings dispersion and its time-variation are essential for counter-cyclical markups. To show this, we compare our model to two benchmarks. The first is an economy where earnings dispersion is constant, always equal to its steady-state value. The second benchmark is an economy where there is no earnings dispersion, only a representative consumer. In both benchmarks, the correlation of markups with GDP is positive. This recalls our qualitative result from the static illustrative model, where holding dispersion fixed, an increase in aggregate productivity causes markups to increase.

When dispersion is constant and equal to its unconditional mean, many of our calibration targets look similar. The x -good markup (33%), the aggregate markup (12%), the average labor supply (0.33), average profit share (0.30), and the standard deviation and autocorrelation of log GDP (0.017, 0.78) are all close to their benchmarks. The key difference is the correlation of log markups and log GDP (0.23). Markups switched from being counter-cyclical to pro-cyclical. Alternatively, when earnings dispersion is zero, aggregates are either insufficiently volatile or almost perfectly cyclical.

3.7. Earnings vs. consumption dispersion

An important question is whether earnings dispersion is a meaningful measure of inequality to feed into the model. Our model is calibrated to earnings dispersion because of the availability of reliable estimates of its cyclical properties. To measure dispersion in a number of business cycles requires a panel data set with a long time-series dimension. Either income, including capital income and transfers, or consumption are arguably more appropriate measures. But replacing earnings with income is unlikely to change our results: while labor earnings are only 63% of income for the average household, earnings and income dispersion have remarkably similar levels and cross-sectional variation (Diaz-Gimenez et al., 1997).

A more serious challenge is to replace earnings dispersion with consumption dispersion. Storesletten et al. (2004) claim that consumption dispersion is only 72% of earnings dispersion. They create a long panel data set by using age characteristics of the PSID respondents to construct synthetic food consumption data back to 1930, just like they did with earnings. The long sample allows them to estimate a consumption process with counter-cyclical dispersion. Since, in our model, household earnings $w_i n_i$ and total consumption expenditure $c_i + \int_0^1 p_j x_{ij} dj$ are identical (up to the common π), our

¹⁰ In our calibration, aggregate log productivity has a quarterly persistence of 0.80 and an innovation standard deviation of 0.032 which implies an unconditional quarterly standard deviation of log productivity that is a function of the persistence and volatility of the innovations: $0.0032/\sqrt{1-0.80^2} = 0.005$. In King and Rebelo (1999), the quarterly standard deviation of log productivity is $0.0072/\sqrt{1-0.979^2} = 0.035$.

Table 3

Results for the model re-calibrated to match low levels of dispersion.

	STY consumption	Amount of dispersion			Data
		75%	50%	25%	
Markups					
Relative std. dev.	0.42	0.66	0.53	0.53	0.36
Correlation	−0.36	−0.16	−0.11	0.02	−0.27
Profit share					
Relative std. dev.	0.78	0.83	0.73	0.67	0.80
Correlation	0.70	0.80	0.94	0.88	0.22
Labor					
Relative std. dev.	0.44	0.46	0.42	0.38	0.90
Correlation	0.98	0.96	0.97	0.98	0.8–0.9
Real wages					
Relative std. dev.	0.18	0.26	0.21	0.16	0.39
Correlation	0.32	0.33	0.12	−0.37	0.16

Relative standard deviations are the standard deviation of the variable in logs divided by the standard deviation of log GDP. Similarly correlations are of the variable in logs with log GDP. The first four columns from the left show the model results when the level of dispersion is lower than in the benchmark model. The last column on the right shows the moments from postwar quarterly US data, summarized from Table 2. The numbered columns under the heading ‘amount of dispersion’ re-set the parameters $\sigma_B, \sigma_R, \sigma_u$ so that steady state earnings dispersion is the listed percentage of its benchmark level but keep the persistence ρ_ξ at its benchmark value. By contrast, the column labeled ‘STY consumption’ uses the stochastic process for food consumption estimated by Storesletten et al. (2004) to re-set all the parameters $\sigma_B, \sigma_R, \sigma_u$ and ρ_ξ . This process has both lower innovation variances and lower persistence. See the online supplementary appendix for further details.

idiosyncratic productivity parameters are reset (Eq. (10)) to match our earnings process to STY’s consumption expenditure process.¹¹ The other parameters are kept at their benchmark values. Table 3 shows that using consumption dispersion instead of income dispersion strengthens our main result: Markups become slightly more counter-cyclical (−0.36 vs. −0.19). This is accomplished without sacrificing fit with other business cycle moments. The average markup rises from 23% to 24% on x-goods and remains at 10% for the average good. Profit shares and labor hours are also unchanged.

The reason that consumption dispersion produces more counter-cyclical markups is that its persistence is lower. When a boom ends, the variance of the shocks to individuals’ earnings (or consumption) rises. Because earnings are highly persistent, more variable shocks increases earnings dispersion very gradually (see Fig. 3). Consumption, which is less persistent, fans out more quickly. Since output reacts quickly to changes in productivity and markups track dispersion closely, when dispersion also reacts quickly to changes in productivity, markups become more correlated (negatively) with output.

Of course, food consumption is not an ideal measure of overall consumption. Krueger and Perri (2005) compare the dispersion of after-tax labor earnings, plus transfers, to the dispersion of consumption, which includes expenditures on non-durables, services, small durables, plus imputed services from housing and vehicles. They find that consumption dispersion was about 74% of earnings dispersion in 1980 and was about 67% of earnings dispersion in 2003.¹² An alternative approach is to ask what a model with realistic risk sharing predicts about the relative size of consumption and income dispersion. For example, Aiyagari (1994) has a coefficient of variation for consumption that is 50–70% that of income.

Every one of these findings suggests that consumption dispersion is between 50% and 75% of earnings dispersion. The second and third columns of Table 3 show that when the model’s earnings dispersion is scaled down to the level of consumption dispersion, the model’s main results survive. Only when consumption dispersion is 25% of earnings dispersion, well below any estimates, do counter-cyclical markups and pro-cyclical real wages disappear.

The difficulty with endogenous risk sharing: Ideally, our model should include a consumption-savings choice, as in Aiyagari (1994) and Krusell and Smith (1998). Then, calibrated counter-cyclical earnings dispersion could endogenously generate the counter-cyclical consumption dispersion that moves markups. The supplementary appendix sketches such a model and shows that the wealth distribution would be a state variable. Krusell and Smith (1998) approximate such a large-dimensional state variable with a small number of moments. However, their approach is unlikely to deliver a close approximation to our model’s true solution.

Krusell and Smith’s wealth distribution only matters because it forecasts this period’s interest rate and next period’s capital rental rate. These are *known* functions of the mean of the wealth distribution. Since this period’s mean wealth is a good forecaster of next period’s mean wealth, and thus future rental rates, keeping track only of the mean of the wealth distribution results in a close approximation to the true solution.

¹¹ Roughly, the persistence of the consumption dispersion process estimated by Storesletten et al. (2004) determines the persistence parameter ρ_ξ and their estimates of the variances of the persistent and transitory components of household consumption determine $\sigma_u^2, \sigma_B^2, \sigma_R^2$. See the online supplementary appendix for details.

¹² Krueger and Perri (2005) report the following cross-sectional relative standard deviation of consumption to standard deviation of earnings: $\sqrt{0.19/0.35} = 0.74$ in 1980 and $\sqrt{0.25/0.55} = 0.67$ in 2003.

In our model, not only does the wealth distribution forecast future interest rates, it also determines x -good producer's prices, current consumption of both goods, labor supply, and profits. These are not known functions of the wealth distribution's moments. Rather, they are determined by a fixed-point problem that uses all the information in the distribution. When higher moments become important to the solution of the model, the [Krusell and Smith \(1998\)](#) technique can produce misleading results ([Carroll, 2000](#)).

To the extent that the [Krusell and Smith \(1998\)](#) model delivers realistic consumption predictions, our exercise that uses consumption in place of earnings data is suggestive for how a model with time-varying earnings dispersion and a consumption-savings choice might perform. Furthermore, because savings allows consumption to differ from earnings, it makes consumption and thus other macroaggregates less correlated with earnings and therefore less correlated with output. Reducing the correlation of macroaggregates with GDP would improve the model's fit with the data.

4. Evaluating indirect model predictions

This section evaluates long-run model predictions and surveys related evidence in the industrial organization literature.

4.1. The long-run slowdown in real wage growth

In the data, earnings dispersion is not just a cyclical variable, it also has a long-run upward trend. Many contemporaneous structural changes in the economy surely contribute to this trend, including a shift from manufacturing to services, skill-biased technological change ([Acemoglu, 2002](#)), and the diffusion of information technology ([Autor et al., 2008](#)). But it is suggestive support for our mechanism if, by incorporating a trend in earnings dispersion, our model can explain other long-run facts in the data.

A long-run change that has been of particular concern to policy-makers is the slowdown in the growth of real wages. The left panel of [Fig. 6](#) illustrates how real wages were keeping pace with labor productivity until the 1970s, when real wage growth slowed down. In the figure, real wages are measured as BLS real compensation per hour, including benefits, in the non-farm business sector, while labor productivity is BLS real output per hour. Both series come from the payroll survey.

To ask if the model produces the same effect, we need to calibrate changes in earnings dispersion and in aggregate productivity. For productivity, we use annual estimates of labor productivity from the BLS, averaged by decade. Earnings dispersion increased by 20% from 1967 to 1996, an average annual rate of 0.66% ([Heathcote et al., 2006](#)). To determine if our model's predictions are consistent with the long-run facts, we simulate six model economies, with different levels of earnings dispersion and productivity. Each economy represents a decade from the 1950s to the 2000s. We choose the 1970s to be the same as our benchmark calibration.

In doing this exercise, our model runs into a well-known problem. GHH preferences are inconsistent with balanced growth. The standard solution to this problem is to scale up the utility weight on leisure as productivity increases so as to keep hours flat. The formula for individual labor supply is $n_i = (w_i/\theta)^{1/\gamma}$. If θ is proportionately scaled up with w_i , average hours will not change. In our model with linear preferences over the x -goods, the utility weight v also needs to be scaled up.

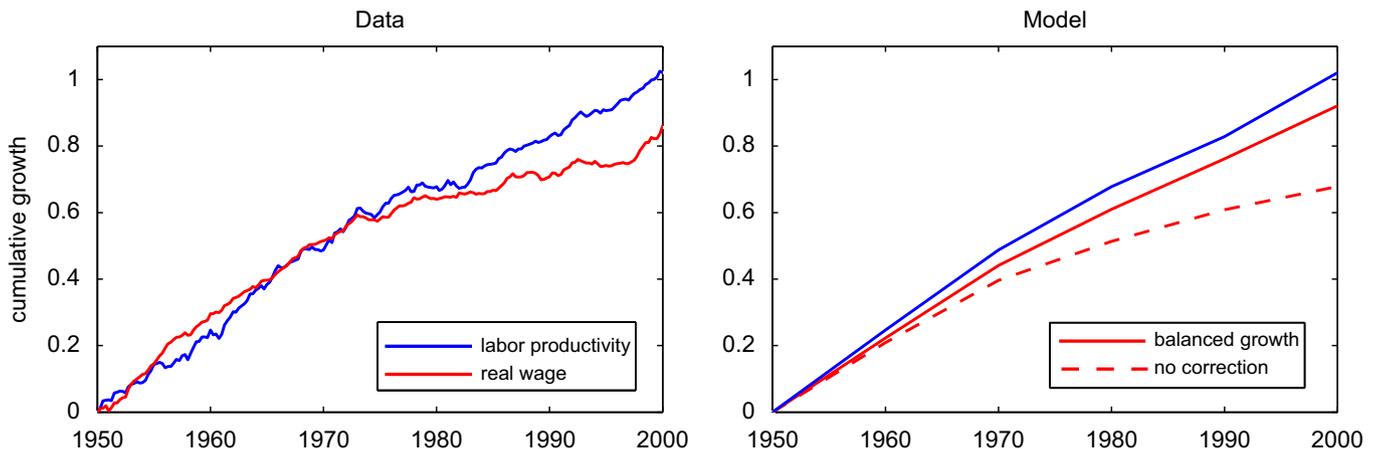


Fig. 6. Productivity and wage growth in data and simulated model. The left panel shows the long-run increase (cumulative growth) in labor productivity and real wages in postwar US data. Labor productivity is measured as real output per hour from the Bureau of Labor Statistics (BLS) payroll survey and real wages are measured as real compensation per hour, also from the BLS payroll survey. The right panel shows the results from our model when we add the decade-by-decade increase in labor productivity and in earnings dispersion estimated by [Heathcote et al. \(2006\)](#). The results labeled 'no correction' use the benchmark preference parameters listed in [Table 1](#). The results labeled 'balanced growth' scale up the utility weight on leisure and the utility weight on x -goods at the rate of aggregate labor productivity growth so as to keep average hours and the expenditure share on x -goods constant. See the online supplementary appendix for further details.

Changing these two parameters at the rate of productivity growth keeps both average hours and expenditure shares constant. We refer to results as having ‘no correction’ when preference parameters are constant and to ‘balanced growth’ results when they are scaled up.

The right panel of Fig. 6 shows that while the balanced growth model predicts only half the relative decline in real wages, the baseline model without correction produces an effect twice as strong as that in the data. In contrast, a standard business cycle model would predict that wages and productivity grow in tandem.

The flip side of the relative decline in real wages is an increase in firms’ profit shares. The balanced growth model’s share of output paid as profits rises steadily from 25% in 1950s to 33% (our calibrated value) in the 1970s to 38% in the 2000s. What happens is that higher dispersion reduces the demand elasticity, prompting higher markups, and, in conjunction with higher productivity, this delivers higher profit shares. In the no correction model, rising productivity has stronger effects, making the rise in profit share more extreme (18% in 1950 to 73% in 2000). As higher productivity increases earnings, the composition of demand changes. Consuming more x -goods means consuming a broader variety of goods and is therefore not subject to the same diminishing marginal returns that set in when c -good consumption increases. Therefore, when earnings increase, x -good consumption rises more than c -good consumption. This effect is big. The expenditure share for x -goods is 22% in 1950 and 75% in 2000. Higher demand for x -goods prompts firms to increase markups, raising profits.

In the data, the evidence on the size of the increase in profit shares is mixed. The share of output not paid out as labor earnings—a very broad definition of profits—rose only by about 5% from 1970 to 1996 (NIPA data). Meanwhile, Lustig et al. (2009) document that net payouts to security holders as a fraction of each firm’s value added—a much more narrow definition of profits—rose from 1.4% to 9% (based on flow of funds data) or 2.3% to 7.5% (NIPA data). While the broad measure suggests that our model over-predicts the rise in profits, the three- to six fold rises in profits reflected in the latter measure suggest that the dramatic profit increases predicted by the model may not be so far from the truth.

One might worry that the increase in earnings dispersion which makes individuals’ earning more volatile would also make the model’s business cycles more volatile. This concern is not founded. Higher dispersion can generate a modest decline in business cycle volatility (see the supplementary appendix for details).

4.2. Evidence from empirical pricing studies

Our results are also qualitatively consistent with the findings of Chevalier et al. (2003). Periods of good-specific high demand (e.g., beer on the fourth of July) are times when consumers’ values for the goods are more similar. While one might expect that high demand would increase prices, the authors find that prices and markups fall. The same outcome would arise in our calibrated model if productivity dispersion σ falls.

Our model would also predict a higher markup when a good is sold to customers with more dispersed valuations. Studies of the effect that willingness-to-pay dispersion has on car dealers’ markups and sales supports this prediction. Using CES data, Goldberg (1996) estimates that blacks’ valuations for new cars are more dispersed than whites’ and that females’ valuations are more dispersed than males’. She finds that, compared to the price paid by white males for the same car, black females (who have the most dispersed valuations) pay \$430 more, black males pay \$270 more and white females pay \$130 more, on average. While the standard errors on Goldberg’s estimates are large, methodologically distinct studies, such as Ayres (1991), obtain almost identical estimates.¹³ While there are many ways to explain these facts, including, of course, racial discrimination, our theory offers one interpretation. Ideally, we would have direct evidence linking the dispersion of consumers’ valuations to the markups firms charge, holding other features of the environment fixed. But so far as we are aware, no empirical studies do this. This would be a productive agenda for future research.

5. Conclusion

Our production economy is set up to capture the intuition that when earnings dispersion is higher, the price elasticity of demand is lower, so sellers optimally raise markups. However, without quantifying the model, the cyclical behavior of prices and markups is ambiguous because the productivity and earnings dispersion effects work in opposite directions. Using estimates of the time-series variation in the earnings distribution, we calibrate the model. Although the model is a simple one, it does a reasonable job of matching the business cycle features of markups and some traditional macroaggregates.

Our model provides a theory of real price rigidity, meaning prices that fluctuate less than marginal cost. By themselves, rigid real prices make business cycles more costly. When interacted with a form of nominal rigidity, real rigidities also amplify the real effects of nominal shocks (Ball and Romer, 1990; Kimball, 1995). Future work could merge this theory with a nominal price-setting friction. If this delivered enough amplification of small nominal shocks, it could further our understanding of monetary policy’s role in the business cycle.

¹³ Goldberg’s (1996) price differentials are not statistically significant, which leads her to conclude that there is no evidence of discrimination. But the high standard errors come from dropping more than half the sample due a missing or inconsistent response. Ayres (1991) finds black males pay \$280 more than white males while Goldberg (1996) estimates that differential to be \$270. For the most imprecisely estimated case, white women, Ayres (1991) finds a differential of \$190 while Goldberg (1996) estimates \$130. See Harless and Hoffer (2002) and Ross (2003) for further discussion of these and related results.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at doi:[10.1016/j.jmoneco.2009.06.006](https://doi.org/10.1016/j.jmoneco.2009.06.006).

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