Did Structural Transformation Affect Aggregate Volatility?

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Abstract

Kuznets (1973) noted that as an economy develops, it shifts resources from agriculture and manufacturing into services, and called this structural transformation. The first two sectors are more volatile than the third, leading some studies to argue that this reallocation reduced volatility. In this paper, I find that this need not be the case: mainstream models that generate the reallocation of resources do not necessarily imply a reduction in aggregate volatility. This supports existing work that suggests that aggregate volatility is largely influenced by the volatility within sectors, more than the reallocation of resources across sectors.

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1 Introduction

The service sector has grown in recent years, at the expense of agriculture and manufacturing. Services are relatively less volatile than manufacturing or agriculture, leading several papers to argue that this can account for some of the reduction in volatility in the U.S. since the 1980s (the "Great Moderation"). I argue that this need not be the case. In fact, I show that in the mainstream models of structural transformation, when augmented to generate business cycle fluctuations, the reallocation has no effect on aggregate volatility.

The paper starts by taking the simplest of these models (a version of Ngai and Pissarides, 2007) and adding shocks that generate business cycle fluctuations. I show analytically that in this model the reallocation of resources has no effect on aggregate volatility.

The intuition is as follows. The force driving the reallocation is a substitution effect: demand for agriculture, manufactures and services is inelastic, so if the relative price of services increases, so does the share of services on GDP. Similarly, the volatility of each sector depends on the volatility of relative prices. That is, expenditure on a particular good depends on how volatile that sector is relative to the other sectors. When that relative volatility does not change, neither does the aggregate volatility of GDP.

A problem with this model is that it counterfactually predicts that the agriculture sector should grow relative to the manufacturing sector, since the price of agricultural goods relative to manufacturing goods has increased. To address this, I develop a more general model, based on Herrendorf et al. (2013), and adding shocks and intermediate goods. Their model is a combination of Kongsamut et al. (2001) and Ngai and Pissarides (2007), and it can capture fairly accurately the main structural transformation in the economy. In addition to the substitution effect, there is a wealth effect: agriculture is an inferior good, manufacturing a normal good, and services a luxury good, so that as an economy grows, resources shift toward services and away from agriculture and manufacturing.

This model cannot be solved analytically, so I calibrate it and perform simulations to find my results. These show hardly any change in the volatility in the economy when comparing the periods 1947 to 1983 with 1984 to 2007. In the model, the volatility of GDP is lower in the second period by only 2%, when in the data it fell by around 40%. This leads me to conclude that structural transformation might have had no effects on aggregate volatility.

The calibration has two key components. The first component is sectoral shares. In 1947, services accounted for roughly 45 percent of consumption. By 2007, this share increased to more than 70 percent. The numbers are similar for intermediate good shares. The second component is the relative volatility of each sector. The theoretical construct predicts that sectoral shocks are closely related to sectoral prices, so I identify these shocks by observing data on prices. I find the service sector is less volatile than the other two sectors, and agriculture is the most volatile sector.

Computing the model is not trivial. Standard techniques used to compute business cycle models do not apply. These techniques often involve computing the steady state of an economy and log-linearizing around the steady state to compute the business cycle. The problem in this case is that there is no steady state, since a feature of these models is that as the economy grows, resources keep shifting from manufacturing and agriculture into services. To work around this issue, I use a technique developed by den Haan and Marcet (1990), the Parameterized Expectations Approximation method. The advantage of this method is that it does not rely on steady state assumptions.

The fact that mainstream models of structural transformation do not necessarily imply that the reallocation reduced volatility does not mean other models of structural transformation cannot. Moro (2012) develops a model consistent with structural transformation with two sectors and finds that structural transformation can account for about 30% of the reduction in GDP volatility. A very important contribution of this paper is to show how the composition of intermediate goods has changed, making them important for accounting for business cycle fluctuations. This is why I add intermediate goods to Herrendorf et al. (2013). Moro (2015) performs a similar exercise to compare volatilities across countries.

The difference between Moro and myself is that I measure volatilities during the process of structural transformation, in the same way as the national accounts measure this volatility. Moro, on the other hand, measures the volatility in two steady states: one with a low share of services, and one with a high share of services. Observing the volatility along the transition as opposed to comparing steady states implies that structural transformation does not affect aggregate volatility.

Ngouana (2013) calibrates a model of structural transformation to OECD countries. By design, the model matches the reduction in volatility in US during the Great Moderation. Then via counterfactuals that prevent the economies' reallocation toward the service sector, he finds the volatility increases. His model is different than mine in several ways. First, it is static, in the sense that there is no endogenous state variable. Second, and probably more important, labor enters the utility function in a non standard way. Labor is non convex, and the amount of hours worked in each sector is different, and so is dislike of working in each sector. This forces the model to deliver different aggregate implications for time worked in each sector, particularly for volatility.

Da Rocha and Restuccia (2006) study whether different agricultural shares across countries can account for the different volatilities observed across countries. Their results show that larger agricultural shares are associated with more volatile economies. My findings suggest that the link is not necessarily causal.

Perez-Quiros and McConnell (2000) is at odds with these papers, concluding that "*since the aggregate volatility drop stems from a reduction in volatility within the durable goods sector itself, its source is clearly not a shift in the composition of output across broad sectors of the economy.*" Along these lines, Carvalho and Gabaix (2013) find evidence that aggregate volatility is largely influenced by the volatility within microeconomic sectors. Thus, combining their findings with mine, the conclusion is that the reduction in volatility was due to a reduction in microeconomic volatility, and sectoral reallocation did not play an important role. This is also consistent with Arias et al. (2007), who explore the behavior of standard real business cycles to account for the reduction in volatility. They find that these models can account for the reduction in volatility only when the shocks fed to the model becomes less volatile.

This paper is organized as follows. Section 2 presents the data on structural transformation and the different volatilities across sectors. Section 3 shows analytically, in the simplest model of structural transformation, that the reallocation of resources does not necessarily entail a change in aggregate volatility. Section 4 develops a model of structural transformation and business cycles and defines the equilibrium. Section 5 calibrates the model. Section 6 discusses the results and section 7 concludes.

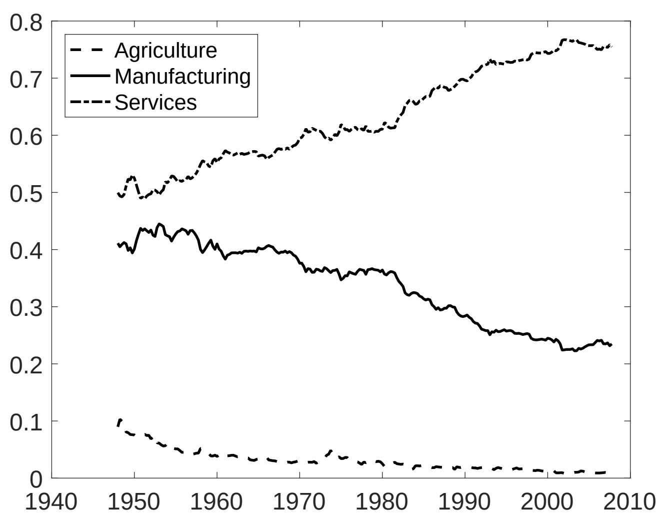
2 Data

This section describes the data that motivates the main question in the paper: that resources have shifted from the agricultural and manufacturing sectors to the service sector, and the service sector is less volatile than the other two sectors.

Figure 1 shows the evolution of sectoral shares in the United States from 1947 through 2007.

The data is Value Added by Industry in the BEA website. Agriculture includes agriculture, forestry, fishing, and hunting. Manufacturing includes mining; construction; utilities; and manufacturing. Services comprises the sectors wholesale trade; retail trade; transportation and warehousing; information, finance, insurance, real estate, rental, and leasing; educational services, health care, and social assistance; arts, entertainment, recreation, accommodation, and food services; other services, except government. This picture shows the evidence

Figure 1: Sectoral Shares on GDP



Kuznets focused on when depicting the structural transformation feature of growth. While in 1947 services represented about 50 percent of total value added, by 2007 this share grew to about 75 percent.

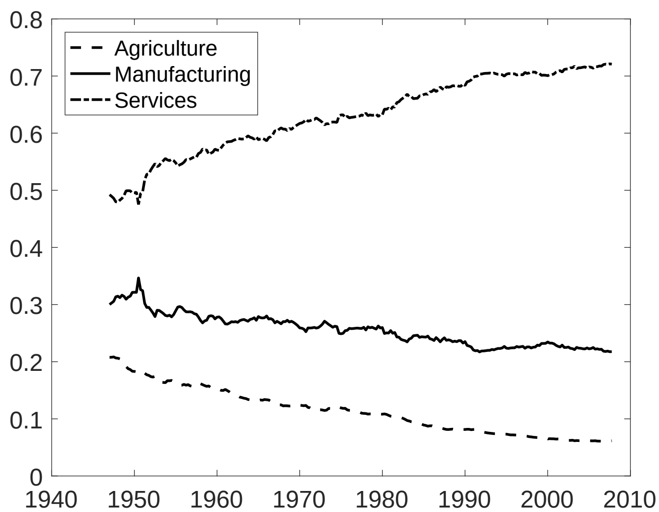
Theories of structural transformation focus more on the consumption aspect of structural transformation. To show this evolution for consumption, I proceed as follows. Private current consumption expenditures comes from NIPA Table 2.3.5. Government current consumption expenditure comes from NIPA Table 3.9.5. I use quarterly data from 1947.1 through 2007.4.

As in Herrendorf et al. (2013), I define the following:

- Agriculture is “Food and beverages purchased for off-premises consumption”
- Manufactures are “manufacturing” except “Food and beverages purchased for off-premises consumption”
- Services are taken directly from the classification of “Services” in NIPA

Consumption divided into these three sectors is shown in Figure 2. The share of services in

Figure 2: Sectoral Shares on Consumption

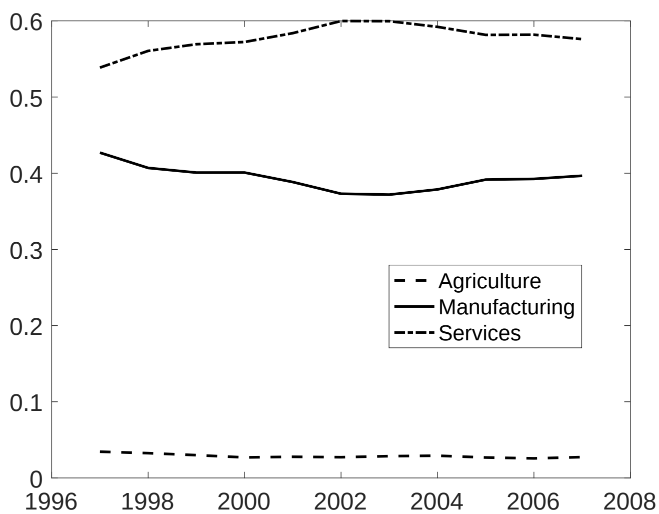


consumption grew from about 48 percent to about 72 percent.

I do not find evidence of changes in the composition of investment. Analyzing data from input output tables from 1947 through 2007, the shares are fairly constant and definitively do not show a clear trend. Investment is over 90% conformed by the manufacturing sector.

There is a clear pattern of structural transformation in the composition of intermediate goods as Moro (2012) noticed. The BEA publishes intermediate goods by sector, and the trend toward a more intensive use of services in intermediate goods is evident. Figure 3 displays these shares. The weight of services on intermediate goods increases from 55 percent in 1997 to 59 percent in 2007, reaching 60% in 2002 (data starts in 1997).

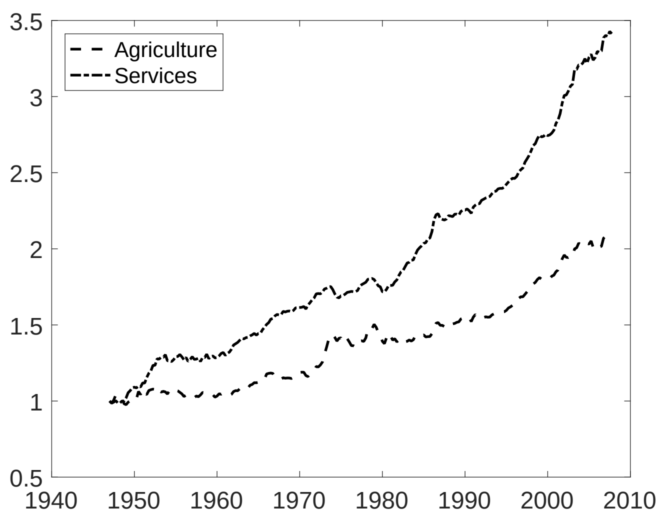
Figure 3: Sectoral Shares on Intermediate Goods



Models of structural transformation have accounted for the shift of resources toward services by combining preferences for agriculture, manufactures and services that have low elasticities of substitution with a disproportionate sectoral growth rate. These rely either on inelastic demands and different growth rates of prices, or on income effects. Ngai and Pissarides (2007) model a utility function that generates inelastic demands. Thus, if a good becomes relatively more expensive, expenditures on that good will increase. Figure 4 shows the prices of agriculture and services relative to manufacture. The increase in expenditures in services is explained in this model by services becoming more expensive. However, agriculture also became more expensive relative to manufacture, which would imply counterfactually that the agriculture share grew relative to manufacture, presenting a problem. Kongsamut et al. (2001)works more via income effects. In this model, agriculture is an inferior good, manufacture is a normal good, and services is a luxury good, which explains the increase in services and reduction in agriculture.

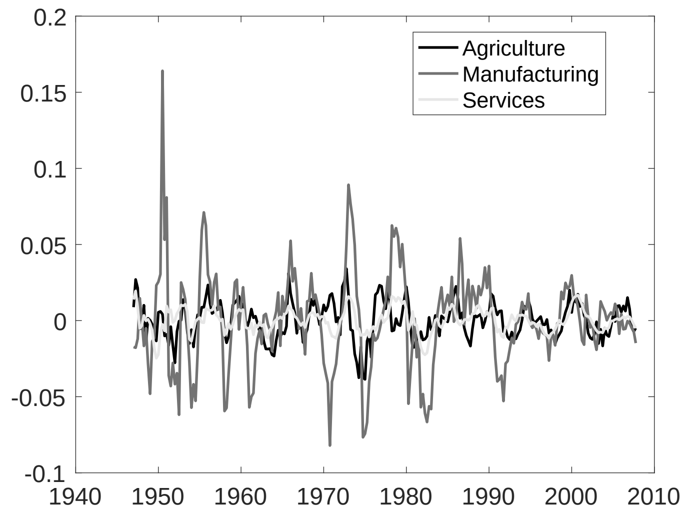
Figure 4 shows that both agriculture and service prices increased relative to manufacturing. Given the aforementioned assumptions, this means that the technology grew fastest in manufactures (followed by agriculture).

Figure 4: Price of Agriculture and Services relative to Manufacture



The reason why the increasing share of resources in the service sector might contribute to a reduction in aggregate volatility is that services is less volatile than the other sectors. This can be seen by studying the volatility of the detrended real consumption in each sector. To detrend, I use a Hodrick Prescott with a smoothing parameter equal to 1600. Figure 5 shows the cyclical component of each sector measured by the real consumption in each sector. Clearly, services is much less volatile than the other two sectors. The standard deviation of the cyclical component of services is 0.0076, manufacturing is 0.0317, and agriculture is

Figure 5: Sector Volatility



0.0122. In section 4, I measure the volatility of each sector in an alternative way, motivated by the theory the section develops, and also find that services is the least volatile sector.

Thus, given that services are less volatile than agriculture and manufacturing, and as the economy grows the share of services increases, the question is whether growth can account for a reduction in aggregate volatility.

3 A Simple Model

Consider a simplified version of Ngai and Pissarides (2007). Time is discrete and runs $t = 0, 1, \ldots, \infty$. Preferences are

$$\sum_{t=0}^{\infty} \beta^t \log\left(\left(\omega_a^{1/\mu} c_a^{\frac{\mu-1}{\mu}} + \omega_m^{1/\mu} c_m^{\frac{\mu-1}{\mu}} + \omega_s^{1/\mu} c_s^{\frac{\mu-1}{\mu}}\right)^{\frac{\mu}{\mu-1}}\right)$$

where a stands for the agricultural sector, m is manufacturing, and s is services. Technologies are

$$y_a = e^{z_{at}} h_{at}$$

$$y_m = e^{z_{mt}} h_{mt}$$

$$y_s = e^{z_{st}} h_{st}$$

Assuming that the consumer has one unit of labor each period, feasibility implies

$$h_{at} + h_{mt} + h_{st} = 1 \quad \forall t$$

Each sector grows at a different, exogenous growth rate. In this model, one can replicate the facts about structural transformation by assuming that the service sector has the lowest growth, followed by manufacturing, and then agriculture, paired with inelastic demand, that is, $0 < \mu < 1$.

Intuitively, the fact that demands are inelastic implies that as the price of one good increases relative to another good, spending on that good increases. Thus, for consumption of services to increase relative to manufacturing and agriculture, the price of services must increase relative to the price of the other two sectors, which is what the data suggests.

The data measures the volatility of GDP, and the purpose of this analysis is to see whether this changes with the sectoral composition. To obtain a measure of GDP, it is convenient to work with the decentralized equilibrium, where p_{jt} is the price of sector j at time t and w_t is the wage rate. Then, GDP (Y) in this economy is

$$Y_t = p_{at}c_{at} + p_{mt}c_{mt} + p_{st}c_{st}$$

Since there are no endogenous state variables, the equilibrium only depends on the realizations of the shocks z_{jt}. This implies that the consumer and the firm can solve their maximization problems statically. Thus, a decentralized competitive equilibrium for this economy is a list of allocations $\{c_{at}, c_{mt}, c_{st},\ h_{at}, h_{mt}, h_{st}\}_{t=0}^{\infty}$ and prices $\{p_{at}, p_{mt}, p_{st}, w_t\}_{t=0}^{\infty}$ such that

- The representative consumer takes prices as given and solves, for all t,

$$\max_{(c_{at}, c_{mt}, c_{st}) \geq 0} \log \left(\left(\sum_{j=a,m,s} \omega_j^{1/\mu} c_{jt}^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}} \right)$$

$$s.t.$$

$$p_{at}c_{at} + p_{mt}c_{mt} + p_{st}c_{st} = w_t$$

- Firms take prices as given and solve, for all t

$$\max_{h_j \geq 0} p_{jt}e^{z_{jt}}h_{jt} - w_t h_{jt}, \quad j = a, m, s$$

- Markets clear. For all t,

$$c_{jt} = p_{jt} e^{z_{jt}} h_{jt}, \quad j = a, m, s$$
$$\sum_{j=a,m,s} h_{jt} = 1$$

The equilibrium is as follows. Let $p_{mt} = 1$ be the numeraire for all t. From the first order conditions of the firm problem,

$$w_t = e^{z_{mt}} \tag{1}$$
$$p_{at} = e^{z_{mt}} e^{-z_{at}} \tag{2}$$
$$p_{st} = e^{z_{mt}} e^{-z_{st}} \tag{3}$$

From the first order conditions to the consumer problem and the technologies,

$$h_{at} = e^{\frac{1-\mu}{\mu}(z_{mt} - z_{at})} \frac{\omega_a}{\omega_m} h_{mt}$$
$$h_{st} = e^{\frac{1-\mu}{\mu}(z_{mt} - z_{st})} \frac{\omega_s}{\omega_m} h_{mt}$$

Adding the market clearing condition,

$$h_{mt} = \frac{1}{e^{\frac{1-\mu}{\mu}(z_{mt} - z_{at})} \frac{\omega_a}{\omega_m} + 1 + e^{\frac{1-\mu}{\mu}(z_{mt} - z_{st})} \frac{\omega_s}{\omega_m}} \tag{4}$$
$$h_{at} = \frac{e^{\frac{1-\mu}{\mu}(z_{mt} - z_{at})} \frac{\omega_a}{\omega_m}}{e^{\frac{1-\mu}{\mu}(z_{mt} - z_{at})} \frac{\omega_a}{\omega_m} + 1 + e^{\frac{1-\mu}{\mu}(z_{mt} - z_{st})} \frac{\omega_s}{\omega_m}} \tag{5}$$
$$h_{st} = \frac{e^{\frac{1-\mu}{\mu}(z_{mt} - z_{st})} \frac{\omega_s}{\omega_m}}{e^{\frac{1-\mu}{\mu}(z_{mt} - z_{at})} \frac{\omega_a}{\omega_m} + 1 + e^{\frac{1-\mu}{\mu}(z_{mt} - z_{st})} \frac{\omega_s}{\omega_m}} \tag{6}$$

Equations (4) through (6) contain the main insights of the model. Assume first that z_m

grows at the same rate as z_s, and z_a grows faster. Then since $\mu < 1, h_m$ grows in time, and h_a falls. This fact accounts for the first part of structural transformation, when manufacture grows and agriculture falls.

Next consider that if z_m grows faster than z_s, h_m falls at the expense of h_s, accounting for the second part of the structural transformation process, when manufacturing and agriculture fall and services increase.

In terms of volatility, note that h_j equals consumption in sector j. Take for example the manufacturing sector. The shock z_{mt} matters only with respect to the shocks z_{at} and z_{st}. In other words, the differences $z_{mt} - z_{at}$ and $z_{mt} - z_{st}$ drive the volatility of h_{mt}. As long as this relative volatility does not change, neither does the volatility of the manufacturing sector. The same is true for the other two sectors. So sector volatilities do not change. Next, I show that neither does aggregate volatility in this model. GDP is

$$
\begin{aligned}
Y_t &= p_{at}c_{at} + p_{mt}c_{mt} + p_{st}c_{st} = \\
&= e^{z_{mt}} e^{-z_{at}} e^{z_{at}} e^{\frac{1-\mu}{\mu}(z_{mt}-z_{at})} \frac{\omega_a}{\omega_m} h_{mt} + e^{z_{mt}} h_{mt} + e^{z_{mt}} e^{-z_{st}} e^{z_{st}} e^{\frac{1-\mu}{\mu}(z_{mt}-z_{st})} \frac{\omega_s}{\omega_m} h_{mt} \\
&= e^{z_{mt}} h_{mt} \left[e^{\frac{1-\mu}{\mu}(z_{mt}-z_{at})} \frac{\omega_{at}}{\omega_{mt}} + 1 + e^{\frac{1-\mu}{\mu}(z_{mt}-z_{st})} \frac{\omega_s}{\omega_m} \right] = \\
&= e^{z_{mt}}
\end{aligned}
$$

Thus, the only way that volatility can change in time is if the volatility of z_{mt} changes in time, that is, if the microeconomy changes, but this has nothing to do with macroeconomic changes, as the reallocation of resources across sectors. This is in line with Carvalho and Gabaix (2013), who find that the changes in microeconomic volatility can account fairly well for changes in macroeconomic volatility.

A problem with this simple model is that, to generate the reallocation of resources first from agriculture to manufacturing and services, and then from agriculture and manufacturing to services, the prices must decrease in agriculture relative to manufacturing. This is not what we observe, since agriculture prices in the data grew relative to manufacturing prices, as suggested in Figure 4. To address this, the next section develops this same result for a full fledge model of structural transformation, with capital, intermediate goods, and a more general utility function.

4 The Full Model

Time is discrete and runs $t = 0, 1, \ldots, \infty$. There is a measure one of identical households with preferences given by the following utility function,

$$U = E \sum_{t=0}^{\infty} \beta^t \left[\frac{\left[\sum_{j=a,m,s} \omega_j^{1/\mu} (c_{jt} + \bar{c}_j)^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}(1-\tau)}}{1-\tau} \right] \tag{7}$$

Herrendorf et al. (2013) show that this function can capture fairly well the rise in the share of services over manufacturing and agriculture on consumption given $\mu < 1$ and $\bar{c}_a < \bar{c}_m < \bar{c}_s$.

The production of the different goods requires capital, labor, and intermediate goods. The technology for producing these goods is

$$y_{jt} = e^{z_{jt}} \left(k_{jt}^{\alpha} h_{jt}^{1-\alpha} \right)^{\nu} n_{jt}^{1-\nu} \tag{8}$$

for $j = a, m, s$, where n is the intermediate good.

The shocks z_{jt} are independent random variables. Assume they are governed by stochastic processes $F_j(z)$. The investment good technology is the manufacturing good, as in Moro

(2012) among others. Capital is accumulated using investment in standard ways

$$k_{t+1} = (1-\delta)k_t + x_t \tag{9}$$

The intermediate good is produced with a combination of each consumption good. The functional form defers from a standard Cobb Douglas assumption so that, in equilibrium, the share of each input changes as in the data. Figure 3 shows how these shares have changed since 1947. In 1947, 64 percent of intermediate goods were services, and 28 percent of intermediates were manufacturing goods. In 2009 these shares changed to 86 percent and 13 percent, respectively.

The technology to produce the intermediate good is

$$n_t = \left[\sum_{j=a,m,s} \lambda_j^{1/\varphi} q_{jt}^{\frac{\varphi-1}{\varphi}} \right]^{\frac{\varphi}{\varphi-1}} \tag{10}$$

where the λ_j's are constant denoting the relative weight of each good and q_{jt} is the quantity of good j used to make the intermediate good in period t. As in the case of the utility function, I choose this functional form to replicate the observed pattern of the composition of intermediate goods in the economy. The main difference is that this function features constant returns to scale, which is convenient for aggregation.

Feasibility implies

$$y_{at} = c_{at} + q_{at} \tag{11}$$

$$y_{mt} = c_{mt} + x_{mt} + q_{mt} \tag{12}$$

$$y_{st} = c_{st} + q_{st} \tag{13}$$

$$n_t = \sum_{j=a,m,s} n_{jt} \tag{14}$$

$$k_t = \sum_{j=a,m,s} k_{jt} \tag{15}$$

$$1 = \sum_{j=a,m,s} h_{jt} \tag{16}$$

4.1 Equilibrium

I solve for a recursive solution for the social planner. This optimal allocation is the equilibrium allocation in this model, with no frictions or incompleteness. The social planner solves

$$V(z,k) = \max_{\{c_a,c_m,c_s,k'\}\geq 0} \left[\frac{\left[\sum_{j=a,m,s} \omega_j^{1/\mu} (c_j + \bar{c}_j)^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}(1-\tau)}}{1-\tau} \right] + \beta E V(z',k'|z_a,z_m,z_s) \tag{17}$$

$s.t.$ equations (8) through (16)

Define the aggregate consumption good as

$$C = \left[\sum_{j=a,m,s} \omega_j^{1/\mu} (c_j + \bar{c}_j)^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}$$

The first order conditions to this problem imply that

$$c_j + \bar{c}_j = \frac{\omega_j}{\omega_m}(c_m + \bar{c}_m), \quad j = a, s$$

Thus,

$$C = \frac{c_m + \bar{c}_m}{\omega_m} \left[\sum_{j=a,m,s} \omega_j^{\mu} \right]^{\frac{\mu}{\mu-1}}$$

The difference with the simple model is that with capital and intermediate goods it is no longer the case that c_m is a function of only the shock to the manufacturing sector, so the result is not as straightforward. Thus, to see whether structural transformation affects volatility, I calibrate and simulate the model.

As in the simple model problem, to obtain a measure of GDP I define prices for the agriculture, manufacturing, and services goods. Once I find the equilibrium allocations, I derive the implied prices to compute measured GDP. The next proposition describes what these prices are.

Proposition 1 *Let $p_{jt}, j = a, m, s,$ be the price of the consumption good in sector j and v_t be the price of the intermediate good. In equilibrium, these prices are*

$$v_t = \left[\sum_{j=a,m,s} \lambda_j p_{jt}^{1-\varphi} \right]^{\frac{1}{1-\varphi}} \tag{18}$$

$$p_{at} = e^{z_{mt}} e^{-z_{at}} \tag{19}$$

$$p_{st} = e^{z_{mt}} e^{-z_{st}} \tag{20}$$

Proof I omit the subindex t for the proof. Equation (18) is a Dixit Stiglitz price index, that is, the minimum cost to buy one unit of the intermediate good.

Equations (19) and (20) come from the first order conditions of the firms:

$$\max p_j e^{z_j} (h_j^{1-\alpha} k_j^{\alpha})^{\nu} n_j^{1-\nu} - wh_j - rk_j - vn_j$$

where w is the wage rate and r the rental price of capital. Let $\tilde{y}_j = (h_j^{1-\alpha} k_j^{\alpha})^{\nu} n_j^{1-\nu}$. The first order conditions imply, for $j = a, m, s$,

$$p_j e^{z_j} \frac{\tilde{y}_j}{h_j} = w$$
$$p_j e^{z_j} \frac{\tilde{y}_j}{k_j} = r$$
$$p_j e^{z_j} \frac{\tilde{y}_j}{n_j} = v$$

From these equations, it is straightforward to see that, for $j = a, m, s$,

$$\frac{(1-\alpha)k_j}{\alpha h_j} = \frac{w}{r}$$
$$\frac{(1-\nu)k_j}{\alpha \nu n_j} = \frac{v}{r}$$

Thus, the ratios k/h and k/n is the same for all sectors, which implies that $\frac{\tilde{y}_j}{h_j}$, $\frac{\tilde{y}_j}{k_j}$ and $\frac{\tilde{y}_j}{n_j}$ are the same for all sectors. Given that $p_m = 1$, for $j = a, s$,

$$p_j e^{z_j} \frac{\tilde{y}_j}{h_j} = p_j e^{z_j} \frac{\tilde{y}_m}{h_m} = e^{z_m} \frac{\tilde{y}_m}{h_m} \Rightarrow p_j = e^{z_m} e^{-z_j}$$

■

Given these prices, GDP in period t is

$$Y_t = p_{at} c_{at} + p_{mt}(c_{mt} + x_t) + p_{st} c_{st}$$

4.2 The Euler Equation

Solving problem (17) and using the prices as defined in equations (19) through (20), the Euler equation is

$$\frac{1}{C} = E\left\{\frac{\beta}{C'}\left(\alpha\nu\left(\frac{(1-\nu)}{v'}\right)^{\frac{1-\nu}{\nu}} e^{\frac{2z'_m}{(1+\nu)}} k'^{\alpha-1} + 1 - \delta\right)\right\} \tag{21}$$

This equation is key to find the computational solution to the problem, as outlined in the next section.

4.3 Solution

Solving the problem presents a computational challenge. Standard techniques commonly used in real business cycle models cannot be applied in this case, since there is no steady state. To work around this issue, I use the parameterized expectation approximation technique proposed by den Haan and Marcet (1990).

The specific algorithm is described in Appendix A. Intuitively, it works by approximating the unknown part of the Euler equation with a function of state variables. The Euler equation is equation (21).

The right hand side of this equation is unknown. By definition, it must depend on the state variables of the model: z_{at}, z_{mt}, z_{st} and k_t. The algorithm postulates a log linear relationship between the left hand side and a function of these state variables. In fact, the variables I use to predict this term are $z_{at}, z_{mt}, z_{st}, v_t$ and k_t. These are the variables that yielded the best results among the options explored. The particular functional form for this relation is

$$\begin{aligned}\log \Psi(k_t, z_{at}, z_{mt}, z_{st}, v_t) =& \eta_1 + \eta_2 \log(k_t) + \eta_3 z_{at} + \eta_4 z_{mt} + \eta_5 z_{st} + \\ & \eta_6 \log(v_t) + \eta_7 (\log(k_t))^2 + \eta_8 \log(k_t) \log(v_t) z_{mt}\end{aligned} \tag{22}$$

This method consists of "guessing" parameters for the η's in the above expression. Based on this guess, run the model for many periods, compute the term on the right hand side of the Euler equation, and run a regression between the log of this term and the variables used as predictors. This yields new estimates for the η's. These are used to update the initial guesses. The process stops when the updated guesses and the new estimates are sufficiently close.

5 Calibration

One period is one quarter, and I use quarterly data for the United States from 1947 to 2007. Consider the stochastic processes that govern the shocks in each sector, $F_j(z)$. I assume their growth rate follows an AR(1) process with unconditional mean γ_j. That is, let $g_{j,t} = z_{j,t} - z_{j,t-1}$, then,

$$g_{j,t+1} = \rho g_{j,t} + (1-\rho)\gamma_j + \varepsilon_t, \quad \rho \in (-1, 1), \varepsilon_t \sim N(0, \sigma_j^2) \tag{23}$$

This assumption implies that the log of the growth of the prices of each consumption good follows an AR (1) process.[1] To see this, note that for $j = a, s$,

$$\log\left(\frac{p_{j,t+1}}{p_{j,t}}\right) = (z_{m,t+1} - z_{m,t}) - (z_{j,t+1} - z_{j,t}) =$$
$$= \rho[(z_{m,t} - z_{m,t-1}) - (z_{j,t} - z_{j,t-1})] + (1-\rho)(\gamma_m - \gamma_j) + \varepsilon_{m,t} - \varepsilon_{j,t}$$
$$= \rho \log\left(\frac{p_{j,t}}{p_{j,t-1}}\right) + (1-\rho)(\gamma_m - \gamma_j) + \varepsilon_{m,t} - \varepsilon_{j,t} \tag{24}$$

Figure 6 plots the growth rate of the prices of the agriculture good and service good relative to the manufacturing good. At first sight, the series seem to be autorregressive.

Next, I estimate the parameters in equation (24). Since by assumption $\varepsilon_{m,t}$ is not correlated with either $\varepsilon_{a,t}$ or $\varepsilon_{s,t}$, let $\varepsilon_{ma,t} = \varepsilon_{m,t} - \varepsilon_{a,t}$ and $\varepsilon_{ms,t} = \varepsilon_{m,t} - \varepsilon_{s,t}$ and treat these as a new random shocks. Notice that the assumptions imply $E(\varepsilon_{ma,t}) = E(\varepsilon_{ms,t}) = 0$ and $Var(\varepsilon_{ma,t}) = \sigma_m^2 + \sigma_a^2$ and $Var(\varepsilon_{ms,t}) = \sigma_m^2 + \sigma_s^2$.

Equation (24) can identify $\rho, \gamma_m - \gamma_a, \gamma_m - \gamma_s, \sigma_m^2 + \sigma_a^2$ and $\sigma_m^2 + \sigma_s^2$. Next I show how to identify $\sigma_a^2 + \sigma_s^2$, and therefore identify all σ_a, σ_m and σ_s.

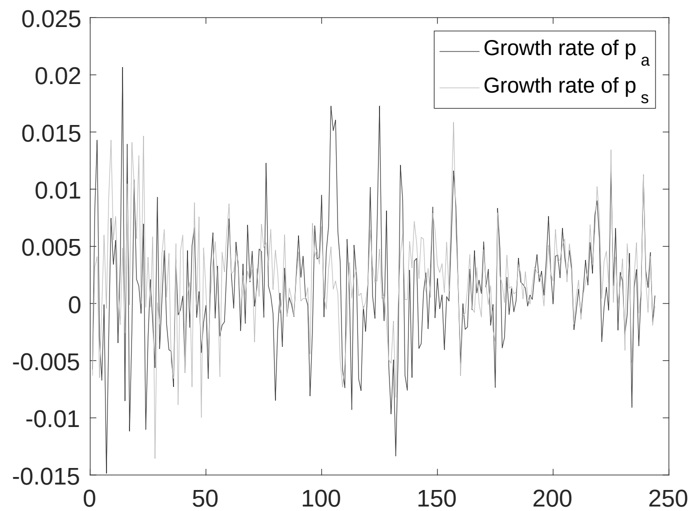
Notice

$$\log\left(\frac{p_{s,t+1}}{p_{s,t}}\right) - \log\left(\frac{p_{a,t+1}}{p_{a,t}}\right) = (z_{a,t+1} - z_{a,t}) - (z_{s,t+1} - z_{s,t}) =$$
$$= \rho((z_{a,t} - z_{a,t-1}) - (z_{s,t} - z_{s,t-1})) + (1-\rho)(\gamma_s - \gamma_a) + \varepsilon_{at} - \varepsilon_{st} =$$
$$= \rho\left[\log\left(\frac{p_{s,t}}{p_{s,t-1}}\right) - \log\left(\frac{p_{a,t}}{p_{a,t-1}}\right)\right] + (1-\rho)(\gamma_s - \gamma_a) + \varepsilon_{at} - \varepsilon_{st} \tag{25}$$

This equation can identify $\rho, \gamma_s - \gamma_a$ and $\sigma_a^2 + \sigma_s^2$. Notice that this equation estimates ρ in

[1]Notice that I am forcing the autocorrelation parameters ρ to be the same for all sectors. Without this assumption the algebra using relative prices would not follow.

Figure 6: Growth rate of Relative Prices



a different way than equation (24). Call the estimate in equation (24) ρ_0 and the one in equation (25) ρ_1. Let

$$\sigma_{as} = \sigma_a^2 + \sigma_s^2$$

$$\sigma_{ma} = \sigma_a^2 + \sigma_m^2$$

$$\sigma_{ms} = \sigma_m^2 + \sigma_s^2$$

From here, get all the σ's as follows:

$$\underbrace{\sigma_{ma} - \sigma_m^2}_{\sigma_a^2} + \underbrace{\sigma_{ms} - \sigma_{ms}}_{\sigma_s^2} = \sigma_{as}$$

So

$$\sigma_m = \sqrt{\frac{1}{2}(\sigma_{ma} + \sigma_{ms} - \sigma_{as})}, \sigma_a = \sqrt{\sigma_{ma}} - \sigma_m, \sigma_s = \sqrt{\sigma_{ms}} - \sigma_m$$

Notice that one cannot do the same with the γ's since the equations are not linearly independent, so I identify γ_m by matching the growth rate in consumption per capita in the data.

Summarizing, I perform the following regressions. I regress simultaneously the two equations implied by equation (24) (setting $j = a$ and $j = s$) and I regress by OLS the equation implied in (25). Notice that the two equations in equation (24) and equation (25) are linearly dependent, and therefore I cannot regress them simultaneously.

The equations to be regressed are (the first two are regressed simultaneously, under the constraint that the parameter ρ is the same on both equations):

$$g_{a,t} = \gamma_{ma} + \rho_0 g_{a,t-1} + \varepsilon_{ma,t}$$

$$g_{s,t} = \gamma_{ms} + \rho_0 g_{s,t-1} + \varepsilon_{ms,t}$$

$$\Delta g_{sa,t} = \gamma_{sa} + \rho_1 \Delta g_{sa,t-1} + \varepsilon_{sa,t}$$

where $g_{j,t} = \log\left(\frac{p_{j,t+1}}{p_{j,t}}\right)$ and $\Delta g_{sa,t} = \log\left(\frac{p_{s,t+1}}{p_{s,t}}\right) - \log\left(\frac{p_{a,t+1}}{p_{a,t}}\right)$.

Table 1 shows the results of the different estimations. The term in parenthesis is the standard error. All results are significant at the 1% level. Notice ρ_0 and ρ_1 are not statistically different from each other. And I cannot reject the hypothesis that $\gamma_{ma} - \gamma_{ms} = \gamma_{as}$.

Coefficient	Estimate
ρ_0	0.1666049
	(0.044553)
ρ_1	0.2631568
	(0.0621528)
γ_{ma}	0.0011342
	(0.0003459)
γ_{ms}	0.0018535
	(0.0002858)
γ_{as}	0.006358
	(0.0002979)
std(ε_{ma})	0.0053121
std(ε_{ms})	0.0041863
std(ε_{sa})	0.00457

Table 1: Estimates in the stochastic processes.

Interpreting these coefficients implies that $\gamma_m - \gamma_a = 0.0014$, or that the rate of growth in manufacturing is 0.14 percent larger than in agriculture, and that $\gamma_m - \gamma_s = 0.0022$, so that the rate of growth in manufacturing is 0.22 percent larger than in services. Also, this implies $\sigma_a = 0.0040, \sigma_m = 0.0035$ and $\sigma_s = 0.0023$. This confirms that services is the least volatile sector.

The parameters in the utility function are $\omega_a, \omega_m, \omega_s, \bar{c}_a, \bar{c}_a, \bar{c}_a$, and μ. Herrendorf et al. (2013) shows that normalizing one of the non homotheticity parameters does not affect the results, so I set $\bar{c}_m = 0$. I also normalize $\omega_m = 1$. From Herrendorf et al. (2013), I set $\mu = 0.81$. The rest of the parameters are calibrated to match:

- The share of manufacturing to total consumption in 1947.1
- The share of services to total consumption in 1947.1
- The share of manufacturing to total consumption in 2007.4

- The share of services to total consumption in 2007.4

The parameters in the production function of the intermediate good are calibrated similarly. These parameters are $\varphi, \lambda_a, \lambda_m$, and λ_s. I normalize $\lambda_m = 1$. The rest of the parameters match the following moments:

- The share of manufacturing in total intermediates in 1987
- The share of services in total intermediates in 1987
- The share of services in total intermediates in 2007

The remaining parameters are calibrated as follows. ν is set to match the share of intermediates on total output in the economy, from the 2007 input output tables. α is set so that the share of labor income is 2/3 of total value added.

Table 2 summarizes the targets and the results of the calibration.

6 Results

I perform 20,000 simulations of an economy with 1,000 periods. Of these, 4,081 converge to a solution. In each successful simulation, I retain only the last 244 periods for the analysis, to match the 244 quarters from 1947.1 through 2007.4.

6.1 Goodness of Fit

Before documenting the results, it is worth to explore the predictive power of these regressions. Consider equation (22), the key equation relating the algorithm method used for

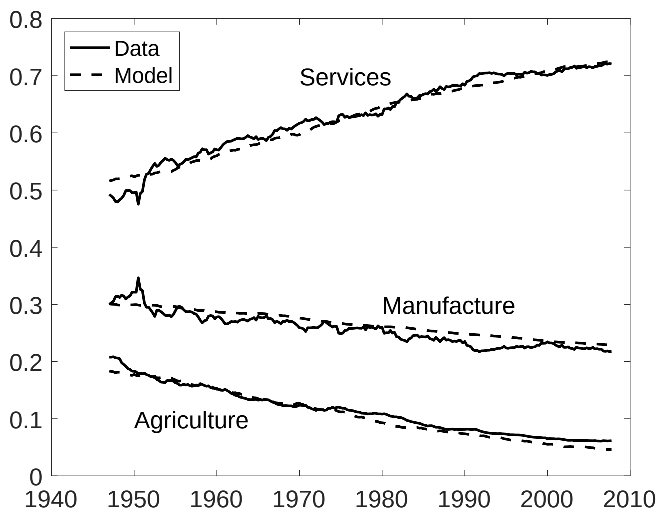
Table 2: Calibration

Parameter	Target	Value
α	Wage income to value added is 70%	0.3000
β	Risk free interest rate of 1%	0.9900
τ	log preferences	1.0000
δ	Match an investment to output ratio of 20%	0.0200
ν	Share of value added on total output	0.4522
μ	Herrendorf et al. (2013)	0.8100
$\bar{c}_a$	Match sector shares	-0.2573
$\bar{c}_m$	Normalization	0.0000
$\bar{c}_s$	Match sector shares	0.8080
λ_a	Match intermediate shares	0.0635
λ_m	Normalization	1.0000
λ_s	Match intermediate shares	1.2617
φ	Match intermediate shares	0.8854
ρ	Price regressions	0.1666
σ_a	Price regressions	0.0040
σ_m	Price regressions	0.0035
σ_s	Price regressions	0.0023
γ_a	Price regressions	0.0014
γ_m	Match increase in real consumption	0.0029
γ_s	Price regressions	0.0006

solving the model. The R^2 in this relationship describes the accuracy of the predictions of the agents in this economy, and if it were low, then the algorithm would not be successful and the results less reliable. The R^2 is extremely high (the average across simulations is 0.999901), suggesting that the algorithm can be relied upon.

The model also does a good job in replicating the pattern of structural transformation. Figure 7 shows the data together with the result of one simulation. The closeness of the curves confirms the good job the model does.

Figure 7: Data vs. Model



An area in which the model does not perform well is that the overall variance of the cyclical component of consumption is smaller than in the data. I obtain the cyclical component by detrending the data using a Hodrick Prescott filter with smoothing parameter 1,600. In the data, the standard deviation of the cyclical component of real consumption is equal to 0.0126. In the simulations, the average is 0.005. This being said, I also ran the simulations augmenting the variance of each sector so that the standard deviation is 0.05 and the results do not change.

Table 3: Results

Relative St Dev	Data	Model (Average across simulations)
Output	0.53	0.98
Consumption	0.57	1.01
Investment	0.58	0.97

6.2 Aggregate Volatility

To measure how well the model can account for the reduction in volatility, I proceed as follows. I produce series for GDP, consumption, and investment in the model. I then detrend these series using an HP filter with smoothing parameter 1,600. Finally, I study the deviations from trend by diving these into two periods. The first covers the quarters between 1947 and 1983, and the second covers the quarters between 1984 and 2007. The model produces a very minor reduction in aggregate volatility of output and investment, and no reduction in the volatility of consumption (in fact, this increases slightly). Table 3 shows the standard deviation in the second period divided by the first period in the data, and the average of this ratio across simulations in the model. While the full model can account for a larger drop than the simple model in section 5, the reduction is too small to matter.

This drives the conclusion that the shift in resources from high volatility sectors like agriculture and manufacture to low volatility sectors like services has hardly any effect on aggregate volatility. All the reduction in volatility observed during the Great Moderation must be accounted by microeconomic changes, and not by the macroeconomic reallocation of resources.

7 Conclusion

The US economy in recent history has become more intensive in services, rather than manufacturing or agriculture. Services is less volatile than manufacturing or agriculture. The combination of these two observations has led many researchers to attribute some of the reduction in aggregate volatility that we know as Great Moderation to the reallocation of resources.

In this paper, I show that this need not be the case. Moreover, using traditional models of structural transformation, enhanced to account for business cycle volatility, I conclude that the reallocation of resources most likely played no role in the reduction in aggregate volatility.

What this implies is that the reduction in volatility must come from microeconomic changes in sector volatility, consistent with the findings of Carvalho and Gabaix (2013), and leaving no role for the macroeconomic reallocation mechanism.

Contrary to ideas proposed in other papers, such as Moro (2012), Moro (2015) or Ngouana (2013), development does not necessarily reduce volatility via structural transformation. Developing countries should not expect its volatility to decrease just because they grow. To reduce volatility, a country must make sound policy, aiming at reducing within sector volatility, not hope to reduce it by shifting resources between sectors.

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Appendix A The Parameterized Expectations Approximation

The model is solved using an algorithm developed by den Haan and Marcet (1990). Since I do not know how the expectation of future utility looks like (the right hand side of the Euler equation (21)), I need to approximate it. Standard techniques approximate it by loglinearizing the first order conditions and using a Taylor expansion around the steady state. This is not possible in this case since there is no steady state.

The Parameterized Expectations Approximation Method approximates the left hand side of the Euler equation, which is unknown to the economist, with a function of the state variables. These are the aggregate capital stock K, and the shocks z_a, z_m, z_s. The Euler condition is:

$$\frac{1}{C} = E\left\{\frac{\beta}{C'}\left(\alpha\nu\left(\frac{(1-\nu)}{v'}\right)^{\frac{1-\nu}{\nu}} e^{\frac{2z_m'}{(1+\nu)}} K'^{\alpha-1} + 1 - \delta\right)\right\}$$

The problem with this equation is that agents have to make forecasts on C', z_m' and K'. The solution proposed by den Haan and Marcet is to use the state variables to predict these future variables.

The algorithm uses as state variables the aggregate stock of capital K, the individual shocks $z = (z_a, z_m, z_s)$ and the price of the intermediate good v.

A crucial assumption is which function to use to approximate this expectation. I follow den

Haan and Marcet (1990)'s suggestion and use the following functional form[2]

$$E\left\{\frac{\beta}{C'}\left(\alpha\nu\left(\frac{(1-\nu)}{v'}\right)^{\frac{1-\nu}{\nu}} e^{\frac{2z'_m}{(1+\nu)}}K'^{\alpha-1}+1-\delta\right)\right\}=\Psi(K_t,z_{xt},P_t)$$

where

$$\begin{aligned}\log\Psi(K,z_a,z_m,z_s,v)=&\eta_1+\eta_2\log(K)+\eta_3 z_a+\eta_4 z_m+\eta_5 z_s+\\&\eta_6\log(v)+\eta_7(\log(K))^2+\eta_8\log(K)\log(v)z_m\end{aligned}$$

Given this function, I proceed as follows:

1. Pick some initial $\eta_i, i=1,\dots,8$.
2. Given states K, z_j, v and η's, compute $\Psi_t=\Psi(K_t,P_t)$ get C
3. Get K' from the market clearing condition and v' from equation (18).
4. Repeat this procedure for all t, obtaining the entire sequences of $\{C_t,K_t,v_t\}$.
5. Use these sequences to compute

$$Y_{t+1}=\frac{\beta}{C_{t+1}}\left(\alpha\nu\left(\frac{(1-\nu)}{v_{t+1}}\right)^{\frac{1-\nu}{\nu}} e^{\frac{2z'_{m,t+1}}{(1+\nu)}}K_{t+1}^{\alpha-1}+1-\delta\right)$$

6. Obtain new η's by regressing (call these $\tilde{\eta}$)

$$\begin{aligned}\log(Y_{t+1})=&\tilde{\eta}_1+\tilde{\eta}_2\log(K_t)+\tilde{\eta}_3 z_{at}+\tilde{\eta}_4 z_{mt}+\tilde{\eta}_5 z_{st}+\\&\tilde{\eta}_6\log(v_t)+\tilde{\eta}_7(\log(K_t))^2+\tilde{\eta}_8\log(K_t)\log(v_t)z_{mt}+error_t\end{aligned}$$

[2] I have tried with other functions as well and obtain similar results.

7. Compare η with $\tilde{\eta}$

- If $\sum_{i=1}^{5}(\eta_i - \tilde{\eta}_i)^2 > 1e^{-7}$, set $\eta_i = \Gamma\eta_i + (1-\Gamma)\tilde{\eta}_i, \Gamma \in (0,1]$ and go to step 2 (I use $\Gamma = 0.9$)
- Otherwise stop iteration

The estimates obtained vary across simulations, but they stay very close to each other. Table 4 shows the average across simulations.

Table 4: Mean of Estimated Parameters

	η_1	η_2	η_3	η_4	η_5	η_6	η_7	η_8	R^2
Estimate	1.04	-0.85	1.43	-33.66	-31.54	58.05	0.10	-0.45	0.99