

Essays on structural change, total factor productivity growth and
government debt

by

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B.A., Kwame Nkrumah University of Science and Technology, Kumasi,
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AN ABSTRACT OF A DISSERTATION

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Abstract

This dissertation comprises three chapters. The first chapter addresses differences in the growth rate of total factor productivity across sectors. The second chapter explores the effect of government debt on productivity growth, with focus on the decomposed components of productivity growth. The third chapter explores the aggregate and sector-level effects of shocks to total factor productivity across sectors.

The first chapter, co-authored with Dr. William Blankenau, explores whether total factor productivity (TFP) growth differs across the manufacturing, service, and agriculture sectors. Sector-level labor productivity can be calculated directly from available data. However, this measure depends on sector-level prices and capital/labor ratios as well as TFP. To isolate the effect of TFP requires a multi-sector model of economic growth that allows for differential TFP growth. We use a version of a multi-sector model of structural change to identify relative productivity growth rates in a large group of countries. For our benchmark parameterization, we find that TFP has grown faster in the agriculture sector than in the manufacturing sector at all income levels, but this difference decreases with per capita output. We find that TFP for services has grown more rapidly than for manufacturing in low-income countries. This difference also decreases with per capita output and is negative at higher levels of income. The findings support differential TFP growth rates as a source of industrial dynamics and allow such models to explain a wider set of dynamics.

In the second chapter, I revisit the relationship between government debt and labor productivity growth, offering a novel focus on the decomposed components of labor productivity growth: the intra-industry and structural change components. Using a panel dataset of 103 countries from 1950 to 2017, labor productivity growth is decomposed into its constituent components, and panel fixed effects, system GMM, and dynamic panel threshold models are employed to estimate the effects of government debt on labor productivity. The results show

that high levels of government debt significantly reduce total productivity growth, primarily through a negative effect on the intra-industry component, while the structural change component remains unaffected. Threshold analysis reveals non-linear effects, with dynamic thresholds of 31% and 94% for total productivity growth and the intra-industry component, respectively. Exogenously imposed thresholds confirm significant negative effects beyond a 60% debt-to-GDP ratio. The study also identifies the crowding-out of private and public investment as key channels through which government debt affects labor productivity. Subgroup analysis reveals that the adverse effects of debt are pronounced in emerging and developing economies, while advanced economies show no statistically significant effects. Robustness checks, using 3-year intervals and external debt instead of general government debt, confirm the consistency of the results. Overall, the findings underscore the importance of prudent fiscal management and highlight that the composition of labor productivity growth, particularly within-industry improvements, is central to understanding the macroeconomic consequences of government debt.

The third chapter, co-authored with Dr. William Blankenau, revisits the role of sectoral total factor productivity (TFP) shocks in shaping macroeconomic and sectoral dynamics within a multi-sector model. We adapt the structural change framework of [Ngai & Pissarides \(2007\)](#) to incorporate stochastic, sector-specific TFP shocks and examine their business cycle implications. The model features three sectors: manufacturing, agriculture, and services, with the manufacturing sector producing a good used for both consumption and investment, while the other two produce pure consumption goods. Under the baseline scenario with flexible prices, frictionless labor markets, and uniform initial productivity levels, only shocks to the investment good (manufacturing) affect aggregate outcomes. Shocks to the consumption sectors influence only sectoral dynamics. These results arise primarily from the absence of labor market frictions and the assumption of flexible prices. Sector-level analysis shows that the impulse responses of sectoral variables depend largely on initial TFP levels and the degree of substitutability between goods. Introducing labor adjustment costs enables shocks to the consumption sectors to propagate to the aggregate economy. Moreover, whether these shocks are expansionary or contractionary depends on the degree of substitutability across

goods and the initial TFP levels of the shocked sector. Overall, the results highlight how labor market frictions, consumption flexibility, and varying sectoral productivity levels shape the transmission and macroeconomic relevance of sectoral TFP shocks.

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Dedication

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Chapter 1

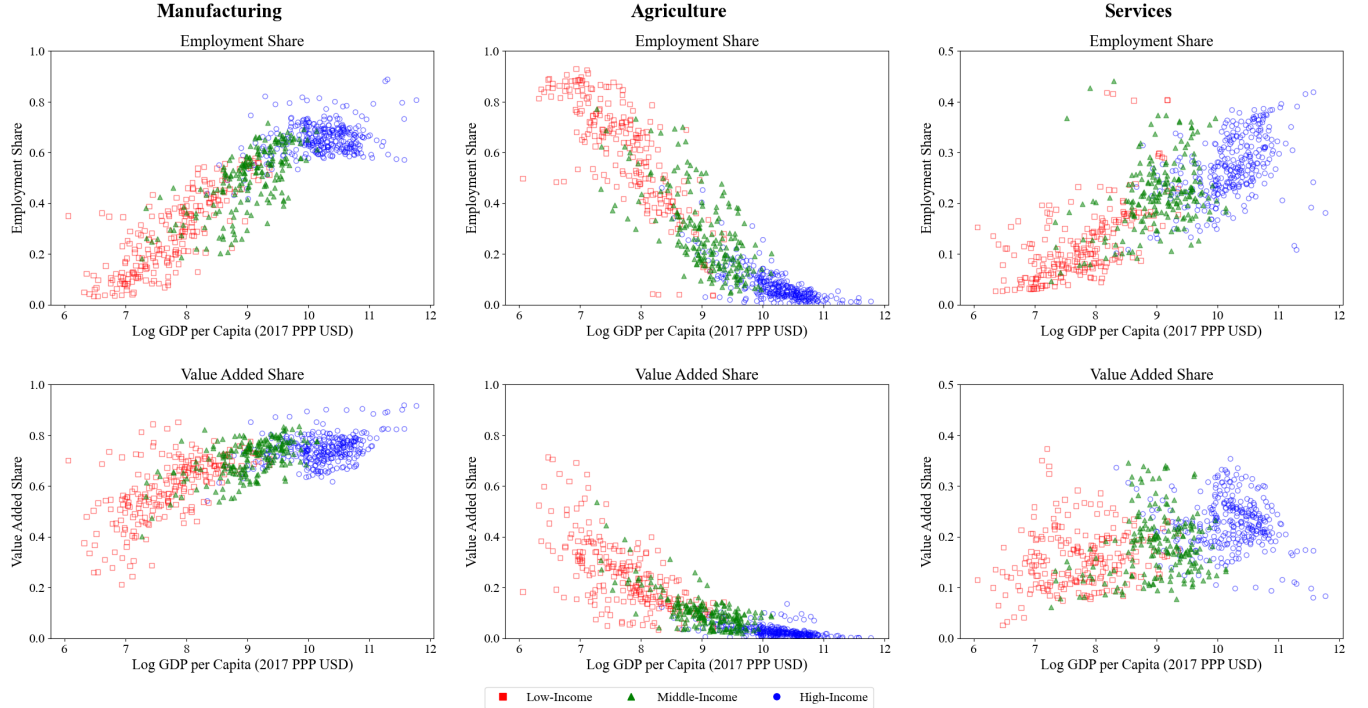
Does total factor productivity growth differ across sectors?

1.1 Introduction

In the early stages of economic development, increased output per capita commonly coincides with an increased share of the labor force employed in the manufacturing and service sectors, along with a decreased share employed in agriculture. The share of an economy's value added attributable to these sectors follows a similar pattern. At higher levels of development, these relationships in manufacturing weaken and may even reverse. The relationships persist in the agriculture and service sectors, even as agriculture approaches very low shares of employment and value added. These kinds of inter-sectoral labor reallocation that occur with economic transformation are what is mostly termed as structural change in the development literature ([Świecki, 2017](#)).

[Figure 1.1](#) provides panel data evidence of the transition from agriculture to manufacturing and services. The figure shows employment shares and value added shares at 5-year intervals for a large group of low-, middle-, and high-income countries. The strength of the relationships is striking. For example, among the lower decile of real GDP per capita observations, the labor and value added shares for manufacturing average 14% and 46%. For the

Figure 1.1: Patterns of structural change



Note: Figure [Figure 1.1](#) presents scatter plots of the log of GDP per capita against the sector employment shares and value added shares. The squares represent low-income countries, the triangles represent middle-income countries, and the circles represent high-income countries. Data on real GDP in 2017 PPP \$ and population are obtained from the Penn World Tables. Shares and labor productivity in PPP terms are computed from [Dieppe et al. \(2020\)](#).

top decile, the averages are 66% and 77%. Analogous measures for agriculture are 79% and 41% for the lower decile and 3% and 1.5% for the upper decile.

As a central feature of the world’s development experience, explaining these trends has been a key goal for some researchers exploring the foundations of economic growth. Several explanations can be found in the literature. [Echevarria \(1997\)](#), [Matsuyama \(1992\)](#), [Kongsamut et al. \(2001\)](#), and [Laitner \(2000\)](#) and others model structural change as stemming from differences in income elasticities. The papers use nonhomothetic preferences, and they generally argue that as income levels rise, households spend less on agricultural goods and more on services. This shift in demand triggers a decline in employment shares in agriculture and a corresponding increase in employment shares in services.¹ [Matsuyama \(2009\)](#) and [Uy et al. \(2013\)](#) also identify international trade as an important mechanism

¹This mechanism is supported by findings from [Comin et al. \(2021\)](#).

for structural change. They argue that the same fundamental forces can produce markedly different patterns of structural change depending on whether the economy is closed or open. In a closed economy, rapid productivity growth in manufacturing tends to reduce the sector's share of employment. However, in an open economy, manufacturing employment may increase due to specialization driven by comparative advantage ([Świecki, 2017](#)).

The earliest explanation of structural change remains central to the discussion. Sectoral differences in total factor productivity (TFP) as the driving force of structural change were proposed by [Baumol \(1967\)](#) and [Baumol et al. \(1985\)](#). In their framework, the economy has two sectors: a progressive sector that is more productive and uses capital and newer technologies, and a stagnant sector that uses labor as input and produces mostly services as the final output. They argue that because of factor mobility, the production costs and prices of the stagnant sector will continue to rise, a phenomenon known as the “Baumol’s cost disease”. Over time, the stagnant sector, which is less productive, will continue to attract more labor to satisfy demand, even though it is relatively less productive. Other prominent recent papers exploring this channel include [Ngai & Pissarides \(2007\)](#) and [Acemoglu & Guerrieri \(2008\)](#). Essentially, high TFP in a sector reduces its need for labor, causing labor to shift towards sectors with lower TFP growth.

From quantitative studies, differential TFP growth rates arise as a potentially important explanation of these trends. [Herrendorf et al. \(2014\)](#) attributes the decline in agricultural shares and the corresponding rise in service sector shares in most advanced countries to the fact that the agricultural sector had the highest TFP growth, while the service sector recorded the lowest. [Świecki \(2017\)](#) builds a model nesting four different explanations and finds sector-biased technological progress to be the most significant of these in explaining the decline in manufacturing shares and the corresponding rise in service sector shares in developed economies.

This chapter contributes to the literature on structural change by exploring cross-country differences in sectoral TFP growth rates in a large number of countries. At the aggregate level, cross-country TFP growth rates can be calculated from residuals in calibrated production functions. However, in considering TFP at the sector level, additional challenges arise.

Computing sector-level TFP values requires data on sector-level nominal value added, labor inputs, capital inputs, and prices. For most countries, the first two of these are available, while the second two are not.²

To study unobserved TFP, we build a sectoral growth model to map available data to unobserved TFP growth. Specifically, we develop a version of the model presented by [Ngai & Pissarides \(2007\)](#). Our version of this model has three sectors: manufacturing, agriculture, and services. The manufacturing sector produces both investment and consumption goods, while other sectors produce only consumption goods. Structural change arises through general equilibrium adjustments to differential growth rates of TFP by sector.

[Ngai & Pissarides \(2007\)](#) is a convenient starting point for our investigation. Most importantly, it allows a wide variety of sector-level dynamics to arise from different TFP growth rates. This includes a hump-shaped pattern for the labor shares for some sectors, which we discuss below. Moreover, a special case of their model allows balanced growth. As such, stable growth in aggregate measures arises despite distinctly unstable growth in the industries comprising these aggregates.³ This proves particularly convenient along the balanced growth path. Even off the balanced growth path, the model allows simple expressions for productivity differences.

The model requires only relative labor shares and the savings rate to find relative growth rates in productivity. Labor shares by sector are available from the Global Productivity database. We use the savings rates that arise in a calibrated version of the model. We begin by considering a special case of the model under which a closed-form solution exists. We then consider cases with a more realistic calibration and more realistic dynamics. We conclude our analysis by considering a small open economy version of the model.

A first implication of our model is that the underlying assumption of differential TFP growth rates in [Ngai & Pissarides \(2007\)](#) and other work is well supported. We refer to the

²[Herrendorf et al. \(2014\)](#) notes that verifying the characteristics of TFP growth within sectoral value-added production functions across countries is challenging, largely due to difficulties in accurately computing TFP. One of the main issues is that estimating real value-added requires information on the real quantity of intermediate inputs, which is seldom available for most countries.

³A related literature considers other underlying trends in labor markets that allow balanced growth in aggregates. See, for example [Blankenau & Cassou \(2006\)](#).

TFP growth rate in a sector minus the TFP growth rate in manufacturing as relative TFP growth. For agriculture, relative TFP growth is positive for each country group we consider; i.e., TFP growth in agriculture exceeds that in manufacturing. For services, relative TFP growth is non-zero in each country group. However, this is negative for the highest income group and positive for other groups.

A second implication is that relative TFP growth varies with per capita income. For agriculture, we find a significant negative relationship between relative TFP growth and per capita income. However, for all income levels spanned by our data, the conditional point estimate for relative TFP growth is positive. For services, we again find a significant negative relationship. For lower-income countries, the conditional point estimate for relative TFP growth is again positive, but for sufficiently large values, this is negative.

Overall, the findings show that differential TFP growth rates can be the source of observed sectoral dynamics. In the [Ngai & Pissarides \(2007\)](#) model, when the highest TFP growth is found outside the manufacturing sector, the manufacturing sector will see an increase in its labor inputs. However, this may be hump-shaped along the way as the TFP growth rates of other sectors fall below that of the manufacturing sector.⁴ We find that agriculture has the most rapid TFP growth rate. Thus, the model can explain the trends above.

Our finding of falling relative TFP growth can allow for a wider set of dynamics. A number of researchers have found that manufacturing has a hump-shaped pattern through development.⁵ The data in [Figure 1.1](#) hints at this. At high levels of output per person, the labor share appears to taper off and even fall with per capita output. While this pattern can arise for other goods in the [Ngai & Pissarides \(2007\)](#) model, it cannot for manufacturing. However, they consider only the case of differential but constant TFP growth rates. Our results suggest that manufacturing may eventually be the sector with the greatest TFP growth rate and will thus begin to lose employment share, yielding a hump-shaped profile of manufacturing employment shares.

In the next section, we present a description of the data to establish the facts about

⁴These results presume an elasticity of substitution for goods less than one, but they consider both cases.

⁵This behavior of manufacturing is noted by [Van Neuss \(2019\)](#), [Herrendorf et al. \(2014\)](#), and [Duarte & Restuccia \(2010\)](#).

structural change and provide additional insights. We then present the model in Section 3. In Section 4, we present a description of the calibration of the parameters used. In Section 5, we present the results, and in Section 6, we present the sensitivity analysis. We then conclude in Section 6.

1.2 Data description

We begin by exploring the process of structural change using the Global Productivity dataset compiled by [Dieppe et al. \(2020\)](#). This dataset contains value added and employment for nine broad sectors for about 103 countries, ranging from 1950 to 2017.⁶ They pool data from different sources including the World Bank World Development Indicators, the OECD STAN database, KLEMS, the Groningen Growth and Development Center (GGDC) database ([De Vries et al., 2015](#)), the Expanded Africa Sector Database (EASD) ([Mensah et al., 2018](#)), the APO Productivity Database, UN data, ILOSTAT, and national sources. We extract data ranging from 1975 to 2017. This is to allow for enough countries to be included in our sample, especially when we conduct the two-period analysis in our baseline estimation. Data on the gross domestic product (GDP), population, the market exchange rate, and price level of output-side real GDP relative to the United States are from the Penn World Tables (PWT 10.01).⁷

To allow for cross-country comparison, we convert value added in national prices into Purchasing Power Parity (PPP) terms. We do this by first converting the market exchange rate into PPP form by dividing it by the relative price level of GDP. We then divide the value added in national prices by the PPP exchange rate to make them comparable. Consistent with much of the empirical growth literature, we concentrate on 5-year non-overlapping intervals of the data for our analysis.

We consider a three-sector aggregation. That is, we aggregate the nine sectors into three

⁶Initial sectors include Agriculture, forestry, and fishing; Mining and quarrying; Manufacturing; Utilities; Construction; Trade services; Transport services; Financial and Business Services; and Other services.

⁷The price level of output-side real GDP is a purchasing power parity (PPP)-adjusted measure of prices across countries. The 2017 price of US GDP is the base price. We use this to adjust the value added in local currency to PPP terms.

broad sectors we call manufacturing, agriculture, and services. Our choice of three sectors is motivated by the fact that we build our baseline model as a three-sector model. While the model could be extended to include additional sectors, using three sectors simplifies the analysis and helps focus on the broader patterns of structural change, as highlighted by the stylized facts. Details about the aggregation process are provided in the calibration section.

We classify countries into high-income (HIC), middle-income (MIC), and low-income (LIC) groups based on the World Bank's income classifications as cited in [Nada et al. \(2022\)](#). The World Bank divides countries into four categories: low-income, lower-middle-income, upper-middle-income, and high-income. For our purposes, we group low-income and lower-middle-income countries together under LIC, while our middle-income countries (MIC) correspond to the World Bank's upper-middle-income countries. Our high-income countries align directly with the World Bank's high-income classification. Our sample contains 43 HICs, 30 MICs, and 30 LICs.

We examine structural change in our dataset by analyzing trends in employment shares, value-added shares, and labor productivity across the three main sectors. [Figure 1.1](#) already gives some insight into the patterns of structural change we observe in our data. We observe that, with increasing income levels, both manufacturing and service sectors show rising employment and value-added shares, while the share of agriculture declines. Although not conclusive, manufacturing shares appear to follow the hump-shaped pattern frequently discussed in the literature. In the subsequent figures, we delve deeper into sector shares and productivity trends to offer further insights into the dynamics of structural change in our data.

[Figure 1.2](#) shows the evolution of sector employment shares for HICs, MICs, and LICs. The first column presents the trends for all countries, while the second column presents the annual average across the income groups. [Figure 1.3](#) and [Figure 1.4](#) are similarly organized presentations of value-added shares and labor productivity.

We consider manufacturing in Panels A and B of [Figure 1.2](#) - [Figure 1.4](#). We observe that HICs have higher manufacturing employment and value-added shares compared to MICs and LICs, though these shares are increasing across all income groups. Labor productivity in the

sector is also increasing across all countries.

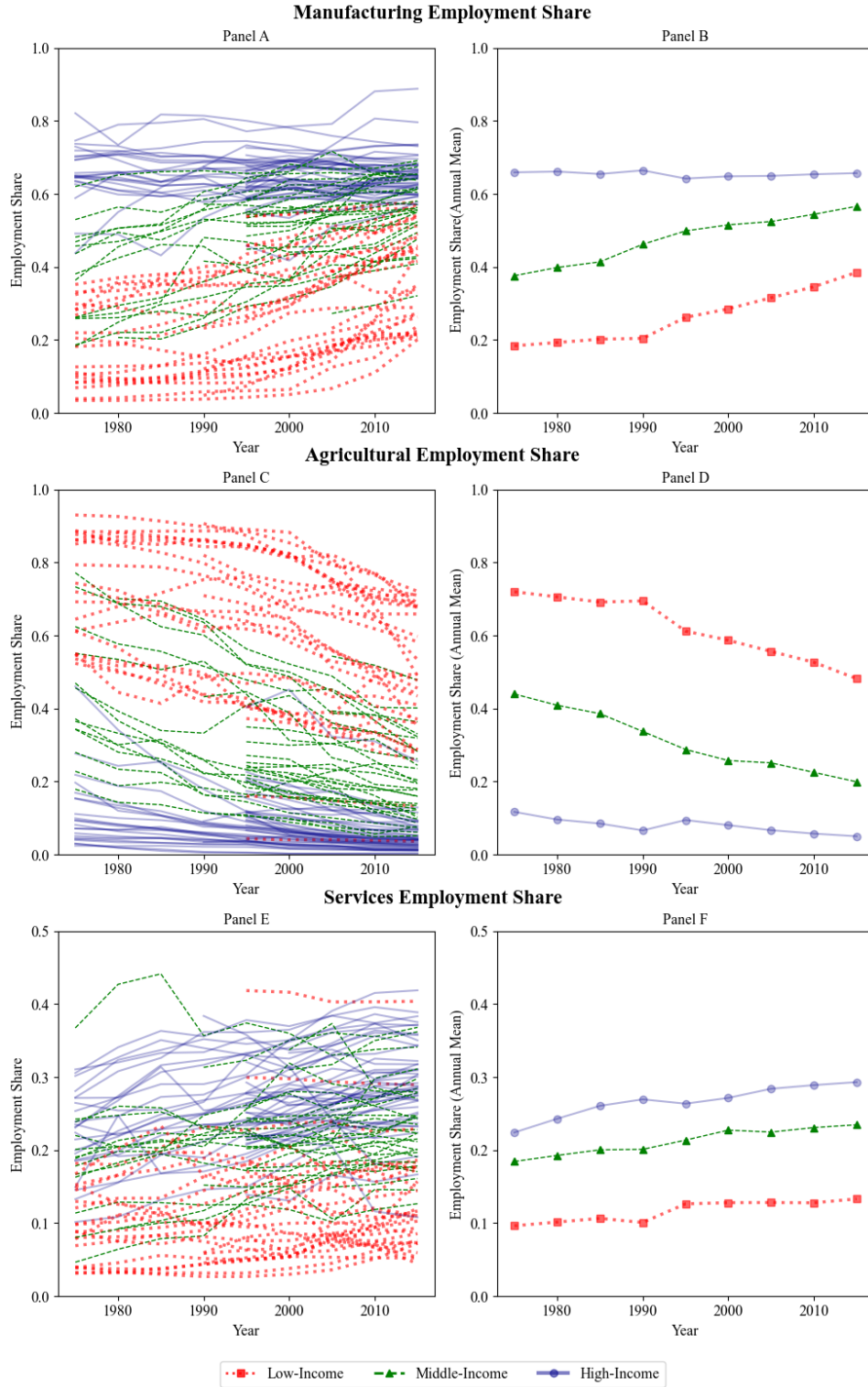
Looking at the agricultural sector, we observe a decline in employment shares for all countries (Panels C and D in [Figure 1.2](#)), in line with the stylized facts of structural change. Using hours worked, [Duarte & Restuccia \(2010\)](#) also find a similar decline in employment shares for the agricultural sector. [Sposi \(2019\)](#) also finds a similar trend for a sample of 41 countries from 1995 to 2011. Other papers, such as [Van Neuss \(2019\)](#) and [Herrendorf et al. \(2014\)](#), observe similar trends as well.

Another feature of this data is that LICs have a substantially larger share of employment in agriculture than MICs and HICs. This pattern corresponds with the declining value-added share of the agricultural sector portrayed in panels C and D of [Figure 1.3](#). It is worth noting that despite the low and declining agricultural employment shares for HICs, panels A and B in [Figure 1.3](#) show that the sector is relatively more productive in HICs compared to MICs and LICs. This is likely driven by significant capital-labor substitution that occurs across in the agricultural sector in HICs.

Concerning the service sector, the literature notes that the process of structural change is characterized by a steady increase in its employment share. Panels E and F in [Figure 1.2](#) exhibit such trends in the services employment shares. All countries experience a steady increase in the service employment share over time. These trends align with findings by [Van Neuss \(2019\)](#) and [Sposi \(2019\)](#). However, HICs have higher employment shares than MICs and LICs. The lowest service sector employment shares are recorded by LICs. It must be noted, however, that despite the rise in employment share in the service sector, Panels E and F in [Figure 1.3](#) show that there is a decline in its share in value added, especially for HICs. For MICs and LICs, the value added is relatively stable over time. However, Panels E and F of [Figure 1.4](#) show increasing labor productivity in the service sector.

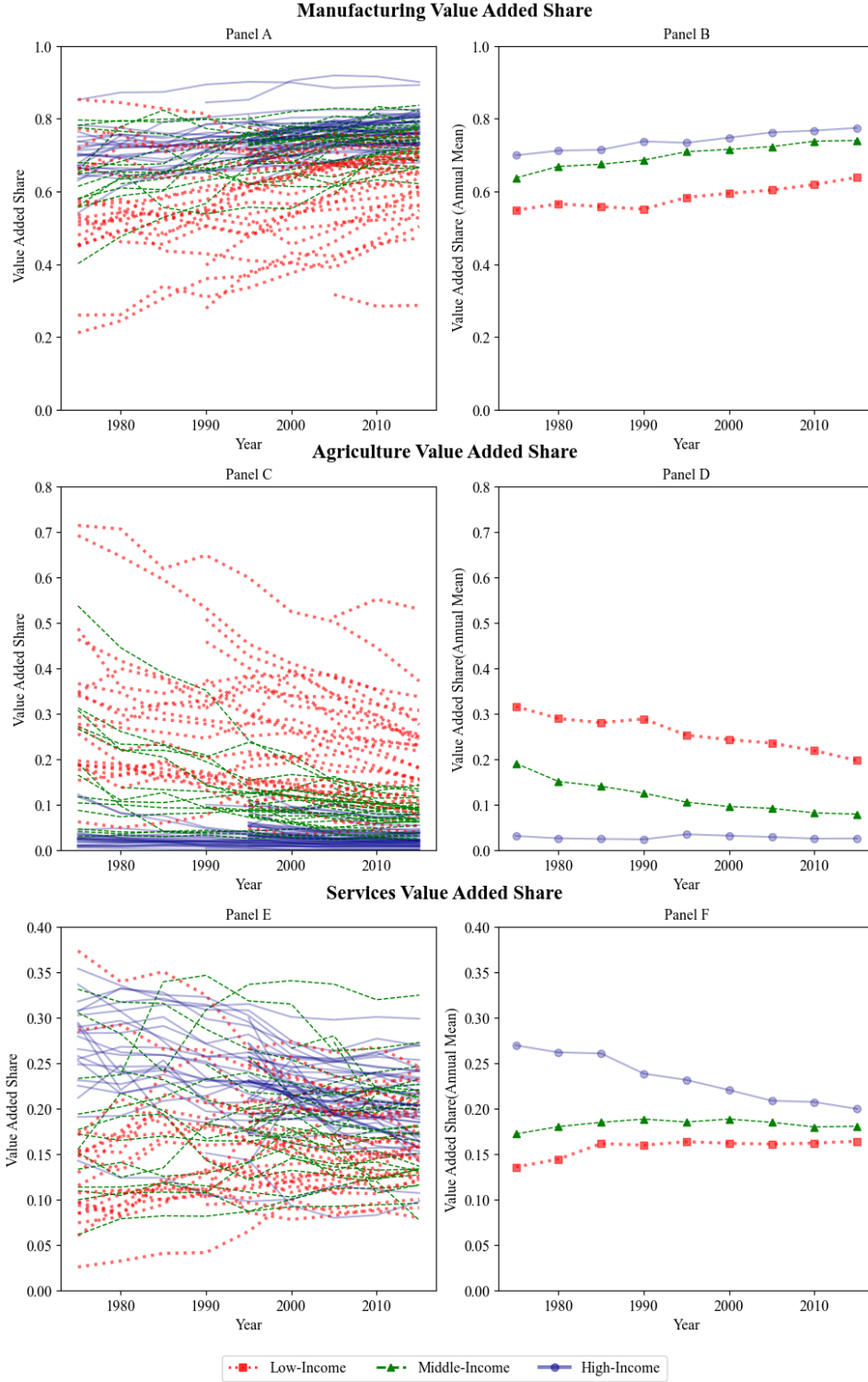
As stated in the introduction, differential TFP growth rates have been suggested as the underlying cause of the data discussed in this section. Of course, the plausibility of such models requires that TFP growth rates indeed differ. However, this cannot be ascertained directly from the data. This requires data on nominal value added and labor inputs, as presented above. However, it additionally requires data on prices (to recover real output)

Figure 1.2: Sector employment shares



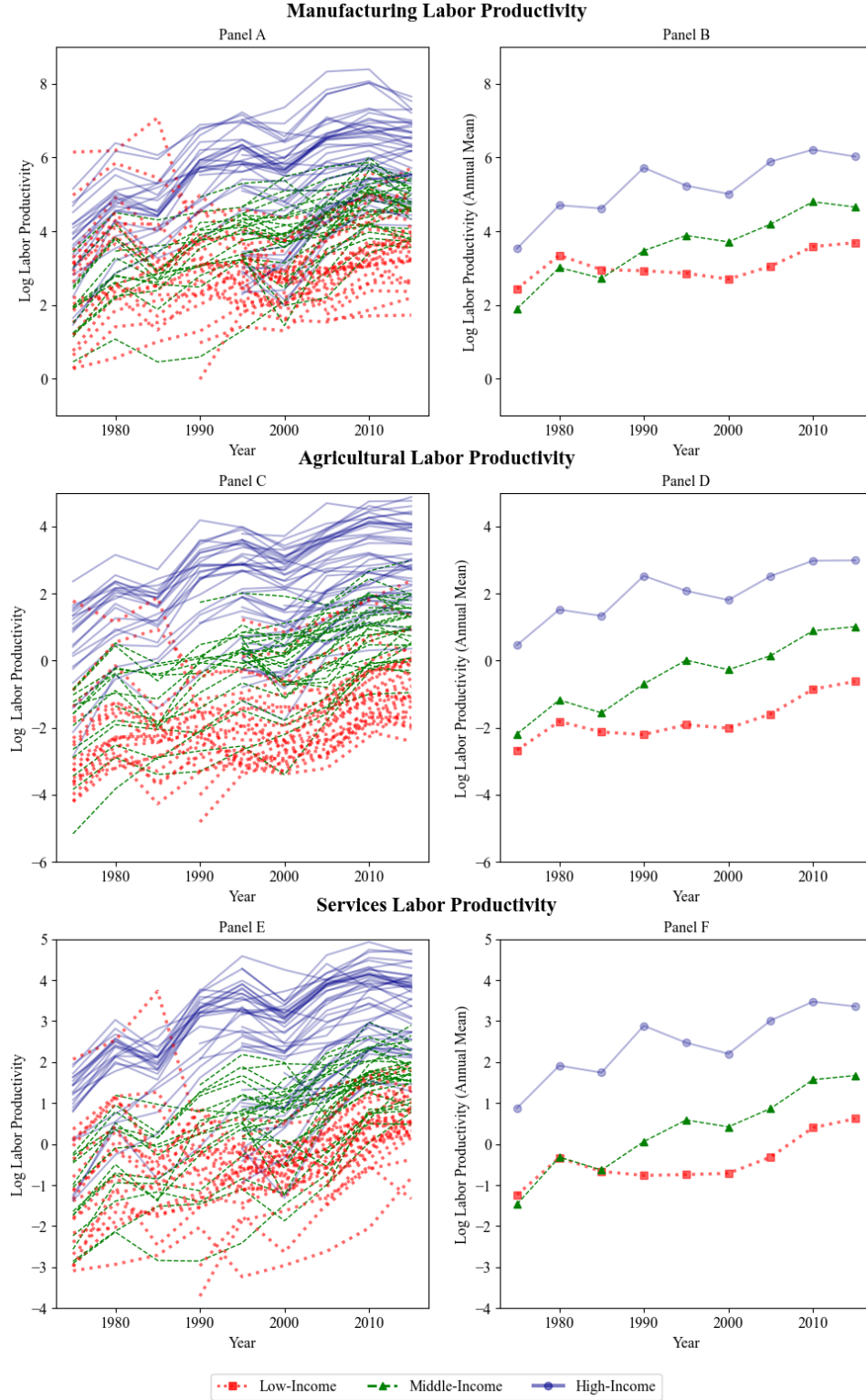
Note: Figure 1.2 shows sector employment shares for manufacturing (panels A and B), agriculture (panels C and D), and services (Panels E and F). Countries are grouped into low (dotted lines), middle (dashed lines), and high (solid lines) income countries. Panels A, C, and E present the data for all countries in the sample, while panels B, D, and F present averages for the various income groups. Data is in 5-year intervals starting from 1975.

Figure 1.3: Sector value added shares



Note: Figure 1.3 shows sector value-added shares for manufacturing (panels A and B), agriculture (panels C and D), and services (Panels E and F). Countries are grouped into low (dotted lines), middle (dashed lines), and high (solid lines) income countries. Panels A, C, and E present the data for all countries in the sample, while panels B, D, and F present averages for the various income groups. Data is in 5-year intervals starting from 1975.

Figure 1.4: Sector labor productivity



Note: Figure 1.4 shows sector labor productivity for manufacturing (panels A and B), agriculture (panels C and D), and services (Panels E and F). Countries are grouped into low (dotted lines), middle (dashed lines), and high (solid lines) income countries. Panels A, C, and E present the data for all countries in the sample, while panels B, D, and F present averages for the various income groups. Data is in 5-year intervals starting from 1975.

and capital inputs. This data does not exist for most countries. To isolate the effect of TFP requires a multi-sector model of economic growth that allows for differential TFP growth.

1.3 The model

To identify sector-level relative TFP growth rates, we develop a version of the model presented in [Ngai & Pissarides \(2007\)](#). Ngai and Pissarides consider how different productivity growth rates across sectors influence structural change in an economy. In a special case, they show that the aggregate economy reduces to the familiar Ramsey-Cass-Koopman model. As such, complex patterns of structural change can arise while the aggregate economy is on its balanced growth path or on a trajectory toward balanced growth. Our discrete-time version of this model has several additional distinctions, which we address as they arise below. However, the key feature of varied sector-level employment and output patterns comprising balanced growth remains.

A representative infinitely lived agent has preferences given by

$$u_t(\cdot) \equiv \sum_{j=0}^{\infty} \tilde{\beta}^j \ln \phi_t$$

where

$$\phi_t \equiv \left(\sum_{j=0}^{m-1} \omega_j c_{j,t}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}.$$

Parameter restrictions are $0 < \tilde{\beta} < 1$, $\varepsilon, \omega_j > 0$ and $\sum_0^{m-1} \omega_j = 1$. The ϕ_t term is a constant elasticity of substitution combination of m distinct consumption goods available to the consumer in period t . Each good is indexed by j so that $c_{j,t}$ is the quantity of good j consumed in period t . This is expressed in intensive form. We provide additional information regarding this below. The relative importance of good j in consumption is ω_j , the elasticity of substitution between goods is ε , and $\tilde{\beta}$ discounts future utility flows.

Each consumption good is produced competitively in its own sector by a representative

firm. The production function in sector j is

$$Y_{j,t} = K_{j,t}^\theta (A_{j,t} N_{j,t})^{1-\theta}$$

where $0 < \theta < 1$ is the share parameter and $A_{j,t}$ gauges total factor productivity in sector j . Inputs into the production of good j are capital, $K_{j,t}$, and labor, $N_{j,t}$. One of the industries, which we refer to as Good 0 (Manufacturing), produces a good used for both consumption and investment. Others are used only for consumption. Ngai and Pissarides show that along the balanced growth path, the growth rate in their model is equal to the growth rate of $A_{0,t}$ plus the growth rate of the population. This feature also arises in our model. In anticipation of this, for ease of presentation, we normalize output, consumption, investment, and the capital stock in period t by the investment sector (Sector 0), which serves as the numeraire good. Specifically, we divide these variables by $A_{0,t}N_t$ where N_t is the total population and use lower case variables to express these intensive form values. Moreover, we find it convenient to express $K_{j,t}$ and $N_{j,t}$ as shares of K_t and N_t employed in sector j .⁸ Given this, we can express the period t resource constraints as

$$y_{0,t} = (s_{0,t}k_t)^\theta (a_{0,t}n_{0,t})^{1-\theta} = c_{0,t} + i_t \quad (1.1)$$

$$y_{j,t} = (s_{j,t}k_t)^\theta (a_{j,t}n_{j,t})^{1-\theta} = c_{j,t} \quad (\forall j > 0). \quad (1.2)$$

Here, k_t , i_t , and $c_{j,t}$, $j \in \{0, 1, \dots, m-1\}$ represent the total capital stock, total investment, and the total consumption of good j , respectively, each expressed in per-effective-labor units by dividing by $A_{0,t}N_t$. We define $a_{j,t} \equiv \frac{A_{j,t}}{A_{0,t}}$ as the relative productivity of sector j to the investment sector. The goods are indexed from 0 to $m-1$, with Good 0 denoting the investment good. The shares of K_t and N_t employed in sector j are given by $s_{j,t}$ and $n_{j,t}$ so $s_{j,t}, n_{j,t} \geq 0$ and $\sum_0^{m-1} s_{j,t} = \sum_0^{m-1} n_{j,t} = 1$. These constraints hold because, as stated above, Good 0 serves a dual purpose: it is both consumed and used as the sole investment good. In contrast, goods from the other sectors are used exclusively for consumption.

⁸Ngai and Pissarides also express $N_{j,t}$ as a share of N_t employed in sector j .

Since only sector 0 is used to produce capital, and some sector 0 output is consumed, the intensive form law of motion for capital is

$$k_{t+1} (1 + \gamma_N) (1 + \gamma_0) = (1 - \delta) k_t + y_{0,t} - c_{0,t}. \quad (1.3)$$

Here $\gamma_N, \gamma_0 > -1$, are the exogenous growth rates of the population and sector 0 total factor productivity growth while $0 < \delta < 1$ is the rate at which capital depreciates. These are also part of $0 < \tilde{\beta} \equiv \beta (1 + \gamma_N) (1 + \gamma_0) < 1$ so that $\tilde{\beta}$ accounts for both for time preferences, $0 < \beta < 1$, and these growth rates.

As mentioned above, this model allows structural change in the disaggregated economy while preserving the transitional and steady state features of the Ramsey model for the aggregate economy. As in Ngai and Pissarides (2007), structural change in our model stems from differing total factor productivity growth rates across industries. The aggregate economy refers to the paths of k_t and i_t as well as

$$\begin{aligned} c_t &\equiv \sum_{j=0}^{m-1} p_{jt} c_{j,t} \\ y_t &\equiv \sum_{j=0}^{m-1} p_{jt} y_{j,t}. \end{aligned}$$

Proposition 1 demonstrates that the aggregate economy can be tracked without reference to the disaggregated economy and thus independently of structural change. All proofs are in the appendix.

Proposition 1. *The aggregate economy can be expressed by the following Bellman equation for the social planner's problem:*

$$v(k_t) = \max_{k_{t+1}} \left\{ \ln(k_t^\theta + (1 - \delta) k_t - k_{t+1} (1 + \gamma_N) (1 + \gamma_0)) + \tilde{\beta} v(k_{t+1}) \right\}. \quad (1.4)$$

With a solution for k_{t+1} from Equation (1.4), it is straightforward to find $\frac{c_t}{y_t}$. This ratio proves to be the only result from the aggregate economy that is required to understand

structural change in the disaggregated economy, as shown in Proposition 2.

Proposition 2. *The following relationships hold in the disaggregated economy:*

$$s_{0,t} = n_{0,t} = \frac{c_t}{y_t} \frac{1}{Z_t} + 1 - \frac{c_t}{y_t} \quad (1.5)$$

$$s_{j,t} = n_{j,t} = \frac{c_t}{y_t} \frac{z_{j,t}}{Z_t}, \quad (\forall j > 0) \quad (1.6)$$

where

$$z_{j,t} \equiv \left(\frac{\omega_j}{\omega_0} \right)^\varepsilon a_{j,t}^{(1-\varepsilon)(1-\theta)} \quad (1.7)$$

$$Z_t \equiv 1 + \sum_{j=1}^{m-1} z_{j,t}. \quad (1.8)$$

The $n_{0,t}$ and $n_{j,t}$ variables are identical to those in [Ngai & Pissarides \(2007\)](#). From these relationships, we can find expressions for the relative TFP of a sector, relative to the sector producing the investment good. This is presented in Proposition 3 below.

Proposition 3. *TFP of sector j relative to sector 0 is*

$$a_{jt} = \left(\frac{\left(\frac{\omega_j}{\omega_0} \right)^\varepsilon}{z_{jt}} \right)^{\frac{1}{(1-\varepsilon)(1-\theta)}} \quad (1.9)$$

and relative TFP growth for sector j is

$$(\gamma_j - \gamma_0) = \ln \left(\frac{a_{j,t}}{a_{j,0}} \right) t^{-1} \quad (1.10)$$

where γ_j and γ_0 are the growth rates of TFP in sector j and sector 0 respectively.

Given these relationships between the aggregate and disaggregated economy expressed in Proposition 2, we proceed by finding $\frac{c_t}{y_t}$ from the solution to Equation (1.4) and using this in equations of structural change. We do this in several steps. First, we consider a case with a closed-form solution to the Bellman equation. While requiring that $\delta = 1$, this

has the advantage of providing clear and intuitive results. Moreover, as argued below, the assumption is a reasonable one when we consider a long time frame. We next allow $\delta \neq 1$ but consider only the steady. Again, this allows closed-form solutions. Trading off our restriction on δ for a steady state restriction has the advantage of allowing us to consider shorter time frames. Finally, we solve the dynamic programming problem, yielding a value for $\frac{c_t}{y_t}$ both along the balanced growth path and in transition. The key finding here is that our more restricted cases sufficiently capture the results of the model.

A useful observation throughout this analysis arises from Equations (1.5). Rearranged, this is

$$1 - n_{0,t} = \frac{c_t}{y_t} \frac{Z_t - 1}{Z_t}. \quad (1.11)$$

An implication of Equation (1.8) is that $0 < (Z_t - 1) Z_t^{-1} < 1$. As such, Equation (1.11) requires

$$1 - n_{0,t} < \frac{c_t}{y_t}. \quad (1.12)$$

Since $(1 - n_{0,t})$ is the share of both time and capital spent on pure consumption goods, this is a requirement that the share of output that is consumed must exceed the share of resources going to produce the pure consumption goods. This is intuitive since part of c_t is the consumption/investment good. However, we will often take $n_{0,t}$ as observable while $\frac{c_t}{y_t}$ arises endogenously from the model. As such, there is no assurance that the inequality holds. When it does not, the underlying cause is a small observed $n_{0,t}$. In essence, the model cannot address the situation of a very small manufacturing sector, and we must drop such economies from consideration by this model. We address this in our sensitivity analysis, where we extend the model to the small open economy case. This loosens the constraint and allows the inclusion of more countries.

1.4 Parameter calibrations

We calibrate our model to fit a three-sector economy. We propose to make the sector employment shares observable by combining the nine sectors in the Global Productivity dataset

into three sectors called manufacturing, agriculture, and service. We take a somewhat different approach to the aggregation than is common in the literature. Our manufacturing sector is made up of the following sectors: manufacturing, mining and quarrying, utilities, construction, trade services, transport services, and financial and business services. This is somewhat different from the conventional manufacturing sector in the literature. Our approach has two motivations. First, the manufacturing good in our model is both a consumption and an investment good and thus is broader in nature than in some other studies. More importantly, this sector must produce a large enough share of output to cover savings and some consumption. This requirement is relaxed, but only modestly, when we consider the small open economy model. For many developing countries, the manufacturing sector is small. This necessitates including other sectors in the investment goods sector. In contrast, [Cai \(2015\)](#), [Van Neuss \(2019\)](#), and [Herrendorf et al. \(2014\)](#) use mining and quarrying, manufacturing, and construction as the manufacturing sector. We show later that our results are robust to alternative aggregation of the manufacturing good.

With seven of nine sectors included in manufacturing, each remaining sector contains only one sector. Our agricultural sector is referred to as ‘Agriculture, forestry, and fishing’, and our service sector includes what is referred to as ‘other services’ in the Global Productivity dataset. As stated earlier, we use 5-year intervals between 1975 and 2017.

We select parameter values from the economic growth literature. [Table 1.1](#) contains our annual parameter calibrations. We follow [Schmitt-Grohé & Uribe \(2003\)](#) and set the share of capital in output, θ , to 0.32. [Gollin \(2002\)](#) computes labor shares for different countries and finds that for most countries, both developed and developing, labor shares range between 0.65 and 0.80, implying capital shares ranging from 0.2 to 0.35. Our choice of 0.32 for capital shares falls within this range. [Schmitt-Grohé & Uribe \(2003\)](#) use a discount factor, β , of 0.96 for annual data. We use this as our annual measure.⁹

We set the annual population growth rate and GDP growth rate to 0.01 and 0.02, respectively. We set the annual depreciation rate, δ , at 10% following [DeJong & Dave \(2012\)](#) and

⁹This translates to 0.82 for our 5-year interval data. That is $(0.96)^5 = 0.82$.

Table 1.1: Parameter values for calibration

Description	Parameter	Values
Share of capital	θ	0.32
Discount factor	β	0.96
Population growth rate	γ_N	0.05
GDP growth rate	γ_0	0.02
Depreciation rate	δ	0.1
Elasticity of substitution across goods	ϵ	0.3
Weight of good in aggregate consumption		
Manufacturing (Good 0)	ω_0	0.15
Agriculture (Good 1)	ω_1	0.1
Services (Good 2)	ω_2	0.75

Woodford (1999).¹⁰ We follow (Ngai & Pissarides, 2004) to set the elasticity of substitution, ϵ , across goods to 0.3 as a baseline. This implies that goods from the sectors are poor substitutes. In the model presented by (Ngai & Pissarides, 2004), this assumption is required for the coexistence of structural change and balanced growth. The weighting parameters, ω_i , are chosen as 0.15 for manufacturing, 0.1 for agriculture, and 0.75 for services following (Cai, 2015).

1.5 Results

1.5.1 Special case 1: $\delta = 1$

We start with the special case where we assume full depreciation. With $\delta = 1$, finding the solution to Equation (1.4) is straightforward. Using the guess-and-verify approach we find

$$\frac{c_t}{y_t} = 1 - \tilde{\beta}\theta \quad (1.13)$$

where $\tilde{\beta} = (1 + \gamma_n)(1 + \gamma_0)\beta$. From the arguments surrounding Equation (1.11), a value of Z_t consistent with this can be found only if $n_{0,t} > \tilde{\beta}\theta$. This constraint is not severe but does exclude some developing countries. Setting $\delta = 1$ is justifiable when the time frame

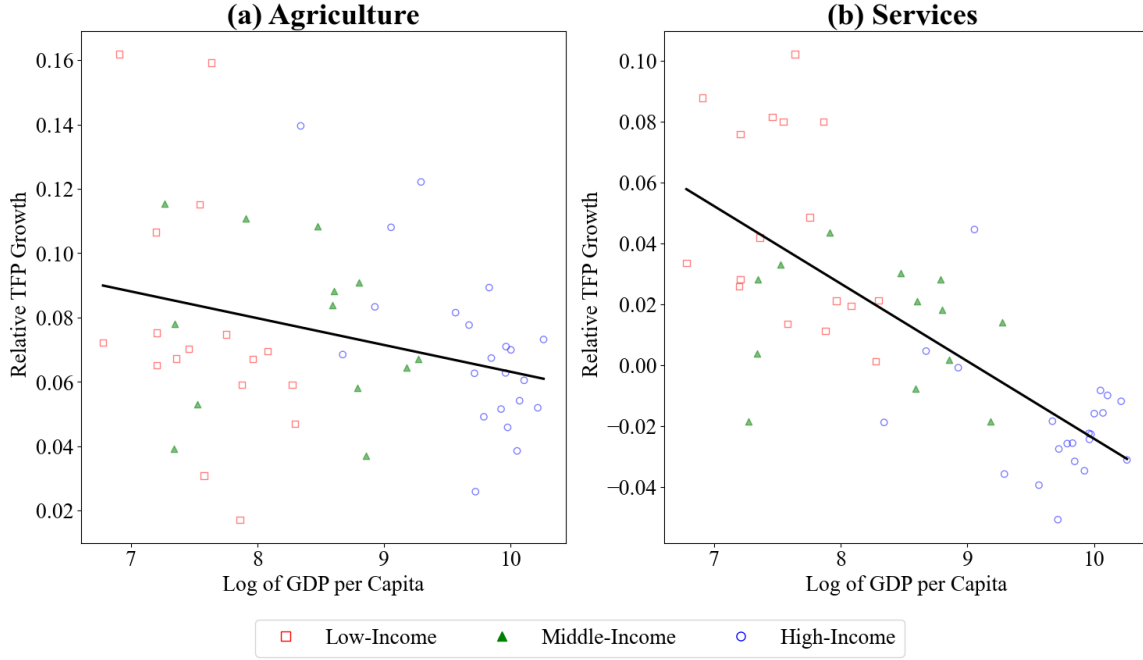
¹⁰This implies a 5-year depreciation rate of about 0.41. That is: $1 - (1 - 0.1)^5 = 0.41$.

under consideration is long. We set a time period to be 43 years, which is the length of our dataset. With an annual depreciation of 10%, 43 years correspond to a depreciation rate of about 0.99, making our length of time sufficient for the assumption of full depreciation. [Schmitt-Grohé & Uribe \(2003\)](#) set $\beta = .96$ in a model without γ_n or γ_0 . To match this, we set our composite of these three items to $\tilde{\beta} = .96$. This translates to 0.17 for the time period of 43 years.

Computing values for $\frac{c_t}{y_t}$ from Equation (1.13) and applying that to the equations of structural change illustrated under Propositions 2 and 3 allows us to compute the relative TFP growth rate for the agricultural and service sectors relative to the manufacturing sector. These are plotted against the log of GDP per capita in [Figure 1.5](#). The main implications of our results are that sectors have differential TFP growth rates and that these TFP growth differentials vary with per capita income. From panel (a) of [Figure 1.5](#), we observe a negative and significant correlation between the relative TFP growth rates in agriculture and GDP per capita. Note also that although the relative TFP values are declining with income levels, they are positive for all countries. This implies that TFP in the agricultural sector remains higher than in the manufacturing sector, but the differences in their growth rates decrease as incomes increase. This relationship establishes the basis for the decline in the agricultural employment shares and a corresponding rise in the manufacturing employment shares suggested by Ngai and Pissarides. The main finding of their paper is that when TFP growth rates differ across sectors, and goods are poor substitutes, labor tends to move away from the sectors with higher TFP growth towards the sectors with lower TFP growth rates. Hence, our findings will suggest a shift of employment away from the agricultural sector towards the manufacturing sector.

Panel (b) also shows a negative and significant correlation between the relative TFP growth rates in the service sector and GDP per capita. For low-income countries, TFP grows faster in the service sector compared to manufacturing. Notice that for most of the developed countries, the relative TFP growth rates are negative, implying that TFP is growing faster in the manufacturing sector compared to the service sector. Following the conclusions of Ngai and Pissarides, this explains the rise in service sector employment in developed economies

Figure 1.5: Sector TFP growth rates relative to manufacturing



1.5.2 Special case 2: Balanced growth

In this case, we allow for $\delta \neq 1$ and consider the steady state. This allows for a closed-form solution.

Proposition 4. *In the general model along the balanced growth path of the aggregate economy, the consumption share of output is:*

$$\frac{c_t}{y_t} = 1 - \frac{((1 + \gamma_n)(1 + \gamma_0) - (1 - \delta))\beta\theta}{1 - \beta(1 - \delta)}.$$

Since models such as [Ngai & Pissarides \(2007\)](#) rely on differential TFP growth rates as the drivers of industrial dynamics, we begin with a discussion of whether, in fact, these TFP growth rates differ. We conduct a similar exercise as before and compute relative TFP values. We use the 5-year interval data and the corresponding calibrations. [Table 1.2](#) provides convincing evidence that growth rates differ by sector.

Table 1.2: Test of significance of means

Income Group	Variable	Mean	t-statistic	Confidence Interval
LIC	Agricultural relative TFP growth	0.147	4.28	[0.079, 0.215]
	Services relative TFP growth	0.107	3.45	[0.045, 0.169]
MIC	Agricultural relative TFP growth	0.125	8.59	[0.096, 0.153]
	Services relative TFP growth	0.066	5.07	[0.041, 0.092]
HIC	Agricultural relative TFP growth	0.077	14.07	[0.066, 0.088]
	Services relative TFP growth	-0.010	-2.62	[-0.018, 0.003]

This table considers the average across income groups of the calculated relative TFP rates for each of agriculture and services. If non-zero, growth rates differ by sector. We find that for each country group and for each of agriculture and services, we can reject the null hypothesis that the average is zero. Moreover, in each case, the higher income group has the lower average relative TFP growth rate. For services, the average is negative for the high-income group.

These results are another indication of generally positive relative TFP growth rates, which decrease with income; that is, they are suggestive of the results in [Figure 1.5](#). We

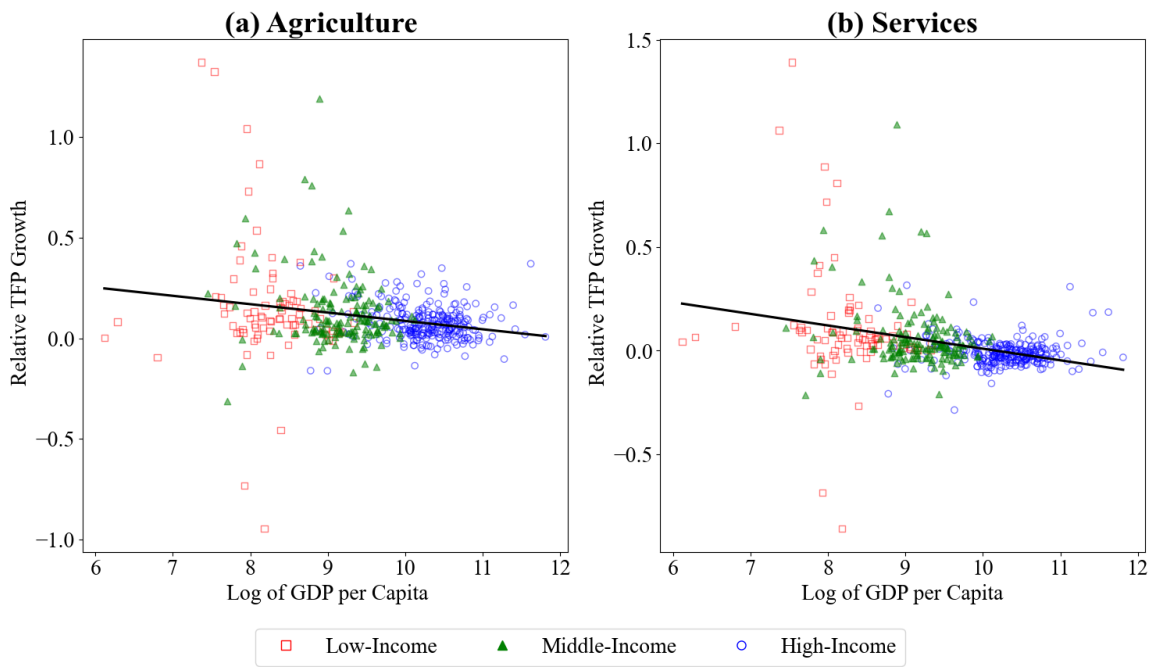
find further evidence of the robustness of the result from [Figure 1.6](#). Here we present figures analogous to [Figure 1.5](#) but using 5-year periods. Relative TFP growth rates are plotted against the log of GDP per capita. We set the vertical limits to be between -1 and 1 to improve visualization, even though all values are included in the analysis. Similar to the earlier findings, we observe that the relative TFP growth rates of agriculture and services are negatively correlated with GDP per capita, with the difference decreasing with higher income levels.

In [Figure 1.7](#), we plot the log of the TFP ratios ($a_{i,t}$) for the agricultural and service sectors relative to manufacturing. Panels A and C present the plots for all countries, while Panels B and D present the averages across the income groups. Across all countries, we notice increasing TFP ratios for both the agriculture and service sectors relative to the manufacturing sector. This suggests that both agriculture and services are getting more productive relative to manufacturing over time. This confirms the earlier finding that relative to the manufacturing sector, TFP in the agricultural and service sectors grows more slowly in richer countries compared to poorer countries. Hence, the first case, though simplified, generally captures the expected trends in TFP growth.

However, we note that LICs have much steeper lines compared to the other groups. The lines for HICs are relatively flatter. These slopes suggest that the growth rates of these ratios may be slowing down as countries get richer.

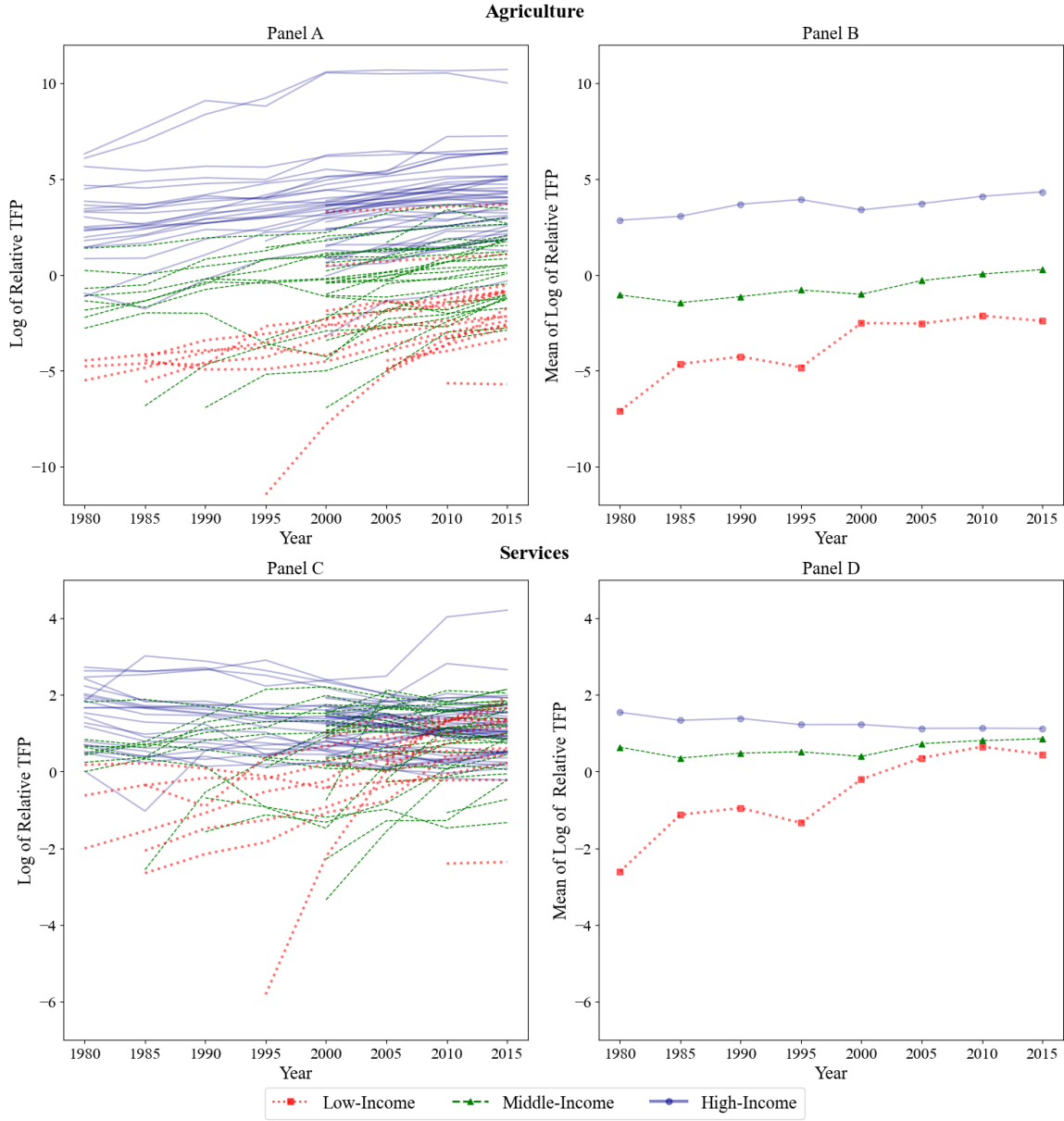
We also solve for $\frac{c_t}{y_t}$ numerically along the transition path to the steady state. This gives us values for the range of 5-year periods in our data. This can be seen as the scaling of the equations in Proposition 2. Although not reported, the results are very similar to the earlier findings. This suggests that our results remain robust both on the balanced growth path and in the transition toward balanced growth.

Figure 1.6: Sector relative TFP growth rates ($\delta \neq 1$)



Note: Figure 1.6 presents scatter plots between the relative TFP growth rates and the log of GDP per capita for the case where $\delta \neq 1$ using the 5-year interval data. The squares represent low-income countries, the triangles represent middle-income countries, and the circles represent high-income countries. The coefficient and the t-values for the best-fit line for panel (a) are -0.04 and -5.0, while those of panel (b) are -0.06 and -7.64, respectively.

Figure 1.7: Sector relative TFP (5-year intervals)



Note: Figure 1.7 presents the log of the estimates of TFP ratios relative to the manufacturing good from our model. We use the 5-year interval data. Panels A and C present the series for all the countries, and Panels B and D present the mean values grouped by the Income groupings. Countries are grouped into low (dotted lines), middle (dashed lines), and high (solid lines) income countries.

1.6 Sensitivity analysis

1.6.1 Alternative aggregation of the manufacturing sector

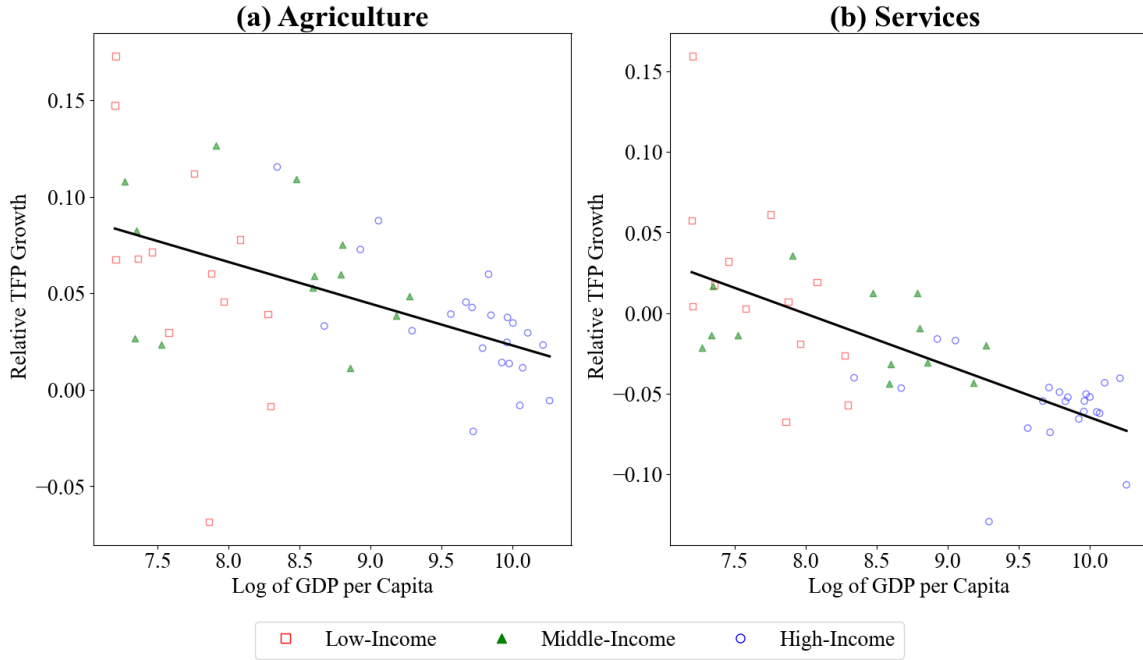
We conduct a sensitivity analysis to determine if our results are driven by the number of sub-sectors aggregated into the manufacturing sector. Recall that our manufacturing good was made up of the following sectors in the Global Productivity dataset: Mining and quarrying; Manufacturing; Utilities; Construction; Trade services; Transport services; and Financial and Business. It could be argued that our manufacturing sector includes sectors that are not typically categorized as manufacturing. In this section, we show that our findings are robust to an alternative aggregation of the manufacturing sector. We adopt the aggregation by [Cai \(2015\)](#), [Van Neuss \(2019\)](#), and [Herrendorf et al. \(2014\)](#). Their manufacturing sector includes mining and quarrying, manufacturing, and construction. The service sector now includes utilities, trade services, transport services, and financial and business services. The agricultural sector remains the same. This has a minor consequence on our results. The only effect is the loss of some countries with very small manufacturing sectors. Otherwise, the results remain qualitatively similar as shown in [Figure 1.8](#) and [Figure 1.9](#).

1.6.2 Small open economy

We extend our model to consider the small open economy case, as this may be a more appropriate framework for considering sector dynamics in many of the countries in our data. Most importantly, the model above requires investment to arise from current domestic production. For countries with small manufacturing industries, this restriction potentially leads to our inability to compute their relative TFP growth rates. To gauge the robustness of our findings, we modify the model to allow debt finance of investment at an exogenous interest rate. Generally, we show that apart from allowing some countries with smaller manufacturing sectors to be captured, the patterns observed in the baseline results do not change.

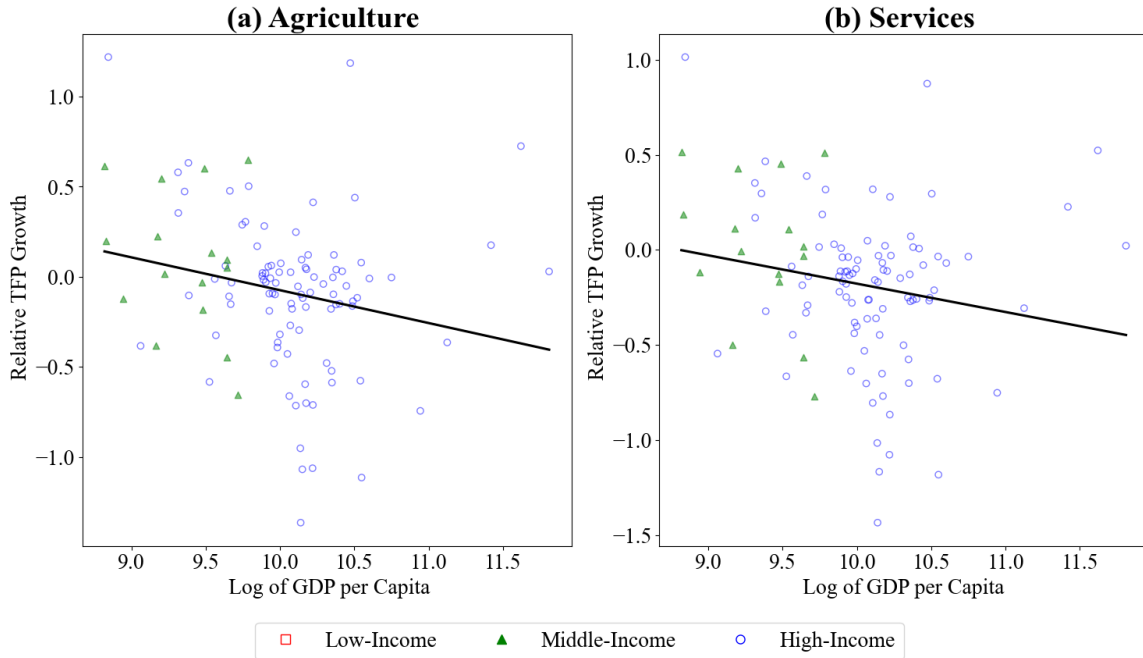
With the potential for debt financing, output in the manufacturing sector minus con-

Figure 1.8: Sector relative TFP growth rates (special case ($\delta = 1$))



Note: Figure 1.8 presents scatter plots between the relative TFP growth rates and the log of GDP per capita under the special case where $\delta = 1$. Compared to Figure 1.5, this figure has fewer countries because of the narrower aggregation of the manufacturing sector. The relationships between relative TFP and GDP per capita remain unchanged. The squares represent low-income countries, the triangles represent middle-income countries, and the circles represent high-income countries. The coefficient and the t-values for the best-fit line for panel (a) are -0.01 and -3.94, while those of panel (b) are -0.03 and -6.61, respectively.

Figure 1.9: Sector relative TFP growth rates (special case ($\delta \neq 1$))



Note: Figure 1.9 presents scatter plots between the relative TFP growth rates and the log of GDP per capita under the special case where $\delta \neq 1$, using the 5-year interval data. Compared to Figure 1.6, this figure has fewer countries because of the narrower aggregation of the manufacturing sector. We see that all the LICs are missing from the data. The relationship between relative TFP and GDP per capita remains unchanged. The squares represent low-income countries, the triangles represent middle-income countries, and the circles represent high-income countries. The coefficient and the t-values for the best-fit line for panel (a) are -0.18 and -2.36, while those of panel (b) are -0.15 and -2.01, respectively.

sumption from this sector may not equal investment. Thus, we introduce $i_{0,t}$ to denote investment through this channel and rewrite the resource constraint in Equation (1.1) as

$$y_{0,t} \equiv (s_{0,t} k_t)^\theta n_{0,t}^{1-\theta} = c_{0,t} - i_{0,t}. \quad (1.14)$$

Investment with debt finance is

$$i_t = i_{0,t} + d_t - (1+r) d_{t-1} \quad (1.15)$$

where d_t is period t debt and $(1+r) d_{t-1}$ is the repayment of prior debt at the exogenous real interest rate r so that the law of motion for capital is

$$k_{t+1} (1 + \gamma_N) (1 + \gamma_0) = (1 - \delta) k_t + i_t. \quad (1.16)$$

We omit adjustment costs commonly present in similar models to be more succinct and make the common assumption that $\beta = (1+r)^{-1}$ to allow for balanced growth. Proposition 5 demonstrates that again only $\frac{c_t}{y_t}$ is required from the aggregate economy to track sector dynamics, and that aggregate dynamics can be tracked without knowledge of industrial dynamics. Moreover, in this case $\frac{c_t}{y_t}$ is constant. Note also that we are assuming that debt is used to finance imports of the investment or the manufacturing good, and that only the investment good is imported. This implies that the change in debt is equal to net exports. That is:

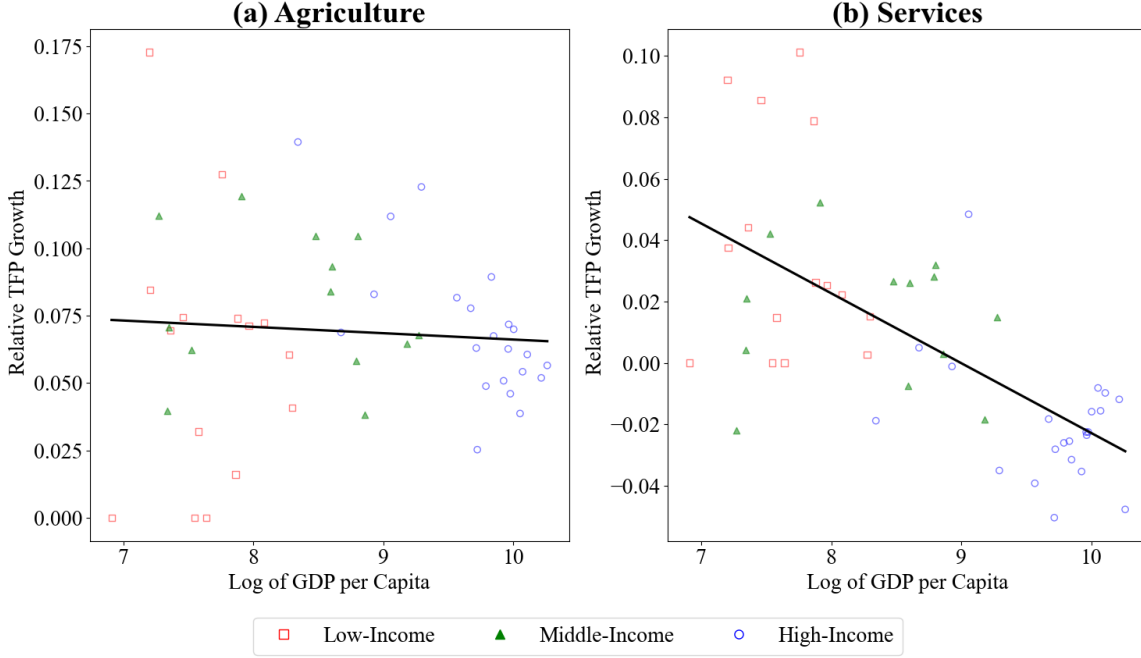
$$(1+r) d_{t-1} - d_t = x_t - m_t. \quad (1.17)$$

In this setup, exports (x_t) are exogenous. As a result, imports (m_t) must adjust to ensure that this relationship holds. This gives rise to Proposition 5 below:

Proposition 5. *In the small open economy model with debt finance, the relationships in Proposition 2 holds, and the aggregate economy can be expressed by*

$$\frac{c_t}{y_t} = \frac{c}{y} = 1 - \frac{((1 + \gamma_N) (1 + \gamma_0) - (1 - \delta)) \beta \theta}{1 - \beta (1 - \delta)} - \frac{x_t - m_t}{y}. \quad (1.18)$$

Figure 1.10: Sector relative TFP growth rates under small open economy ($\delta = 1$)

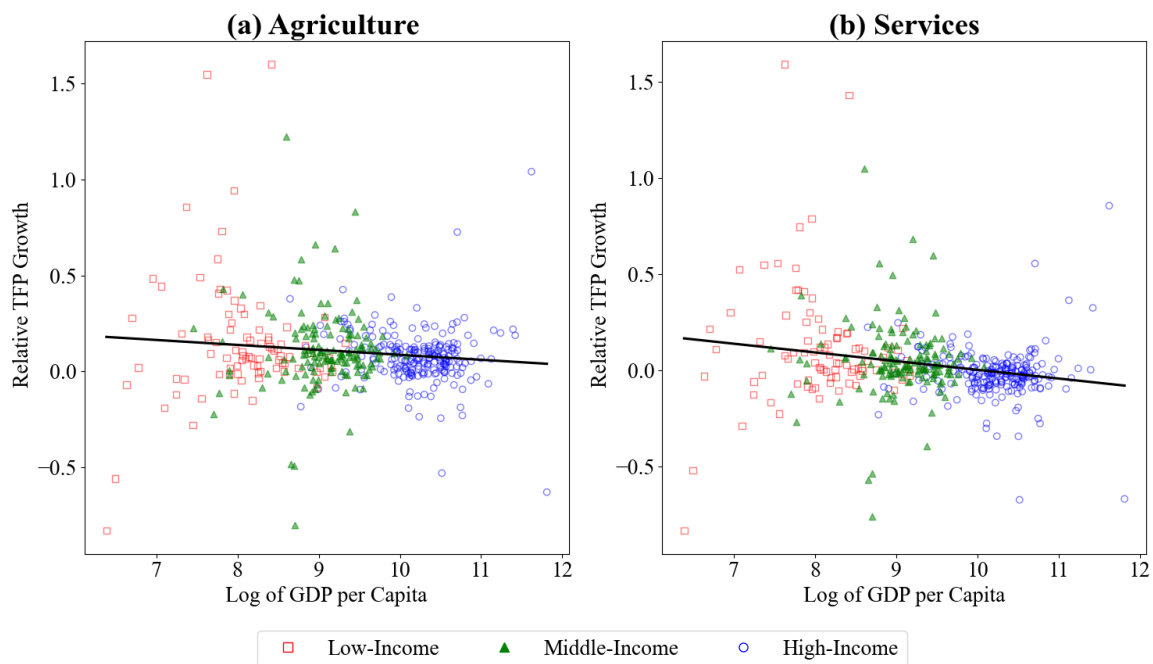


Note: Figure 1.10 presents scatter plots between the relative TFP growth rates and the log of GDP per capita under the special case where $\delta = 1$ under a small open economy framework. Compared to the baseline case in Figure 1.5, the correlation between relative TFP growth and GDP per capita is similar. The squares represent low-income countries, the triangles represent middle-income countries, and the circles represent high-income countries. The coefficient and the t-values for the best-fit line for panel (a) are -0.00 and -0.49, while those of panel (b) are -0.02 and -6.15, respectively.

Where $\frac{x_t - m_t}{y}$ is the share of net exports in GDP. We again take this term as observable and calibrate it using data. We extract data on the share of merchandise exports and imports in GDP from the Penn World Table. The difference between these two variables gives us the share of net exports in GDP. We use this alongside the parameter calibrations to compute values for $\frac{c_t}{y_t}$ from Equation (1.18) and further use that to extract the relative TFP growth rates as before. Under the case where $\delta = 1$, we use the average of the net export share in GDP over the entire time period for each country as the measure for $\frac{x_t - m_t}{y}$. In the case where $\delta \neq 1$, we use the 5-year averages instead.

We present these results in Figure 1.10 and Figure 1.11 respectively. In the case where $\delta = 1$, we observe results similar to our baseline results. However, we see a weaker relationship between relative TFP growth in agriculture and GDP per capita. However, all values are still positive, suggesting that TFP still grows faster in the agricultural sector compared to

Figure 1.11: Sector relative TFP growth rates under small open economy ($\delta \neq 1$)



Note: Figure 1.11 presents scatter plots between the relative TFP growth rates and the log of GDP per capita under the special case where $\delta \neq 1$ under a small open economy framework, using the 5-year interval data. Compared to Figure 1.6, the relationship between relative TFP and GDP per capita remains unchanged. The squares represent low-income countries, the triangles represent middle-income countries, and the circles represent high-income countries. The coefficient and the t-values for the best-fit line for panel (a) are -0.03 and -0.011, while those of panel (b) are -0.05 and -4.73, respectively.

the manufacturing sector. The negative correlation between the relative TFP in services and GDP per capita remains strong, with most HICs having the TFP in the manufacturing sector grow faster than the service sector. In [Figure 1.11](#), we plot the values for the case where $\delta \neq 1$. Here, we again observe the same correlations as before. Essentially, our results are robust to re-specifying the model as a small open economy model.

1.6.3 Alternate parameter calibrations across income groups

In this section, we also show that our results remain robust to the use of different parameter calibrations across income groups. [Table 1.3](#) presents the parameter values chosen for each income group. The parameter values are chosen based on literature and available data. Capital intensities vary significantly across income levels. For example, [Caselli & Feyrer \(2007\)](#) show that the marginal productivity of capital is significantly higher in developing countries compared to developed ones. This suggests that developed economies exhibit higher capital intensities. The point is emphasized by [Hall & Jones \(1999\)](#) and [Caselli \(2005\)](#). Consequently, using a uniform capital share across income groups may obscure relevant structural heterogeneity. Following [Gollin \(2002\)](#), who estimate capital shares between 0.2 and 0.35, we set the capital share at 0.35 for high-income countries (HICs), 0.30 for middle-income countries (MICs), and 0.25 for low-income countries (LICs).

Regarding depreciation, [Schündeln \(2013\)](#) notes that differences in depreciation rates can account for a significant portion of the variation in per capita incomes across countries. We generally expect depreciation rates to be higher in developing countries due to factors such as poorer infrastructure and capital quality. The Penn World Table provides annual estimates of average depreciation rates. Using these, we compute average values by income group: HICs exhibit a rate of approximately 4%, MICs 4.6%, and LICs 4.4%. We adopt these as our group-specific annual depreciation rates.

The discount factor reflects the degree of patience or the rate at which individuals discount the future, and this too may vary across countries. [De Lipsis \(2021\)](#) document heterogeneity in discount factors not only across countries, but also across income groups. In

Table 1.3: Parameter values for calibration by income groups

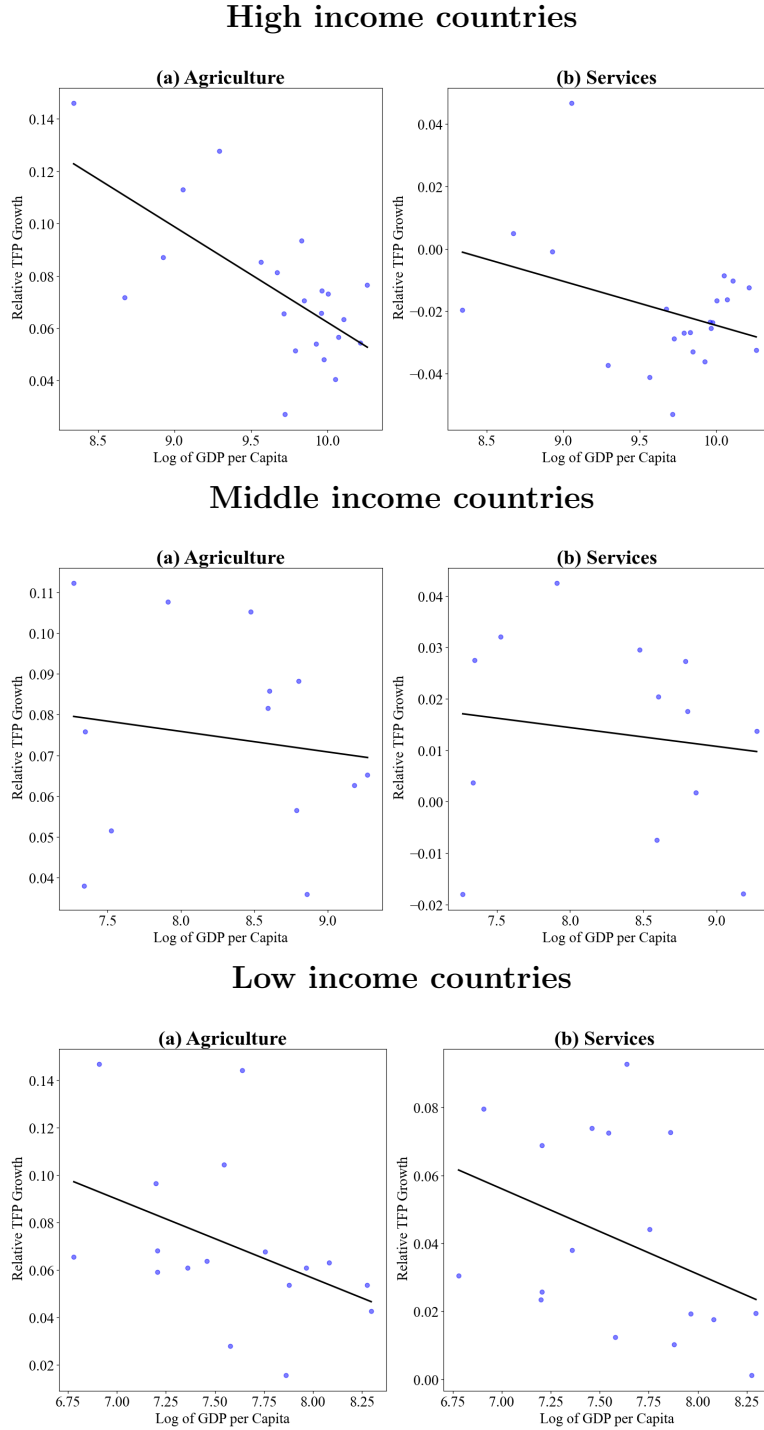
Description	Parameter	HIC	MIC	LIC
Share of capital	θ	0.35	0.30	0.25
Discount factor	β	0.96	0.9	0.85
Population growth rate	γ_N	0.013	0.015	0.025
GDP growth rate	γ_0	0.04	0.047	0.043
Depreciation rate	δ	0.04	0.046	0.044
Elasticity of substitution across goods	ϵ	0.3	0.3	0.3
Weight of good in aggregate consumption				
Manufacturing (Good 0)	ω_0	0.15	0.35	0.3
Agriculture (Good 1)	ω_1	0.1	0.25	0.45
Services (Good 2)	ω_2	0.75	0.40	0.25

developed economies with robust financial systems, individuals are likely to be more patient and more willing to postpone current consumption for future gains. In contrast, in developing economies with weaker financial systems, households tend to be more impatient. Accordingly, we set the annual discount factor to 0.96 for HICs, 0.90 for MICs, and 0.85 for LICs.

Based on data from the Penn World Table, we compute the average annual population growth rates as 1.3% for HICs, 1.5% for MICs, and 2.5% for LICs. The corresponding average annual real GDP growth rates are 4.4% for HICs, 4.7% for MICs, and 4.3% for LICs. We maintain the elasticity of substitution at 0.3 across all groups.

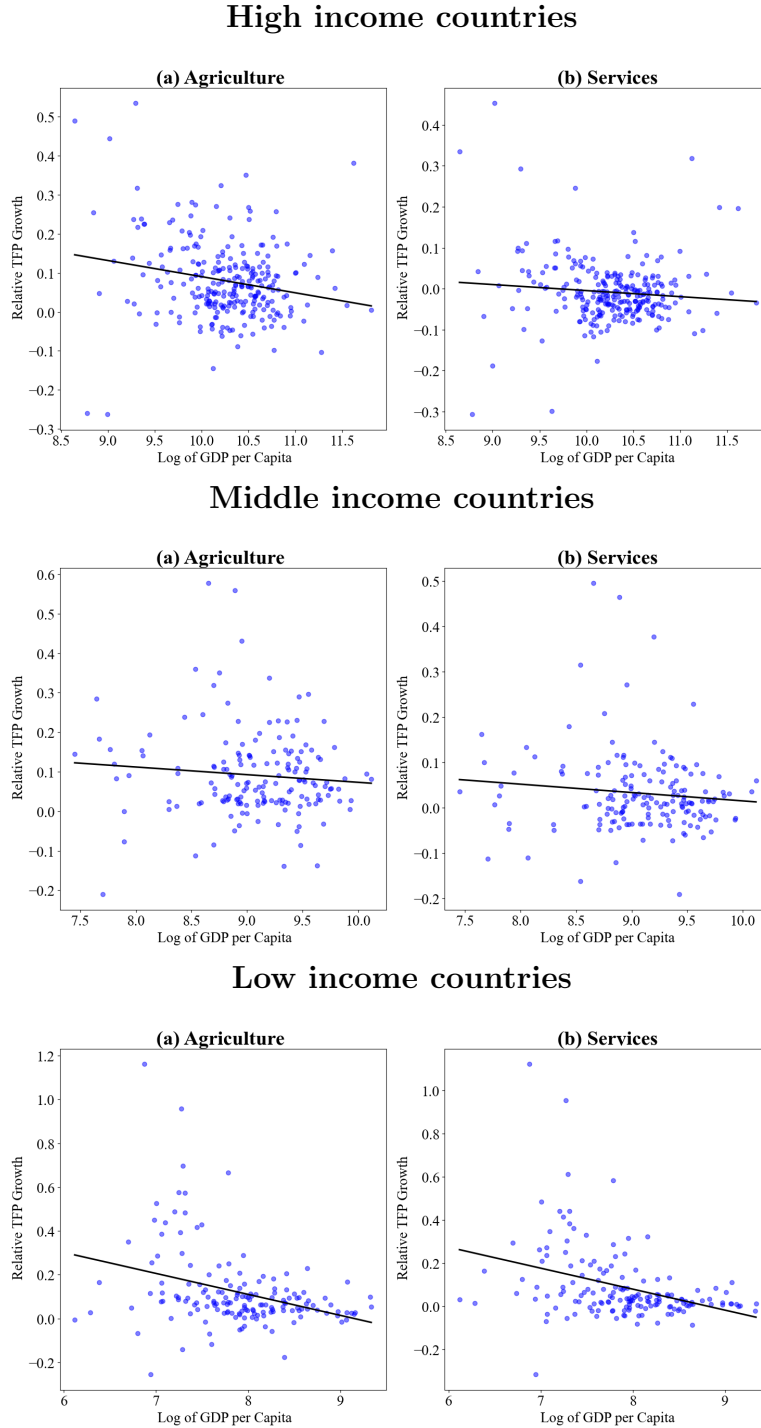
For LICs, we adjust the consumption weights across sectors to reflect their predominantly agrarian structure. Subsistence agriculture remains a major component of consumption in these economies; accordingly, we set the expenditure share on agriculture at 0.45, manufacturing at 0.30, and services at 0.25. For MICs, the shares are set to 0.25, 0.35, and 0.40 for agriculture, manufacturing, and services, respectively, reflecting economies in transition with expanding industrial and service sectors. For HICs, we retain the previously established values that are characteristic of developed economies.

Figure 1.12: Sector relative TFP growth rates for each income group ($\delta = 1$)



Note: Figure 1.12 presents scatter plots between the relative TFP growth rates and the log of GDP per capita under the special case where $\delta = 1$ for the various income groups, using the 5-year interval data. Compared to Figure 1.5, the relationship between relative TFP growth and GDP per capita remains unchanged across all income groups. The coefficients and the corresponding t-values for the best-fit lines are presented below: HIC: a(-0.04, -4.07) b(-0.01, -1.74), MIC: a(-0.01, -0.48) b(-0.00, -0.46), LIC a(-0.03, -1.81), b(-0.03, -1.62).

Figure 1.13: Sector relative TFP growth rates for each income group ($\delta \neq 1$)



Note: Figure 1.12 presents scatter plots between the relative TFP growth rates and the log of GDP per capita under the special case where $\delta \neq 1$ for the various income groups, using the 5-year interval data. Compared to Figure 1.6, the relationship between relative TFP growth and GDP per capita remains unchanged across all income groups. The coefficients and the corresponding t-values for the best-fit lines are presented below: HIC: a(-0.04, -3.39) b(-0.01, -1.56), MIC: a(-0.02, -1.19) b(-0.02, -1.40), LIC a(-0.10,-4.46), b(-0.10, -4.88).

The results are presented in Figures 1.12 and 1.13. Figure 1.12 shows the results under the assumption of full depreciation, while Figure 1.13 relaxes this assumption. As observed in both figures, the relationship between relative TFP growth rates and GDP per capita remains consistent with the baseline results. Across all income groups, the agricultural sector exhibits a higher TFP growth rate relative to the manufacturing sector, although the gap narrows as income levels rise. Similar patterns hold for the service sector. These findings suggest that our results remain robust when accounting for income group-specific parameter calibrations.

1.7 Conclusion

Variations in TFP growth rates across different sectors have been identified as one of the key drivers of structural change. For example, a popular finding of [Ngai & Pissarides \(2007\)](#) is that differences in TFP growth rates cause labor to shift from sectors with high TFP growth towards sectors with low TFP growth. This highlights the significance of TFP growth as a central mechanism in the structural transformation of economies, reinforcing its importance in shaping long-term economic trajectories.

The problem that arises is that sector-level TFP is mostly unobserved in the data, complicating the confirmation of the assumption of differential TFP growth rates made by these models. We contribute to the literature by building a discrete version of the model by [Ngai & Pissarides \(2007\)](#) and utilizing the features of the model to compute relative sector TFP growth rates. The model allows for the features of balanced growth to be maintained at the aggregate level while allowing for the dynamics of structural change at the sector level. We show that the consumption share of output is the only thing needed from the aggregate economy to track the dynamics at the sector level.

We proceed to solve for the consumption share of output under assumptions that allow for a closed-form solution and by dynamic programming. We calibrate the model as a three-sector model (manufacturing, agriculture, and services) and show that with data on sector employment shares, which is readily available, and some calibrations for the model

parameters, relative TFP growth rates can be computed.

Our results show significant TFP differentials across sectors, with these differentials varying at different income levels. Relative to manufacturing, TFP growth in agriculture is higher, with the difference declining with increasing income levels. A similar trend is observed for the TFP growth in services relative to manufacturing. These trends give rise to the patterns of structural change suggested by [Ngai & Pissarides \(2007\)](#). TFP in agriculture grows faster than in manufacturing, leading to employment shifts towards manufacturing and a decline in employment shares in agriculture. We also observe that for HICs, TFP in manufacturing grows faster than services, which explains the typical rise in service employment shares in HICs.

In our sensitivity analysis, we show that our results are robust to an alternative aggregation of the manufacturing good, re-specifying the model as a small open economy model, and calibrating the model parameters differently each income group to account for specific structural differences.

An important limitation of this study is our inability to account for the possibility that sectors are becoming increasingly capital-intensive. This structural shift may lead to evolving skill requirements for workers, which could, in turn, influence the direction of labor reallocation across sectors. It would therefore be more appropriate to distinguish between the reallocation patterns of skilled and unskilled labor. However, due to data limitations, we are unable to make this distinction. Future research could usefully extend this work along that dimension. Similarly, future work could potentially distinguish between embodied and disembodied capital, as this could provide for a broader set of dynamics.

In conclusion, our results underscore the critical role of sectoral TFP growth in driving structural change across economies. These findings not only reinforce the importance of sectoral dynamics in economic development but also highlight the value of multi-sector models in understanding the evolving structure of economies over time.

Chapter 2

Government debt and labor productivity growth: Decomposing the effects

2.1 Introduction

The relationships between government debt and economic growth and labor productivity remains relevant as both developed and developing countries continue to grapple with rising fiscal deficits and debt levels, especially in the wake of the recent global financial crisis ([Reinhart & Rogoff, 2010b](#)). The conventional view is that fiscal policy is less stimulative at elevated debt levels. This is primarily due to heightened expectations of future tax increases, which influence current consumption and investment decisions, ultimately leading to lower output ([Bi et al., 2016](#)). Using a neoclassical framework, [Modigliani \(1961\)](#) and [Peter \(1965\)](#) provide theoretical support for this view. [Peter \(1965\)](#) suggests that the need to raise taxes to service debt interest payments has two effects. First, taxes reduce the available lifetime consumption. Taxes also reduce disposable income, which reduces savings and the capital stock.

Empirically, much of the existing literature focuses on the impact of government debt

on economic growth, while relatively little attention has been given to its relationship with labor productivity growth. For instance, [Checherita & Rother \(2010\)](#) identify a non-linear relationship between government debt and economic growth in the Euro-area. Their findings suggest that lower levels of debt contribute positively to economic growth, but this effect turns negative when the debt-to-GDP ratio surpasses 90% to 100%. Similar nonlinearities are found by [Kumar & Woo \(2010\)](#), [Égert \(2013\)](#), [Presbitero \(2012\)](#), and [Baum et al. \(2013\)](#). On the other hand, [Lof & Malinen \(2014\)](#) do not find any evidence of a negative relationship between government debt and economic growth. They conclude that at best, the relationship is ambiguous.

Regarding labor productivity growth, only two notable works address how government debt affects productivity growth. [Salotti & Trecroci \(2016\)](#) examine this relationship in 20 OECD countries. Labor productivity is measured using the growth rate of GDP per hour worked, the growth rate of real output per unit of labor input, and total factor productivity. Their findings conclude that high government debt has a negative effect on productivity growth. Similarly, [Carvelli & Trecroci \(2021\)](#) explore this relationship for a sample of 75 OECD and non-OECD countries using the growth of output per worker as a proxy for labor productivity. They also find that government debt is negatively associated with labor productivity.

This chapter contributes to the literature in two ways. The current studies examining the impact of government debt on labor productivity growth rely on macro-level proxies such as GDP per hour worked, output per unit of labor input, or total factor productivity. While informative, these proxy measures may not accurately capture the underlying concept of labor productivity, potentially leading to measurement bias or limited insight into the true drivers of labor productivity growth. A key contribution of this study is the use of aggregate labor productivity as a sector-weighted sum of sector-level productivity, using detailed data on value added and employment across sectors. This is a more direct and precise measure of labor productivity growth.

The approach suggested above also allows for the decomposition of labor productivity growth into its underlying components, allowing for the estimation of the effects of govern-

ment debt on each component, a contribution that is unique to this study. Decomposing labor productivity growth is one of the recent advancements in the productivity literature. It allows for a clearer understanding of the key drivers of productivity improvements. Studies such as [McMillan et al. \(2011\)](#), [M. P. Timmer & Szirmai \(2000\)](#), and [M. Timmer et al. \(2015\)](#) have developed methodologies to decompose productivity growth into two primary components: the intra-industry component and the structural change component.

The intra-industry component captures productivity growth arising from improvements in labor productivity within individual sectors. The structural change component represents productivity growth driven by the reallocation of labor across sectors, typically reflecting shifts from low-productivity sectors to high-productivity sectors.

From a policy perspective, this decomposition has two key implications. First, identifying which component predominantly drives productivity growth can help shape targeted policy measures aimed at enhancing overall productivity. Second, when examining the impact of macroeconomic factors, such as government debt, on productivity growth, it is crucial to determine whether the effect operates through intra-industry improvements or sectoral labor reallocation. A clear understanding of these channels will enable policymakers to design more precise and effective interventions.

Utilizing sector-level data on value-added and employment from the Global Productivity Database (GPD) compiled by [Dieppe \(2021\)](#), this chapter decomposes labor productivity growth into the intra-industry and structural change components, following the methodology of [McMillan et al. \(2011\)](#). Panel fixed effects and system GMM methods are applied to estimate the effects of government debt on productivity growth and its components. A dynamic panel threshold model with endogenous regressors is also employed to identify debt thresholds internally, while exogenous debt thresholds are explored for robustness. The channels for the impact of government debt are also explored following [Checherita-Westphal & Rother \(2012\)](#).

The chapter finds that high levels of government debt are associated with reduced productivity growth. Among the components of productivity growth, the intra-industry component is the most affected, while the structural change component shows no statistically significant

effects. The dynamic panel threshold model identifies debt thresholds of 31% and 94%, beyond which the negative impact of government debt on total productivity growth and the intra-industry component, respectively, becomes significant. Additionally, using exogenously imposed debt thresholds following [Reinhart & Rogoff \(2010a\)](#) reveals a threshold of 60%, beyond which the negative effects are also statistically significant.

The chapter further identifies the crowding-out of private and public sector investment as possible channels through which government debt affects labor productivity. A subgroup analysis reveals that the effects of government debt are more pronounced in emerging and developing economies, with no significant effects found for advanced economies.

Sensitivity checks show that the baseline findings are robust to the use of a 3-year interval instead of the 5-year interval used in the baseline estimation. The results are also robust to the use of external debt instead of domestic debt.

The rest of the chapter is organized as follows: Section 2 discusses the data used and their respective sources. Section 3 outlines the methodology for decomposing productivity growth, while Section 4 describes the empirical estimation methodologies employed. Section 5 provides some summary statistics. Section 6 presents the estimation results, and Section 7 presents some robustness checks. The chapter ends with conclusions and policy, and further research recommendations in Section 8.

2.2 Data

To conduct labor productivity growth decomposition, industry-level data on value-added and employment are obtained from the Global Productivity Database compiled by [Dieppe \(2021\)](#). The dataset contains statistics for 9 broad sectors across 103 countries¹¹, spanning from 1950 to 2017. The dataset is populated from multiple sources including the OECD STAN database, the World KLEMS database, the Groningen Growth and Development Center (GGDC) database ([De Vries et al., 2015](#)), the Expanded Africa Sector Database

¹¹The sectors include: Agriculture, forestry, fishing; Mining and quarrying; Manufacturing; Utilities; Construction; Trade services; Transport services; Business and Financial Services; Other services.

([Mensah et al., 2018](#)), the APO Productivity Database, the UN database, and the ILOSTAT database.

Recognizing the gradual nature of productivity growth and structural transformation, the data is segmented into 5-year non-overlapping intervals. For government debt and other control variables, non-overlapping 5-year averages are used, except for the population growth rate, which is computed as the percentage change in population for each 5-year interval. This approach mirrors the methodology employed by [Afonso & Jalles \(2013\)](#) and [Salotti & Trecroci \(2016\)](#) in their examination of economic growth, where they utilize five-year averages. [Aizenman & Sushko \(2011\)](#) argue that this procedure also dampens the effect of short-run business fluctuations. The final dataset used for the estimation is a sample of 85 countries spanning from 1950 to 2015. Data on value-added is in millions of local currency. This is converted to Purchasing Power Parity (PPP) in US dollars using the nominal exchange rate data and the price level of GDP relative to the USA from the Penn-World table.

Data on government debt to GDP is sourced from the historical public debt database provided by the IMF. This database was first compiled by [Ali Abbas et al. \(2011\)](#). General government includes central government debt plus any applicable state and local level government debt. The data is compiled by bringing together databases from other researchers and institutional bodies, government publications, and publications of the League of Nations, the United Nations, and the International Financial Statistics (IFS).

Other variables such as the index of human capital, and capital stock at current PPPs, Real GDP, number of persons employed, the internal rate of return, total factor productivity, and the population are sourced from the Penn World Table, while trade openness is sourced from the World Bank Development Indicators (WDI). Private and public gross fixed capital formation as a percentage of GDP are sourced from the Investment and Capital Stock Database (ICSD) of the IMF, and the current account balance as a percentage of GDP is taken from the World Economic Outlook (WEO) dataset by the IMF. A detailed description of the variables and their data sources and transformations is provided in [Table B.1](#) in the appendix.

2.3 Productivity growth decomposition

Labor productivity growth typically stems from two primary sources. Firstly, productivity advancements may arise from within sectors, facilitated by intra-industry improvements in capital accumulation and technological innovations. Additionally, productivity growth can be driven by the reallocation of labor across sectors, shifting from low-productivity sectors to high-productivity ones. The first step in this analysis is to decompose aggregate labor productivity growth into these two components.

Consider a country with data on value-added and employment for 9 sectors. For each country (j), the value added for each sector (i) at time (t) is represented as Q_{jit} . Similarly, represent the number of persons employed in each sector as L_{jit} . Define sector-level labor productivity and employment shares, respectively, as:

$$y_{jit} = \frac{Q_{jit}}{L_{jit}}.$$

$$l_{jit} = \frac{L_{jit}}{L_{jt}}.$$

Hence, aggregate labor productivity in a country can be defined as the weighted sum of the productivity across all sectors, where the weight is the respective sector's employment share. That is:

$$LP_{jt} = \sum_{i=1}^9 y_{jit} l_{jit}. \quad (2.1)$$

It is important to note that the value-added data used in this study does not exclude the contribution of capital at the sectoral level. Data on value added attributable solely to labor are generally not available, necessitating the use of the broader definition of value added. As a result, the measure of labor productivity employed here, though commonly used in the literature, does not fully isolate the contribution of labor inputs. Instead, it reflects a broader notion of productivity that encompasses the effects of capital deepening and total factor productivity.

Considering a period $[0,1]$ where 0 is the beginning of the period and 1 is the end of the

period, the change in aggregate labor productivity at the end of the period is:

$$LP_{j,1} - LP_{j0} = \sum_{i=1}^9 y_{ji1} l_{ji1} - \sum_{i=0}^9 y_{ji0} l_{ji0}. \quad (2.2)$$

With some rearranging and algebraic manipulation, Equation (2) can be expressed in growth terms as:

$$\frac{LP_{j1} - LP_{j0}}{LP_{j0}} = \frac{1}{LP_{j0}} \sum_{i=1}^9 (y_{ji1} - y_{ji0}) l_{ji0} + \frac{1}{LP_{j0}} \sum_{i=1}^9 (l_{ji1} - l_{ji0}) y_{ji1}. \quad (2.3)$$

This is the decomposition presented by [McMillan et al. \(2011\)](#). The first term on the right-hand side is the intra-industry component. It is measured as the sum of the changes in industry labor productivity weighted by the industry employment shares at the beginning of the period. Because the employment shares are held constant, any changes in this component can only be attributed to intra-industry improvement in labor productivity. The second term is the structural change component. This is a weighted sum of the changes in employment shares with the sector productivity levels as weights. This captures the labor productivity effect of labor reallocation across the sectors. As a result, a positive value for the structural change component implies a movement of labor from less productive to more productive sectors. Other authors, such as [M. P. Timmer & Szirmai \(2000\)](#), provide alternative three-component decompositions. However, the approach of [McMillan et al. \(2011\)](#) is adopted for simplicity.¹²

¹²The procedure by [M. P. Timmer & Szirmai \(2000\)](#) decomposes productivity growth into three components: the intra-industry effect, the static shift effect, and the dynamic shift effect. The summation of the static shift effect and the dynamic shift effect is equivalent to the structural change component presented by [McMillan et al. \(2011\)](#).

2.4 Empirical methodology

2.4.1 Baseline specification

To estimate the effect of government debt on labor productivity growth and its components, I borrow from growth equations that link economic growth to the level of capital and population growth. Productivity growth and its components replace economic growth. Capital is measured as the logarithm of capital stock per worker (*log_cap_st_pw*). Capital stock per worker is computed by dividing the capital stock by the total number of persons employed. The population growth rate (*pop_gr*) is calculated for each 5-year interval. Consistent with the convergence literature, the log of initial GDP per capita (*log_init_gdpcap*) for each 5-year interval is included. The model is augmented to include government debt as a percentage of GDP (*gov_debt_gdp_{jt}*).

Other control variables are included based on their potential explanatory power from existing empirical studies. These include trade openness (*top*), computed as the sum of exports and imports as a share of GDP. This is added to expand the model beyond a closed economy. Human capital (*hc*) proxied by the index of human capital from the Penn World table is also included. This index is computed based on years of school and returns to education. Both exogenous and endogenous growth models emphasize the importance of human capital in economic growth and productivity. [Mankiw et al. \(1992\)](#) advocate for the inclusion of human capital separately as an input in the production function, as it improves the performance of the Solow growth model. Endogenous growth models capture human capital by modeling total factor productivity as a function of human capital. The view is that a better-educated labor force is capable of adopting and implementing new technologies, making them more productive ([Benhabib & Spiegel, 1994](#)). The baseline specification is:

$$Z_{jt} = \alpha_0 + \beta_1 gov_debt_gdp_{jt} + \phi_1' X_{jt} + \varphi_j + \eta_t + \epsilon_{jt}. \quad (2.4)$$

Three separate regressions are estimated, with total productivity growth (*tot_p_gr*), the structural change component (*st_change*), and the intra-industry component (*intra_ind*) serving

as the dependent variables in each case. Hence, Z_{jt} is a vector of these variables. Government debt is the 5-year non-overlapping average of government debt to GDP for a country, and β_1 is the respective coefficient. The vector X_{jt} contains 5-year non-overlapping averages of the control variables, and ϕ'_1 is a vector of their respective coefficients. φ_j and η_t are the country and time-fixed effects respectively, and ϵ_{jt} is the error term.

The baseline estimation is a panel fixed effects model corrected for heteroscedasticity and autocorrelation. The panel fixed effects estimation accounts for unobserved country-specific heterogeneities that may significantly impact the estimates. While adding fixed effects controls for country-specific characteristics, it does not deal with any potential issues of endogeneity. Most of the variables on the right-hand side could be functions of productivity growth and its components as well. For example, countries that have higher levels of productivity growth may have high GDP growth and can accommodate higher levels of debt. Addressing endogeneity usually requires the use of instrumental variable techniques. However, with difficulty in getting good instruments for all the variables in the model, the model is re-specified as a dynamic panel model, allowing for the utilization of the two-step system-GMM estimation technique proposed by [Blundell & Bond \(1998\)](#). The dynamic model is specified as:

$$Z_{jt} = \gamma'_1 Z_{jt-1} + \beta_2 gov_debt_gdp_{jt} + \phi'_2 X_{jt} + \varphi_j + \eta_t + \epsilon_{jt}. \quad (2.5)$$

The system GMM allows for a consistent estimation of dynamic panel models while using lag differences as instruments for endogenous variables ([Arellano & Bover, 1995](#)). In this specification, all variables are endogenized and instrumented using their lags. The two-step process is preferred because it is asymptotically more efficient compared to the one-step process.

2.4.2 Exploring thresholds

Examining the presence of non-linear effects of government debt on productivity growth and its components is highly relevant. Nonlinearities in the impact of government debt on

macroeconomic variables are well established in the literature. In growth literature, studies such as [Caner et al. \(2010\)](#), [Kourtellis et al. \(2013\)](#), [Égert \(2015\)](#), and [Law et al. \(2021\)](#) have explored the non-linear relationship between government debt and growth. While some studies, such as [Checherita-Westphal & Rother \(2012\)](#), introduce squared terms of government debt to test for nonlinearities, others, including [Afonso & Jalles \(2013\)](#), impose exogenous debt thresholds. Additionally, studies like [Caner et al. \(2010\)](#) and [Law et al. \(2021\)](#) employ dynamic panel threshold models, where the thresholds are determined endogenously. This chapter follows [Kremer et al. \(2013\)](#) to use a dynamic panel model with endogenous regressors. The most popular panel threshold model used in the literature is the [B. E. Hansen \(1999\)](#) method. This method, however, is unable to handle endogenous regressors. [Kremer et al. \(2013\)](#) extend this model to include endogenous regressors. The method uses the cross-sectional threshold model proposed by [Caner & Hansen \(2004\)](#) and applies it in a dynamic setup, allowing for endogeneity through the use of GMM-type estimators. The model is presented as follows:

$$Z_{jt} = \varphi_j + \gamma_2 Z'_{jt-1} + \beta_3 gov_debt_gdp_{jt} I(gov_debt_gdp_{jt} \leq \lambda) + \beta_4 gov_debt_gdp_{jt} I(gov_debt_gdp_{jt} > \lambda) + \phi'_2 X_{jt} + \xi_{jt}. \quad (2.6)$$

Government debt is both the regime-dependent and the threshold variable. $I(\cdot)$ is an indicator function indicating the debt regime, and λ is the debt threshold. The coefficients β_3 and β_4 are the regression slopes for low and high debt regimes, respectively.

The first step of the estimation method is to eliminate the country-specific effects φ_j through a fixed effects transformation. In this step, a forward orthogonal transformation procedure, as suggested by [Arellano & Bover \(1995\)](#) is used. With this method, the average of all future observations of a variable is subtracted from its current value, avoiding the problem of serial correlation of the lagged dependent term that usually arises from differencing dynamic panel models.

The next step involves estimating a reduced form regression for all the endogenous variables as a function of the instruments. The endogenous variables in the structural equation

are then replaced by their predicted values from the reduced form regressions. Equation (6) is then estimated for a series of fixed debt thresholds (λ). The sum of squared residuals for each threshold, represented as $S(\lambda)$, is obtained. The selected threshold is the one with the smallest sum of squared residuals ($\hat{\lambda} = \arg \min_{\lambda} S_n(\lambda)$).

I also impose exogenous government debt thresholds of 30%, 60%, and 90% following [Reinhart & Rogoff \(2010a\)](#) for robustness. Dummy variables for these thresholds are interacted with the government debt variable. This procedure allows for detecting changes in the effect of debt on productivity growth and its components in a step-wise manner. This specification is written as:

$$Z_{jt} = \alpha_1 + \kappa_1 gov_debt_gdp_{jt} Dum30 + \kappa_2 gov_debt_gdp_{jt} Dum3060 + \kappa_3 gov_debt_gdp_{jt} Dum3090 + \kappa_4 gov_debt_gdp_{jt} Dum90 + \phi'_3 X_{jt} + \varphi_j + \eta_t + \nu_{jt}. \quad (2.7)$$

Where $Dum30$, $Dum3060$, $Dum6090$, and $Dum90$ are the dummy variables taking of 1 if the average debt to GDP is less than or equal to 30% of GDP, between 30% and 60%, between 60% and 90%, and above 90% of GDP respectively.

2.4.3 Exploring channels for the impact of government debt

Another relevant question in the growth and labor productivity literature is the channels through which government debt may impact economic growth and labor productivity. Though important, empirical studies on this subject have been limited and largely inconclusive. For example, [Pattillo et al. \(2004\)](#) explore the channels through which government debt affects productivity growth in a panel of 61 developing countries between 1969 and 1998. They rely on the growth accounting process to identify total factor productivity, capital accumulation, and human capital as the determinants of economic growth and estimate the effects of government debt on these variables. They find that approximately one-third of the negative effect of debt on economic growth occurs through capital accumulation, while two-thirds of the effect is transmitted through total factor productivity growth.

Schclarek (2004) also identifies capital formation and total factor productivity as relevant channels. Similarly, Checherita-Westphal & Rother (2012) explore the relationship between government debt and economic growth in 12 Euro-area countries over 40 years, starting from 1970. They find that debt has a nonlinear relationship with economic growth and identify private savings, private investment, and total factor productivity growth as the possible channels through which this nonlinear effect is transmitted.

Examining similar relationships in Portugal, Silva (2020) finds that only public and private investments serve as relevant channels for government debt. Likewise, Qureshi & Liaqat (2020), in studying the impact of external debt on economic growth, identify savings and investment as the primary transmission channels. Lastly, Hassan & Meyer (2021) explore these relationships for sub-Saharan Africa and find that interest rates serve as a relevant channel for the transmission of external debt's effects on economic growth, while savings are not a significant channel.

Although these papers relate to economic growth, the channels proposed also affect labor productivity and are therefore relevant for this study. For instance, Ramirez (2000) and Ramirez (2002) have established that public and private investments significantly affect labor productivity, while Liu et al. (2022) establishes a significant relationship between interest rates and labor productivity. Growth models and production theory establish a strong link between Total Factor Productivity (TFP) and labor productivity. For example, in the Solow (1956) model, output is a function of capital, labor, and TFP, with labor productivity increasing either due to capital deepening or improvements in TFP.

Therefore, following Checherita-Westphal & Rother (2012), I explore public investments, private investments, and total factor productivity as possible channels for the transmission of the effects of government debt on labor productivity growth and its components. Interest rates and savings are not explored because of data limitations. The following regressions are estimated:

$$priv_inv_gdp_{jt} = \alpha_2 + a_1 gov_debt_gdp_{jt} + \phi'_3 Q_{jt} + \varphi_j + \eta_t + \varsigma_{jt}. \quad (2.8)$$

$$gov_inv_gdp_{jt} = \alpha_3 + a_2 gov_debt_gdp_{jt} + \phi'_4 S_{jt} + \varphi_j + \eta_t + \vartheta_{jt}. \quad (2.9)$$

$$tfp_{jt} = \alpha_2 + a_4 gov_debt_gdp_{jt} + \phi'_5 R_{jt} + \varphi_j + \eta_t + \vartheta_{jt}. \quad (2.10)$$

Where $gov_inv_gdp_{jt}$ is government investment proxied by government gross fixed capital formation as a percentage of GDP, $priv_inv_gdp_{jt}$ is private sector investment proxied by gross fixed capital formation in the private sector as a percentage of GDP, and tfp_{jt} is total factor productivity.¹³

Q_{jt} , S_{jt} , and R_{jt} are vectors of covariates in each of the regressions. The covariates chosen are according to the established literature on this subject (Checherita-Westphal & Rother, 2012; Qureshi & Liaqat, 2020; Ramirez, 2002; Silva, 2020). For private investment, the covariates (Q_{jt}) include initial GDP per capita, average corporate tax rates, the internal rate of return, the population growth rate, the growth rate of GDP per capita, trade openness, the index of human capital, and government investment to GDP. For government investment, the covariates (S_{jt}) include initial GDP per capita, the population growth rate, the growth rate of GDP per capita, trade openness, private investment to GDP, the index of human capital, and the current account balance as a percentage of GDP. For TFP, the covariates (R_{jt}) include initial GDP per capita, the population growth rate, the growth rate of GDP per capita, trade openness, private investment to GDP, government investment to GDP, and the index of human capital.

These equations are estimated with both fixed effects and the system GMM. Thresholds are also explored using the endogenous threshold model and the exogenously imposed thresholds as well.

2.5 Descriptive statistics

Table 2.1 presents the general summary statistics for all the variables of interest for the full sample. Productivity growth averages approximately 14%. A significant portion of this

¹³The TFP value is computed using the formula $TFP_{ij} = \frac{CGDP_i^o}{CGDP_j^o} \times Q_{ij}^T$. Where $CGDP^o$ is real GDP and Q_T is a Törnqvist quantity index of factor inputs, which can be used for comparing productivity between two countries i and j . The values are normalized to the USA. See Feenstra et al. (2015) for more details.

growth is attributed to the intra-industry component (11%). Only about 3% is attributed to structural change. The industry breakdown of productivity growth is presented in Table 2.2. Except for financial services, the average of the intra-industry component is higher than the structural change component for all the sectors. In the agricultural and manufacturing sectors, the average of the structural change component is negative. By construction, the structural change component is driven by inter-industry labor reallocation. Hence, these negative averages suggest a movement of labor out of these sectors. This pattern of labor movement is a well-documented stylized fact about structural change in the literature (Cai, 2015). Another point to note is that compared to other sectors, all the service sectors record relatively higher averages of the structural change contribution to productivity growth. This suggests a movement of labor towards the service sectors. The summary statistics of all the other control variables across all estimations are also presented in Table 2.1.

In Figure 2.1, productivity growth and its components are broken down by government debt levels. Debt thresholds of 30%, 60%, and 90% are adopted following Reinhart & Rogoff (2010a). The pattern observed in the figure provides an early understanding of the association between government debt and productivity growth. Productivity growth decreases as debt levels increase. The lowest average productivity growth is recorded when debt levels exceed 90%. Also, across all debt levels, the intra-industry component contributes the most to productivity growth. For debt levels less than 30% of GDP, the intra-industry component is more than 4.7 times the structural change component. For debt levels between 30% and 60%, it is about 2.8 times the structural change component while for debt levels between 60% to 90% and above 90%, the intra-industry component is about 3.5 times, and 1.03 times respectively. Figures 2.3, 2.4, and 2.4 present correlations between government debt and productivity growth and its components, grouped by debt levels. The correlation coefficients and their respective p-values are reported as well. For debt levels below 30%, between 30% and 60%, and between 60% and 90%, there is no significant correlation between government debt and productivity growth and its components. However, for debt levels above 90% of GDP, there is a significant negative correlation between government debt and productivity growth and the structural change component. The correlation with the within

component is negative but not significant. These correlation patterns suggest the possible presence of threshold effects, where the effects of government debt are only significant at higher debt levels.

Table 2.1: Summary statistics

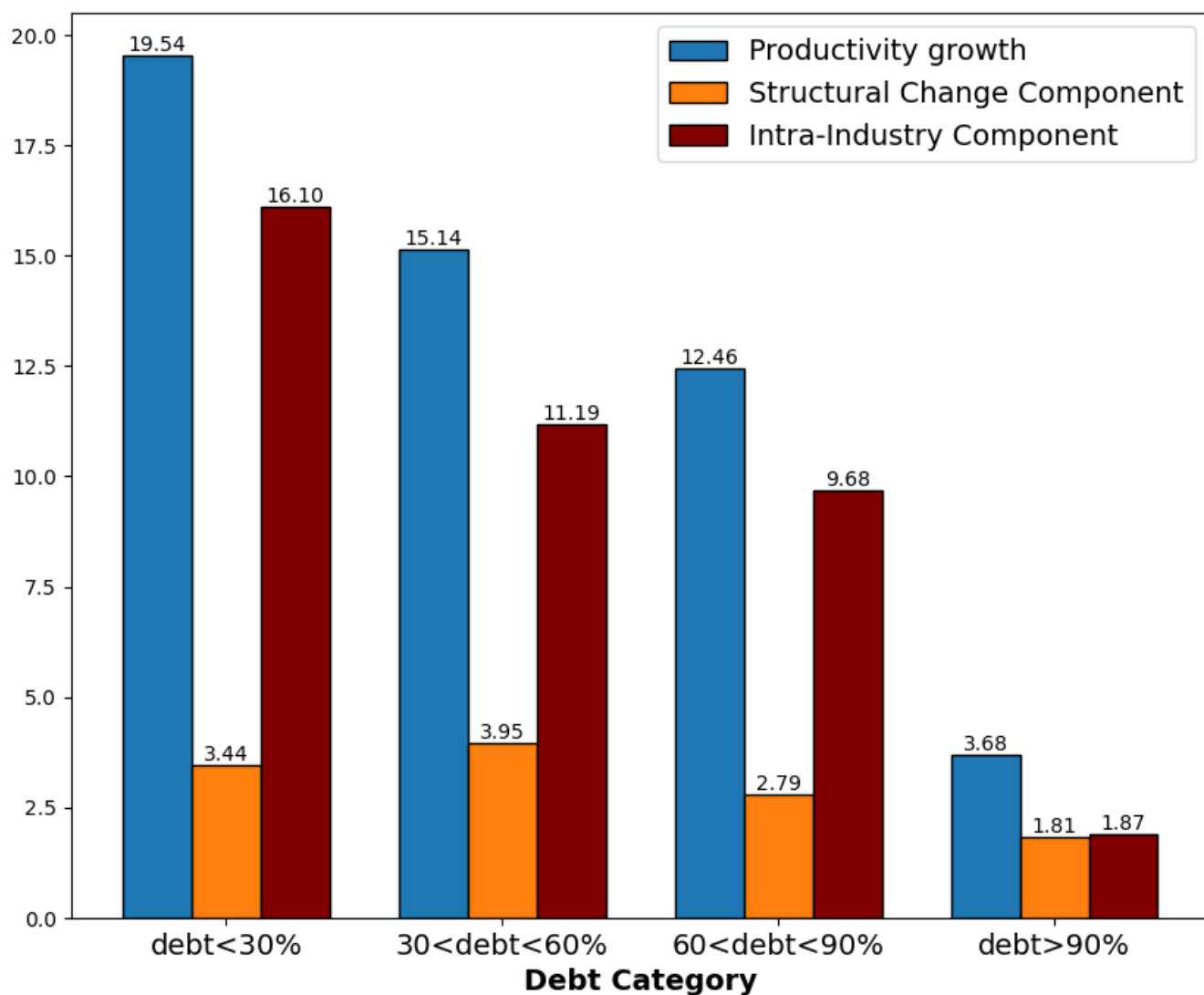
	Mean	Std Dev.	Min	Max	Obs
Total productivity growth (tot_p_gr)	14.29	24.17	-71.27	264.95	712
Intra-industry component(intra_ind)	10.97	23.08	-69.65	241.2	712
Structural change component(st_change)	3.32	6.6	-52.38	32.87	712
Government debt (%GDP) (gov_debt_gdp)	53.67	33.94	0.13	236.1	719
Trade openness (top)	77.03	57.45	5.6	425.16	718
Log of initial GDP per capita (log_init_gdpcap)	9.11	1.22	5.98	11.67	815
Log of capital stock per worker (log_cap_st_pw)	11.09	1.49	6	13.48	811
Population growth (pop_gr)	0.06	0.06	-0.24	0.91	815
Total factor productivity (tfp)	0.97	0.19	0.4	2.1	719
Index of human capital (hc)	2.36	0.74	1.01	3.99	795
Internal rate of return (irr)	0.121	0.07	0.01	0.50	725
Private sector investment (%GDP) (priv_inv_gdp)	14.24	6.03	0.39	37.3	789
Government investment (gov_inv_gdp)	4.61	3.30	0.38	31.48	789
Current account balance (%GDP) (curr_bal_gdp)	-1.51	6.72	-33.12	36.7	652
Average corporate tax rates (tax_rate)	31.01	9.65	0	61.63	634

2.6 Estimation results

2.6.1 Panel fixed effects and system GMM

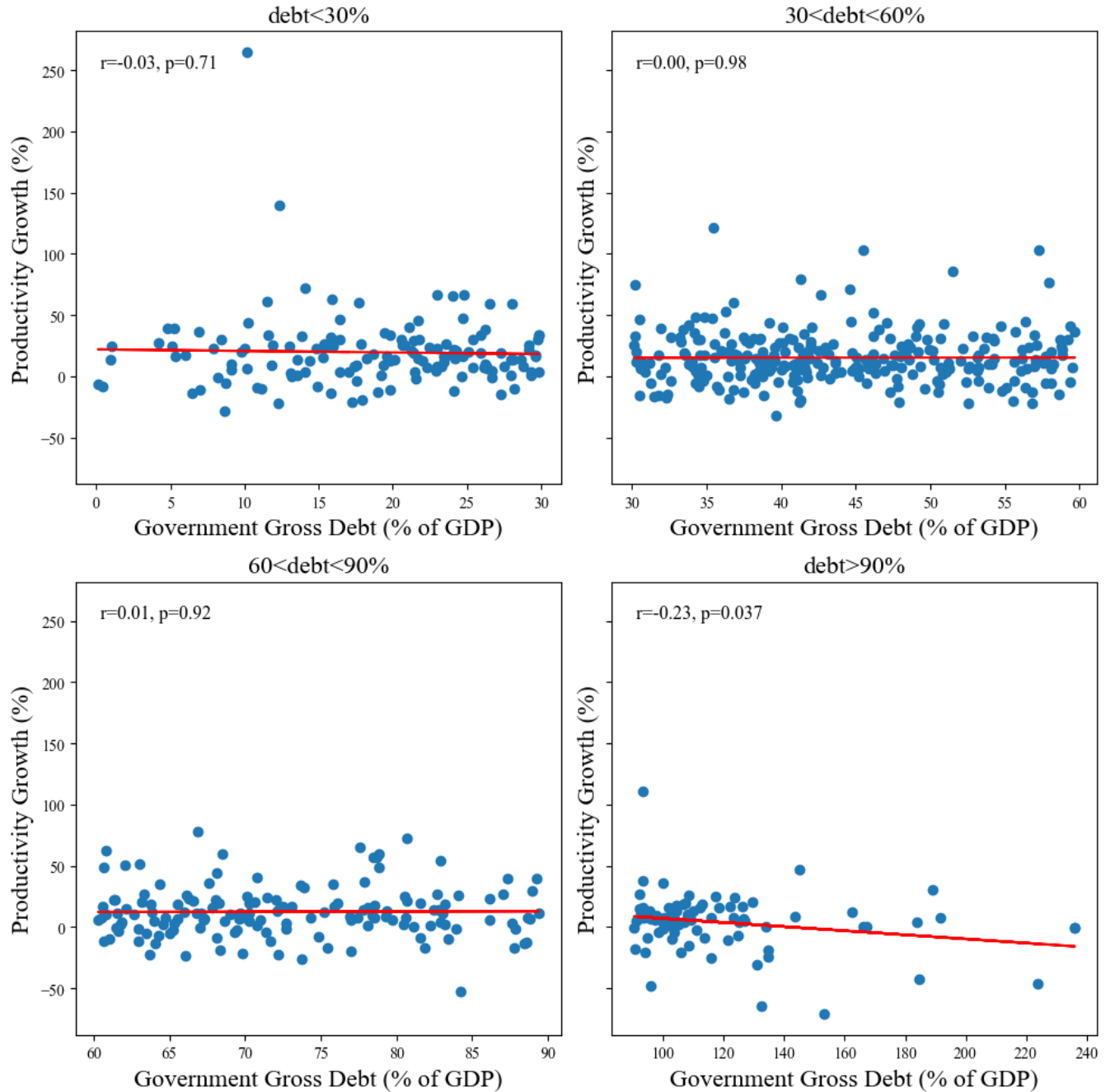
Table 2.3 presents the panel fixed effects and system GMM estimations for the relationship between government debt and labor productivity growth, along with its components. In the fixed effects model, country and time-fixed effects are included to account for any unobserved country-specific and time-varying characteristics. For the system GMM estimation, the two-step process is employed to improve efficiency. All variables are treated as endogenous, with up to three lags used as instruments. As is conventional in most GMM estimations, year dummies are included in the regressions. The Hansen over-identification test is conducted to determine the validity of the instruments used in the estimations (L. P. Hansen, 1982). Across all estimations, the high p-values indicate that the null hypothesis of instrument validity is not rejected, implying that the instruments are valid. The validity of the estimates also requires a test of first- and second-order autocorrelations. First-order autocorrelation (AR(1)) is expected due to the first difference transformation employed by the system GMM. However, if the instruments are valid, the residuals should not exhibit second-order autocor-

Figure 2.1: Productivity growth decomposition by debt category



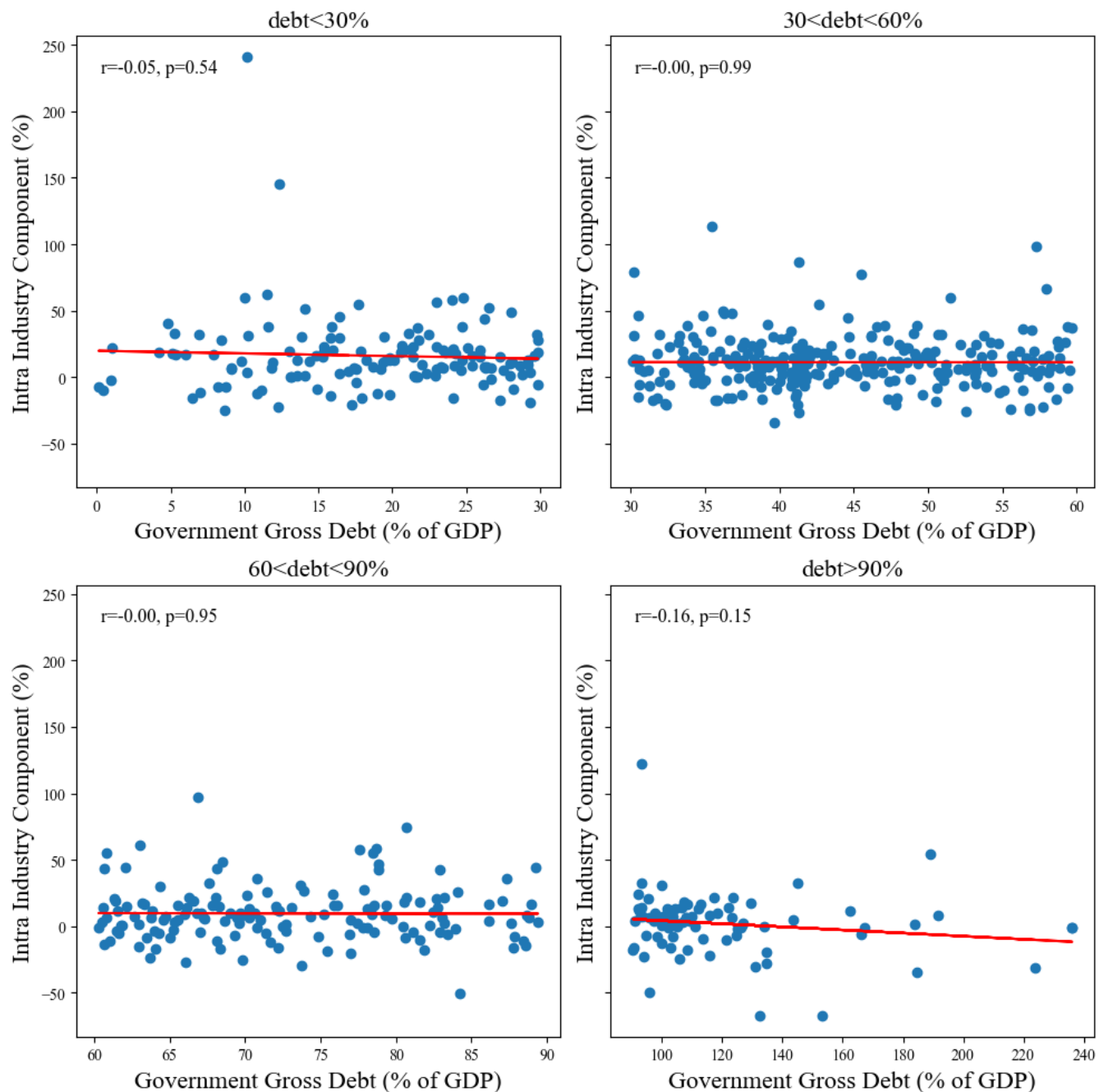
Note: Figure 2.1 shows productivity growth decomposed into its components based on the [McMillan et al. \(2011\)](#) procedure. The data is categorized by debt levels. Following [Reinhart & Rogoff \(2010a\)](#), thresholds of 30%, 60% and 90% are utilized. Higher debt levels are associated with low levels of productivity growth. Across all debt categories, the intra-industry component contributes more to productivity growth.

Figure 2.2: Correlation between total productivity growth and government debt



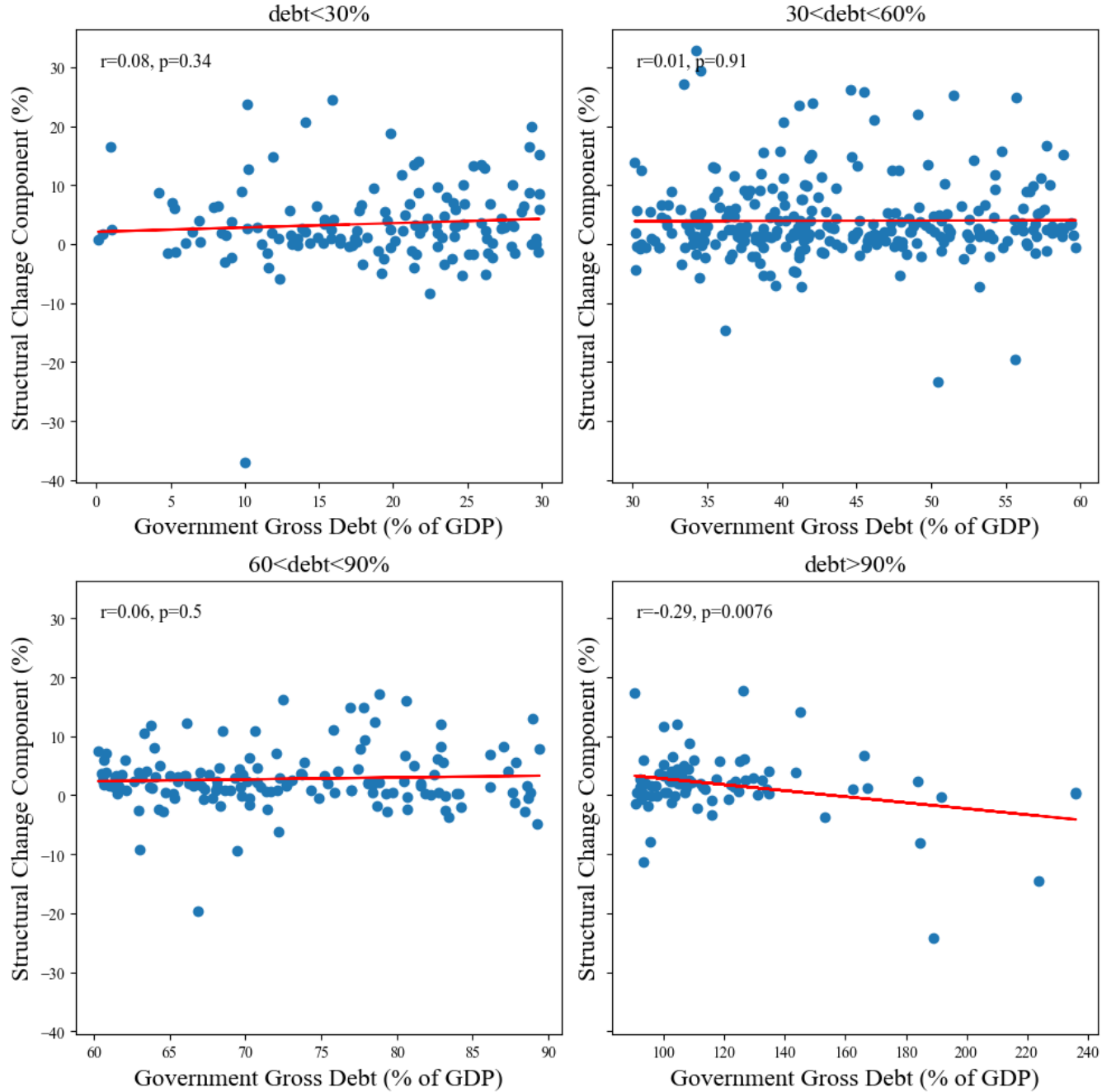
Note: Figure 2.2 shows a correlation between government debt and productivity growth. The data is categorized by debt levels. No statistically significant correlations exist at lower debt levels. A negative and significant correlation is, however, noticed for debt levels above 90%.

Figure 2.3: Correlation between the intra-industry component and government debt



Note: Figure 2.3 shows a correlation between government debt and the intra-industry component of productivity growth. The data is categorized by debt levels. There are no statistically significant correlations between government debt and the intra-industry component across all debt levels.

Figure 2.4: Correlation between the structural change component and government debt



Note: Figure 2.4 shows a correlation between government debt and the structural change component of productivity growth. The data is categorized by debt levels. No statistically significant correlations exist at lower debt levels. A negative and significant correlation is, however, noticed for debt levels above 90%.

Table 2.2: Average sector distribution of productivity growth

	Intra-industry component	Structural change component	Total productivity growth
Agriculture	0.23	-0.25	-0.02
Manufacturing	0.8	-0.39	0.41
Mining	0.12	0.01	0.13
Utilities	0.08	0.002	0.082
Construction	0.16	0.04	0.2
Trade services	0.38	0.15	0.53
Transport services	0.24	0.13	0.37
Financial services	0.37	0.71	1.08
Other services	0.59	0.2	0.79

Note: [Table 2.2](#) presents the average values of productivity growth and its components by the 9 sectors. Except for financial services, the structural change component contributes the least to productivity growth across the sectors. For the agricultural and manufacturing sectors, the structural change component contributes negatively to productivity growth.

relation (AR(2)). The tests are conducted using the test statistics proposed by [Arellano & Bond \(1991\)](#). Across all models, there is no evidence of second-order serial correlation, as shown by the high p-values of the Arellano-Bond test statistics in all models.

For both fixed effects and system GMM results, total productivity growth, the structural change component, and the intra-industry component serve as the dependent variables. Consistent with the literature, there is a negative association between government debt and productivity growth. This negative relationship persists for both components of productivity growth. However, while the coefficient for the structural change component is insignificant, the coefficient for the intra-industry component is strongly significant.

This relationship remains consistent across the fixed effects and system GMM estimations, suggesting that government debt primarily affects productivity growth through the intra-industry component. Regarding total productivity growth, the fixed effects results align with the findings of [Salotti & Trecroci \(2016\)](#). However, their system GMM estimates were insignificant. The results are also in line with [Carvelli & Trecroci \(2021\)](#), who find evidence of a negative effect of government debt on labor productivity using a system GMM estimation. Similarly, [Blavy \(2006\)](#) finds a negative effect of public debt on productivity growth in

Jamaica, while for sub-Saharan Africa, [Wamboye & Tochkov \(2015\)](#) also find that external debt negatively impacts labor productivity growth.

This chapter is novel in its estimation of the impact of government debt on the decomposed components of labor productivity growth. By distinguishing between the structural change and intra-industry components, it provides a more nuanced understanding of how government debt influences productivity dynamics. The findings suggest that while aggregate productivity growth declines with rising government debt, the primary channel through which this occurs is the effect government debt has on within-industry productivity improvements rather than through inter-sectoral labor movements. This distinction is crucial for policymakers, as it highlights the importance of fostering within-industry efficiency improvements while mitigating the potential crowding-out effects of excessive debt accumulation.

Regarding the control variables, initial GDP per capita is positively associated with total productivity growth and the intra-industry component across both fixed effects and system GMM results. The population growth rate, the log of capital stock per worker, and trade openness have no significant effects across all models. Human capital is negatively associated with total productivity growth and the structural change component for the fixed effects model, while the relationship is significant for total productivity growth and the intra-industry component for the system GMM estimates.

Table 2.3: Panel fixed effects and system GMM estimates

Variable	Fixed Effects			System-GMM		
	tot_p_gr	st_change	intra_ind	tot_p_gr	st_change	intra_ind
gov_debt_gdp	-0.213*** (0.070)	-0.013 (0.018)	-0.199*** (0.058)	-0.655*** (0.137)	0.022 (0.018)	-0.573*** (0.112)
log_init_gdpcap	14.786*** (5.173)	1.639 (2.130)	13.147** (6.202)	69.213* (37.045)	-0.549 (2.751)	50.090* (29.036)
pop_gr	4.252 (0.070)	2.569 (4.483)	10.362 (29.463)	-83.637 (88.151)	10.627 (21.187)	-33.834 (57.477)
log_cap_st_pw	4.072 (4.507)	1.040 (1.447)	3.031 (4.149)	1.827 (20.569)	-1.029 (1.963)	16.863 (17.931)
hc	-22.913** (9.742)	-9.768*** (3.367)	-13.145 (8.409)	-153.929** (59.612)	1.250 (2.988)	-142.964*** (54.510)
top	0.021 (0.077)	0.000 (0.018)	0.021 (0.066)	0.217 (0.180)	0.006 (0.008)	0.189 (0.156)
L.tot_gr				0.057 (0.104)		
L.st_change					0.212*** (0.077)	
L.intra_ind						0.032 (0.094)
intercept	-103.93 (69.838)	1.115 (17.571)	-105.050 (67.762)	-232.616* (124.868)	10.776 (8.954)	-262.720 (118.145)
Hansen overid. test				8.98	15.31	4.93
Arellano-Bond AR(1) test				-2.18**	-3.25***	-2.17**
Arellano-Bond AR(2) test				-1.17	1.08	-1.48
No. of instruments				26	35	25
No. of groups				94	85	94

Note: Table 2.3 presents the results for the estimates for the panel fixed effects and the system GMM estimations. Statistical significance is represented as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ respectively. The insignificant Hansen test statistic implies instrument validity. The insignificant Arellano-Bond test for AR(2) implies no second-order autocorrelation.

2.6.2 Threshold analysis

In this section, the results of the threshold analysis are presented. Debt thresholds are first endogenously determined using the dynamic debt threshold model presented in Equation (6). All the variables are treated as endogenous, and up to 2 lags are used as instruments. The results are summarized in Table 2.4. The determined government debt thresholds are about 31%, 41%, and 94% for total productivity growth, the structural change component, and the intra-industry component respectively. All the thresholds are statistically significant using the 95% confidence intervals.

For total productivity growth, the coefficient for government debt is positive when government debt is below the threshold of 31%, and negative above the threshold. However, only the coefficient for the higher debt regime is statistically significant. Regarding the intra-industry component, government debt has a negative effect above and below the threshold of 94%. Similarly, only the coefficient for the higher debt regime is statistically significant. Consistent with the baseline results, the effect of government debt on the structural change component remains statistically insignificant across all debt regimes.

The results for the exogenous debt threshold model are reported in Table 2.5. Based on the fixed effects estimates, the negative effect of government debt on total productivity growth and the intra-industry component is significant at debt levels above 60%. The system GMM results yield similar threshold values, reinforcing the robustness of the findings.

The thresholds identified in the dynamic threshold model differ from those determined by the exogenously imposed debt threshold model. This difference may arise from methodological variations between the two approaches. While the exogenous model applies predetermined debt thresholds, the dynamic panel threshold model derives the thresholds directly from the data. Despite these differences in threshold values, the core finding that excessive government debt impairs productivity growth, particularly through its intra-industry component, remains robust.

Table 2.4: Dynamic panel threshold analysis

Variables	tot_p_gr	st_change	intra_ind
Threshold Estimates			
$\hat{\lambda}$	31%	41%	94%
95% Confidence Interval	[20.801-95.506]	[21.068-93.721]	[20.025- 84.145]
Impact of Government Debt to GDP			
$\hat{\beta}_3$	0.226 (0.646)	-0.059 (0.216)	-0.117 (0.216)
$\hat{\beta}_4$	-0.269** (0.110)	-0.035 (0.096)	-0.290** (0.126)
L.tot_p_gr	0.164* (0.092)		
L.st_change		0.051 (0.175)	
L.intra_ind			0.179*** (0.067)
log_init_gdpcap	-19.826 (22.671)	-2.803 (7.231)	-10.001 (12.122)
pop_gr	-37.557 (85.660)	7.422 (26.723)	-89.623 (84.203)
hc	8.511 (17.976)	1.063 (2.979)	0.461 (11.130)
top	0.021 (0.055)	0.001 (0.015)	0.039 (0.045)
log_cap_st_pw	8.734 (10.517)	1.169 (3.618)	4.784 (6.593)
intercept	89.366 (69.578)	14.050 (14.455)	56.844 (49.740)
Observations	500	431	509
Countries	93	94	94
Number of instruments	70	70	71

Note: Table 2.4 shows results from the dynamic panel threshold model with endogenous regressors. Estimated debt thresholds are 31% (total productivity), 94% (intra-industry), and 36% (structural change). Higher debt is associated to lower growth in total productivity and the intra-industry component. Standard errors are in parentheses; significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: Exogenous debt threshold analysis

Variable	Fixed Effects			System-GMM		
	tot_gr	st_change	intra_ind	tot_gr	st_change	intra_ind
Dum30*debt	0.104 (0.182)	0.040 (0.060)	0.064 (0.174)	0.123 (0.436)	0.054 (0.125)	-0.065 (0.413)
Dum3060*debt	-0.083 (0.097)	0.014 (0.028)	-0.097 (0.091)	-0.279 (0.218)	-0.043 (0.068)	-0.019 (0.195)
Dum6090*debt	-0.126* (0.070)	-0.001 (0.021)	-0.128* (0.066)	-0.321* (0.189)	-0.027 (0.052)	-0.331** (0.162)
Dum90*debt	-0.177*** (0.050)	-0.006 (0.015)	-0.171*** (0.045)	-0.482*** (0.151)	-0.022 (0.033)	-0.468*** (0.126)
log_init_gdpcap	14.786* (7.689)	1.620 (2.092)	13.166* (7.162)	61.321* (32.211)	0.705 (4.269)	47.567 (26.780)
pop_gr	14.696 (32.755)	3.180 (9.591)	11.516 (108.685)	-86.535 (16.720)	-23.439 (26.625)	-42.441 (72.763)
log_cap_st_pw	10.767** (4.567)	1.028 (1.177)	2.700 (19.885)	-4.098 (2.536)	-2.894 (2.551)	7.293 (18.197)
hc	-22.929*** (7.748)	-9.785*** (2.855)	-13.143* (7.419)	-122.246*** (43.543)	2.194 (5.799)	-115.487*** (43.460)
top	0.023 (0.056)	0.000 (0.014)	0.023 (0.055)	0.181 (0.149)	-0.006 (0.013)	0.157 (0.131)
L.tot_gr				0.127 (0.127)		
L.st_change					0.124 (0.113)	
L.intra_ind						0.107 (0.114)
intercept	-105.99** (53.086)	0.370 (15.075)	-106.36** (50.883)	-189.896* (101.531)	24.618* (12.933)	-210.746** (100.868)
Hansen overid. test				16.73	13.15	10.56
Arellano-Bond test for AR(1)				-2.79***	-3.06***	-2.69***
Arellano-Bond test for AR(2)				-1.06	1.31	-1.48
No. of instruments				32	33	31
No. of groups				94	85	94

Note: Table 2.5 reports results from the exogenous debt threshold model. Debt thresholds are defined as: Dum30 (< 30%), Dum3060 (30–60%), Dum6090 (60–90%), and Dum90 (>90%). The 60% threshold marks the point beyond which debt significantly reduces total productivity growth and its intra-industry component. Standard errors are in parentheses; significance: *** p<0.01, ** p<0.05, * p<0.1.

2.6.3 Analysis by income groups

To further investigate the heterogeneity in the results, I conduct a disaggregated analysis by income groups. Following [Dieppe \(2021\)](#), countries are grouped into Advanced Economies (AEs) and Emerging and Developing Economies (EMDEs). In this classification, AEs correspond to high-income countries, while EMDEs include both middle- and low-income countries. This two-group classification simplifies the analysis and helps avoid sample size issues associated with more granular categorizations. The IMF also commonly groups emerging and developing economies together, as these countries often face similar debt vulnerabilities and financial challenges ([International Monetary Fund. Strategy, n.d.](#)). By examining the debt-productivity growth relationship separately for AEs and EMDEs, group-specific patterns can be identified, providing further insights to better inform policy formulation.

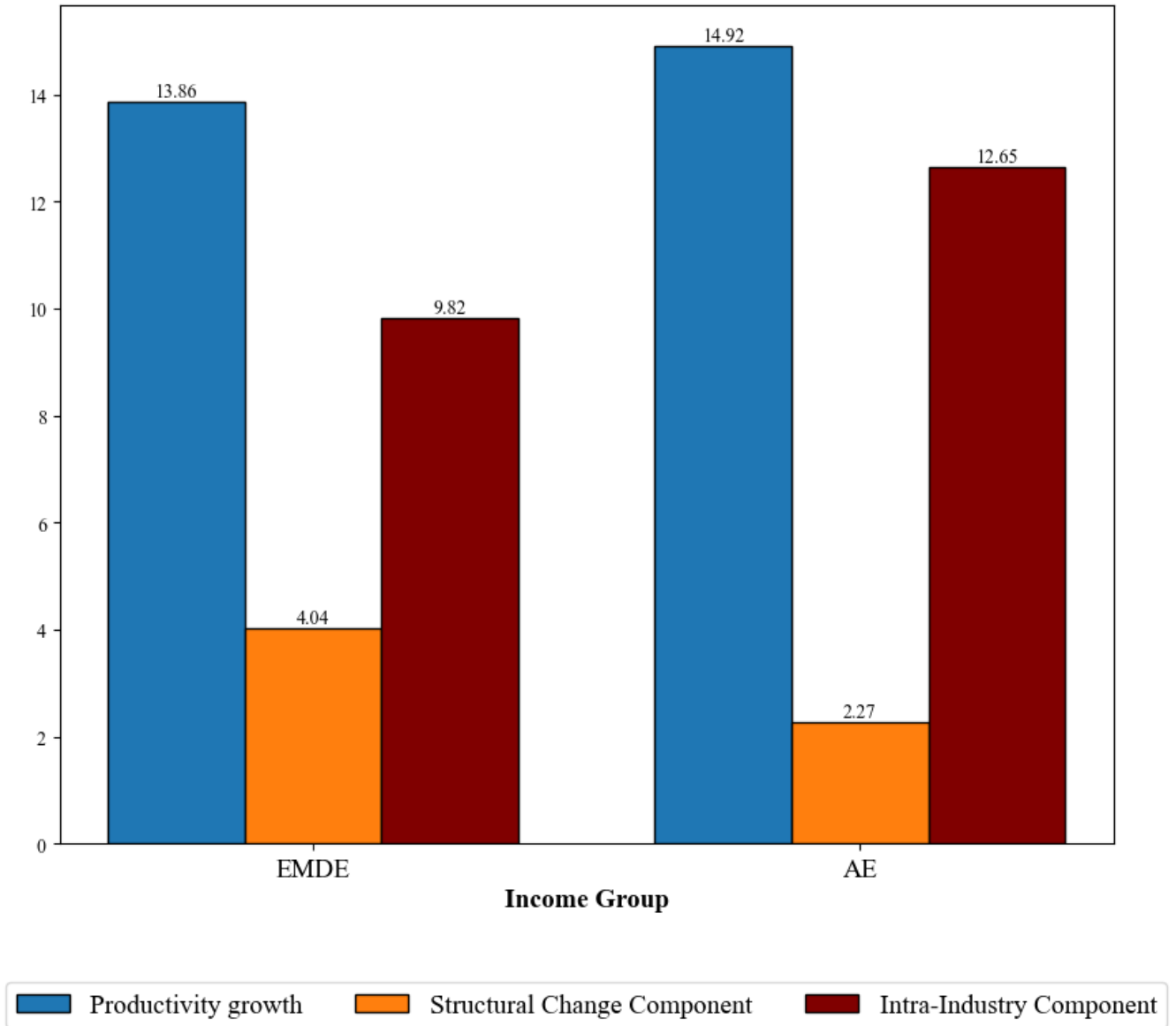
The dataset contains 43 advanced economies and 60 emerging and developing economies. Figure 2.5 presents the average productivity growth and its components, grouped by AEs and EMDEs. Across both groups, the intra-industry component emerges as the primary driver of productivity growth. The intra-industry component accounts for a slightly higher share of total average productivity growth in AEs (85%) compared to EMDEs (71%). Conversely, the structural change component contributes a larger share to productivity growth in EMDEs (29%) than in AEs (15%). Broadly, this suggests that emerging and developing economies still have considerable potential for productivity gains through productive inter-sectoral labor reallocation compared to advanced economies, where most of the productive reallocation may have already occurred.

Tables 2.6 and 2.7 present the fixed effects and system GMM estimations for Advanced Economies (AEs) and Emerging and Developing Economies (EMDEs), respectively. As shown in Table 2.6, no statistically significant effects of government debt on overall productivity growth or its components are found for AEs, although the estimated coefficients are negative. This suggests that while there may be a negative association between government debt and productivity in advanced economies, the effects are not strong enough. These results hold consistently across both fixed effects and system GMM specifications, indicating

a degree of resilience in productivity performance in the face of rising debt levels among high-income countries. This could reflect stronger institutional frameworks, more effective debt management, or greater fiscal space in AEs, which may mitigate the adverse effects of debt accumulation.

In contrast, Table 2.7 shows that for EMDEs, government debt has a statistically significant negative effect on both total labor productivity growth and the intra-industry component, while the effect on the structural change component remains insignificant. These results are robust across both estimation methods. These findings highlight that developing economies are more vulnerable to the adverse effects of rising debt on labor productivity growth. This is likely due to the structural constraints, limited fiscal space, and other constraints that emerging and developing countries face. These insights reinforce the need for prudent debt management and productivity-enhancing policies in EMDEs to ensure that debt accumulation does not undermine long-term growth prospects.

Figure 2.5: Productivity growth decomposition by income groups



Note: Figure 2.5 presents the averages of productivity growth and its components grouped by income levels. AE represents Advanced Economies, and EMDE represents Emerging and Developing Economies.

Table 2.6: Fixed effects and system GMM estimates for AEs

Variable	Fixed Effects			System-GMM		
	tot_p_gr	st_change	intra_ind	tot_p_gr	st_change	intra_ind
gov_debt_gdp	-0.024 (0.061)	0.000 (0.019)	-0.024 (0.050)	-0.075 (0.085)	-0.000 (0.014)	-0.075 (0.089)
log_init_gdpcap	27.637** (12.902)	6.248 (6.131)	21.390 (9.881)	9.961 (12.699)	-0.031 (2.337)	59.860 (11.773)
pop_gr	26.781 (30.495)	10.283*** (3.637)	16.498 (31.064)	3.262 (52.271)	11.317 (6.618)	-7.023 (41.091)
log_cap_st_pw	17.881 (11.329)	-1.386 (2.157)	19.268 (11.930)	-8.836 (12.289)	-2.090 (2.089)	-5.192 (13.032)
hc	-38.136*** (10.426)	-9.172 (7.066)	-28.964*** (7.920)	-33.581*** (9.918)	-6.171** (2.961)	-28.034*** (8.872)
top	0.102* (0.059)	0.003 (0.009)	0.105* (0.063)	0.016 (0.035)	0.002 (0.008)	0.017 (0.035)
L.tot_gr				0.006 (0.173)		
L.st_change					-0.233* (0.119)	
L.intra_ind						-0.006 (0.146)
intercept	-388.39 (149.58)	-17.118 (43.920)	371.27 (122.84)	130.198 (112.024)	10.776 (8.954)	-262.720 (118.145)
Hansen overid. test				19.31	13.36	20.25
Arellano-Bond AR(1) test				-1.67**	-1.98**	-1.96**
Arellano-Bond AR(2) test				-1.75*	0.78	-1.26
No. of instruments				31	31	31
No. of groups				42	42	42

Note: Table 2.6 presents the baseline fixed effects and system GMM estimates for Advanced economies (AEs). Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7: Fixed effects and system GMM estimates for EMDEs

Variable	Fixed Effects			System-GMM		
	tot_p_gr	st_change	intra_ind	tot_p_gr	st_change	intra_ind
gov_debt_gdp	-0.220** (0.107)	0.002 (0.031)	-0.222** (0.087)	-0.400*** (0.137)	-0.013 (0.036)	-0.421*** (0.152)
log_init_gdpcap	16.116* (9.677)	1.479 (2.041)	14.637 (9.513)	8.443 (11.267)	-2.273 (3.091)	9.177 (20.303)
pop_gr	5.265 (92.713)	-0.335 (18.999)	5.599 (77.112)	-98.348 (74.045)	-65.854 (70.446)	-104.087 (105.803)
log_cap_st_pw	-0.761 (5.850)	0.527 (1.337)	-1.288 (5.683)	-0.377 (10.906)	0.356 (2.255)	-10.476 (16.885)
hc	-26.255 (16.517)	-12.160*** (3.620)	-14.095 (15.973)	-42.073* (24.728)	-5.260 (2.991)	-17.420 (30.539)
top	0.071 (0.171)	0.026 (0.027)	0.045 (0.153)	0.530** (0.249)	0.074 (0.046)	0.660** (0.287)
L.tot_p_gr				0.125 (0.081)		
L.st_change					0.153 (0.155)	
L.intra_ind						0.108 (0.130)
intercept	-55.326 (81.169)	9.196 (43.920)	-64.522 (77.935)	36.038 (42.743)	32.745 (21.778)	68.366 (58.663)
Hansen overid. test				25.12	2.57	12.77
Arellano-Bond AR(1) test				-3.23**	-3.03***	-2.76***
Arellano-Bond AR(2) test				-0.86	1.39	-1.32
No. of instruments				37	24	24
No. of groups				52	52	52

Note: Table 2.7 presents the baseline fixed effects and system GMM estimates for Emerging and Developing Economies (EMDEs). Standard errors are in parentheses. Statistical significance is represented as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.8: Dynamic panel threshold estimates for EMDEs

Variables	tot_p_gr	st_change	intra_ind
Threshold Estimates			
$\hat{\lambda}$	83%	34%	83%
95% Confidence Interval	[21.685-88.568]	[21.685-88.568]	[21.685- 88.568]
Impact of Government Debt to GDP			
$\hat{\beta}_3$	0.239 (0.261)	-0.028 (0.150)	-0.263 (0.217)
$\hat{\beta}_4$	-0.331** (0.161)	-0.051** (0.026)	-0.256** (0.122)
L.tot_p_gr	0.192** (0.075)		
L.st_change		-0.032 (0.116)	
L.intra_ind			0.160** (0.072)
log_init_gdpcap	-49.045*** (16.532)	-0.416 (6.553)	-15.110 (21.760)
pop_gr	-152.223*** (41.093)	-3.948 (19.375)	-263.867*** (74.214)
hc	17.043 (11.341)	0.432 (2.654)	-2.149 (11.858)
top	0.081 (0.068)	0.003 (0.024)	0.097* (0.055)
log_cap_st_pw	17.970** (7.439)	-0.304 (3.371)	5.113 (7.474)
intercept	228.929*** (70.327)	12.639 (19.953)	117.999 (107.476)
Observations	290	290	283
Countries	52	52	51
Number of instruments	72	68	73

Note: Table 2.8 reports dynamic panel threshold estimates for EMDEs. Standard errors are in parentheses; significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9: Exogenous debt threshold estimates for EMDEs

Variable	Fixed Effects			System-GMM		
	tot_gr	st_change	intra_ind	tot_gr	st_change	intra_ind
Dum30*debt	0.060 (0.267)	0.068 (0.102)	-0.009 (0.262)	-0.515 (0.563)	0.133 (0.116)	-0.325 (0.606)
Dum3060*debt	-0.080 (0.157)	0.038 (0.053)	-0.119 (0.148)	-0.539* (0.305)	0.061 (0.073)	-0.549* (0.328)
Dum6090*debt	-0.071 (0.116)	0.024 (0.039)	-0.095 (0.108)	-0.167 (0.206)	-0.037 (0.051)	-0.148 (0.232)
Dum90*debt	-0.200** (0.089)	0.009 (0.030)	-0.210*** (0.079)	-0.287** (0.139)	-0.009 (0.039)	-0.302*** (0.133)
log_init_gdpcap	16.268* (9.356)	1.620 (2.092)	14.795* (8.881)	7.388 (14.035)	2.249 (2.981)	12.759 (15.157)
pop_gr	8.467 (62.052)	1.204 (14.789)	7.262 (51.836)	-124.587 (84.48)	-36.135 (16.061)	-62.169 (99.799)
log_cap_st_pw	-1.466 (5.571)	0.502 (1.365)	-1.968 (5.164)	-5.544 (12.477)	-4.005 (2.503)	-9.318 (12.440)
hc	-27.561*** (10.615)	-12.210*** (3.631)	-15.352 (10.759)	-22.148 (14.040)	-3.710 (3.968)	-11.746 (9.554)
top	0.072 (0.101)	0.023 (0.032)	0.048 (0.098)	0.355** (0.159)	-0.092 (0.061)	0.279** (0.134)
L.tot_gr				0.127 (0.127)		
L.st_change					0.194 (0.147)	
L.intra_ind						0.177 (0.115)
intercept	-53.638 (55.412)	8.100 (17.261)	-61.738 (53.570)	60.531* (36.691)	29.116 (10.691)	26.880 (41.958)
Hansen overid. test				36.63	17.56	26.37
Arellano-Bond test for AR(1)				-3.32***	-2.56**	-3.09***
Arellano-Bond test for AR(2)				-0.86	1.17	-1.04
No. of instruments				49	40	40
No. of groups				52	52	52

Note: Table 2.9 presents the exogenous debt threshold estimates for Emerging and Developing Economies (EMDEs). Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

I proceed to conduct the threshold analysis for only the EMDEs. The dynamic panel threshold results are presented in Table 2.8. The identified debt threshold is 83% for both total productivity growth and the intra-industry component. Similar to earlier results, only the coefficients for the higher debt regimes are statistically significant. The exogenously imposed debt threshold, results in Table 2.9, show that the negative effect of government debt is significant only at debt levels above 90% of GDP. This is close to the 83% threshold determined by the dynamic panel threshold model. These findings suggest that while moderate levels of debt may not directly impair productivity growth in EMDEs, high levels of debt can be detrimental to productivity growth, especially through their effects on within-industry productivity improvements.

2.6.4 Channels for the impact of government debt

Tables 2.10, 2.11, and 2.12 present the fixed effects and system GMM estimates, the dynamic debt threshold estimates, and the exogenously imposed debt threshold estimates, respectively, for private investment, government investment, and TFP as potential channels through which government debt operates. Across both the fixed effects and system GMM results, government debt is found to have a negative effect on private investment, proxied by gross capital formation in the private sector as a percentage of GDP. This suggests that increased government debt crowds out private-sector investment. Similar findings are made by Islam & Nguyen (2024) and Akomolafe et al. (2015). The reduction in private-sector investment may, in turn, hinder productivity growth, particularly the intra-industry component that relies on within-industry investments to enhance labor productivity.

The endogenous debt threshold model identifies a debt threshold of 81%, while the exogenous debt threshold model sets the threshold at 60%. In the dynamic model, the coefficients for both above and below the threshold are negative and statistically significant, indicating that government debt consistently has an adverse impact on private investment. Similarly, in the exogenous debt threshold model, all debt threshold coefficients are negative, though statistical significance is observed only at debt levels above 60%.

From Table 2.10, government debt is also found to negatively affect public sector investment, proxied by government gross fixed capital formation as a percentage of GDP. This relationship holds across both fixed effects and system GMM estimations. The negative effects could be due to the reduction in government expenditure on public investment and the maintenance of public infrastructure as part of efforts to reduce service accumulated debts and reduce the debt burden (Chalk & Tanzi, 2004; Checherita-Westphal & Rother, 2012).

It is well established that increased public investment positively impacts productivity growth through improvements in infrastructure, human capital, and technological innovation (Aschauer, 1989; Ramirez, 2002; Sardoni, 2024). Therefore, a negative effect of government debt on public sector investment would likely lead to a decline in overall productivity growth and its components. This confirms that public investment serves as another channel through which government debt influences economic performance.

The dynamic debt threshold estimation results in Table 2.11 identify a lower debt threshold of 68% for the effect of government debt on public investment, compared to 81% for private-sector investment. The dynamic model shows significant coefficients for both high- and low-debt regimes. However, the coefficient for the high-debt regime is significant at the 1% level, whereas the coefficient for the low-debt regime is only significant at the 10% level. This suggests that while government debt negatively affects public investment at all debt levels, its impact is more pronounced and statistically significant in higher debt regimes.

The exogenously imposed debt thresholds in Table 2.12 reveal a much lower debt threshold of 30% compared to the 68% estimated by the dynamic threshold model. From Table 2.10, there is no evidence of any significant relationship between government debt and total factor productivity growth. This implies no evidence of total factor productivity as a possible channel for the effect of government debt.

Table 2.10: Fixed effects and system GMM estimates for private investment, government investment, and TFP

Variable	Fixed Effects			System-GMM		
	priv_inv_gdp	gov_inv_gdp	tfp	priv_inv_gdp	gov_inv_gdp	tfp
gov_debt_gdp	-0.020*** (0.005)	-0.019*** (0.004)	-0.000 (0.000)	-0.041** (0.015)	-0.011* (0.006)	-0.001 (0.000)
log(init_gdpcap)	11.583*** (3.759)	0.243 (0.783)	0.406 (0.065)	3.021 (2.021)	-0.325 (0.836)	0.027 (0.029)
pop_gr	41.106*** (13.097)	0.033 (2.993)	0.467 (0.299)	6.599 (11.720)	-5.423 (9.133)	0.108 (0.757)
gdppc_gr	-0.302 (0.980)	0.599*** (0.955)	0.234*** (0.056)	1.290 (2.438)	3.0122 (2.677)	0.704*** (0.143)
hc	-6.121** (2.588)	-9.768*** (3.367)	-0.459*** (0.102)	-2.352 (3.292)	-0.118 (1.148)	-0.016 (0.059)
top	-0.016 (0.014)	0.002 (0.005)	0.000 (0.001)	-0.01 (0.009)	0.003 (0.003)	0.000 (0.000)
tax_rate	0.032 (0.033)			0.117* (0.061)		
irr	3.491 (9.396)			-0.227 (11.042)		
priv_inv_gdp		-0.047 (0.035)	-0.009*** (0.002)		0.081** (0.036)	-0.005 (0.004)
gov_inv_gdp	-0.012 (0.146)		-0.012** (0.005)	-0.026 (0.279)		-0.017*** (0.006)
tfp	-12.870*** (4.332)	-0.158 (0.994)		-4.991 (5.365)	3.042* (1.581)	
curr_balance		-0.048** (0.020)			-0.006 (0.039)	
L.priv_inv_gdp				0.606*** (0.112)		
L.gov_inv_gdp					0.569*** (0.142)	
L.tfp						0.733*** (0.090)
intercept	-67.760** (30.192)	8.438 (6.908)	-1.539 (0.532)	-6.647** (9.445)	1.206 (5.532)	-0.185 (0.248)
Hansen overid. test				29.27	33.81	35.55
Arellano-Bond AR(1) test				-3.65**	-2.40***	-3.36***
Arellano-Bond AR(2) test				-1.38	-0.76	0.80
No. of instruments				50	50	45
No. of groups				83	83	83

Note: Table 2.10 reports fixed effects and system GMM estimates for debt transmission channels. Standard errors are in parentheses; significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.11: Dynamic threshold results for private investment, government investment, and TFP

Variables	priv_inv_gdp	gov_inv_gdp	tfp
Threshold Estimates			
$\hat{\lambda}$	81%	68%	31%
95% Confidence Interval	[20.673-97.488]	[21.231-98.514]	[27.976- 89.274]
Impact of Government Debt to GDP			
$\hat{\beta}_3$	-0.083** (0.042)	-0.036* (0.184)	-0.001 (0.003)
$\hat{\beta}_4$	-0.068*** (0.019)	-0.038*** (0.012)	-0.002*** (0.001)
L.priv_inv_gdp	0.219* (0.123)		
L.gov_inv_gdp		0.206*** (0.062)	
L.tfp			0.715*** (0.116)
log(init_gdpcap)	4.508** (2.086)	0.358 (0.872)	0.072 (0.058)
pop-gr	16.627 (13.809)	4.146 (6.793)	0.121 (0.543)
gdppc-gr	6.577 (4.610)	-1.395 (1.472)	0.199 (0.101)
hc	-1.367 (2.532)	-0.145 (1.015)	-0.057 (0.054)
top	-0.014 (0.016)	0.001 (0.006)	0.000 (0.000)
tax_rate	-0.041 (0.059)		
irr	-5.806 (9.818)		
gov_inv_gdp	0.364** (0.176)		-0.002 (0.004)
priv_inv_gdp		-0.012 (0.050)	-0.003 (0.003)
tfp	-3.046 (5.765)	-0.793 (1.763)	4.784
curr_balance		-0.036 (0.038)	
intercept	-20.126 (12.801)	3.026 (4.882)	-0.114 (0.364)
Observations	387	431	466
Countries	83	94	83
Number of instruments	60	70	80

Note: Table 2.11 presents the dynamic debt threshold results for exploring the channels for the effect of government debt. Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.12: Exogenous debt threshold estimates for private investment, government investment, and TFP

Variable	Fixed Effects			System-GMM		
	priv_inv_gdp	gov_inv_gdp	tfp	priv_inv_gdp	gov_inv_gdp	tfp
Dum30*debt	-0.009 (0.031)	-0.013 (0.012)	0.000 (0.001)	-0.053 (0.038)	-0.018 (0.161)	0.000 (0.001)
Dum3060*debt	-0.027 (0.017)	-0.015** (0.007)	-0.000 (0.000)	-0.068*** (0.024)	-0.019* (0.011)	-0.001 (0.001)
Dum6090*debt	-0.024** (0.012)	-0.020*** (0.005)	-0.000 (0.000)	-0.053*** (0.016)	-0.016* (0.009)	-0.001* (0.000)
Dum90*debt	-0.028*** (0.009)	-0.018*** (0.004)	-0.000 (0.000)	-0.050*** (0.013)	-0.013* (0.007)	-0.001 (0.000)
log(init_gdpcap)	11.689*** (2.107)	0.267 (0.575)	0.407*** (0.032)	3.349** (1.689)	0.012 (0.676)	0.059** (0.023)
pop_gr	40.760*** (10.306)	0.346 (2.146)	0.485** (0.218)	7.014 (12.234)	-2.393 (4.180)	0.041 (0.257)
hc	-6.148*** (1.889)	-1.835*** (0.587)	-0.458*** (0.062)	-2.738 (2.375)	-0.116 (1.027)	-0.075** (0.036)
top	-0.016 (0.011)	0.002 (0.004)	0.000 (0.010)	0.008 (0.149)	-0.001 (0.003)	0.000 (0.000)
gdppc_gr	12.055*** (2.075)	0.656 (0.834)	0.233*** (0.053)	9.776*** (2.797)	-2.118* (1.263)	0.277*** (0.131)
irr	4.053 (6.664)			-0.442 (10.701)		
tax_rate	0.033 (0.024)			-0.109* (0.060)		
curr_balance		-0.048*** (0.017)			-0.056** (0.023)	
priv_inv_gdp		-0.045* (0.024)	-0.009*** (0.001)		-0.013 (0.032)	-0.003 (0.002)
gov_inv_gdp	-0.012 (0.140)		-0.013*** (0.004)	0.019 (0.268)		-0.005*** (0.004)
tfp	-12.808*** (2.778)	-0.140 (0.808)		-5.734 (4.492)	1.766 (1.563)	
L.priv_inv_gdp				0.601*** (0.113)		
L.gov_inv_gdp					0.633*** (0.155)	
L.tfp						0.673*** (0.052)
intercept	-67.935** (16.326)	8.062*0 (4.864)	-1.564*** (0.310)	-7.650 (9.443)	0.892 (3.320)	0.019 (0.162)
Hansen overid. test				29.04	41.71	55.02*
Arellano-Bond test for AR(1)				-3.31***	-2.72***	-3.26***
Arellano-Bond test for AR(2)				-1.61	-1.31	-0.21
No. of instruments				56	59	62
No. of groups				83	83	83

Note: Table 2.12 presents the exogenous debt threshold results for exploring the channels for the effect of government debt. Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

2.7 Robustness checks

2.7.1 Alternative three-year aggregation

In this section, I show that the main results are robust to alternative frequency of measuring productivity growth. I use a 3-year non-overlapping interval for the decomposition of productivity growth, and 3-year averages for government debt and the control variables, in place of the 5-year intervals used in the baseline analysis. While 5-year periods are commonly employed to smooth out short-term fluctuations and highlight medium to long-term dynamics, 3-year intervals capture more frequent shifts in macroeconomic conditions that may have implications for productivity growth. This alternative specification helps verify whether the observed relationships between government debt and productivity growth and its components are sensitive to the choice of interval length. By comparing the results across both interval structures, I ensure that the findings are robust to variations in the frequency of measurement.

The results for the main fixed effects and system GMM estimations are presented in Table B.2 in the appendix. Table B.3 shows the dynamic debt threshold results, and Table B.4 provides the exogenous debt threshold results. The findings are largely consistent with those from the 5-year interval analysis. Government debt continues to have a significant negative effect on total productivity growth and the intra-industry component, while no significant effects are observed on the structural change component.

The dynamic debt threshold model estimates debt thresholds of 32%, 41%, and 37% for total productivity growth, the structural change component, and the intra-industry component, respectively. The thresholds for total productivity growth and the structural change component match those identified in the 5-year interval results. However, the threshold for the intra-industry component is substantially lower than the 94% identified in the 5-year interval analysis. Notably, the finding that only the coefficients for the high-debt regimes are statistically significant for both total productivity growth and the intra-industry component still holds. This reinforces the conclusion that high debt levels are particularly detrimental

to productivity growth, especially through the intra-industry component.

The exogenous debt threshold estimates, based on the system GMM results, identify a threshold of 30%, with higher debt levels negatively affecting both productivity growth and the intra-industry component. This represents a lower threshold compared to the 60% identified under the 5-year interval specification. Although different thresholds are observed, the results taken together demonstrate the robustness of the debt-productivity growth relationship to alternative time aggregations and reinforce the importance of maintaining sustainable debt levels.

2.7.2 Using external debt in place of general government debt

As a further robustness check, I show that the main findings are robust to alternative measurement of government debt. I re-estimate the main models using external debt in place of general government gross debt. While the baseline analysis captures total public debt, comprising both domestic and external components, this alternative specification focuses specifically on a country's reliance on foreign borrowing. Studies such as [Umaru et al. \(2013\)](#) and [Atique & Malik \(2012\)](#) have attempted to distinguish between the effects of external debt and domestic debt. [Umaru et al. \(2013\)](#) finds that while external debt negatively affects economic growth for Nigeria, domestic debt has a positive effect. A similar analysis by [Atique & Malik \(2012\)](#) for Pakistan shows that both domestic and external debt negatively affect economic growth. It is therefore relevant to determine if the findings in this chapter hold when the focus is on only external debt. The IMF historical debt database does not have data on external debt, hence, I utilize external debt data from the World Development Indicators (WDI). However, it is important to note that the external debt data is limited for most countries in the sample. Only about 50 countries out of the sample of 103 countries have enough data points for reliable analysis. The limited nature of this data may limit the generalizability of the results in this section. Despite this constraint, the estimation provides a useful perspective on whether the observed debt-productivity relationships hold when concentrating on only external debt.

Table B.5 in the appendix presents the fixed effects and system GMM estimates for the impact of external debt on productivity growth and its components. Consistent with earlier results, external debt is found to have a significant negative effect on total productivity growth and the intra-industry component. These estimates are statistically significant across both the fixed effects and system GMM specifications. This relationship aligns with findings in the literature on the impact of external debt. For instance, ? report similar negative effects of external debt on labor productivity growth for a sample of Sub-Saharan African countries. Likewise, using total factor productivity as a proxy for labor productivity, [Beyene & Kotosz \(2022\)](#) also find that external debt has a negative impact on total factor productivity. Overall, the results indicate that the negative relationship between public debt and productivity growth is robust to the use of external debt as an alternative measure.

2.8 Conclusion

This chapter investigates the impact of government debt on productivity growth, with a novel emphasis on its decomposed components: intra-industry productivity growth and structural change components. Using a comprehensive panel dataset of 103 countries from 1950 to 2017, the study applies fixed effects, system GMM, and dynamic panel threshold models to analyze the relationship between government debt and labor productivity growth.

The results show that high levels of government debt significantly reduce total productivity growth, primarily through a negative effect on the intra-industry component. The structural change component, by contrast, remains largely unaffected by changes in government debt. These findings are robust across fixed effects and system GMM estimations and highlight that the main productivity losses from debt accumulation arise mainly from the effects on within-industry productivity improvements. Exploration of the possible channels reveals that these effects arise largely due to the crowding-out effects of government debt on private and public investment.

Threshold analysis reveals the presence of nonlinear effects. The dynamic threshold model identifies critical debt levels of 31% for total productivity growth and 94% for the

intra-industry component beyond which the negative impacts of government debt become statistically significant. The exogenous threshold model also confirms these effects at debt levels exceeding 60% of GDP. These results suggest that moderate levels of debt may not be harmful, but exceeding certain thresholds can significantly hamper productivity gains.

Disaggregated analysis by income groups reveals that the negative effects of government debt on productivity growth are more pronounced in emerging and developing economies compared to advanced economies, suggesting that the structural limitations faced by emerging and developing economies may make them more vulnerable to the negative consequences of high levels of government debt on productivity growth.

Robustness checks show that the main results are robust to the use of 3-year intervals instead of the 5-year intervals employed in the baseline. The estimates are also robust to the use of external debt in place of general government debt.

Overall, the findings highlight that the composition of productivity growth and the channels through which it is affected matter for understanding the macroeconomic consequences of government debt. Prudent fiscal management and targeted productivity-enhancing investments ensure that debt accumulation does not compromise long-term economic performance. Given that the intra-industry component is both the largest contributor to productivity growth and the most adversely affected by government debt, special attention needs to be paid to the implications of high government debt on within-industry efforts at increasing labor productivity.

Future research could extend this analysis by examining how institutional quality moderates the relationship between government debt and productivity growth and its components. In addition, investigating the roles of other macroeconomic variables such as monetary policy, foreign direct investment, and trade openness in shaping the components of productivity growth would further enhance our understanding of how productivity responds to broader macroeconomic dynamics.

Chapter 3

Sectoral total factor productivity shocks and resource reallocation in a multi-sector model of structural change

3.1 Introduction

Structural change, defined as the systematic reallocation of economic activity across sectors over time, is a defining feature of long-run economic development. As countries grow, labor and capital typically shift away from agriculture and toward manufacturing and services. Understanding the forces behind this process is essential for explaining differences in productivity, income levels, and economic resilience across countries. A growing body of literature has explored the drivers of intersectoral reallocation over time. For example, [Echevarria \(1997\)](#), [Matsuyama \(1992\)](#), [Kongsamut et al. \(2001\)](#), and [Laitner \(2000\)](#) identify differences in income elasticities as key drivers of sectoral shifts, while [Matsuyama \(2009\)](#) and [Uy et al. \(2013\)](#) emphasize the role of international trade in driving structural transformation.

Among the earliest explanations for structural change is the differential growth in sectoral

total factor productivity (TFP). Foundational works such as [Baumol \(1967\)](#), [Herrendorf et al. \(2014\)](#), [Duarte & Restuccia \(2010\)](#), [Acemoglu & Guerrieri \(2008\)](#), and [Ngai & Pissarides \(2007\)](#) underscore this mechanism. A prominent theoretical contribution in this literature is the model developed by [Ngai & Pissarides \(2007\)](#). In their multi-sector framework, one sector produces a good that serves both consumption and investment purposes, while all other sectors produce pure consumption goods. A notable feature of this model is its separation between aggregate dynamics and sectoral composition, allowing balanced growth to be preserved at the macro level while maintaining structural change at the sector level. They find that labor tends to move away from sectors with relatively high TFP growth toward those with lower growth, consistent with observed empirical patterns.

Parallel to this, a growing body of empirical and theoretical research highlights the significant role of sectoral shocks in shaping aggregate macroeconomic dynamics. For instance, [Atalay \(2017\)](#) shows that sector-specific shocks can account for a large portion of aggregate output fluctuations, even in the absence of large aggregate disturbances. [Malysheva & Sarte \(2011\)](#) emphasize that input-output linkages can amplify the effect of sectoral shocks and propagate them across the economy. Similarly, [Andrade et al. \(2023\)](#) find that sectoral shocks can have pronounced effects in open economies with asymmetric production and trade structures.

[Foerster et al. \(2022\)](#) provide complementary evidence by showing that changes in sector-specific trends, particularly in TFP and labor input growth, have had persistent and non-trivial effects on aggregate U.S. output growth. They argue that sectoral trends transmit to the aggregate economy mainly through the economy’s production networks. They conclude that sector-specific factors in TFP and labor growth have historically explained about three-fourths of the low-frequency variations in US GDP. Their analysis demonstrates how persistent sectoral developments can generate macroeconomic consequences through compositional effects. [Horvath \(2000\)](#) also shows that even independent sectoral shocks can generate aggregate fluctuations when sectors are connected through sparse but potent input-output linkages. [Acemoglu et al. \(2017\)](#) further establish that idiosyncratic microeconomic shocks can lead to macroeconomic tail risks, especially when combined with sectoral dominance and

dense production networks.

In a related contribution, [Baqaee & Farhi \(2019\)](#) show how nonlinearities in production networks can amplify sectoral disturbances. Nonlinearities magnify negative sectoral shocks and attenuate positive shocks, leading to fat-tailed and negatively skewed distributions of aggregate output. [Carvalho \(2014\)](#) also contributes by arguing that the structure of production networks can endogenously generate aggregate comovement from micro-level disturbances, even in the absence of aggregate shocks. Finally, [Tervala \(2007\)](#) analyzes productivity shocks in the nontraded goods sector within a small open economy model, finding that such shocks can yield counterintuitive macroeconomic effects depending on price rigidities and substitution elasticities. Taken together, these findings highlight the need to understand not only the long-run sources of structural change but also the short-run transmission and amplification of sector-specific productivity shocks.

In light of the literature on the importance of sector-level TFP shocks and the growing interest in structural change models, this paper addresses an important question: Can a model originally developed to explain structural change under balanced growth also shed light on the aggregate and sectoral dynamics of sectoral TFP shocks? While multi-sector models of structural change, such as [Ngai & Pissarides \(2007\)](#), have been instrumental in exploring the drivers of intersectoral reallocation, no attention has been given to exploring these models in a business cycle setting. Incorporating stochastic shocks enables us to assess the ability of such models to capture short-run dynamics and the transmission of sector-specific disturbances to both aggregate and sectoral outcomes. Understanding the dynamics of these shocks at both the aggregate and sectoral levels can guide policymakers in designing targeted countercyclical measures, such as sector-specific investment incentives, to enhance the resilience of the overall economy. Moreover, recognizing the interconnectedness of sectors provides valuable insights for developing policies that strengthen sectoral responses and mitigate the spillover effects of sector-specific shocks.

In this paper, we focus on the [Ngai & Pissarides \(2007\)](#) model of structural change, and extend it to a stochastic environment to analyze the sectoral and aggregate effects of sector-specific TFP shocks. The model's multi-sector structure and its clean analytical separation

between aggregate dynamics and sectoral reallocation offer a natural setting to examine how such shocks propagate through the economy, interact with factor allocation, and shape macroeconomic outcomes.

We specify a discrete-time version of the [Ngai & Pissarides \(2007\)](#) model, incorporating several modifications to adapt it to a real business cycle (RBC) framework. In particular, we introduce King-Plosser-Rebelo (KPR) preferences, which include a labor-leisure trade-off and are commonly used in RBC models to capture household intertemporal decisions and endogenous labor supply. These preferences allow for a more realistic representation of household responses to sectoral shocks, particularly through both consumption and labor allocation. We incorporate sector-specific TFP shocks and explore how these disturbances propagate within the economy, influencing both aggregate and sector-specific outcomes.

We calibrate the model for a three-sector economy with manufacturing, agriculture, and services. The manufacturing sector's good is used for both consumption and investment, while the agriculture and service sector goods are pure consumption goods. The results for our baseline model show that, with a frictionless labor market, flexible prices, and uniform initial sector TFP levels, only shocks to the sector producing the investment good (manufacturing) affect the aggregate economy. In contrast, shocks to sectors producing pure consumption goods have no macroeconomic implications. This result is primarily due to the assumption of a frictionless labor market and flexible prices. This assumption allows sector-specific shocks to pure consumption sectors to be fully absorbed through adjustments in sectoral employment and consumption, without impacting the macroeconomic aggregates. Also, by the structure of the model, only sectors directly linked to capital accumulation (via investment) can influence aggregate dynamics. Since pure consumption sectors do not contribute to investment, productivity shocks in these sectors merely lead to labor and consumption reallocation without aggregate consequences.

A positive productivity shock in the investment-producing sector raises output, consumption, investment, capital, and hours worked on impact, with the effects gradually fading over time. Hours worked eventually decline, suggesting an increasing substitution of leisure for labor as productivity improves. At the sectoral level, such shocks increase the employment

share of the manufacturing sector while decreasing employment shares in the other sectors.

In contrast, a TFP shock to the pure consumption sectors leads to a decline in employment in the shocked sector and a corresponding increase in employment in the other sectors. Varying the initial TFP levels across sectors reveals that shocks to a relatively more productive consumption sector result in less labor reallocation compared to shocks to less productive sectors. In essence, a shock to a less productive sector triggers efficient labor reallocation toward more productive sectors, generating substantial productivity gains.

The sectoral dynamics are also examined under a higher elasticity of substitution between goods. The results show that with increased substitutability, the sectoral responses to TFP shocks in the pure consumption sectors exhibit a notable reversal. A productivity shock to a sector now leads to an increase in that sector's employment share, while employment in the other sectors declines. This reversal occurs because greater substitutability allows relative price changes to induce stronger shifts in consumption patterns, reallocating demand toward the more productive sector. As a result, the sector experiencing the productivity shock absorbs a larger share of economic activity.

To address the limitation of the baseline model that shocks to the pure consumption sectors have no aggregate effects, we modify our model to include labor adjustment costs while maintaining flexible prices. These adjustment costs hinder costless labor reallocation and capture frictions observed in real-world labor markets. In this modified setting, shocks to the pure consumption sectors begin to influence aggregate variables. Importantly, we find that in the baseline model with uniform sector productivity levels, TFP shocks to the pure consumption sectors have contractionary aggregate effects, primarily due to the efficiency losses associated with labor reallocation in the presence of labor adjustment costs. These contractionary effects are reduced and can be reversed when the shocked sector is relatively more productive, and are amplified when the shocked sector is less productive.

The remainder of this paper is structured as follows: Section 2 presents the model. Section 3 discusses the calibration of model parameters. Section 4 presents our baseline results, including impulse response functions and simulated moments. Section 5 introduces labor adjustment costs and examines their implications. Section 6 conducts a sensitivity

analysis with respect to substitution elasticity. Section 7 concludes the chapter.

3.2 The model

To explore the stochastic properties of the [Ngai & Pissarides \(2007\)](#) model of structural change, we revisit the discrete-time version presented in Chapter 1. The model emphasizes differences in sector-level TFP growth rates as key drivers of structural change in the economy. Its multi-sector structure and the separation it creates between the aggregate economy and the sectoral dynamics make it a promising framework for studying the impact of total factor productivity shocks on the aggregate economy and the inter-sectoral dynamics.

We assume an economy with multiple sectors, each producing a good competitively according to the following production function.

$$Y_{j,t} \equiv \hat{a}_{j,t} K_{j,t}^\theta (\tilde{A}_{j,t} N_{j,t})^{1-\theta}, \quad \forall_j. \quad (3.1)$$

Where $0 < \theta < 1$ is the share parameter, $\hat{a}_{j,t}$ is the stochastic component and $\tilde{A}_{j,t}$ is the deterministic component of total factor productivity in sector j respectively. The amount of capital and hours used in the production of the sector j good are $K_{j,t}$ and $N_{j,t}$ respectively. One of the sectors produces a good (Good 0) used for both consumption and investment, while all other sectors produce only consumption goods. For ease of presentation, we normalize the production function by the investment good, dividing it by $\tilde{A}_{0,t} L_t$, where L_t is the total population. We also find it convenient to write $K_{j,t}$ and $N_{j,t}$ as shares of K_t and N_t employed in industry j , where K_t and N_t are the total capital and hours worked, respectively. In Section C.1 of the appendix, the above transformations are applied to transform the production function into its intensive form below

$$y_{j,t} \equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^\theta n_{j,t}^{1-\theta} k_t^\theta h_t^{1-\theta}. \quad (3.2)$$

Where $y_{j,t}$ is sector j 's output per effective worker, k_t is capital per effective worker, $s_{j,t}$

and $n_{j,t}$ are shares of capital and hours worked for sector j at time t respectively, such that $\sum_0^{m-1} s_{j,t} = \sum_0^{m-1} n_{j,t} = 1$. The intensive form of the deterministic component of TFP in sector j is $a_{j,t}$, and h_t is the share of total hours worked.

To set the model in the real business cycle framework, we make the following changes to the preference structure. In line with the real business cycle literature and following [Boppart & Krusell \(2020\)](#), we adopt the King-Plosser-Rebelo (KPR) preferences that allow for a labor-leisure choice. We express the preferences in intensive form. A representative infinitely lived agent has preferences given by:

$$u_t(\cdot) \equiv E_t \sum_{j=0}^{\infty} \beta^j \left(\ln \phi_t - \frac{\psi h_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} \right) \quad (3.3)$$

where

$$\phi_t \equiv \left(\sum_{j=0}^{m-1} \omega_j c_{j,t}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}. \quad (3.4)$$

E_t is the expectations operator, β discounts future utility flows, ψ is a measure of the disutility of labor, and h_t is the number of hours worked in intensive form. The parameter $\eta > 0$ is the Frisch elasticity of labor supply. This is the percentage change in hours when the wage is changed by 1 percent, keeping the marginal utility of consumption constant. The ϕ_t term is a constant elasticity of substitution combination of m distinct consumption goods available to the consumer in period t . Each good is indexed by j so that $c_{j,t}$ is the quantity of good j consumed in period t in intensive form. The relative importance of good j in consumption is ω_j , and the elasticity of substitution between goods is ε . The following parameter restrictions apply: $0 < \beta < 1$, $\varepsilon, \eta, \omega_j > 0$ and $\sum_0^{m-1} \omega_j = 1$.

Since Good 0 is both a consumption good and the only investment good, the output of Good 0 is shared between consumption and investment. The remaining sectors produce pure consumption goods, and so their entire output is consumed. Following this, the resource

constraints are

$$y_{0,t} \equiv \hat{a}_{0,t} a_{0,t}^{1-\theta} s_{0,t}^\theta n_{0,t}^{1-\theta} k_t^\theta h_t^{1-\theta} = c_{0,t} + i_t \quad (3.5)$$

$$y_{j,t} \equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^\theta n_{j,t}^{1-\theta} k_t^\theta h_t^{1-\theta} = c_{j,t}, \quad \forall j \neq 0 \quad (3.6)$$

where $c_{0,t}$ is the consumption of the investment good (Good 0), $c_{j,t}$ is the consumption of the pure consumption goods, and i_t is investment in time t .

To realistically capture the gradual nature of capital accumulation and investment dynamics, we incorporate convex capital adjustment costs through a quadratic functional form. We show in Section C.1 of the appendix that the intensive form of the law of motion of capital is

$$k_{t+1} = (1 - \delta) k_t + i_t - \frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 k_t. \quad (3.7)$$

Where $\frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2$ represents capital adjustment costs with $\psi_k > 0$ and the depreciation of capital is represented by δ . This approach to adjustment costs penalizes deviations of the investment-to-capital ratio from its steady-state level. [Groth \(2005\)](#) supports this specification, showing that a convex adjustment cost function fits aggregate data well and captures the gradual investment responses. [R. W. Cooper & Haltiwanger \(2006\)](#) and [R. Cooper et al. \(1999\)](#) also provide empirical support for the use of convex capital adjustment costs, arguing that convex adjustment costs play an important role in understanding fluctuations at the industry or aggregate level. This makes the convex formulation appropriate for our purposes.

Sector-level productivity shocks are modeled as an autoregressive process of order one (AR(1)). Specifically, the log-deviation of sector j 's TFP from its steady state evolves according to

$$\ln(\hat{a}_{j,t}) = \rho_j \ln(\hat{a}_{j,t-1}) + \epsilon_{j,t}, \quad \epsilon_{j,t} \sim N(0, 1), \quad \rho_j > 0. \quad (3.8)$$

This formulation captures the persistence of sector-specific productivity innovations over time, with the parameter ρ_j governing the degree of persistence. The shocks are assumed to

be normally distributed and uncorrelated across sectors.

A social planner solves the following problem:

$$\begin{aligned}
L = \max_{\Omega_t, k_{t+1}} E_t \sum_{t=0}^{\infty} \beta^t & \left(\ln \phi_t - \frac{\psi h_t^{1+\frac{1}{\eta}}}{1 + \frac{1}{\eta}} \right) \\
& + \lambda_{c,j,t} \left(\hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^{\theta} n_{j,t}^{1-\theta} h_t^{1-\theta} k_t^{\theta} - c_{j,t} \right), (\forall j > 0) \\
& + \lambda_{c,0,t} \left(\hat{a}_{0,t} a_{0,t}^{1-\theta} s_{0,t}^{\theta} n_{0,t}^{1-\theta} h_t^{1-\theta} k_t^{\theta} - i_t - c_{0,t} \right) \\
& + \lambda_{n,t} \left(1 - \sum_{j=0}^{m-1} n_{j,t} \right) \\
& + \lambda_{s,t} \left(1 - \sum_{j=0}^{m-1} s_{j,t} \right) \\
& + \lambda_{k,t} \left(k_{t+1} - \left(1 - \delta - \frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 \right) k_t - i_t \right),
\end{aligned}$$

where $\Omega_t \equiv \{c_{i,t}, n_{i,t}, s_{i,t}, h_t\} \ i \in \{0, 1, \dots, m-1\}$.

Aggregate output and consumption are defined as

$$y_t \equiv \sum_{j=0}^{m-1} p_{j,t} y_{j,t} \quad (3.9)$$

$$c_t \equiv \sum_{j=0}^{m-1} p_{j,t} c_{j,t} \quad (3.10)$$

where $p_{j,t}$ is the price of good j relative to the price of good 0, which is our numeraire good.

As stated earlier, the model establishes a clear separation between aggregate and sectoral dynamics, allowing for balanced growth at the aggregate level while structural change occurs across sectors. This structure implies that the aggregate economy can be analyzed independently of sectoral dynamics. We state this formally in Proposition 6.

Proposition 6. *The aggregate economy, represented by y_t, c_t, i_t, h_t , and k_t , can be tracked*

by the following set of equations without any reference to any sector-level dynamics.

$$1 = E_t \left[\frac{\beta c_t}{c_{t+1}} \left(\left(1 - \delta - \frac{\psi_k}{2} \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right)^2 + \psi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \frac{i_{t+1}}{k_{t+1}} \right) \hat{a}_{0,t} a_{0,t}^{1-\theta} \theta h_{t+1}^{1-\theta} k_{t+1}^{\theta-1} \right) \right] \quad (3.11)$$

$$\psi h_t^{\frac{1}{\eta} + \theta} = \frac{1}{c_t} (1 - \theta) \hat{a}_{0,t} a_{0,t}^{1-\theta} k_t^\theta \quad (3.12)$$

$$k_{t+1} = (1 - \delta) k_t + i_t - \frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 k_t \quad (3.13)$$

$$y_t = \hat{a}_{0,t} a_{0,t}^{1-\theta} h_t^{1-\theta} k_t^\theta \quad (3.14)$$

$$i_t = y_t - c_t. \quad (3.15)$$

From the equations in Proposition 6, we observe that the set of equations governing the aggregate economy does not include any sector-specific variables (i.e, there are no j terms in the system of equations)

Another implication of Proposition 6 is that, at the aggregate level, the model effectively reduces to a one-sector framework in which only the investment-producing sector (Good 0) directly influences aggregate capital accumulation and growth. Since capital is produced exclusively using Good 0, and investment is the sole mechanism through which future productive capacity is built, only shocks affecting this sector can propagate to the aggregate economy. In contrast, the pure consumption sectors produce goods that are consumed but do not contribute to the capital stock. As a result, total factor productivity (TFP) shocks to these sectors may alter the composition of output or relative prices across sectors, but they do not affect the path of aggregate output, consumption, or investment.

As we argue later, another key contributing factor to this result is the assumption of perfect labor mobility and flexible prices, which allow labor to be reallocated seamlessly across sectors. This frictionless adjustment enables the economy to fully absorb productivity shocks in the consumption sectors through reallocation, thereby limiting their aggregate impact. While still maintaining flexible prices, we later introduce labor market frictions through labor adjustment costs, and show that in the presence of these frictions, shocks to

the pure consumption sectors now have aggregate implications.

While sector-level shocks to the pure consumption sectors do not affect the aggregate economy, shocks to the aggregate economy translate to all the sectors. This can be seen from the set of equations describing the sector-level dynamics in Proposition 7.

Proposition 7. *The following relationships hold in the disaggregated economy:*

$$s_{0,t} = n_{0,t} = 1 - \frac{c_t}{y_t} \frac{Z_t - 1}{Z_t} \quad (3.16)$$

$$s_{j,t} = n_{j,t} = \frac{z_{j,t}}{Z_t} \frac{c_t}{y_t}, \quad \forall j > 0 \quad (3.17)$$

$$\text{where } z_{j,t} \equiv \left(\frac{\omega_j}{\omega_0} \right)^\varepsilon \left(\frac{\hat{a}_{0,t}}{\hat{a}_{j,t}} \right)^{1-\varepsilon} \left(\frac{a_{0,t}}{a_{j,t}} \right)^{(1-\theta)(1-\varepsilon)} \quad (3.18)$$

$$Z_t \equiv \sum_{j=0}^{m-1} z_{j,t}. \quad (3.19)$$

Importantly, Equations (3.16) and (3.17) contain $\frac{c_t}{y_t}$, which is the consumption-output-ratio from the aggregate economy, implying that changes in this ratio affect the sector dynamics. Also, Equation 3.18 contains the productivity shock ($\hat{a}_{0,t}$) from the aggregate economy, implying that a shock from the aggregate economy will affect the sectoral shares through its effect on $z_{j,t}$.

As shown in Chapter One, there are significant trends in the deterministic relative sector productivities ($a_{j,t}$), which imply corresponding trends in sectoral demand ($z_{j,t}$), rendering these variables non-stationary. The equations in Proposition 7 therefore imply that all sectoral variables exhibit trends and are non-stationary. However, to solve the model, it must be linearized around a stochastic or stationary steady state. This means the model cannot be linearized around non-stationary variables. To address this, we assume constant deterministic relative sector productivities, which eliminates the trends in $z_{j,t}$ and allows for proper linearization of the model. The drawback of this approach is that we are unable to capture the dynamics of the trended variables in response to sectoral TFP shocks. Nevertheless, we can still compare steady states by varying the constant sector TFP values. The model

is solved using Dynare, which employs a log-linearization approach around the deterministic steady state. The software automatically derives the first-order conditions from the optimization problems, computes the steady-state values, and performs a first-order Taylor approximation of the equilibrium conditions, transforming the nonlinear system into a linear rational expectations model. With Equations 3.16 and 3.17 along with $\frac{c_t}{y_t}$ from the aggregate economy, we can track the dynamics of the sector employment shares and capital shares, then from Equations 3.5 and 3.6 with k_t , h_t , and i_t from the macroeconomy, we can track the output for all the sectors. Stochastic sector-specific TFP shocks are then simulated by drawing from the normal distribution, allowing for the analysis of the model's dynamic responses to these shocks.

3.3 Parameter calibrations

Although the model was generally presented to fit multiple sectors, we calibrate the model for a three-sector economy. We call the sector that produces the good used for both consumption and investment (Good 0) the manufacturing sector, while the other two sectors producing pure consumption goods are called agriculture (Good 1) and services (Good 2). The length of a period in our model is one year, so all our parameter values are annual. Table 3.1 contains the values used for the parameters in the model. In the current model, we do not particularly calibrate the parameters to match real-world data, but rather choose values that are used broadly in the literature. However, to allow for some initial comparison with real-world data, we calibrate the standard deviation of TFP shocks to match the volatility of output and consumption as reported by Mendoza (1991) for the Canadian economy.

We follow Schmitt-Grohé & Uribe (2003) to set the share of capital (θ) to 0.32. This value lies within the range of 0.2 to 0.35 suggested by Gollin (2002). Again, following Schmitt-Grohé & Uribe (2003), we set the discount factor to 0.96, implying an annual interest rate of 4%. Other papers in the real business cycle literature, such as Greenwood & Huffman (1991), Mendoza (1991), and Kydland & Prescott (1982) have also used this value. We set annual depreciation (δ) to 4.8% following Cooley & Prescott (1995). Following Ngai & Pissarides

(2004), the elasticity of substitution between goods (ϵ) is set to 0.3, implying that the goods are poor substitutes.

Table 3.1: Calibrations for model parameters

Description	Parameter	Values
Share of capital	θ	0.32
Discount factor	β	0.96
Depreciation rate	δ	0.048
Elasticity of substitution across goods	ϵ	0.3
Frisch elasticity	η	2
Disutility of labor	ψ	0.5
Capital adjustment cost parameter	ψ_k	0.028
Shock persistence parameter	ρ_j	0.95
Standard deviation of sectoral TFP shocks	σ_j	0.58
TFP Parameters		
Manufacturing (Good 0)	$a_{0,t}$	1
Agriculture (Good 1)	$a_{1,t}$	1
Services (Good 2)	$a_{2,t}$	1
Weight of good in aggregate consumption		
Manufacturing (Good 0)	ω_0	0.15
Agriculture (Good 1)	ω_1	0.425
Services (Good 2)	ω_2	0.425

In the original model by [Ngai & Pissarides \(2004\)](#), this parameter has implications for the direction of labor reallocation in the model. As we will show later, the aggregate impact of shocks to TFP in the pure consumption sectors depends on the degree of substitutability between goods. Frisch elasticity (η), which is the elasticity of hours worked with respect to wages, holding marginal utility constant is set to 2. [Peterman \(2016\)](#) states that in macroeconomic models, Frisch elasticity is mostly set between 2 and 4 to allow for models to match the volatility observed in the data.¹⁴ There are no agreed-upon values in the literature for the disutility of labor (ψ). However, in the foundational work of [King et al. \(1988\)](#), they suggest that the parameter should be calibrated to align the steady-state hours worked to empirical observations. Based on this, we adopt a strategy, choosing a value that matches steady-state hours worked at 0.33, which is equivalent to 8 hours a day. To achieve this, we set the disutility parameter (ψ) to 0.5. Again, we follow [Schmitt-Grohé & Uribe \(2003\)](#) and

¹⁴See [Chetty \(2012\)](#) for a discussion on choosing different Frisch elasticity values.

set the parameter for capital adjustment cost (ψ_k) to 0.028. Following [Kydland & Prescott \(1982\)](#), the TFP shock persistence parameter (ρ) is set to 0.95. The standard deviation of shocks is set to 0.58 to match the volatility of output and consumption observed in the data reported by [Mendoza \(1991\)](#).

Regarding sectoral productivity, we emphasize differential sectoral TFP growth rates as the main driver of structural change in the first chapter. We generally observe that the agricultural sector exhibits a higher TFP growth rate compared to services. As a baseline, however, we assume that all sectors start with the same initial TFP by setting the TFP parameters ($a_{j,t}$) to 1. Although this is a simplification, it serves as a benchmark against which we later compare more realistic scenarios. Specifically, we consider a case where TFP in the agricultural sector is increased while TFP in the manufacturing and service sectors remains constant. We also examine a case where agricultural TFP increases and service sector TFP decreases. Because the manufacturing sector good is both a consumption and an investment good, we follow [Cai \(2015\)](#) in setting a lower consumption weight of 0.15 for that sector. We then set an equal consumption weight of 0.425 for the agricultural and service sectors.

3.4 Baseline results

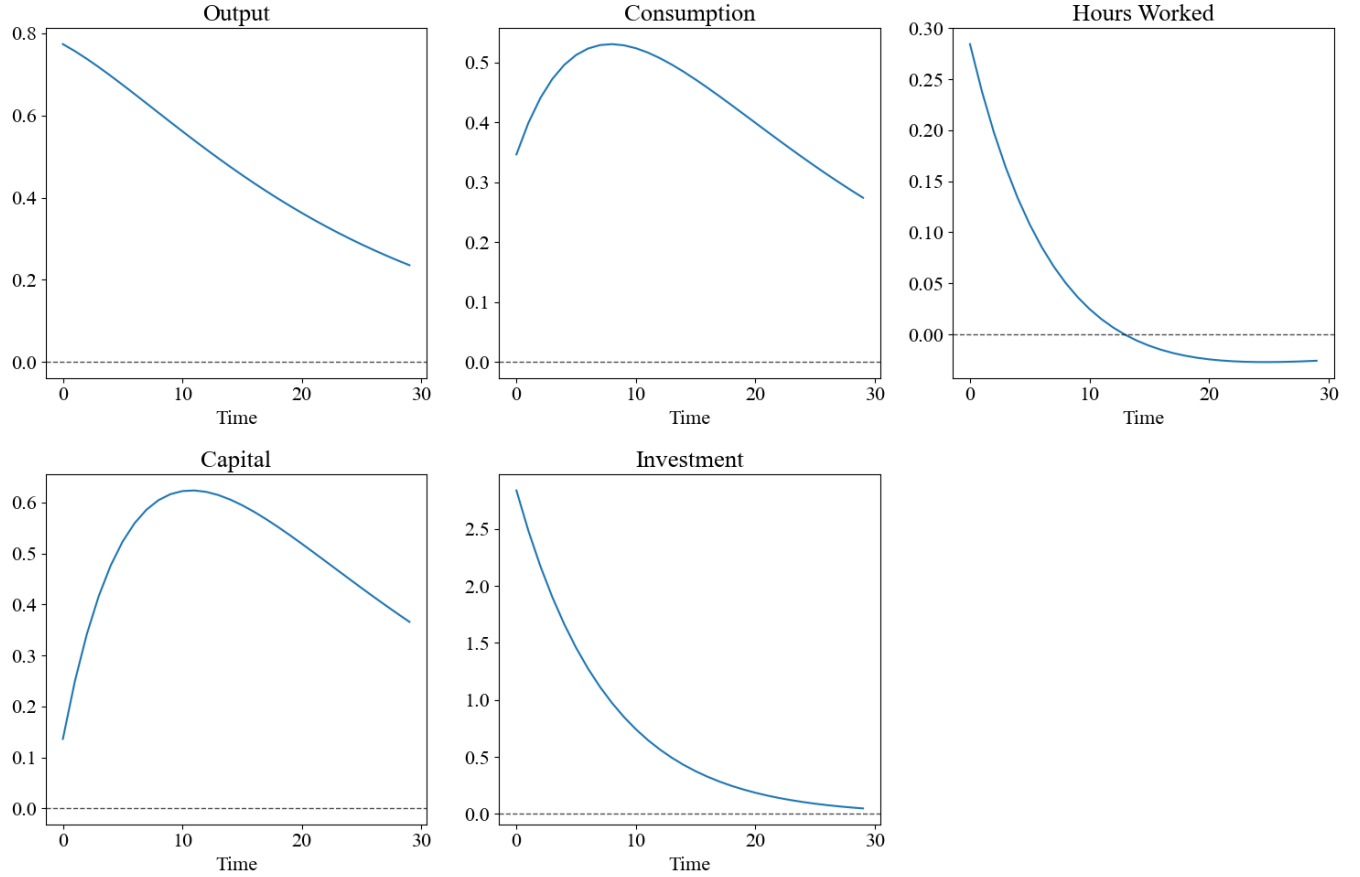
In this section, we present the results for the effects of sector-level TFP shocks on both the aggregate economy and the sectoral dynamics. At the aggregate level, we examine the impact of each shock on output (y_t), consumption (c_t), investment (i_t), capital (k_t), and hours worked (h_t). At the sectoral level, we assess the effects on sector-specific consumption (c_0, c_1, c_2) and labor shares (n_0, n_1, n_2). In the appendix, we show that for a sector j , the share of capital equals the share of labor, and so the impulse response functions for capital shares will be identical to labor shares and are therefore not reported. Notice also that in the baseline model, where we start with equal sector productivities, the model makes no distinction between the pure consumption sectors, which we call the agricultural and service sectors for our purposes. As a result, the impulse response functions for shocks to

these sectors will mirror each other. All shocks are one standard deviation shocks, and the impulse responses represent percentage point changes in response to a one standard deviation TFP shock.

3.4.1 Impact of sector productivity shocks on the aggregate economy

As revealed in Proposition 1, the implication of the model's separation between the aggregate economy and the sector-level dynamics is that only shocks to the investment-producing sector (manufacturing) have implications for the aggregate economy. Shocks to the pure consumption sectors affect the sector-level reallocation without any aggregate implications. Figure 3.1 presents the aggregate implications of TFP shocks to the manufacturing sector. As shown in Figure 3.1, output rises immediately by approximately 0.8 percentage points in response to a one standard deviation shock, reflecting a direct productivity gain, and then gradually reduces as the shock dissipates. Aggregate consumption also increases on impact by about 0.35 percentage points, and continues to rise up to about 0.5 percentage points before declining slowly towards the steady-state as the shock dissipates. Investment increases sharply on impact by more than 2.5 percentage points, and then steadily declines towards the steady-state. On impact, capital increases by about 0.15 percentage points, increasing further to about 0.6 percentage points before slowly declining towards the steady state, indicating gradual capital deepening in response to the shock. Hours worked also increase by about 0.3 percentage points in response to a one standard deviation shock to TFP in the manufacturing sector, as households respond to higher returns to labor by supplying more labor. However, this response is temporary and eventually turns slightly negative, suggesting intertemporal substitution in labor supply. Overall, the results underscore the central role of the manufacturing sector in propagating productivity shocks to the broader economy.

Figure 3.1: Aggregate economy response to a TFP shock to manufacturing (Good 0)



Note: Figure 3.1 shows the impulse responses of key macroeconomic variables to a positive total factor productivity (TFP) shock to the investment-producing sector (Good 0). Output, consumption, and hours worked all rise initially but gradually decline toward their steady states. Notably, capital increases persistently due to higher investment, peaking around period 10 before slowly reverting. Hours worked react sharply but decay quickly, reflecting intertemporal substitution effects.

3.4.2 Sectoral dynamics of productivity shocks

We now present the impulse response functions for the sector-level variables. Figures 3.2 and 3.3 display the responses to productivity shocks in the manufacturing sector (Good 0) and the agricultural sector (Good 1). Because no distinction is made between the pure consumption sectors (Agriculture and Services) in the baseline model, the impulse responses to TFP shocks to the service sector are symmetric to the impulse responses for shocks to agriculture. As a result, the results for the service sector are not reported.

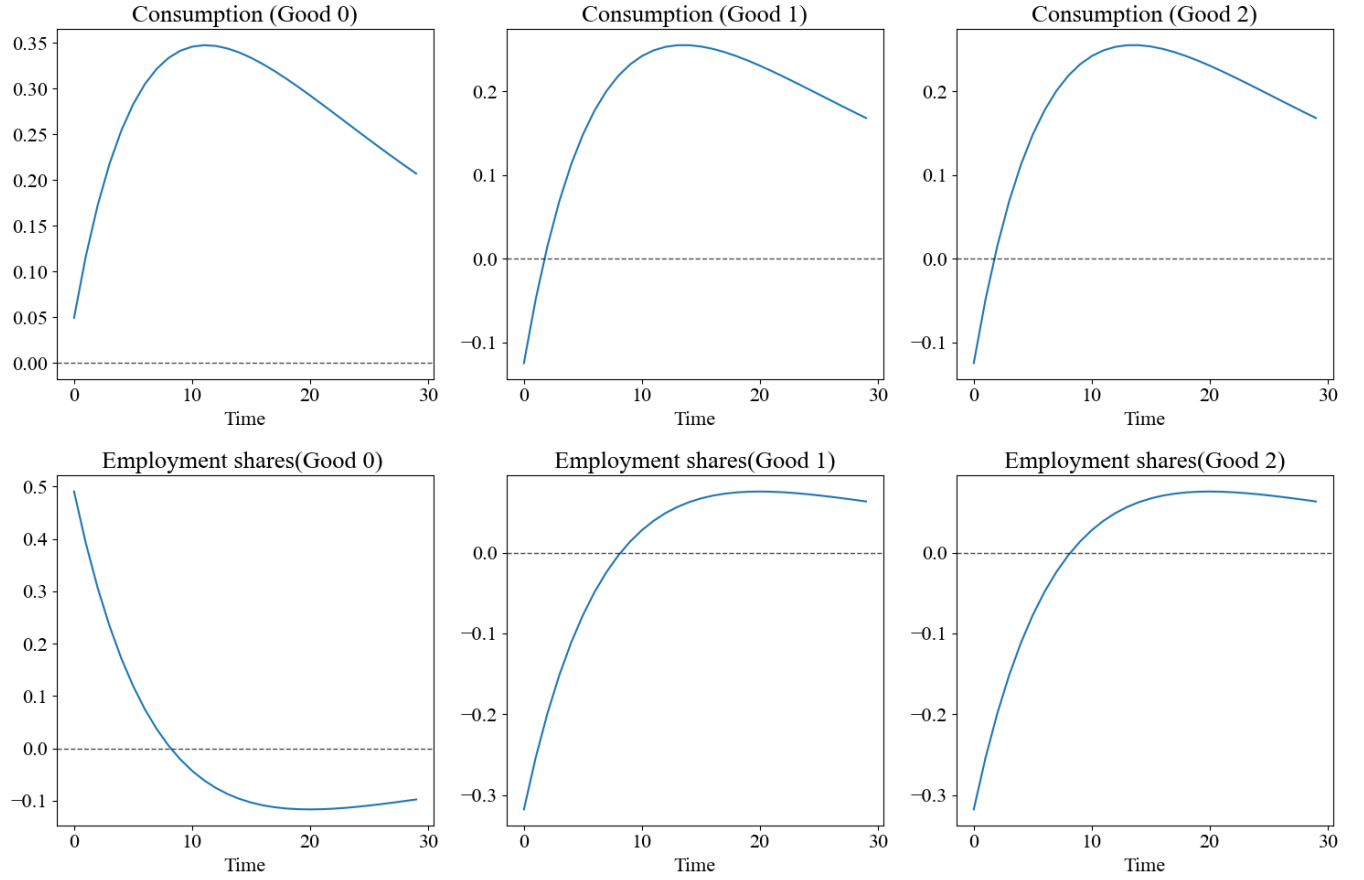
The top row of Figure 3.2 shows that consumption of the manufacturing good increases by about 0.05 percentage points in response to a TFP shock to the sector. The impact remains elevated for extended periods, reaching a peak of around 0.35 percentage points before eventually declining. Notice that the response of the consumption of agricultural and service sector goods is the same. The intuition is that because the model assumes the same elasticity across goods, it implies the same relationship between the pairs, hence the consumption pattern across the non-shocked sectors will be identical. We see that consumption in the agricultural and the service sectors initially declines in response to the shock, but gradually increases, reaching about 0.2 percentage points before declining again towards the steady-state. In the second row, employment in manufacturing rises by about 0.5 percentage points on impact, before declining towards the steady state. Notice also that the pattern of responses of employment shares in agriculture and services is identical. This is due to the fact that they are both pure consumption goods, and we currently make no clear distinction between them. On impact, employment in these sectors declines. As the shock dissipates, the employment shares of the manufacturing sector begin to decline as employment in the other sectors begins to rise. These movements imply an initial reallocation of labor towards manufacturing as it becomes relatively more productive. However, as the shock weakens, its productivity declines, and labor eventually moves back towards the other sectors.

While it is typically expected that labor moves away from the more productive sectors toward less productive ones (consistent with long-run structural change), the observed pat-

tern here reflects the manufacturing good's dual role as both a consumption good and the sole investment good. As such, for consumption of all goods to increase, employment must rise in the manufacturing sector to generate the necessary investment goods required by the other sectors.

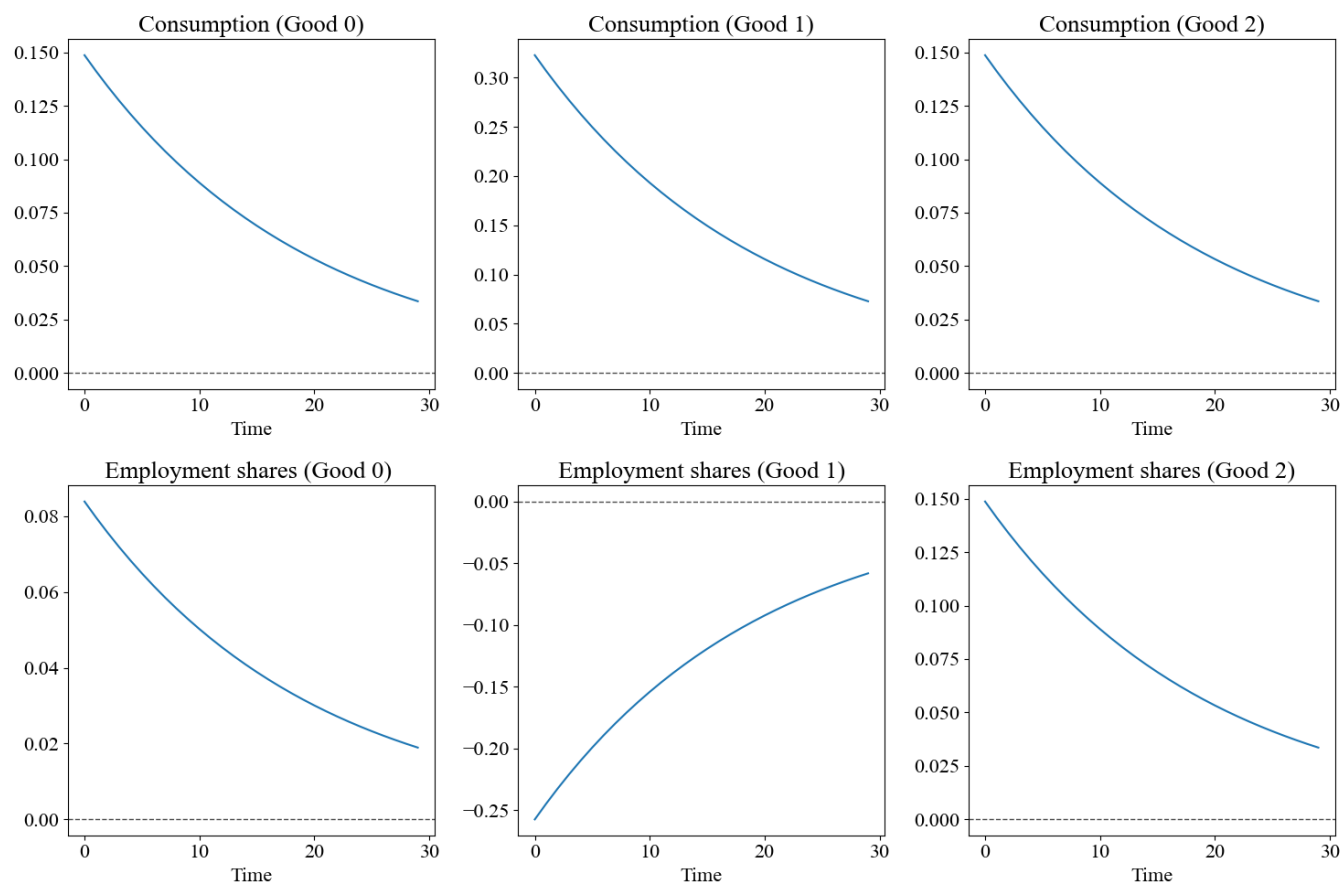
Figure 3.3 illustrates the sectoral responses to a one standard deviation TFP shock to the agricultural sector (Good 1). The top row shows an increase in consumption across all sectors, with the largest response in the agricultural sector. Notice again the symmetric response of consumption in the non-shocked sectors. On impact, consumption of the agricultural good increases by about 0.32 percentage points before gradually declining. The other two sectors experience a relatively lower response on impact (about 0.15 percentage points) and decline slowly afterwards. In the second row, the employment share in agriculture declines by about 0.25 percentage points on impact, while the manufacturing and service sectors experience 0.08 and 0.15 percentage point increases, respectively. This outcome arises because the productivity gain reduces the amount of labor needed to produce the same output in agriculture, freeing up labor for reallocation to other sectors.

Figure 3.2: Sector-level response to a TFP shock to manufacturing



Note: Figure 3.2 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the investment-producing sector (Good 0). On impact, consumption in the manufacturing sector increases while consumption in the other sectors declines. Consumption across all sectors, however, recovers and remains elevated for an extended period. Employment shares in the manufacturing sector increase while those of the other sectors decline.

Figure 3.3: Sector-level response to a TFP shock to agriculture



Note: Figure 3.3 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the agricultural sector. On impact, consumption across all sectors increases on impact, with a gradual decline over time. Employment share in the agricultural sector declines while that of the other sectors increases.

3.4.3 Business cycle moments

The moments for the simulated variables are presented in Table 3.2, including the standard deviations and the relative volatilities. Though the model is not necessarily calibrated to match real data, we provide moments for the Canadian economy provided by Mendoza (1991) for comparison. These moments are also used by Schmitt-Grohé & Uribe (2003). The standard deviation of aggregate output is 2.88, which is very close to the data value of 2.8. Similarly, aggregate consumption has a standard deviation of 2.54, which is close to the data value of 2.46. Consequently, aggregate consumption exhibits moderate volatility relative to output, aligning closely with the relative volatility of consumption reported for the data. Compared to the data, investment exhibits lower volatility. Its relative volatility is also comparatively lower. Capital, however, has a higher standard deviation and relative volatility compared to the data. Importantly, note that similar to the data, investment exhibits higher volatility compared to capital stock, as expected. Hours worked has a lower volatility compared to the data. This possibly reflects the costless reallocation of labor across sectors to maintain an efficient allocation despite sector-specific productivity shocks. The values though not matching the data very closely, exhibit similar patterns of volatility that are typical of RBC models.

Across sectors, we observe balanced relative volatilities of sectoral consumption (ranging from 0.58 to 0.62 of output volatility) relative to output. Employment shares also show balanced relative volatilities with output (0.36 to 0.40).

The correlation structure is presented in Table 3.3. As expected, aggregate variables exhibit strong positive correlations with each other. The correlation between output and consumption is approximately 0.97. Correlations of 0.55, 0.84, and 0.91 are observed between hours worked and output, investment and output, and capital stock and output, respectively. These values are close to what Schmitt-Grohé & Uribe (2003) report for their model.¹⁵

Sectoral employment correlations provide more nuanced insights into resource reallocation. Notably, employment shares across sectors are significantly negatively correlated (e.g.,

¹⁵Schmitt-Grohé & Uribe (2003) report $\text{corr}(y_t, c_t) = 0.94, \text{corr}(y_t, h_t) = 1, \text{corr}(y_t, i_t) = 0.66$.

Table 3.2: Business cycle moments of simulated variables

	Data	Model
<i>Standard deviation</i>		
σ_{y_t}	2.8	2.88
σ_{c_t}	2.46	2.54
σ_{i_t}	9.82	5.86
σ_{h_t}	2.02	0.52
σ_{k_t}	1.38	3.01
σ_{c_0}	-	1.80
σ_{c_1}	-	1.66
σ_{c_2}	-	1.69
σ_{n_0}	-	1.04
σ_{n_1}	-	1.17
σ_{n_2}	-	1.15
<i>Relative volatilities</i>		
$\sigma_{y_t}/\sigma_{y_t}$	1	1
$\sigma_{c_t}/\sigma_{y_t}$	0.87	0.88
$\sigma_{i_t}/\sigma_{y_t}$	3.51	2.03
$\sigma_{h_t}/\sigma_{y_t}$	0.72	0.18
$\sigma_{k_t}/\sigma_{y_t}$	0.49	1.05
$\sigma_{c_0}/\sigma_{y_t}$	-	0.62
$\sigma_{c_1}/\sigma_{y_t}$	-	0.58
$\sigma_{c_2}/\sigma_{y_t}$	-	0.59
$\sigma_{n_0}/\sigma_{y_t}$	-	0.36
$\sigma_{n_1}/\sigma_{y_t}$	-	0.40
$\sigma_{n_2}/\sigma_{y_t}$	-	0.40

Note: Table 3.2 shows the moments for the simulated variables. Some of the moments for the aggregate variables are compared to moments provided by Mendoza (1991) for the Canadian economy. The data ranges from 1946 to 1985. Standard deviations are measured in percent per year.

n_0 and n_2 : -0.58; n_1 and n_2 : -0.32), indicating active labor reallocation between sectors in response to productivity differentials. Sector consumption exhibits strong correlations with aggregate consumption and output, while sectoral employment shares show weak correlations with aggregate output and consumption.

Sectoral consumption variables exhibit strong positive correlations with each other (ranging from 0.88 to 0.90) and moderate correlations with aggregate variables. Notably, the manufacturing sector generally shows stronger correlations with aggregate variables compared to the other sectors. Although not definitive, this observation supports the earlier finding that

Table 3.3: Correlation matrix

	y	c	h	i	k	c_0	c_1	c_2	n_0	n_1	n_2
y	1.00										
c	0.97	1.00									
h	0.55	0.32	1.00								
i	0.84	0.68	0.91	1.00							
k	0.91	0.99	0.16	0.55	1.00						
c_0	0.83	0.91	0.13	0.49	0.92	1.00					
c_1	0.54	0.64	-0.08	0.22	0.68	0.89	1.00				
c_2	0.58	0.67	-0.06	0.24	0.71	0.90	0.88	1.00			
n_0	0.11	-0.12	0.83	0.59	-0.28	-0.13	-0.11	-0.12	1.00		
n_1	0.00	0.14	-0.45	-0.29	0.23	0.13	-0.10	0.29	-0.59	1.00	
n_2	-0.14	0.00	-0.52	-0.40	0.09	0.02	0.23	-0.16	-0.58	-0.32	1.00

Note: Table 3.3 presents the correlations of the variables. Overall, the aggregate variables show high correlations with each other. The employment shares show significant negative correlations with each other, reflecting the reallocation that occurs across sectors.

only shocks to the manufacturing sector propagate to the aggregate economy.

3.4.4 Exploring the model with varied sector productivities.

In this section, we consider more realistic scenarios by varying the initial levels of sectoral TFP to better reflect the empirical patterns documented in Chapter 1. As shown there, total factor productivity growth in the agricultural sector tends to exceed that of the service sector.

Motivated by this pattern, we examine two cases. In the first scenario, the agricultural sector is assigned a higher initial TFP, while the TFP levels in the service and manufacturing sectors remain at their baseline uniform values. Importantly, this change does not alter the fact that only shocks to the manufacturing sector have aggregate implications. As a result, the impulse responses of the macroeconomy remain unchanged and are therefore not reported.

Figures 3.4, 3.5, and 3.6 present the impulse responses of sectoral variables to TFP shocks in the manufacturing, agricultural, and service sectors, respectively. Comparing Figure 3.2 to Figure 3.4, we observe that with increased productivity in the agricultural sector, a

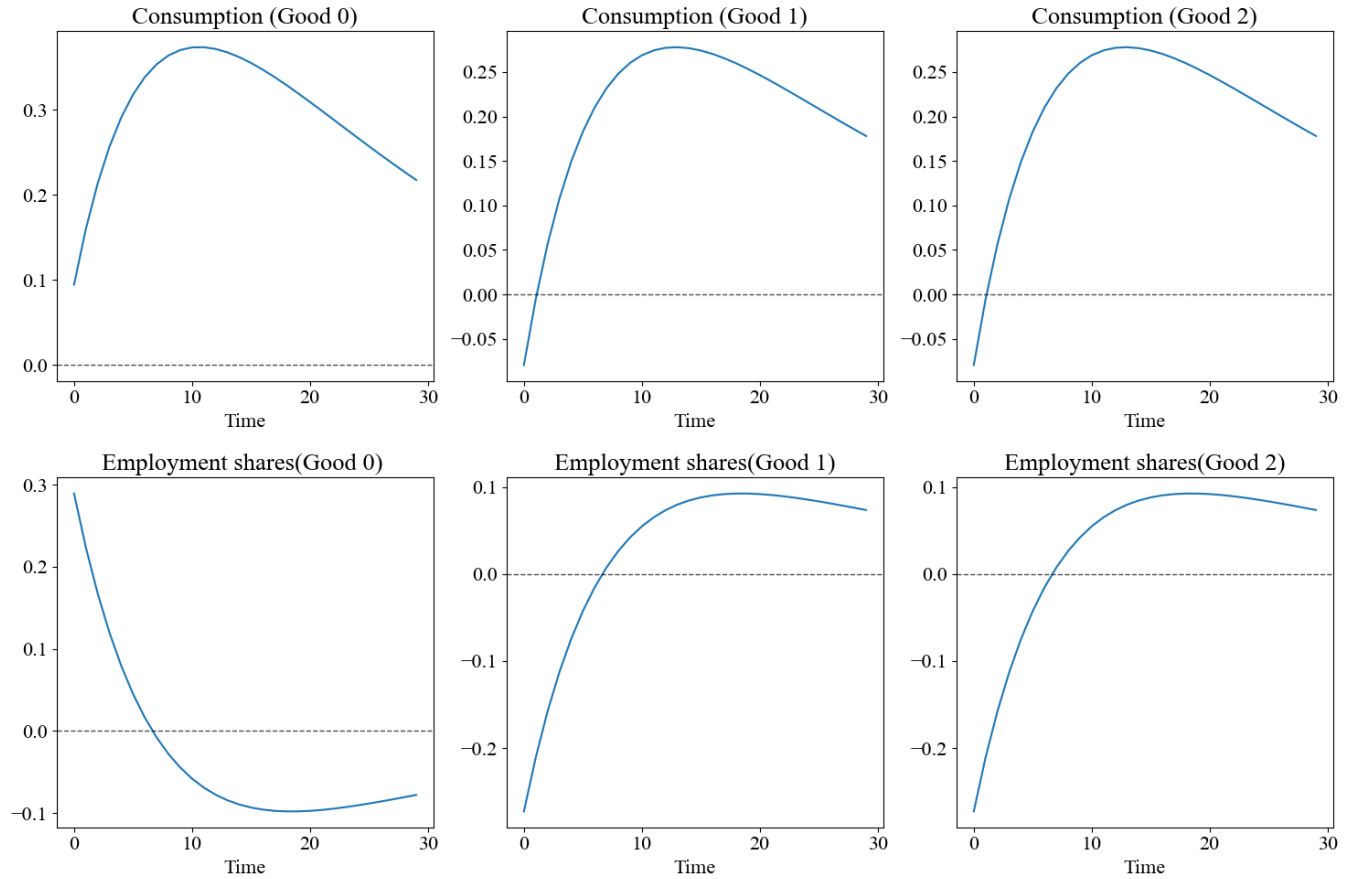
TFP shock to the manufacturing sector leads to a larger increase in the consumption of the manufacturing good on impact, compared to the baseline case. The initial decline in consumption of the agricultural and service sector goods is also lower, and the eventual increase is also higher. For example, consumption of the agricultural good peaked at about 0.2 percentage points in the baseline case, but in this case, it peaks at about 0.25 percentage points. Again, the non-shocked sectors exhibit identical consumption responses. We also notice that the increase in employment shares in the manufacturing sector following the shock is smaller, while the decline in employment shares in the agricultural and service sectors is also correspondingly lower.

These results reflect a key intuition: The relatively more productive agricultural sector reduces the extent of labor reallocation towards the manufacturing sector in response to the shock. This results in consumption gains that accrue to all sectors.

Regarding the impact of a TFP shock to the agricultural sector, a comparison of Figure 3.5 with Figure 3.3 shows that the increase in consumption of the agricultural good, though lower than in the baseline case, is still greater than the increase in consumption of manufacturing and service sector goods. The decline in the agricultural sector's employment share is larger compared to the baseline, while the corresponding increases in the employment shares of the other sectors are smaller. Notably, the increase in the service sector's employment share exceeds that of the manufacturing sector, suggesting that labor reallocates more toward the service sector in response to the shock.

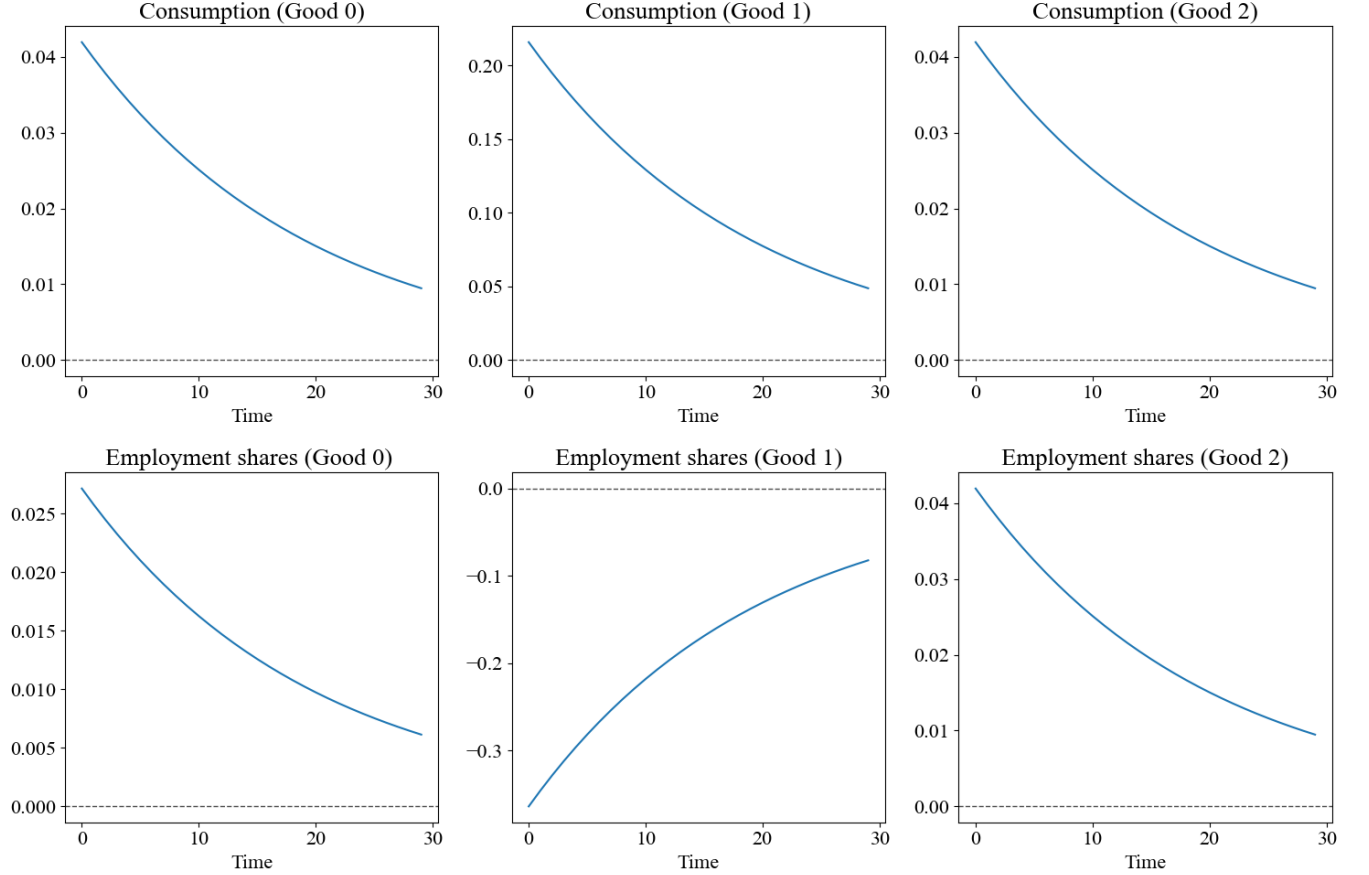
Figure (3.6) presents the sectoral response to TFP shocks to the service sector. Compared to the symmetric version in Figure 3.3, the response of service sector consumption to the shock is significantly larger in this case than in the baseline. For example, in the baseline scenario, a one standard deviation shock to the service sector increases its consumption by about 0.3 percentage points on impact, whereas in this case, the increase is approximately 0.4 percentage points. We also observe that consumption of manufacturing and agricultural goods rises relative to the baseline scenario with uniform TFP levels. Employment in the service sector declines in response to the shock, while employment shares in the agricultural and manufacturing sectors increase more than in the baseline. The rise in agricultural sector

Figure 3.4: Sector-level response to a TFP shock to manufacturing ($a_{1,t} > a_{0,t} = a_{2,t}$)



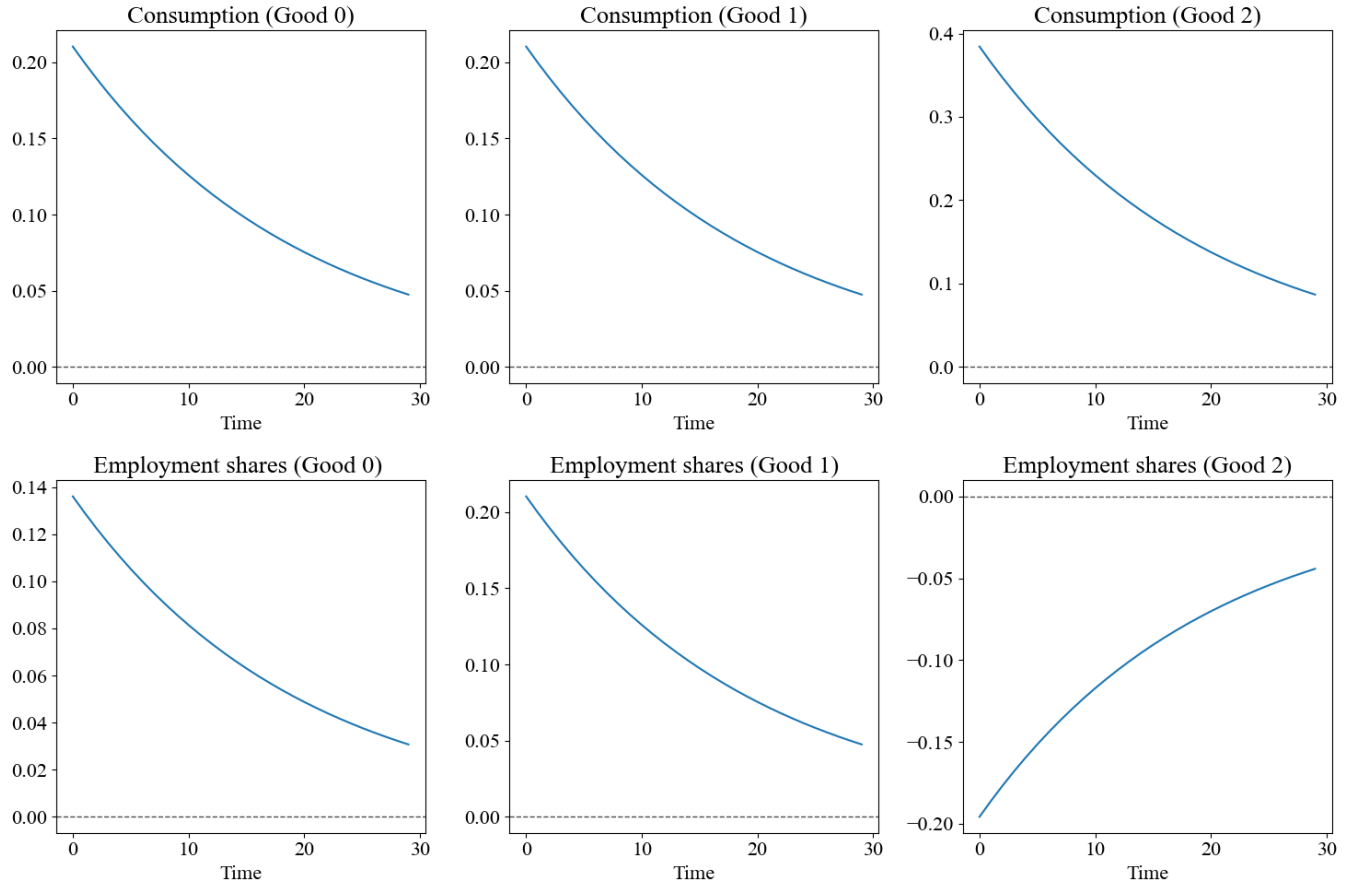
Note: Figure 3.4 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the manufacturing sector, in an economy with relatively higher TFP in the agricultural sector. Consumption across sectors is higher compared to the baseline case. The increase in employment in the manufacturing sector is lower, while the decline in employment shares in the agricultural sector is lower compared to the baseline case. The decline in service sector employment remains largely the same.

Figure 3.5: Sector-level response to a TFP shock to agriculture ($a_{1,t} > a_{0,t} = a_{2,t}$)



Note: Figure 3.5 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the agricultural sector, in an economy with relatively higher TFP in the agricultural sector. Consumption of the agricultural good increases more than in other sectors. The decrease in employment in the agricultural sector is notably higher, while the increase in employment shares in the manufacturing and service sectors is also lower compared to the baseline scenario.

Figure 3.6: Sector-level response to a TFP shock to services ($a_{1,t} > a_{0,t} = a_{2,t}$)



Note: Figure 3.6 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the service sector, in an economy with relatively higher TFP in the agricultural sector. The increase in consumption across all goods is higher compared to the baseline scenario. Employment in the service sector decreases while employment shares in the manufacturing and agricultural sectors increase more than the baseline.

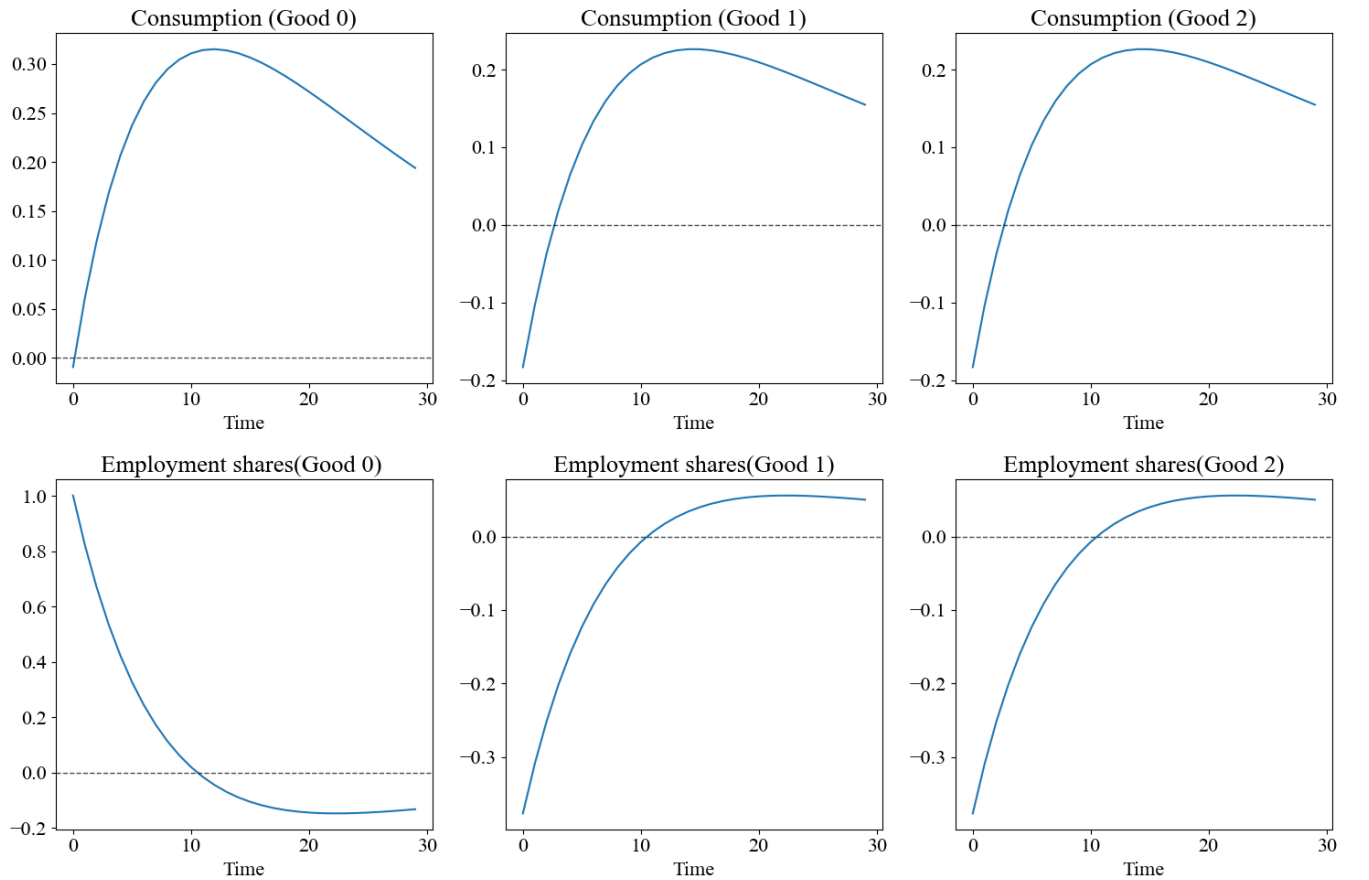
employment exceeds that in manufacturing, suggesting that a larger portion of the labor exiting the service sector reallocates to the more productive agricultural sector.

We now consider the second scenario, in which TFP varies across both the agriculture and service sectors. Specifically, we assign a higher TFP value to the agricultural sector and a lower value to the service sector, consistent with the trends discussed in Chapter One. Figure 3.7 presents the impulse responses to a TFP shock in the manufacturing sector. Compared to the baseline, we now observe that the TFP shock to manufacturing initially leads to a slight decline in consumption of the manufacturing good. However, this effect quickly reverses, with consumption rising to a peak of around 0.3 percentage points before declining again. This response remains much lower than in the baseline and is also lower than in the first scenario. The initial declines in the consumption of agricultural and service goods are significantly larger than in both the baseline and the first scenario. Employment in the manufacturing sector rises more strongly in response to the shock: for example, a one standard deviation shock increases its employment share by about 1 percentage point, compared to 0.5 percentage points in the baseline and 0.3 percentage points in the first scenario. In contrast, the declines in employment shares for the other sectors are considerably larger than in previous scenarios. Overall, the presence of a relatively less productive sector amplifies the reallocation of labor toward it. However, because the manufacturing sector is not the most productive, the gains from this reallocation are limited, as reflected in the lower consumption responses.

Regarding the response to TFP shocks in the agricultural sector, Figure 3.8 shows that the increase in consumption across all sectors is now lower than in the baseline case and in the first scenario. The decline in the employment share of the agricultural sector is larger, while the increases in employment shares in the other sectors are also correspondingly smaller. Notably, the increase in the employment share of the service sector is significantly larger than that of the manufacturing sector. This suggests that more of the labor moving out of the more productive agricultural sector in response to the shock reallocates toward the less productive service sector. This pattern aligns with the broader observation that labor tends to move out of more productive sectors toward relatively less productive ones.

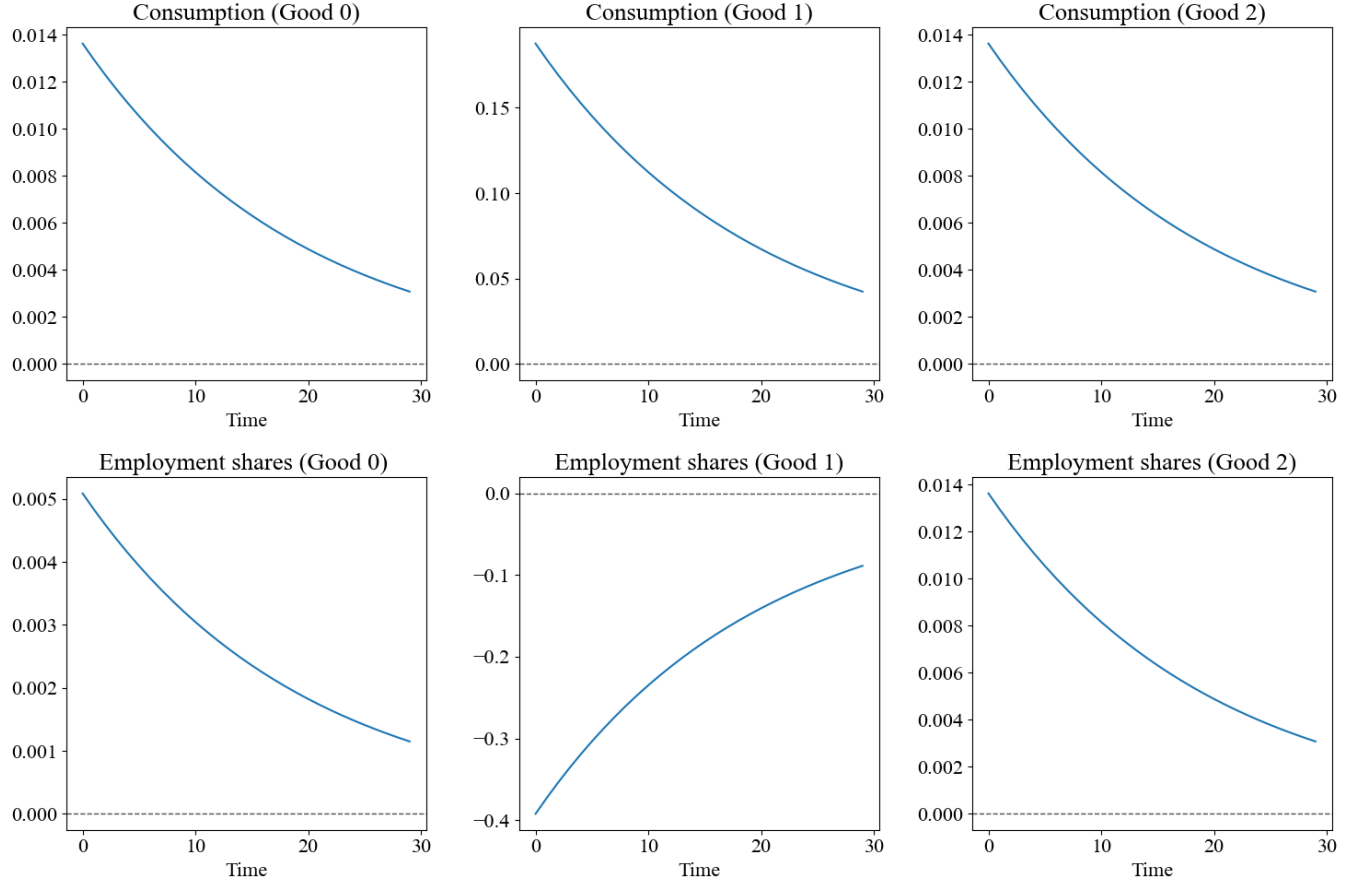
In Figure 3.9, we again observe that a TFP shock to the less productive sector yields more gains in consumption compared to previous scenarios, with the largest increase occurring in the service sector. Similarly, employment drops in the service sector with a corresponding increase in the employment shares of agriculture and manufacturing. Notices again that the increase in agricultural employment is larger than in manufacturing. Essentially, shocks to the least productive sector trigger efficient labor reallocation towards the relatively more productive sectors. This generates significant productivity gains, which are reflected in the increased consumption across sectors.

Figure 3.7: Sector-level response to a TFP shock to manufacturing ($a_{1,t} > a_{0,t} > a_{2,t}$)



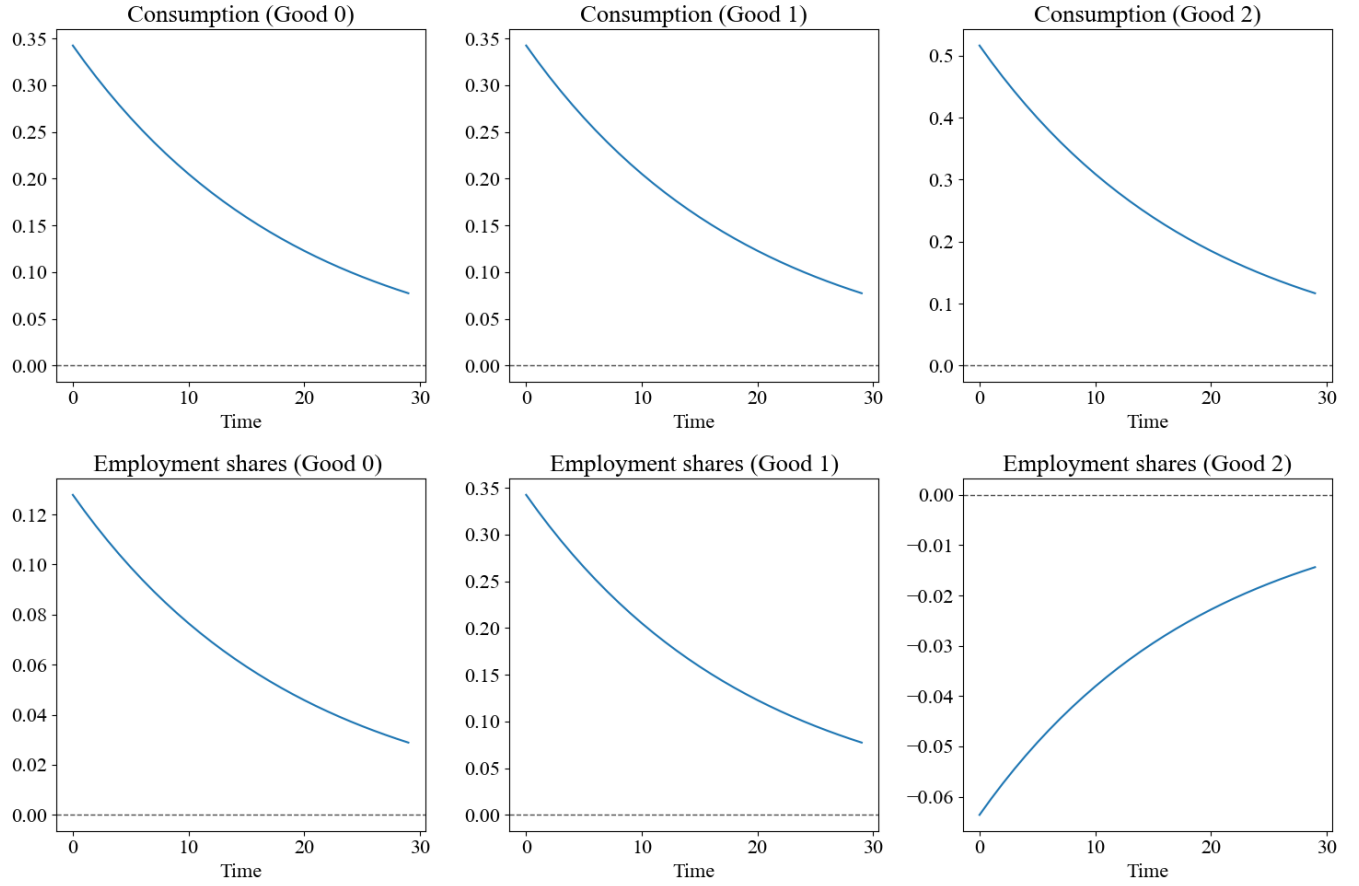
Note: Figure 3.7 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the manufacturing sector, in an economy with relatively higher TFP in the agricultural sector and a lower services sector TFP. The increase in consumption of the manufacturing good is a lot lower than in the baseline case. A similar trend is observed for the consumption of both the agricultural and service sector goods. The increase in employment in the manufacturing sector is notably higher, while the decline in employment shares in the agricultural and service sectors is more pronounced.

Figure 3.8: Sector-level response to a TFP shock to agriculture ($a_{1,t} > a_{0,t} > a_{2,t}$)



Note: Figure 3.8 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the agricultural sector, in an economy with relatively higher TFP in the agricultural sector and a lower services sector TFP. Compared to the baseline case, consumption of the agricultural good increases more, and the increase in consumption of the manufacturing and service sector goods is lower. The decrease in employment in the agricultural sector is notably lower, while the increase in employment shares in the manufacturing and service sectors is also lower compared to the baseline scenario.

Figure 3.9: Sector-level response to a TFP shock to services ($a_{1,t} > a_{0,t} > a_{2,t}$)



Note: Figure 3.9 shows the impulse responses of the sector-level variables to a positive total factor productivity (TFP) shock in the service sector, in an economy with relatively higher TFP in the agricultural sector and a lower services sector TFP. The increase in consumption across all goods is higher compared to the baseline scenario. Employment in the service sector declines, and the increase in employment shares in the manufacturing and agricultural sectors is higher compared to the baseline case.

3.4.5 Exploring impulse responses with increased substitutability

In this section, we focus on how increasing the elasticity of substitution between goods affects the propagation of total factor productivity (TFP) shocks. The elasticity of substitution governs the ease with which demand can be reallocated across goods in response to relative price movements. A higher elasticity implies that consumers and producers more readily substitute between goods from different sectors, potentially amplifying or dampening the effects of sector-specific disturbances.

We change the elasticity of substitution parameter (ε) from 0.3 to 1.5, reflecting increased substitutability. We begin with the baseline case in which TFP is identical across all sectors. It is important to note that changing this parameter does not alter the core result that only TFP shocks to the investment-producing (manufacturing) sector have aggregate implications. Consequently, the impulse responses of the aggregate economy to such shocks to this sector remain largely unchanged and are not reported here.

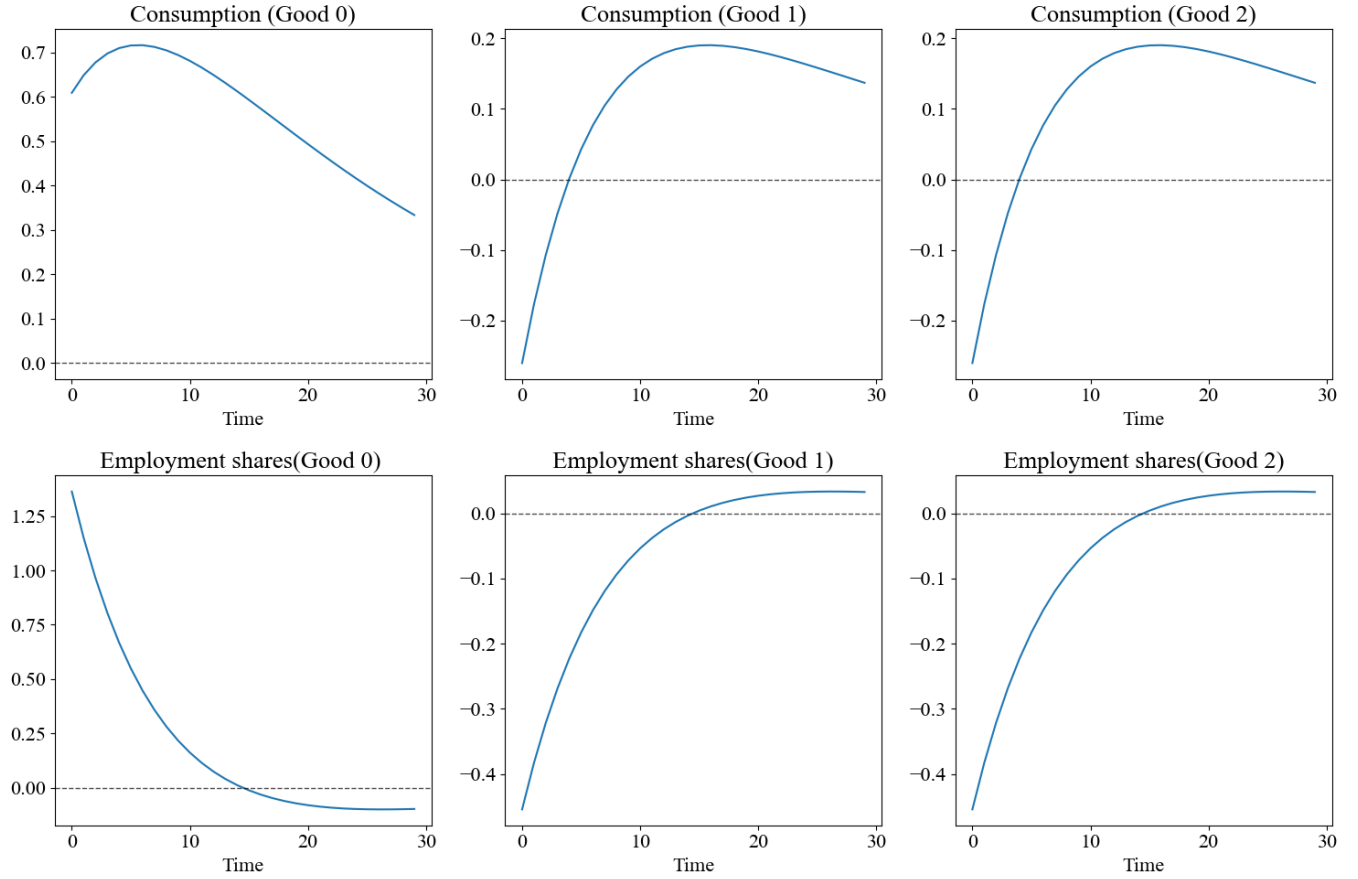
Figures 3.10 and 3.11 present the impulse responses of sector-level variables to TFP shocks in the manufacturing and agricultural sectors, respectively. From Figure 3.10, we observe that with higher substitutability, a TFP shock to the manufacturing sector leads to a significantly larger increase in consumption of the manufacturing good compared to the baseline case. For example, in the baseline scenario with low substitutability, a one standard deviation shock to manufacturing raises consumption of the manufacturing good by about 0.05 percentage points on impact. In contrast, with higher substitutability, the same shock increases consumption by approximately 0.6 percentage points on impact, peaking at around 0.7 percentage points before gradually returning to the steady state. The corresponding reductions in the consumption of agricultural and service goods are also substantially greater than in the baseline case. Similarly, employment in the manufacturing sector rises by about 1.25 percentage points on impact, considerably higher than in the baseline. Employment shares in the agricultural and service sectors decline more sharply as well. These results highlight an important insight: with increased substitutability, consumers are better able to respond to a TFP shock by shifting consumption toward the more productive manufacturing

sector. This shift boosts demand for the manufacturing good and drives a reallocation of labor away from other sectors toward manufacturing.

The impulse responses to TFP shocks to agriculture and services differ markedly under higher substitutability. Comparing Figures 3.11 to Figure 3.3, we see that with a higher elasticity of substitution, a positive productivity shock in the agricultural sector raises consumption and employment within that sector while reducing consumption and employment in both manufacturing and services. A symmetric pattern of reallocation occurs in response to a TFP shock to the service sector and hence are not reported.

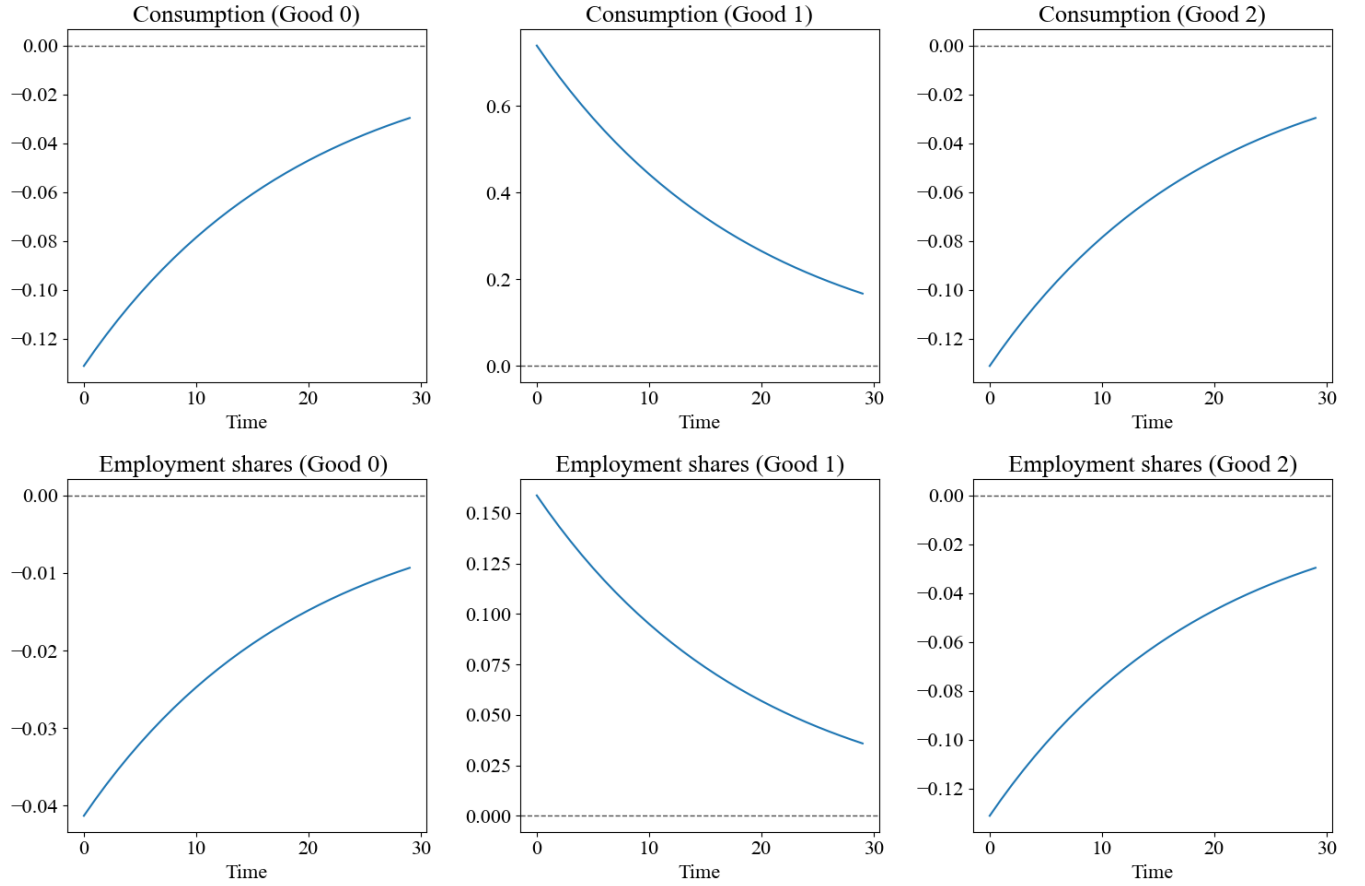
Importantly, with increased substitutability, the sectoral responses to shocks in the pure consumption sectors (agriculture and services) exhibit a notable reversal compared to the low-substitutability case. Under low substitutability, a positive productivity shock in a pure consumption sector led to a decline in that sector's employment share, while employment increased in the other sectors. However, when substitutability is high, the same shocks now raise the employment share in the shocked sector and reduce it in the other sectors. This reversal arises because higher substitutability allows relative price changes to trigger stronger shifts in consumption patterns, reallocating demand in favor of the more productive sector. As a result, the sector experiencing the productivity shock absorbs a larger share of economic activity. This finding highlights the role of substitution elasticity in governing the direction and magnitude of sectoral reallocation, even in the absence of aggregate effects.

Figure 3.10: Sector-level response to a TFP shock to manufacturing ($\varepsilon = 1.5$)



Note: Figure 3.10 shows the impulse responses of the sector level variables to a positive total factor productivity (TFP) shock in the investment-producing sector (Good 0), with higher substitutability between goods. On impact, consumption in the manufacturing sector increases relatively more compared to the baseline case, while consumption in the other sectors declines relatively more. Employment shares in the manufacturing sector also increase relatively more compared to the baseline, while those of the other sectors decline more.

Figure 3.11: Sector-level response to a TFP shock to agriculture ($\varepsilon = 1.5$)



Note: Figure 3.11 shows the impulse responses of the sector level variables to a positive total factor productivity (TFP) shock in the agricultural sector, with higher substitutability. On impact, consumption increases in the agricultural sector, while consumption in the other sectors decreases. Employment shares in the agricultural sector increase while those of the other sectors decrease.

We also consider the two cases of varying sector total factor productivity. Importantly, aside from the size of the effects, the qualitative results remain largely similar to the baseline results and are hence not reported. Together, the results suggest that the degree of substitutability and the levels of initial TFP are important in shaping the sectoral dynamics of sectoral TFP shocks, especially to the pure consumption sectors.

3.5 Introducing labor adjustment costs

In the baseline version of the model, we showed that shocks to sectors producing only consumption goods have no aggregate effects. This outcome is primarily driven by the assumption of perfectly flexible labor reallocation and prices across sectors, which allows sector-specific shocks to pure consumption sectors to be fully absorbed through adjustments in sectoral employment and consumption, without impacting macroeconomic aggregates. While still maintaining flexible prices, we address this limitation by introducing labor adjustment costs into the model. The model incorporates sectoral labor adjustment costs through the following quadratic function:

$$q_{n,j,t} \equiv 1 - \frac{\psi_n}{2} (n_{j,t} - n_{j,t-1})^2, \quad \psi_n > 0. \quad (3.20)$$

This specification captures the idea that reallocating labor across sectors is costly and does not occur instantaneously. The adjustment cost depends on the change in employment within each sector j , penalizing large deviations from the previous period's employment level. The parameter ψ_n determines the severity of the adjustment cost, with larger values implying greater friction in reallocating labor. The updated resource constraints are

$$y_{0,t} \equiv \hat{a}_{0,t} a_{0,t}^{1-\theta} s_{0,t}^\theta n_{0,t}^{1-\theta} q_{n,0,t}^{1-\theta} k_t^\theta h_t^{1-\theta} = c_{0,t} + i_t \quad (3.21)$$

$$y_{j,t} \equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^\theta n_{j,t}^{1-\theta} q_{n,j,t}^{1-\theta} k_t^\theta h_t^{1-\theta} = c_{j,t}, \quad \forall j. \quad (3.22)$$

The adjustment cost term $q_{n,j,t}$ enters the sectoral production function multiplicatively

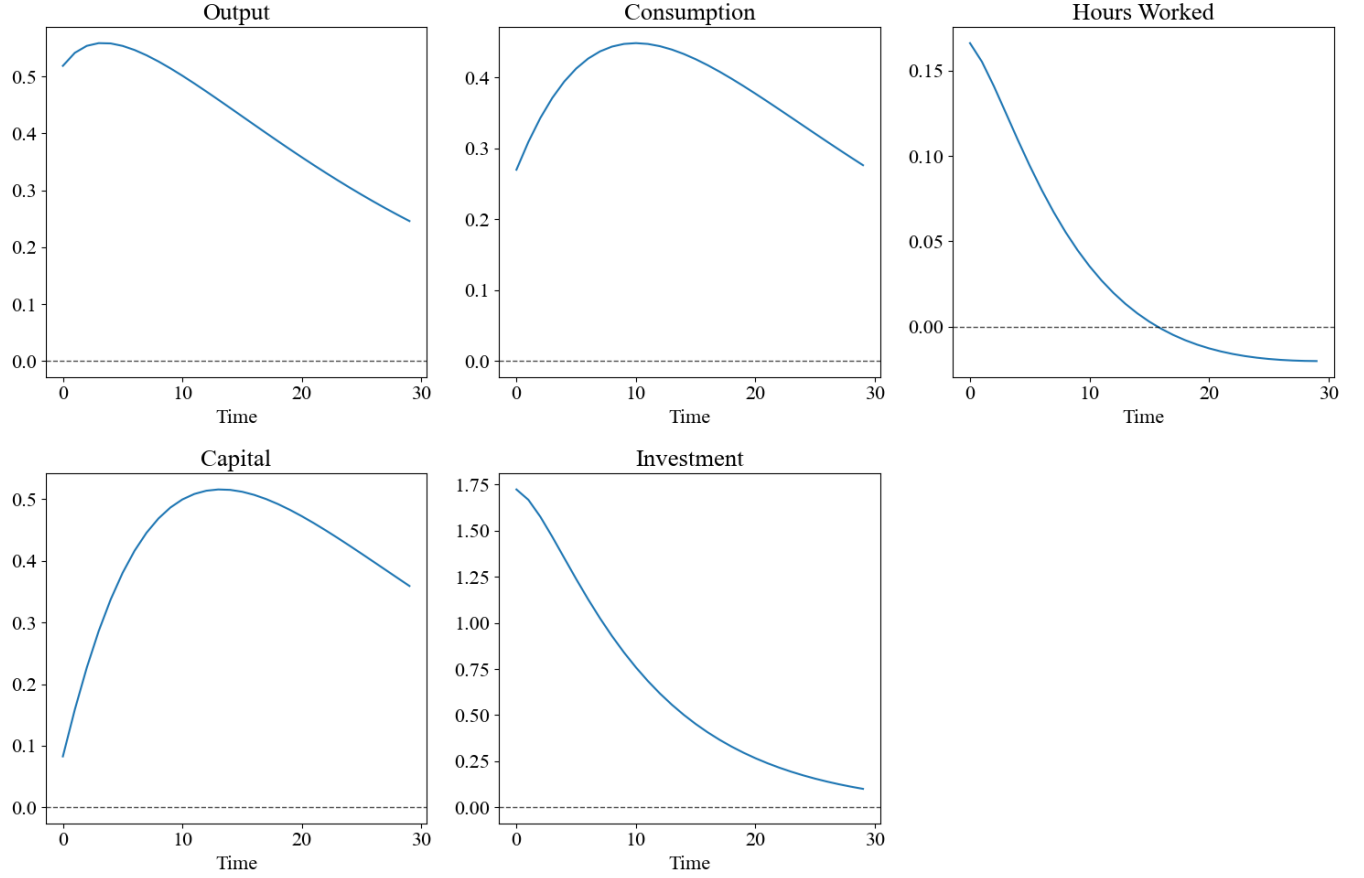
as $q_{n,j,t}^{1-\theta}$ alongside $n_{j,t}^{1-\theta}$. This formulation implies that rapid changes in employment within a sector reduce the effective contribution of labor to output. When employment levels are stable, $q_{n,j,t}$ is close to 1 and has little to no impact. However, as sectoral labor deviates from its previous level, $q_{n,j,t}$ falls below 1, effectively discounting the productivity of labor. This captures the frictions associated with reallocating labor, such as training costs, misallocation, or hiring inefficiencies, and ensures that sectoral output responds more smoothly to shocks.

In the appendix, we present the derivation of the system of equations that incorporates labor adjustment costs. We begin with the baseline case where all initial sectoral TFPs are set to 1 and the elasticity of substitution is low. Figures 3.12 and 3.13 display the impulse responses of the aggregate variables to shocks in the manufacturing and agriculture sectors. Again, in the baseline case, the impulse response of shocks to the service sector is symmetric to the impulse response to a TFP shock in agriculture and hence is not reported. As shown in Figure 3.12, the responses to a productivity shock in the manufacturing sector (Good 0) remain largely similar to those observed in the baseline model without labor adjustment costs.

However, in Figure 3.13, a positive TFP shock to the agricultural sector leads to a decline in aggregate output by approximately 0.035 percentage points on impact. This negative effect is persistent and fades gradually over time. Aggregate consumption follows a similar trajectory, initially declining before slowly recovering. Hours worked also fall on impact but recover quickly towards the steady-state. The capital stock also declines on impact and adjusts more sluggishly, reaching a trough around period 5 before slowly recovering, while investment contracts sharply at first and then quickly converges back to its steady-state.

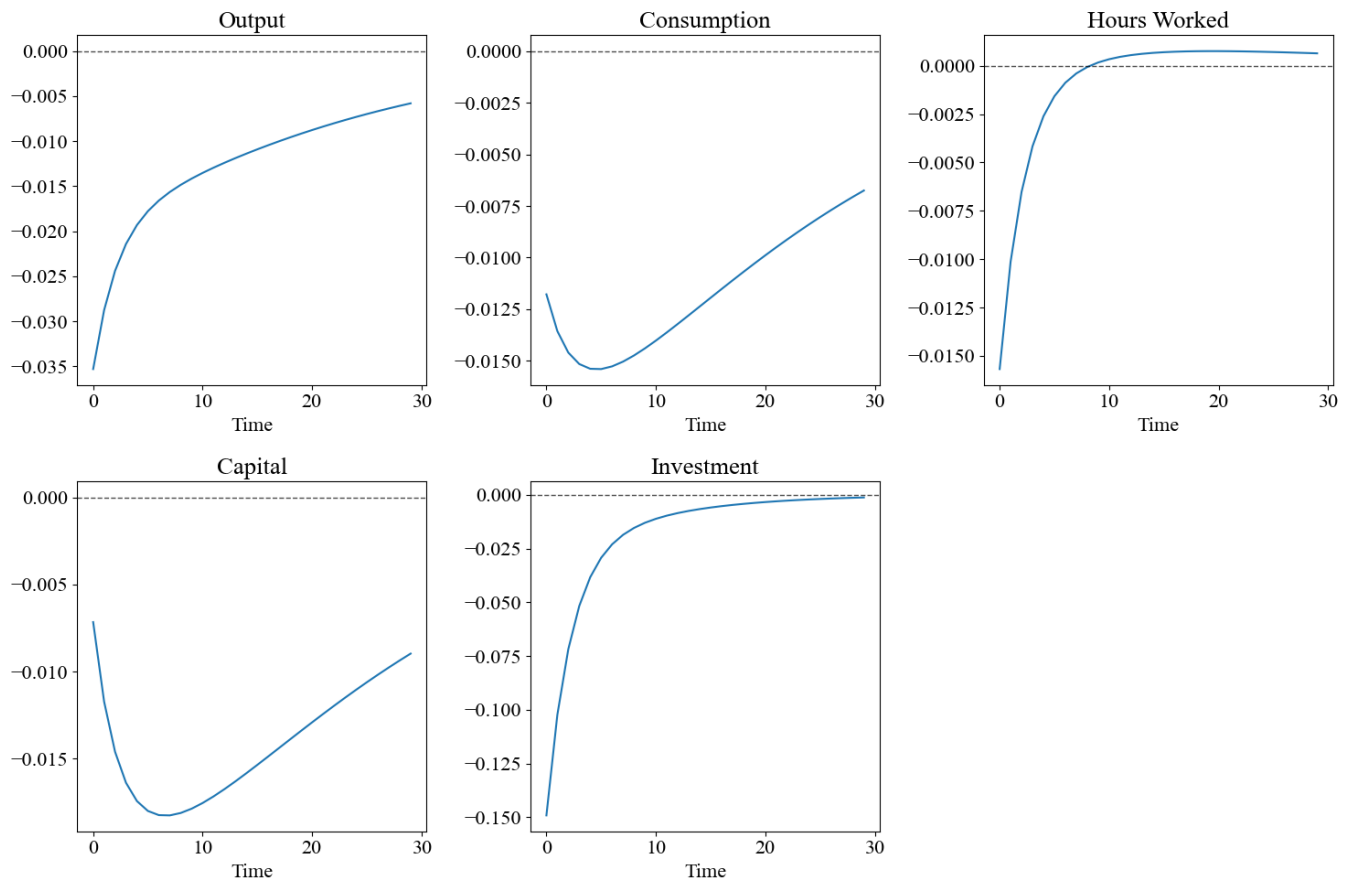
These contractionary effects arise from the impact of labor adjustment costs on labor efficiency. As noted earlier, the way labor adjustment costs are incorporated into the model implies that changes in a sector's employment share reduce the effective contribution of labor to output. Consequently, as labor reallocates away from the agricultural or service sectors in response to TFP shocks, the effective contribution of labor declines, leading to a reduction in aggregate output, and by extension, in consumption, hours worked, capital, and investment.

Figure 3.12: Aggregate economy response to a TFP shock to manufacturing ($\psi_n > 0$)



Note: Figure 3.12 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the manufacturing sector, with labor adjustment costs. Similar to the baseline results, all aggregate variables increase on impact and gradually decline towards their steady states.

Figure 3.13: Aggregate economy response to a TFP shock to agriculture ($\psi_n > 0$)



Note: Figure 3.13 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the agricultural sector, with labor adjustment costs. On impact, all the aggregate variables decline and gradually recover towards their steady states over time.

To address these contractionary effects, we explore the aggregate impulse responses under varying sector TFP levels. Starting with the first scenario, where the starting TFP level in agriculture is higher, while keeping the manufacturing and service sectors uniform. Figures 3.14 and 3.15 present the impulse responses of the aggregate economy to TFP shocks to agriculture and services. Comparing Figure 3.13 to 3.14, we observe that with a more productive agricultural sector, the contractionary effect of a TFP shock is much smaller compared to the baseline case of uniform TFP levels. For instance, while in the baseline case, output declined by about 0.035 percentage points on impact, it now declines by only 0.008 percentage points on impact. Also, the recovery is much faster compared to the baseline case. The decline in aggregate consumption, hours worked, capital stock, and investment is all less pronounced compared to the baseline, and their recovery is also much faster. This suggests that increasing sector productivity offsets the efficiency losses associated with labor reallocation in the presence of labor adjustment costs.

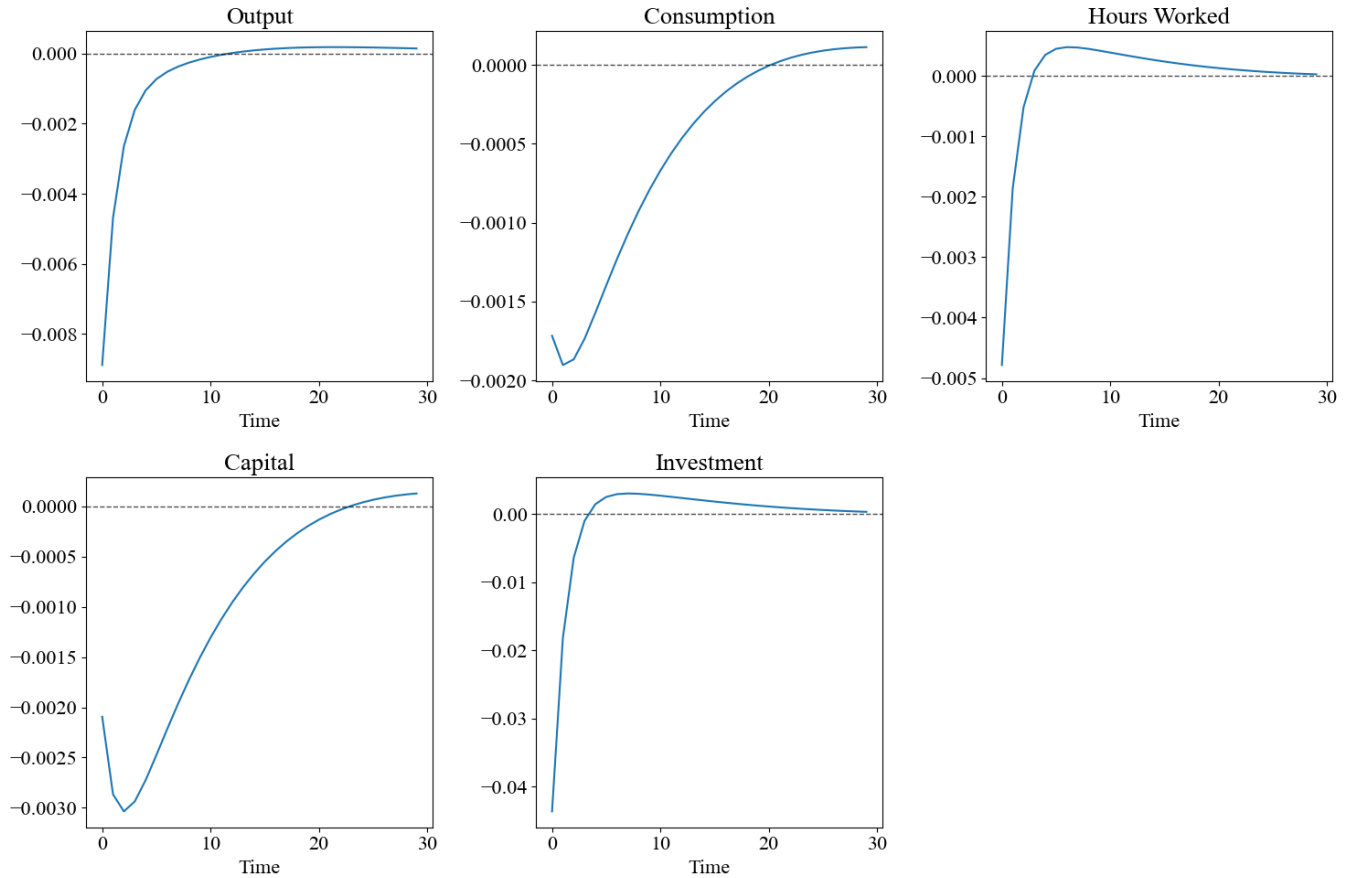
Figure 3.15 shows the aggregate impulse response to a TFP shock to the service sector that is now less productive compared to the agricultural sector. In contrast with the case of a TFP shock to the agricultural sector, we observe that the contractionary effects on the aggregate economy are more pronounced when there is a shock to the less productive service sector. This implies that the efficiency losses associated occasioned by labor reallocation are further pronounced when the shocked sector is less productive.

These results are further confirmed by the second case, where agriculture remains more productive while we lower the TFP in the service sector. The aggregate economy response to TFP shocks to agriculture in this scenario is presented in Figure 3.16. We see a reversal of the contractionary effects of a TFP shock to the agricultural sector. A one standard deviation TFP shock in the agricultural sector now increases aggregate output by about 0.008 percentage points on impact. These effects remain elevated for a considerable period of time. Similarly, aggregate consumption increases by about 0.004 percentage points on impact, with the effect also persisting for a while. A similar pattern is observed for the capital stock. Hours worked also increase on impact and then steadily decline towards the steady-state as the shock dissipates. A similar trend is observed for investment. By making

services less productive, we essentially made agriculture even more productive, relatively, compared to the first scenario. This higher productivity of the sector more than offsets the efficiency losses associated with the presence of labor adjustment costs, resulting in expansionary aggregate effects.

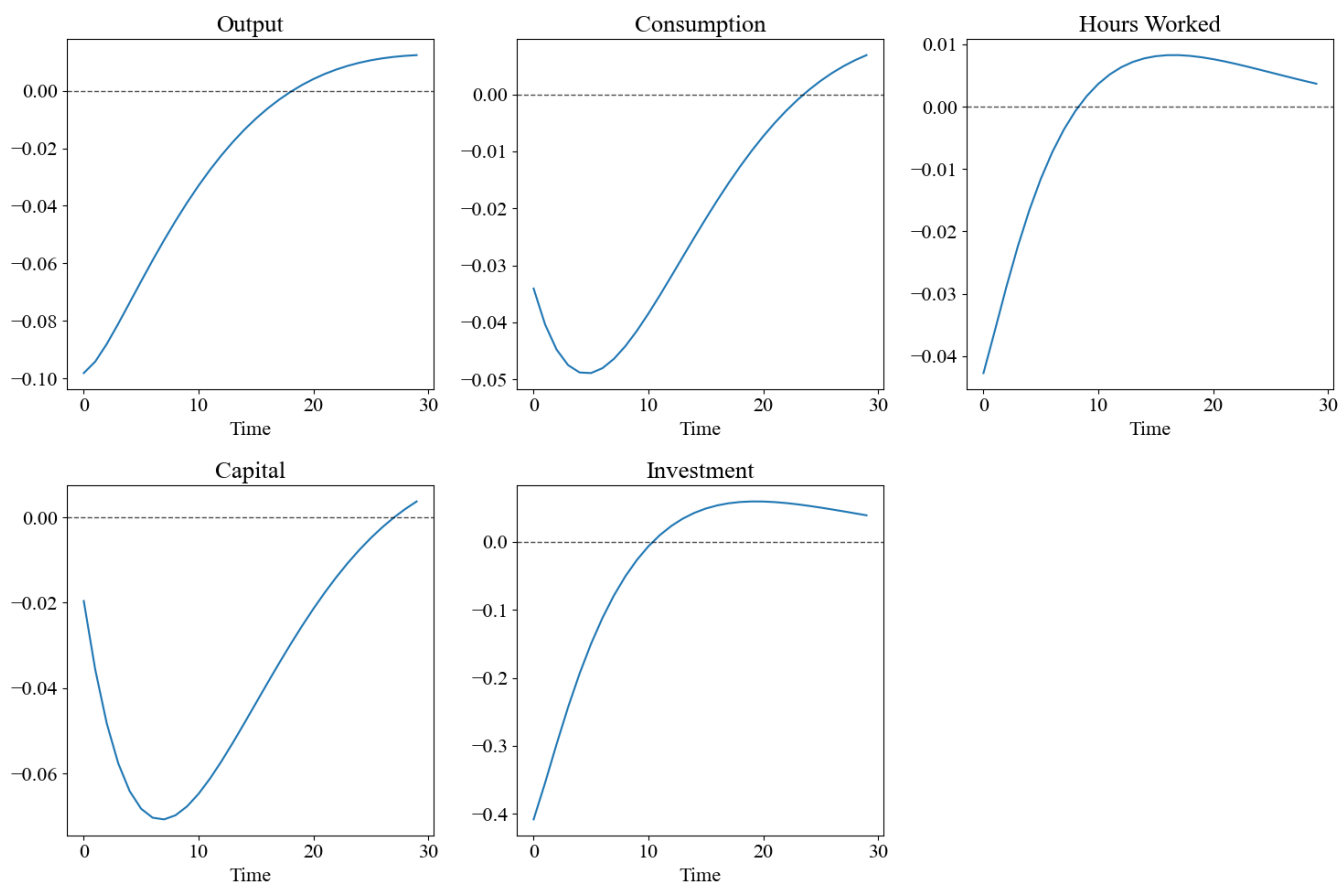
Similarly, Figure 3.17 shows the impulse response of the aggregate economy to productivity shocks in the now less productive service sector. We observe that the contractionary effects are even more pronounced in this case, providing support for earlier findings that the efficiency losses due to labor reallocation are more pronounced when the shocked sector is less productive.

Figure 3.14: Aggregate economy response to a TFP shock to agriculture ($\psi_n > 0$, $a_{1,t} > a_{0,t} = a_{2,t}$)



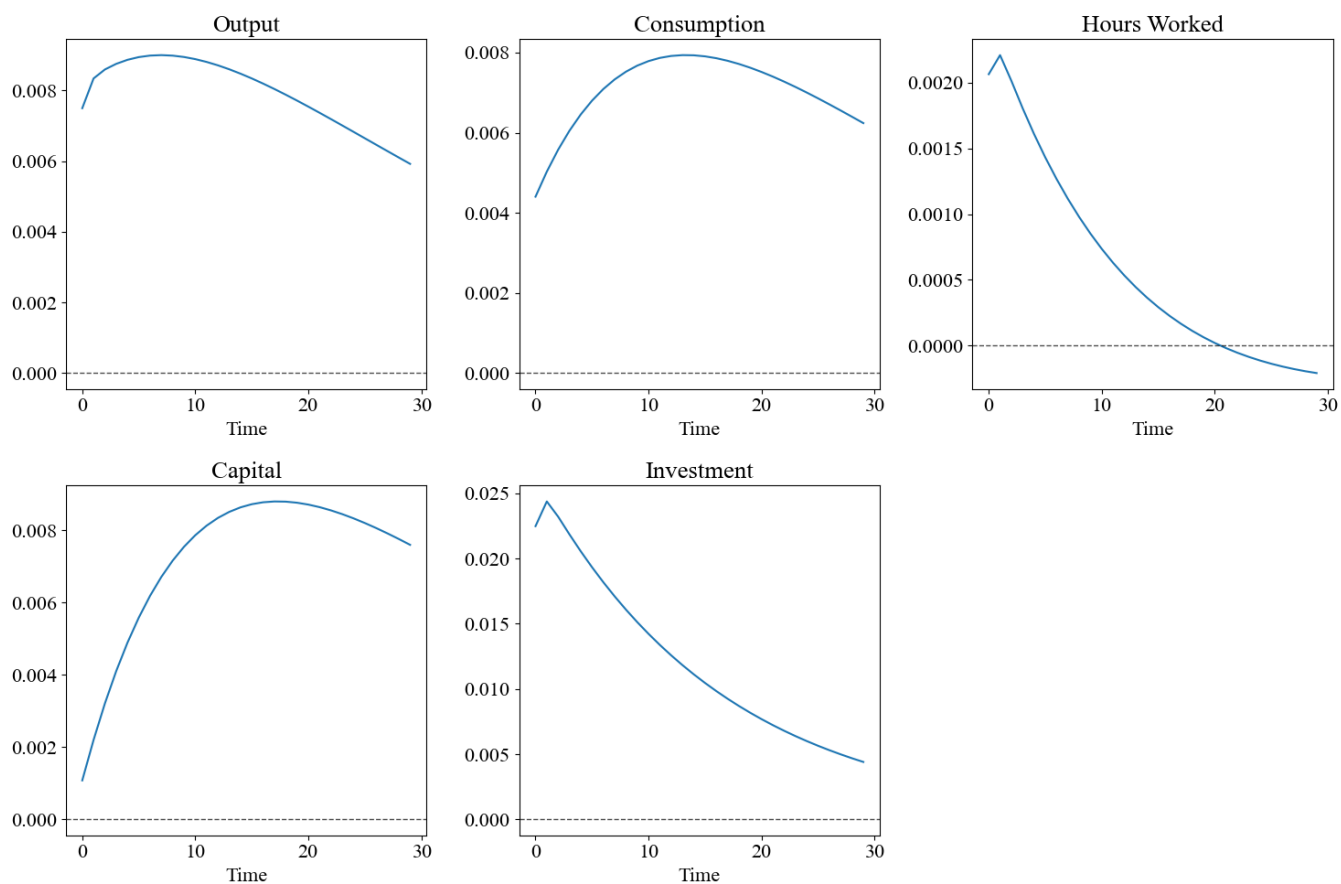
Note: Figure 3.14 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the agricultural sector, with labor adjustment costs and a more productive agricultural sector. The contractionary effect of the shock is much reduced with a more productive agricultural sector.

Figure 3.15: Aggregate economy response to a TFP shock to services ($\psi_n > 0$, $a_{1,t} > a_{0,t} = a_{2,t}$)



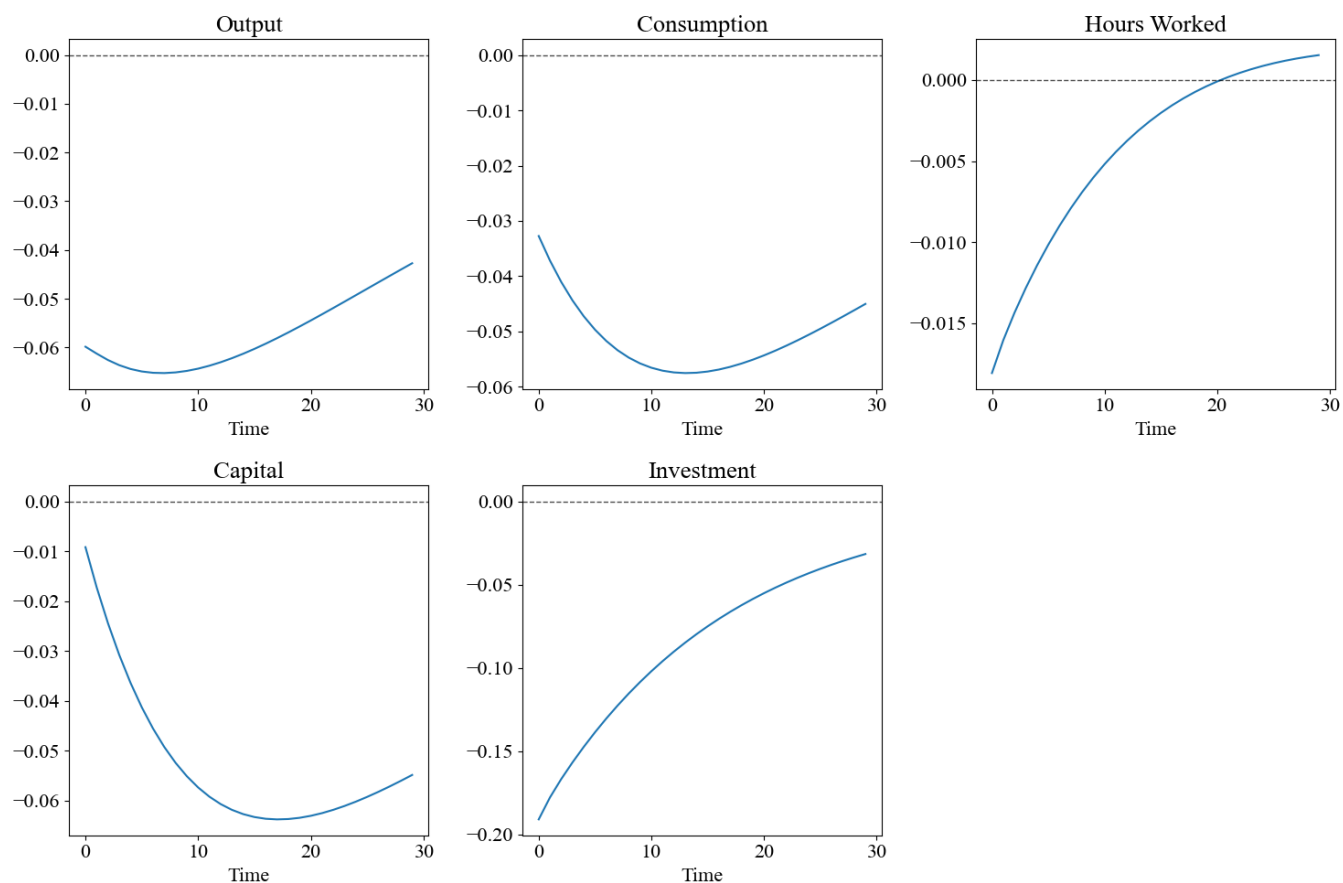
Note: Figure 3.15 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the service sector, with labor adjustment costs, and a more productive agricultural sector. On impact, all the aggregate variables decline and gradually recover towards their steady states over time.

Figure 3.16: Aggregate economy response to a TFP shock to agriculture ($\psi_n > 0$, $a_{1,t} > a_{0,t} > a_{2,t}$)



Note: Figure 3.16 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the agricultural sector, with labor adjustment costs, a more productive agricultural sector, and a less productive service sector. The baseline contractionary effect of the shock is reversed in this scenario.

Figure 3.17: Aggregate economy response to a TFP shock to services ($\psi_n > 0$, $a_{1,t} > a_{0,t} > a_{2,t}$)



Note: Figure 3.17 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the service sector, in a model with labor adjustment costs, a more productive agricultural sector, and a less productive service sector. On impact, all the aggregate variables decline and remain low for extended periods.

3.6 Adjustment cost with higher substitutability

Aside from the role of varying sector productivity influencing the aggregate impact of TFP shocks to the pure consumption sectors, we also explore the dynamics of these shocks under increased substitutability. We argue here that the low substitutability assumed by the model also contributes to these contractionary effects aggregate effects of TFP shocks to the pure consumption sectors. With low substitutability, consumers do not shift spending toward the cheaper good, so the productivity improvement in the shocked sector fails to generate sufficient additional demand to absorb the increased output. As a result, the market value of the sector's output declines, leading to a fall in aggregate output and consumption. This contraction reduces the value of labor, causing hours worked to decline. Investment and capital accumulation correspondingly decline as firms anticipate lower future demand.

We explore this further by considering the impact of these productivity shocks on the prices of the goods as well as the market value of consumption. Normalizing the price of Good 0 to 1, and from Equation (C.29) in the appendix, the price of good j can be written as

$$p_{j,t} = \frac{\omega_j c_{j,t}^{\frac{-1}{\varepsilon}}}{\omega_0 c_{0,t}^{\frac{-1}{\varepsilon}}}.$$

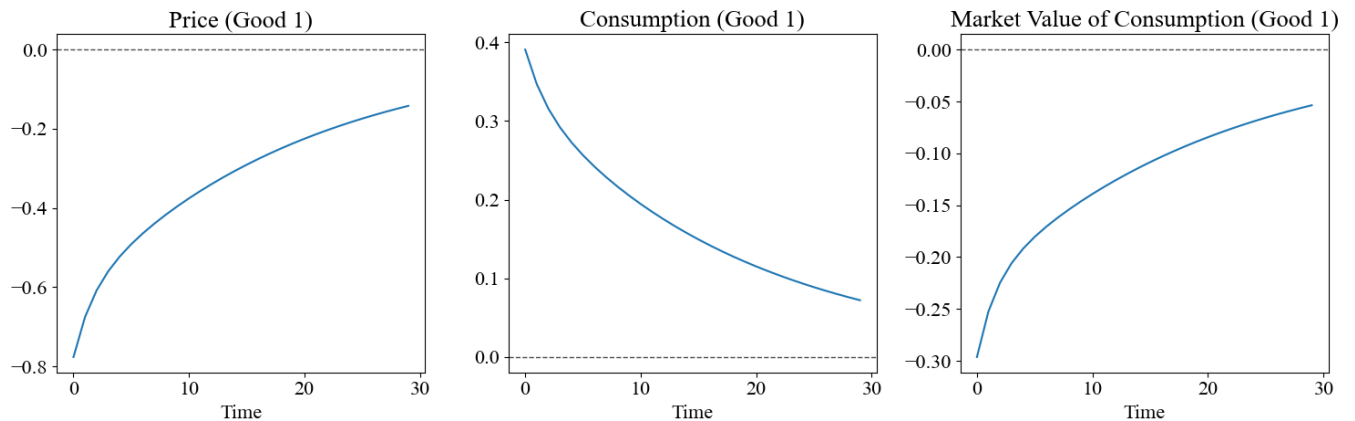
Following from this, the market value of consumption for good j can be written as

$$p_{j,t} c_{j,t} = \frac{\omega_j c_{j,t}^{\frac{\varepsilon-1}{\varepsilon}}}{\omega_0 c_{0,t}^{\frac{-1}{\varepsilon}}}.$$

Figure 3.18 shows the impulse responses of prices, sector consumption, and the market value of consumption for the agricultural good. Notice that the TFP shock leads to a decline in price and an increase in consumption. However, the market value of consumption declines. This implies that the increase in consumption in response to the shock is not enough to offset the fall in prices, resulting in a decline in the market value of consumption. This translates

into a reduction in aggregate output. A similar pattern is observed for the service sector. We now proceed to increase the degree of substitutability and explore the impulse response

Figure 3.18: Impulse responses of prices, consumption, and market value of consumption to TFP shocks to agriculture (Good 1) ($\psi_n > 0$)



Note: Figure 3.18 shows the impulse responses of price, consumption, and the market value of consumption to a positive total factor productivity (TFP) shock in the agricultural sector, in the model with adjustment costs and low substitutability.

of the aggregate economy to a TFP shock in the sectors. The elasticity of substitution is again set to 1.5. Figure 3.19 presents the impulse responses for prices and the market value of consumption for the agricultural sector. With higher substitutability, the marginal value of consumption now increases in response to the TFP shock. This indicates that demand rises sufficiently to offset the price decline, resulting in an increase in the market value of consumption.

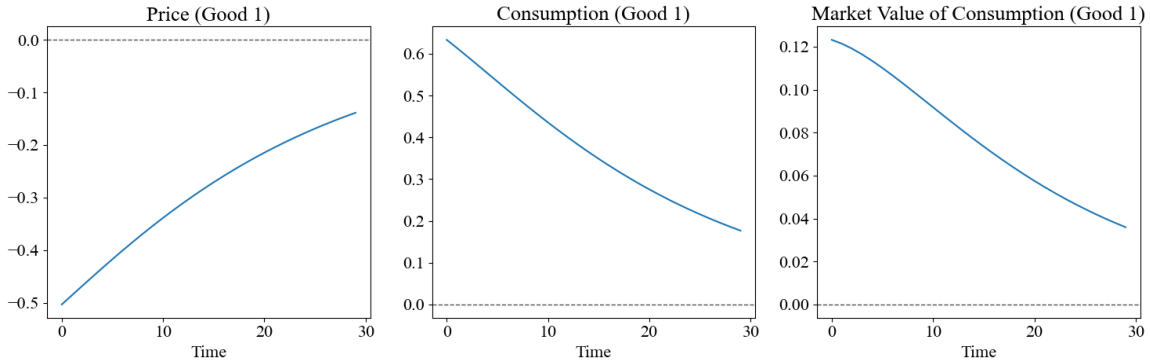
These changes are reflected in the aggregate impulse responses shown in Figure 3.20. Output now responds positively on impact to a sectoral TFP shock to agriculture, in contrast to the negative output response observed under low substitutability. Consumption follows a similar pattern, increasing on impact and then gradually decreasing back towards the steady state. Hours worked also increase initially, reflecting stronger labor supply incentives, but eventually decline, consistent with intertemporal substitution and efficiency improvements. The capital stock rises steadily, peaking around period 10, while investment exhibits an initial surge followed by a sharp decline towards the steady state. This result is similar for the service sector as well.

The key contrast with the low-elasticity of substitution case is that all major macroeconomic variables now exhibit an initial positive response, rather than an immediate contraction. This outcome implies a central mechanism: when substitutability is high, sectoral productivity shocks become expansionary because consumers can effectively reallocate their consumption toward the more productive sector. This reallocation enables the economy to capture the full benefits of the productivity improvement, even in the presence of labor adjustment costs.

Finally, we also consider the two cases of varying sectoral TFP under a high elasticity of substitution. The resulting impulse response functions are presented in Figures C.1 to C.4 in the appendix. The key finding is that the combination of increased substitutability and higher initial TFP levels magnifies the expansionary aggregate effect of a TFP shock. On the other hand, even with high substitutability, a TFP shock to a relatively less productive sector has contractionary aggregate economy effects.

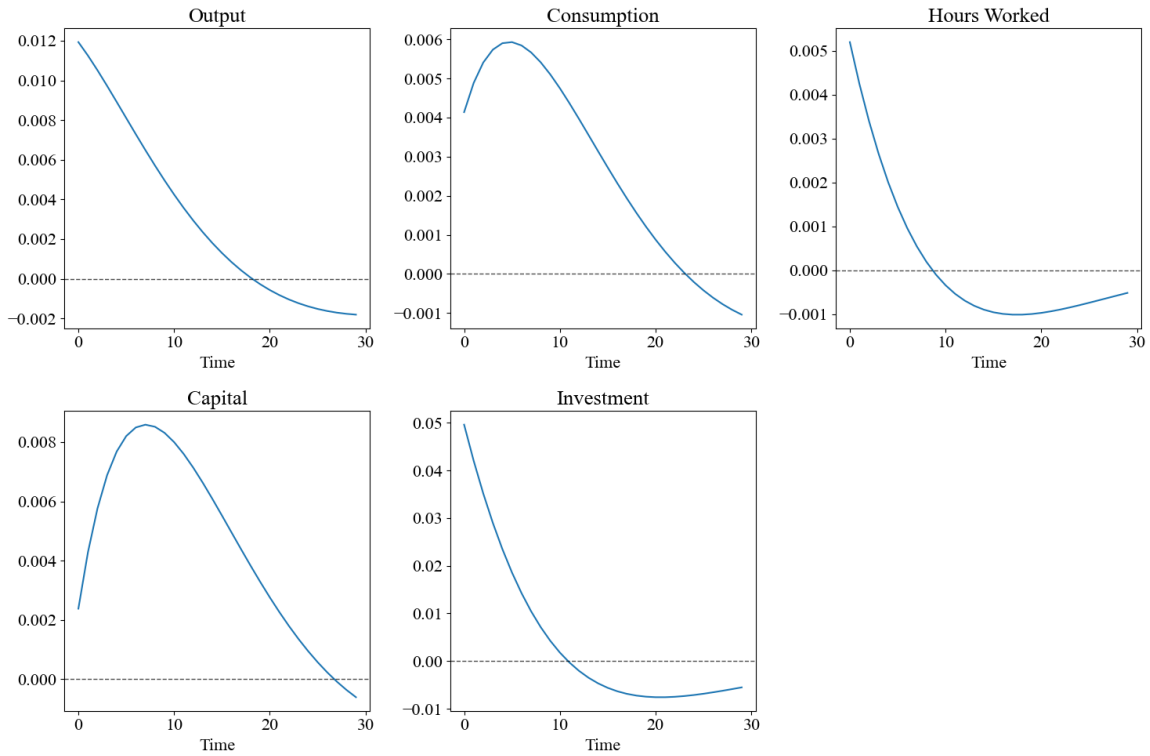
These findings underscore the role of both sectoral productivity differences and substitution elasticities in shaping macroeconomic responses to sector-specific shocks, especially to the pure-consumption sectors. A more productive sector can better leverage a high elasticity of substitution to boost aggregate outcomes, while less productive sectors become less influential in driving macroeconomic dynamics. This highlights the importance of accounting for structural asymmetries when evaluating the effects of technological progress at the sectoral level.

Figure 3.19: Impulse responses of prices, consumption, and market value of consumption to TFP shocks to agriculture (Good 1) ($\psi_n > 0$, $\varepsilon = 1.5$)



Note: Figure 3.19 shows the impulse responses of price, consumption, and the market value of consumption to a positive total factor productivity (TFP) shock in the agricultural sector, in the model with adjustment costs and high substitutability.

Figure 3.20: Aggregate economy response to a TFP shock to agriculture (Good 1) ($\psi_n > 0$, $\varepsilon = 1.5$)



Note: Figure 3.20 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the agricultural sector, in the model with adjustment costs and high substitutability.

3.7 Conclusion

This paper explores the ability of models designed to explain structural change to be used to explore the sectoral and aggregate implications of sector-specific TFP shocks. Building on the model by [Ngai & Pissarides \(2007\)](#), we extend the analysis by embedding the model in a stochastic real business cycle setting with King-Plosser-Rebelo (KPR) preferences. Our goal is to assess how productivity shocks to different sectors affect both the sectoral dynamics and the macroeconomic aggregates.

In the baseline model, where we assume uniform sector TFP levels and no market frictions, we find that only shocks to the manufacturing sector, which produces a good used for both consumption and investment, have meaningful macroeconomic consequences. Shocks to sectors producing pure consumption goods are fully absorbed through the reallocation of labor and consumption across sectors and flexible price adjustments, leaving aggregate variables unaffected.

Positive TFP shocks to the manufacturing sector increase aggregate output, consumption, hours worked, investment, and the capital stock on impact, with these effects gradually declining as the shock dissipates. At the sectoral level, such shocks raise employment in the manufacturing sector, while employment shares in the other sectors decline. When the agricultural sector is more productive, the impact of the manufacturing TFP shock on sectoral reallocation is reduced, and the positive effect on sectoral consumption is amplified. This suggests that a more productive agricultural sector dampens the reallocation of labor toward manufacturing in response to the shock, resulting in broader consumption gains across all sectors. The results also show that, regardless of their initial TFP levels, the pure consumption sectors respond identically to shocks originating in the manufacturing sector.

The sectoral impulse responses also show that TFP shocks to the least productive sectors trigger efficient labor reallocation toward relatively more productive sectors. This reallocation generates substantial consumption across all sectors. In contrast, shocks to already productive sectors result in less labor reallocation, thereby limiting the associated consumption gains.

The baseline results also show that increasing the substitutability between the sectors significantly affects the sectoral response to shocks to the pure consumption goods. With a higher elasticity of substitution, shocks to the agriculture and service sectors increase employment and consumption in the shocked sector while reducing employment and consumption in other sectors. This contrasts with results with a lower elasticity of substitution, where employment declined in the shocked sector. This reversal arises because higher substitutability allows relative price changes to trigger stronger shifts in consumption patterns, reallocating demand in favor of the more productive sector. As a result, the sector experiencing the productivity shock absorbs a larger share of economic activity.

To address the limitation that shocks to the pure consumption sectors do not affect aggregate outcomes, we introduce labor adjustment costs to capture frictions associated with reallocating labor across sectors, while maintaining flexible prices. In this modified model, sectoral productivity shocks in the pure consumption sectors (agriculture and services) begin to propagate to the aggregate economy. In the baseline estimation with uniform initial TFP levels, shocks to the pure consumption sectors have contractionary effects on the aggregate economy. TFP shocks to the agricultural and service sectors lead to declines in all major macroeconomic aggregates. This is largely due to the efficiency losses that arise with labor reallocation in the presence of labor adjustment costs. These contractionary effects can be reduced and even reversed when the productivity of the shocked sector is significantly increased. Similarly, the contractionary effects become more pronounced when the shocked sector is less productive.

We also argue that the contractionary baseline results are partly driven by low substitutability between goods. We show that with a higher elasticity of substitution, shocks to the pure consumption sectors produce expansionary aggregate effects. Low substitutability implies that demand does not easily shift toward the relatively cheaper good following a productivity shock, limiting the ability of the productivity improvement in the shocked sector to generate sufficient additional demand to absorb the increased output. When substitutability is increased, the economy can better exploit sectoral productivity gains, making such shocks expansionary. A combination of high substitutability and higher sector productivity magni-

fies the expansionary effects, while low sector productivity results in contractionary effects regardless of high substitutability.

Our findings emphasize the importance of labor market frictions, sector TFP levels, and consumption flexibility in shaping the transmission of sectoral shocks. They suggest that, while structural change models are powerful tools for understanding long-run sectoral reallocation, incorporating short-run frictions and substitution behavior, and varying sector TFP levels is essential for capturing business cycle dynamics. This framework can be extended further to explore the business cycle dynamics in open economy settings.

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Appendix A

Appendix: Chapter 1

A.1 Proofs of propositions

A.1.1 Propositions 1 and 2

The proofs of Propositions 1 and 2 are intertwined, so we present both in a single proof. Since our model is written in discrete time, it considers sector capital shares rather than the levels ($s_{j,t}k_t$ rather than $k_{j,t}$) and is written in intensive form, the proof differs substantially in style from various results in Ngai and Pissarides (2007). However, the results are analogous to their findings.

Define

$$\Omega_t \equiv \{c_{i,t}, n_{i,t}, s_{i,t}\} \ i \in \{0, 1, ..m - 1\} .$$

The social planner's problem is

$$\begin{aligned}
L = & \max_{\Omega_t, k_{t+1}} \sum_{t=0}^{\infty} \tilde{\beta}^t u_t(\cdot) \\
& + \lambda_{c,j,t} \left((s_{j,t} k_t)^\theta (a_{j,t} n_{j,t})^{1-\theta} - c_{j,t} \right) \quad (\forall j > 0) \\
& + \lambda_{c,0,t} \left((s_{0,t} k_t)^\theta (a_{0,t} n_{0,t})^{1-\theta} - i_t - c_{0,t} \right) \\
& + \lambda_{n,t} \left(1 - \sum_{j=0}^{m-1} n_{j,t} \right) \\
& + \lambda_{s,t} \left(1 - \sum_{j=0}^{m-1} s_{j,t} \right) \\
& + \lambda_{k,t} (k_{t+1} (1 + \gamma_n) (1 + \gamma_0) - (1 - \delta) k_t - i_t).
\end{aligned}$$

For $j \in \{0, 1, \dots, m-1\}$ define

$$y_{j,t} = (s_{j,t} k_t)^\theta (a_{j,t} n_{j,t})^{1-\theta} \quad (\text{A.1})$$

$$\nu_{j,t} \equiv u_t^j(\cdot) = \omega_j c_{j,t}^{\frac{-1}{\varepsilon}} \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \quad (\text{A.2})$$

$$f_{s,j,t} \equiv \theta a_{j,t}^{1-\theta} \left(\frac{s_{j,t}}{n_{j,t}} \right)^{\theta-1} k_t^\theta \quad (\text{A.3})$$

$$f_{n,j,t} \equiv (1 - \theta) a_{j,t}^{1-\theta} \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta k_t^\theta \quad (\text{A.4})$$

$$f_{k,j,t} \equiv \theta a_{j,t}^{1-\theta} \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta k_t^{\theta-1} n_{j,t}. \quad (\text{A.5})$$

For each $j \in \{0, 1, \dots, m-1\}$, we have the following first order conditions from derivatives with respect to $c_{j,t}$, $n_{j,t}$, and $s_{j,t}$:

$$\tilde{\beta}^t \nu_{j,t} = \lambda_{c,j,t} \quad (\text{A.6})$$

$$\lambda_{c,j,t} f_{n,j,t} = \lambda_{n,t} \quad (\text{A.7})$$

$$\lambda_{c,j,t} f_{s,j,t} = \lambda_{s,t} \quad (\text{A.8})$$

The derivatives with respect to i_t , and k_{t+1} are

$$-\lambda_{k,t} = \lambda_{c,0,t} \quad (\text{A.9})$$

$$\lambda_{k,t+1} (1 - \delta) = \sum_{j=0}^{m-1} \lambda_{c,j,t+1} f_{k,j,t} + \lambda_{k,t} (1 + \gamma_n) (1 + \gamma_0). \quad (\text{A.10})$$

Intratemporal optimality: Proposition 2 In this section, we show that Proposition 1 holds. Note that it uses only equations from intratemporal optimality. From the decentralized problem, we know that the ratio of prices for any two goods will equal the ratio of marginal utilities. This and Equations (A.6), (A.7) and (A.8) lead to the following relationships $\forall j, j' \in \{0, 1, \dots, m-1\}$:

$$\frac{p_{j,t}}{p_{j',t}} = \frac{\nu_{j,t}}{\nu_{j',t}} = \frac{f_{s,j',t}}{f_{s,j,t}} = \frac{f_{n,j',t}}{f_{n,j,t}}. \quad (\text{A.11})$$

From the third and fourth of these

$$\frac{s_{j,t}}{n_{j,t}} = \frac{s_{j',t}}{n_{j',t}}. \quad (\text{A.12})$$

Using Equation (A.12), the first and fourth relationships give

$$\frac{p_{j,t}}{p_{j',t}} = \frac{a_{j',t}^{1-\theta}}{a_{j,t}^{1-\theta}}. \quad (\text{A.13})$$

Since good 0 in time t is our numeraire good and given Equation (A.1), output is defined as

$$y_t \equiv \sum_{j=0}^{m-1} \frac{p_{j,t} y_{j,t}}{p_{0,t}} = \sum_{j=0}^{m-1} \frac{p_{j,t}}{p_{0,t}} a_{j,t}^{1-\theta} k_t^\theta s_{j,t}^\theta n_{j,t}^{1-\theta} = \sum_{j=0}^{m-1} \frac{p_{j,t}}{p_{0,t}} a_{j,t}^{1-\theta} k_t^\theta \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta n_{j,t}.$$

Since the $n_{j,t}$ values sum to one, with $p_{0,t} = 1$, and Equations (A.12), (A.13), this is

$$y_t = a_{0,t}^{1-\theta} k_t^\theta \left(\frac{s_{0,t}}{n_{0,t}} \right)^\theta. \quad (\text{A.14})$$

Similarly, aggregate consumption is defined as

$$c_t \equiv \sum_{j=0}^{m-1} \frac{p_{j,t} c_{j,t}}{p_{0,t}} = c_{0,t} \sum_{j=0}^{m-1} \frac{p_{j,t}}{p_{0,t}} \frac{c_{j,t}}{c_{0,t}}. \quad (\text{A.15})$$

From the relationship $\frac{p_{j,t}}{p_{j',t}} = \frac{\nu_{j,t}}{\nu_{j',t}}$ (Equation (A.11)) along with Equation (A.2)

$$\frac{c_{j,t}}{c_{0,t}} = \left(\frac{\omega_0 p_{j,t}}{\omega_j p_{0,t}} \right)^{-\varepsilon}$$

and

$$\frac{p_{j,t} c_{j,t}}{p_{0,t} c_{0,t}} = \left(\frac{\omega_j}{\omega_0} \right)^{\varepsilon} \left(\frac{p_{j,t}}{p_{0,t}} \right)^{1-\varepsilon},$$

so that with Equation (A.13) we have

$$\frac{p_{j,t} c_{j,t}}{p_{0,t} c_{0,t}} = z_{j,t} \quad (\text{A.16})$$

where

$$z_{j,t} \equiv \left(\frac{\omega_j}{\omega_0} \right)^{\varepsilon} \left(\frac{a_{0,t}}{a_{j,t}} \right)^{(1-\varepsilon)(1-\theta)}.$$

It follows from Equations (A.15) and (A.16) that

$$c_t = c_{0,t} Z_t \quad (\text{A.17})$$

where

$$Z_t \equiv \sum_{j=0}^{m-1} z_{j,t}.$$

Rearranging (A.17) to solve for $c_{0,t}$ and putting this expression into Equation (A.16), we find

$$\frac{p_{j,t} c_{j,t}}{p_{0,t}} = \frac{c_t}{Z_t} z_{j,t}. \quad (\text{A.18})$$

Then using $\frac{p_{j,t}}{p_{0,t}} = \frac{f_{n,0,t}}{f_{n,j,t}}$ from Equation (A.11) and Equation (1.2), Equation (A.18) is

$$n_{j,t} = c_t \frac{z_{j,t}}{Z_t} \frac{\left(\frac{k_t s_{0,t}}{n_{0,t}}\right)^{-\theta}}{a_{0,t}^{1-\theta}}.$$

Next on the right-hand side of this, we divide by y_t and multiply by its equivalent from Equation (A.14). Upon simplifying, we find

$$n_{j,t} = \frac{c_t}{y_t} \frac{z_{j,t}}{Z_t}. \quad (\text{A.19})$$

It follows that for $j, j' \neq 0$

$$n_{j',t} = \frac{z_{j',t}}{z_{j,t}} n_{j,t}. \quad (\text{A.20})$$

Moreover, since shares sum to 1, using Equation (A.20) we have

$$1 = n_{0,t} + \sum_{j=1}^{m-1} n_{j,t} = n_{0,t} + \sum_{j=1}^{m-1} \frac{c_t}{y_t} \frac{z_{j,t}}{Z_t} = n_{0,t} + \frac{c_t}{y_t} \frac{1}{Z_t} \sum_{j=1}^{m-1} z_{j,t} = n_{0,t} + \frac{c_t}{y_t} \frac{Z_t - 1}{Z_t}$$

from which

$$n_{0,t} = 1 - \frac{c_t}{y_t} \frac{Z_t - 1}{Z_t}. \quad (\text{A.21})$$

Similarly, since capital shares sum to 1, we can use Equations (A.12) and (A.19) to write

$$1 = s_{0,t} + \sum_{j=1}^{m-1} \frac{s_{0,t}}{s_{j,t}} \frac{n_{j,t}}{n_{0,t}} s_{j,t} = s_{0,t} + \frac{s_{0,t}}{n_{0,t}} \sum_{j=1}^{m-1} n_{j,t} = s_{0,t} + \frac{s_{0,t}}{n_{0,t}} \sum_{j=1}^{m-1} \frac{c_t}{y_t} \frac{z_{j,t}}{Z_t} = s_{0,t} + \frac{c_t}{y_t} \frac{s_{0,t}}{n_{0,t}} \frac{Z_t - 1}{Z_t}.$$

Plugging in for $n_{0,t}$ from (A.21) and solving for $s_{0,t}$ we find $s_{0,t} = n_{0,t}$. Moreover, from this and Equation (A.12)

$$s_{j,t} = n_{j,t}, \forall j. \quad (\text{A.22})$$

This is sufficient for Proposition 2.

Intratemporal optimality: Auxiliary results We next present results that are required for Proposition 1, but use only intratemporal relationships.

Auxiliary result 1. From Equation (A.8) we have

$$\lambda_{c,j,t} = \frac{\lambda_{c,0,t} f_{s,0,t}}{f_{s,j,t}} \quad (\text{A.23})$$

and from Equations (A.3) and (A.5) we have

$$\frac{f_{k,j,t}}{f_{s,j,t}} = \frac{s_{j,t}}{k_t}. \quad (\text{A.24})$$

Together, Equations (A.23) and (A.24) give

$$\lambda_{c,j,t} f_{k,j,t} = \lambda_{c,0,t} f_{s,0,t} k_t^{-1} s_{j,t}$$

so that

$$\sum_{j=0}^{m-1} \lambda_{c,j,t} f_{k,j,t} = \sum_{j=0}^{m-1} \lambda_{c,0,t} f_{s,0,t} k_t^{-1} s_{j,t} = \lambda_{c,0,t} f_{s,0,t} k_t^{-1} \sum_{j=0}^{m-1} s_{j,t} = \lambda_{c,0,t} f_{s,0,t} k_t^{-1}. \quad (\text{A.25})$$

Auxiliary result 2. From Equations (A.6) and (A.9) and the definition of $\tilde{\beta}$

$$\tilde{\beta}^t \nu_{0,t} = \lambda_{c,0,t} = -\lambda_{k,t}. \quad (\text{A.26})$$

Auxiliary result 3. Note that $\nu_{j,t} = \frac{\partial \phi_t}{\partial c_{j,t}} \phi_t^{-1}$. Since ϕ_t is homogenous of degree 1

$$\phi_t = \sum_{j=0}^{m-1} \frac{\partial \phi_t}{\partial c_{j,t}} c_{j,t} = \sum_{j=0}^{m-1} \nu_{j,t} \phi_t c_{j,t}$$

so

$$1 = \sum_{j=0}^{m-1} \nu_{j,t} c_{j,t}.$$

From the first relationship in Equation (A.11) and the definition of c_t

$$1 = \nu_{0,t} \sum_{j=0}^{m-1} p_{j,t} c_{j,t} = \nu_{0,t} c_t$$

so

$$\nu_{0,t} = \frac{1}{c_t}. \quad (\text{A.27})$$

Intertemporal optimality: Proposition 1. From Equation (A.25) updated to period $t + 1$, Equations (A.26) and (A.27) for both periods t and $t + 1$, Equations (A.3) and (A.22) along with the definition of $\tilde{\beta}$, we can write Equation (A.10) as

$$\frac{c_{t+1}}{c_t} = \beta (\theta k_{t+1}^{\theta-1} + 1 - \delta). \quad (\text{A.28})$$

From Equations (A.14), (A.22), and (A.17), into Equation (1.14) we find

$$y_t n_{0,t} = \frac{c_t}{Z_t} + i_t. \quad (\text{A.29})$$

Then with Equation (A.21) into (A.29) and simplifying

$$i_t = y_t - c_t = y_{0,t} - c_{0,t}$$

so that Equation (1.3) can be written as

$$k_{t+1} (1 + \gamma_n) (1 + \gamma_0) = k_t^\theta + (1 - \delta) k_t - c_t. \quad (\text{A.30})$$

Equations (A.28) and (A.30) track the dynamics of c_t , k_t without reference to the disaggregated economy. It is straightforward to verify that Equation (1.11) provides for an equivalent set of equations where we have substituted in for c_t .

A.1.2 Proposition 3

Rearranging equation 1.7 gives the expression for a_{it} . Note that

$$a_{jt} = \frac{A_{jt}}{A_{ot}} = \frac{(1 + \gamma_j)^t}{(1 + \gamma_0)^t}. \quad (\text{A.31})$$

This implies that, considering a beginning period 0 and an end period t , the ratio of relative TFP for sector j can be expressed as:

$$\frac{a_{jt}}{a_{j0}} = \frac{(1 + \gamma_j)^t}{(1 + \gamma_0)^t}. \quad (\text{A.32})$$

Solving for $(\gamma_j - \gamma_0)$ gives the expression for the relative TFP growth rates.

A.1.3 Proposition 4

Setting $k_{t+1} = k_t = k$ and $c_{t+1} = c_t$ in Equation (A.28) and solving for k we have

$$k = \left(\frac{\beta\theta}{1 - \beta(1 - \delta)} \right)^{\frac{1}{1-\theta}}.$$

Dropping time subscripts and solving for c in (A.30) gives

$$c = k^\theta - ((1 + \gamma_n)(1 + \gamma_0) - (1 - \delta))k.$$

Dividing the left side by y and the right by the equivalent k^θ and substituting in for k from the previous expression gives the result.

A.1.4 Proposition 5

Results through Equation (A.28) in Section A.1.1 do not use any equations that have been modified for the small open economy case, and so are unchanged. Defining r_k to be the marginal product of capital, a no-arbitrage condition between capital and bonds in the

decentralized economy requires

$$r = r_k - \delta = \theta k_t^{\theta-1} - \delta. \quad (\text{A.33})$$

This into Equation (A.28) gives

$$\frac{c_{t+1}}{c_t} = \beta (1 + r). \quad (\text{A.34})$$

From Equation (A.34) and our assumption that $\beta = (1 + r)^{-1}$, $c_{t+1} = c_t = c$. From Equations (A.33), A.14, and (A.22) $k_{t+1} = k_t = k$ and $y_{t+1} = y_t = y$.

From Equations (A.14), (A.22), and (A.17), into Equation (1.1) we find

$$yn_{0,t} = \frac{c}{Z_t} + i_{0,t}. \quad (\text{A.35})$$

Then with Equations (A.21) and (1.15) into (A.35) and simplifying

$$i_t = y - c + d_t - (1 + r) d_{t-1}.$$

so that upon solving for c Equation (1.16) can be written as

$$c = k^\theta - k((1 + \gamma_N)(1 + \gamma_0) - (1 - \delta)) + d_t - (1 + r) d_{t-1}$$

Noting $r_k k = (r - \delta) k = (r - \delta) k = \theta y$, dividing each side by y we have

$$\frac{c}{y} = 1 - \frac{\theta}{r - \delta} ((1 + \gamma_N)(1 + \gamma_0) - (1 - \delta)) + \left(\frac{d_t - (1 + r) d_{t-1}}{y} \right).$$

Finally, $(1 + r) d_{t-1} - d_t = x_t - m_t$ and $1 + r = \beta^{-1}$ into this expression gives Equation (1.18).

Appendix B

Appendix: Chapter 2

B.1 Variable descriptions and data sources

Sources include WDI, OECD STAN, KLEMS, GGDC [M. Timmer et al. \(2015\)](#), EASD [Mensah et al. \(2018\)](#), ICSD, PWT 10.01, IMF, and WEO.

Table B.1: Variable descriptions and data sources

Variable	Description	Data Source	Range
Sector-level Value Added	Value added in millions of local currency.	Global Productivity Database compiled by Dieppe et al. (2020) .	1950–2017
Sector-level Employment	Number of persons employed (thousands).	Same as above.	1950–2017
Government Debt (gov_debt_gdp)	General government debt to GDP ratio.	IMF Historical Debt Database.	1970–2017

Continued on next page

Table B.1 continued

Variable	Description	Data Source	Range
Human Capital (hc)	Based on years of schooling and returns to education.	Penn World Table 10.01	1950–2017
Population growth rate (pop_gr)	Percent change in population per 5-year period.	PWT 10.01	1950–2017
Log of initial GDP per capita (log_init_gdpcap)	Log of GDP per capita at the start of each 5-year period.	PWT 10.01	1950–2017
Log of capital stock per worker (log_cap_st_pw)	Log of capital stock divided by employment.	PWT 10.01	1950–2017
Total Factor Productivity (tfp)	TFP level at PPP (USA = 1).	PWT 10.01	1950–2017
Trade openness (top)	Exports + Imports as % of GDP.	World Bank WDI	1960–2017

Continued on next page

Table B.1 continued

Variable	Description	Data Source	Range
Private Sector Investment (priv_inv_gdp)	Private gross fixed capital formation (% of GDP).	ICSD	1960–2017
Public Sector Investment (gov_inv_gdp)	Public gross fixed capital formation (% of GDP).	ICSD	1960–2017
Average Corporate Tax Rate (tax_rate)	Average over time period.	Tax Foundation	1980–2017
External Debt (ext_debt_gdp)	External debt as % of GDP.	World Bank WDI	1960–2017
Current Account Balance (curr_balance)	% of GDP.	WEO	1980–2017

B.2 Results for 3-year intervals

Table B.2: Fixed effects and system GMM estimation results

Variable	Fixed Effects			System-GMM		
	tot_p_gr	st_change	intra_ind	tot_p_gr	st_change	intra_ind
gov_debt_gdp	-0.091*** (0.025)	-0.003 (0.008)	-0.087*** (0.021)	-0.489*** (0.123)	0.009 (0.012)	-0.452*** (0.112)
log(init_gdpcap)	6.838 (4.460)	-0.336 (1.252)	7.174** (3.964)	7.342 (21.271)	-2.23 (2.209)	6.032 (19.608)
pop_gr	4.252 (20.108)	-7.081 (4.595)	11.333 (21.088)	-77.828 (84.626)	-52.712 (44.381)	-29.679 (72.961)
log(cap_st_pw)	1.996 (2.056)	0.940 (0.628)	1.056 (2.105)	10.920 (19.537)	2.013 (1.464)	9.893 (16.736)
hc	-13.548** (6.331)	-4.649** (1.762)	-8.899 (6.041)	-43.213** (19.996)	-2.883 (2.674)	-35.294** (17.444)
top	0.006 (0.036)	0.001 (0.006)	0.005 (0.035)	0.148 (0.075)	0.009 (0.006)	0.130* (0.068)
L.tot_p_gr				0.123 (0.083)		
L.st_change					0.127 (0.102)	
L.intra_ind						0.175* (0.101)
intercept	6.837 (4.460)	6.271 (9.183)	-46.916 (48.694)	-57.396 (124.868)	8.281 (8.244)	-58.037 (118.145)
Hansen overid. test				9.96	15.16*	9.19
Arellano-Bond						
AR(1) test				-3.89***	-3.30***	-4.74**
Arellano-Bond						
AR(2) test				0.92	-0.28	0.69
No. of instruments				25	26	24
No. of groups				94	85	94

Note: Table B.2 presents the fixed effects and system GMM estimates for the baseline results using 3-year intervals. Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.3: Dynamic debt threshold estimates

VARIABLES	tot_p_gr	st_change	intra_ind
Threshold Estimates			
$\hat{\lambda}$	32%	41%	37%
95% Confidence Interval	[19.617-95.259]	[19.618-95.259]	[20.025- 84.145]
Impact of Government Debt to GDP			
$\hat{\beta}_1$	0.166 (0.202)	-0.059 (0.197)	-0.025 (0.208)
$\hat{\beta}_2$	-0.109* (0.063)	-0.035 (0.096)	-0.134** (0.067)
L.tot_p_gr	0.147* (0.083)		
L.st_change		0.051 (0.175)	
L.intra_ind			0.146* (0.081)
log(init_gdpcap)	-16.706** (7.948)	-2.803 (7.231)	-13.387 (8.901)
pop_gr	-38.202 (26.260)	7.422 (26.723)	-16.196 (24.478)
hc	8.534* (4.731)	1.063 (2.979)	7.913 (5.365)
top	0.048** (0.024)	0.001 (0.015)	0.041* (0.022)
log(cap_st_pw)	7.487* (4.492)	1.169 (3.618)	6.104 (4.433)
intercept	58.185** (25.126)	14.050 (14.455)	44.992 (31.817)
Observations	925	849	914
Countries	94	94	94
Number of instruments	209	207	212

Note: Table B.3 presents the dynamic panel threshold estimates for the baseline results using 3-year intervals. Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table B.4: Exogenous debt threshold estimates

Variable	Fixed Effects			System-GMM		
	tot_gr	st_change	intra_ind	tot_gr	st_change	intra_ind
Dum30*debt	0.076 (0.095)	0.016 (0.028)	0.060 (0.094)	-0.063 (0.221)	0.007 (0.060)	-0.047 (0.225)
Dum3060*debt	-0.021 (0.049)	0.011 (0.014)	-0.032 (0.045)	-0.334* (0.172)	-0.043 (0.033)	-0.290* (0.160)
Dum6090*debt	-0.051 (0.035)	0.008 (0.009)	-0.059* (0.033)	-0.348** (0.148)	-0.039 (0.023)	-0.311** (0.128)
Dum90*debt	-0.071** (0.024)	-0.001 (0.007)	-0.069*** (0.023)	-0.408*** (0.125)	-0.032 (0.023)	-0.366*** (0.119)
log(init_gdpcap)	6.719* (3.903)	-0.323 (1.242)	7.042* (3.723)	8.228 (21.456)	1.120 (2.132)	6.759 (20.058)
pop_gr	3.345 (32.607)	-6.926 (13.130)	10.272 (37.080)	-97.895 (88.610)	-61.599** (28.149)	-48.963 (76.327)
log(cap_st_pw)	1.947 (2.016)	0.949 (0.612)	0.998 (1.949)	8.240 (1.873)	0.584 (2.850)	8.089 (14.984)
hc	-13.300*** (4.819)	-4.534*** (1.351)	-8.767* (6.686)	-39.103* (20.061)	-6.278 (6.798)	-32.979* (17.561)
top	0.007 (0.037)	0.000 (0.008)	0.007 (0.037)	0.164** (0.073)	-0.011 (0.016)	0.143 (0.067)
L.tot_gr				0.132* (0.086)		
L.st_change					0.084 (0.132)	
L.intra_ind						0.180* (0.106)
intercept	-42.680 (27.447)	5.209 (10.080)	-47.889 (25.856)	-55.193 (50.056)	3.567 (15.720)	-59.494 (42.810)
Hansen overid. test				11.09	14.16	10.54
Arellano-Bond test for AR(1)				-4.00***	-3.48***	-4.83***
Arellano-Bond test for AR(2)				0.99	-0.61	0.81
No. of instruments				31	30	30
No. of groups				94	94	94

Note: Table B.4 presents the exogenous debt threshold estimates for the baseline results using 3-year intervals. Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

B.3 Using external debt in place of general government debt

Table B.5: Fixed effects and system GMM estimates of the impact of external debt on productivity growth and its components

Variable	Fixed Effects			System-GMM		
	tot_p_gr	st_change	intra_ind	tot_p_gr	st_change	intra_ind
ext_debt_gdp	-0.155** (0.071)	0.001 (0.022)	-0.154** (0.062)	-0.389*** (0.099)	-0.029 (0.029)	-0.417*** (0.105)
log(init_gdpcap)	21.842** (10.147)	0.439 (1.961)	14.637 (9.513)	11.610 (13.479)	-4.096 (3.571)	18.783 (30.116)
pop_gr	-1.929 (95.879)	-3.111 (17.105)	21.403** (9.759)	-109.808 (77.119)	-79.127 (83.528)	-84.667 (107.88)
log(cap_st_pw)	-2.161 (5.950)	0.918 (1.258)	-3.078 (5.694)	-0.954 (13.036)	1.209 (2.766)	-5.109 (19.027)
hc	-35.976* (18.282)	-14.436*** (3.822)	-21.540 (16.953)	-53.832* (31.299)	-5.362 (3.486)	-56.678 (45.484)
top	0.108 (0.199)	0.026 (0.031)	0.081 (0.178)	0.682*** (0.247)	0.136*** (0.053)	0.761*** (0.269)
L.tot_p_gr				0.136* (0.071)		
L.st_change					0.152 (0.178)	
L.intra_ind						0.113 (0.114)
intercept	-75.147 (81.372)	19.053 (12.388)	-94.200 (79.179)	32.657 (44.479)	37.469 (27.729)	10.401 (62.529)
Hansen overid. test				26.12	3.78	27.98
Arellano-Bond						
AR(1) test				-3.27***	-2.72***	-3.06***
Arellano-Bond						
AR(2) test				-0.59	1.40	-0.70
No. of instruments				37	24	24
No. of groups				50	50	50

Note: B.5 presents the fixed effects and system GMM estimates for the baseline estimates when external debt is used in place of general government debt. Standard errors are in parentheses. Statistical significance is represented as follows: *** p<0.01, ** p<0.05, * p<0.1.

B.4 Mathematical derivations of productivity decompositions

Starting from the change in aggregate productivity in Equation 2.2:

$$LP_{j,1} - LP_{j0} = \sum_{i=1}^m y_{i1} l_{i1} - \sum_{i0}^m y_{i0} l_{i0}. \quad (\text{B.1})$$

Dividing through by the beginning period aggregate labor productivity LP_{j0} gives:

$$\frac{LP_{j,1} - LP_{j0}}{LP_{j0}} = \frac{1}{LP_{j0}} \left(\sum_{i=1}^m y_{i1} l_{i1} - \sum_{i0}^m y_{i0} l_{i0} \right). \quad (\text{B.2})$$

Rearrange the summations on the right-hand side:

$$\frac{LP_{j,1} - LP_{j0}}{LP_{j0}} = \frac{1}{LP_{j0}} \sum_{i=1}^m (y_{i1} l_{i1} - y_{i0} l_{i0}). \quad (\text{B.3})$$

Add and subtract the following term: $l_{i0} y_{i1}$:

$$\frac{LP_{j,1} - LP_{j0}}{LP_{j0}} = \frac{1}{LP_{j0}} \sum_{i=1}^m (y_{i1} \cdot l_{i1} - y_{i0} \cdot l_{i0} + l_{i0} y_{i1} - l_{i0} y_{i1}). \quad (\text{B.4})$$

Grouping some terms on the right-hand side gives:

$$\frac{LP_{j,1} - LP_{j0}}{LP_{j0}} = \frac{1}{LP_{j0}} \sum_{i=1}^m (y_{i1} (l_{i1} - l_{i0}) + l_{i0} (y_{i1} - y_{i0})). \quad (\text{B.5})$$

Rearranging and distributing the summation gives the decomposition by [McMillan et al. \(2011\)](#) in Equation 2.3

$$\frac{LP_{j,1} - LP_{j0}}{LP_{j0}} = \frac{1}{LP_{j0}} \sum_{i=1}^m (y_{i1} - y_{i0}) l_{i0} + \frac{1}{LP_{j0}} \sum_{i=1}^m (l_{i1} - l_{i0}) y_{i1}. \quad (\text{B.6})$$

Appendix C

Appendix: Chapter 3

C.1 Intensive form derivations

In this section, we show the derivation of the intensive form of the production function and the law of motion. Dividing the production function in Equation [A.1](#) by $\tilde{A}_{0,t}L_t$ gives

$$\frac{Y_{j,t}}{\tilde{A}_{0,t}L_t} = \hat{a}_{j,t} \left(\frac{K_{j,t}}{\tilde{A}_{0,t}L_t} \right)^\theta \left(\frac{\tilde{A}_{j,t}N_{j,t}}{\tilde{A}_{0,t}L_t} \right)^{1-\theta}. \quad (\text{C.1})$$

The first and second components on the right-hand side of Equation [\(C.1\)](#) can be multiplied by $\frac{K_t}{\tilde{A}_{0,t}L_t}$ and $\frac{N_t}{\tilde{A}_{0,t}L_t}$ respectively to get

$$\frac{Y_{j,t}}{\tilde{A}_{0,t}L_t} = \hat{a}_{j,t} \left(\frac{K_{j,t}}{\tilde{A}_{0,t}L_t} \frac{K_t}{\tilde{A}_{0,t}L_t} \right)^\theta \left(\frac{\tilde{A}_{j,t}N_{j,t}}{\tilde{A}_{0,t}L_t} \frac{N_t}{\tilde{A}_{0,t}L_t} \right)^{1-\theta}. \quad (\text{C.2})$$

We make the following definitions:

$$\begin{aligned}
y_{j,t} &\equiv \frac{Y_{j,t}}{\tilde{A}_{0,t}L_t} \\
s_{j,t} &\equiv \frac{K_{j,t}}{K_t} \\
n_{j,t} &\equiv \frac{N_{j,t}}{N_t} \\
k_t &\equiv \frac{K_t}{\tilde{A}_{0,t}L_t} \\
h_t &\equiv \frac{N_t}{L_t} \\
a_{j,t} &\equiv \frac{\tilde{A}_{j,t}}{\tilde{A}_{0,t}}.
\end{aligned}$$

Substituting these definitions into Equation (C.2) gives the intensive form production function in Equation (3.2).

The law of motion of capital is

$$K_{t+1} = (1 - \delta)K_t + I_t - \frac{\psi_k}{2} \left(\frac{I_t}{K_t} - \delta \right)^2 K_t. \quad (\text{C.3})$$

Dividing through Equation (C.3) by $\tilde{A}_{0,t}L_t$ gives

$$\frac{K_{t+1}}{\tilde{A}_{0,t}L_t} = (1 - \delta) \frac{K_t}{\tilde{A}_{0,t}L_t} + \frac{I_t}{\tilde{A}_{0,t}L_t} - \frac{\psi_k}{2} \left(\frac{I_t}{K_t} \frac{\tilde{A}_{0,t}L_t}{\tilde{A}_{0,t}L_t} - \delta \right)^2 \frac{K_t}{\tilde{A}_{0,t}L_t}. \quad (\text{C.4})$$

Using the definition of k_t from above and $i_t = \frac{I_t}{\tilde{A}_{0,t}L_t}$, Equation (C.4) can be written as

$$\frac{K_{t+1}}{\tilde{A}_{0,t}L_t} = (1 - \delta)k_t + i_t - \frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 k_t. \quad (\text{C.5})$$

Multiplying the left-hand-side of Equation (C.5) by $\frac{\tilde{A}_{0,t+1}L_{t+1}}{\tilde{A}_{0,t}L_t}$ gives

$$\frac{K_{t+1}}{\tilde{A}_{0,t}L_t} \frac{\tilde{A}_{0,t+1}L_{t+1}}{\tilde{A}_{0,t+1}L_{t+1}} = (1 - \delta)k_t + i_t - \frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 k_t. \quad (\text{C.6})$$

The growth rates of $\tilde{A}_{0,t}$ and L_t are defined as

$$\begin{aligned}\tilde{A}_{0,t+1} &\equiv \tilde{A}_{0,t}(1 + g_a) \\ L_{t+1} &\equiv L_t(1 + g_L)\end{aligned}$$

where g_a is the growth rate of $\tilde{A}_{0,t}$ and g_L is the growth rate of $L_{0,t}$. With these definitions and the definition for k_t , Equation (C.6) can be written as

$$k_{t+1}(1 + g_a)(1 + g_L) = (1 - \delta)k_t + i_t - \frac{\psi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 k_t. \quad (\text{C.7})$$

In most RBC models, the focus is usually not on the growth rates g_L and g_a , so we set them to 0 for this paper. This produces the law of motion stated in Equation (3.13).

C.2 Proofs of propositions

C.2.1 Proposition 6

In this section, we derive the set of equations that characterize the aggregate economy and show that the aggregate economy can be tracked without reference to the sectoral dynamics.

The maximization problem generates the following first-order conditions:

$$\lambda_{c,j,t} = \beta^t \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_j c_{j,t}^{\frac{-1}{\varepsilon}}, \forall j \quad (\text{C.8})$$

$$\lambda_{c,j,t} f_{n,j,t} = \lambda_{n,t} \quad (\text{C.9})$$

$$\lambda_{c,j,t} f_{s,j,t} = \lambda_{s,t} \quad (\text{C.10})$$

$$\lambda_{c,0,t} = \lambda_{k,t} \left(\psi_k \left(\frac{i_t}{k_t} - \delta \right) - 1 \right) \quad (\text{C.11})$$

$$\beta^t \psi h_t^{\frac{1}{\eta}} = \sum_{n=0}^{n-1} \lambda_{c,j,t} f_{h,j,t} \quad (\text{C.12})$$

$$\begin{aligned} \lambda_{k,t} = E_t \left[\lambda_{k,t+1} \left(1 - \delta - \frac{\psi_k}{2} \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right)^2 \right. \right. \\ \left. \left. + \psi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \frac{i_{t+1}}{k_{t+1}} \right) - \sum_{n=0}^{n-1} \lambda_{c,j,t+1} f_{k,j,t+1} \right]. \end{aligned} \quad (\text{C.13})$$

The following are the respective marginal productivities

$$\begin{aligned} f_{s,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} \theta \left(\frac{s_{j,t}}{n_{j,t}} \right)^{\theta-1} h_t^{1-\theta} k_t^\theta \\ f_{n,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta h_t^{1-\theta} k_t^\theta \\ f_{k,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} \theta \left(\frac{s_{j,t}}{n_{j,t}} \right)^{\theta-1} s_{j,t} h_t^{1-\theta} k_t^{\theta-1} \\ f_{h,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta n_{j,t} h_t^{-\theta} k_t^\theta. \end{aligned}$$

Also, we define the marginal utilities as

$$v_{j,t} \equiv \beta^t \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_j c_{j,t}^{\frac{-1}{\varepsilon}} \quad (\forall j). \quad (\text{C.14})$$

We know from the decentralized problem that the ratio of prices is equal to the ratio of marginal utilities. That is: $\frac{p_{j,t}}{p_{j',t}} = \frac{v_{j,t}}{v_{j',t}}$. This and Equations (C.8), (C.9) and (C.10) lead to

the following relationships $\forall j, j' \in \{0, 1, \dots, m-1\}$:

$$\frac{p_{j,t}}{p_{j',t}} = \frac{\nu_{j,t}}{\nu_{j',t}} = \frac{f_{s,j',t}}{f_{s,j,t}} = \frac{f_{n,j',t}}{f_{n,j,t}}. \quad (\text{C.15})$$

To arrive at the set of equations in Proposition (6), some auxiliary results are needed.

Auxiliary result 1

In this section, we prove the following important result:

$$\lambda_{c,0,t} = \frac{\beta^t}{c_t}. \quad (\text{C.16})$$

Taking the expression $\frac{p_{j,t}}{p_{0,t}} = \frac{\nu_{j,t}}{\nu_{0,t}}$ and multiplying both sides by $\frac{c_{j,t}}{c_{0,t}}$ gives

$$\frac{p_{j,t}c_{j,t}}{p_{0,t}c_{0,t}} = \frac{\omega_j c_{j,t}^{\frac{\varepsilon-1}{\varepsilon}}}{\omega_0 c_{0,t}^{\frac{\varepsilon-1}{\varepsilon}}} \quad (\text{C.17})$$

$$p_{j,t}c_{j,t} = \frac{\omega_j c_{j,t}^{\frac{\varepsilon-1}{\varepsilon}}}{\omega_0 c_{0,t}^{\frac{\varepsilon-1}{\varepsilon}}} p_{0,t}c_{0,t}. \quad (\text{C.18})$$

Using Equation (C.18), we can substitute for $p_{j,t}c_{j,t}$ in Equation (3.10) to get

$$\frac{\omega_0 c_{0,t}^{-\frac{1}{\varepsilon}}}{p_{0,t}} c_t = \sum_{j=0}^{m-1} \omega_j c_{j,t}^{\frac{1}{\varepsilon}(\varepsilon-1)}. \quad (\text{C.19})$$

Equation (C.19) can be substituted into the definition in Equation (3.4) to get

$$\phi_t = \left(\sum_{j=0}^{m-1} \omega_j c_{j,t}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} = \left(\frac{\omega_0 c_{0,t}^{-\frac{1}{\varepsilon}}}{p_{0,t}} c_t \right)^{\frac{\varepsilon}{\varepsilon-1}}. \quad (\text{C.20})$$

Plugging Equation (C.20) into Equation (C.8) and with the normalization $p_{0,t} = 1$, gives the result in Equation (C.16).

Auxiliary result 2

Here, we show that the ratio of shares is the same across sectors. That is

$$\frac{s_{j,t}}{n_{j,t}} = \frac{s_{j',t}}{n_{j',t}}. \quad (\text{C.21})$$

Using the third and fourth expressions from Equation (C.15), we can write

$$\frac{\hat{a}_{j',t} a_{j',t}^{1-\theta} \theta \left(\frac{s_{j',t}}{n_{j',t}} \right)^{\theta-1} h_t^{1-\theta} k_t^\theta}{\hat{a}_{j,t} a_{j,t}^{1-\theta} \theta \left(\frac{s_{j,t}}{n_{j,t}} \right)^{\theta-1} h_t^{1-\theta} k_t^\theta} = \frac{\hat{a}_{j',t} a_{j',t}^{1-\theta} (1-\theta) \left(\frac{s_{j',t}}{n_{j',t}} \right)^\theta h_t^{1-\theta} k_t^\theta}{\hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta h_t^{1-\theta} k_t^\theta}$$

$$\frac{\left(\frac{s_{j',t}}{n_{j',t}} \right)^{\theta-1}}{\left(\frac{s_{j,t}}{n_{j,t}} \right)^{\theta-1}} = \frac{\left(\frac{s_{j',t}}{n_{j',t}} \right)^\theta}{\left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta}.$$

Simplifying this expression gives the result in Equation (C.21).

Using the result in Equation (C.16) and the marginal productivities $f_{h,j,t}$ and $f_{s,j,t}$, we can clean up Equation (C.12) to get

$$\psi h_t^{\frac{1}{\eta} + \theta} = \frac{1}{c_t} (1-\theta) \hat{a}_{0,t} a_{0,t}^{1-\theta} \left(\frac{s_{0,t}}{n_{0,t}} \right)^{\theta-1} k_t^\theta. \quad (\text{C.22})$$

In the proofs of Proposition 2, we show that $s_{j,t} = n_{j,t}$. Applying this result to Equation (C.22) gives Equation (3.12). Hence, cleaning up Equation (C.13) by plugging in Equation (C.11) and Equation (C.16), together with $s_{j,t} = n_{j,t}$ produces Equation (3.11).

Equation (C.9) implies that $\lambda_{c,j,t} f_{n,j,t} = \lambda_{c,j',t} f_{n,j',t}$. Rearranging this produces

$$\frac{\lambda_{c,j,t}}{\lambda_{c,j',t}} = \frac{f_{n,j',t}}{f_{n,j,t}}. \quad (\text{C.23})$$

However, from the relationship in Equation (C.15), we can write Equation (C.23) as

$$\frac{p_{j,t}}{p_{j',t}} = \frac{\hat{a}_{j',t} a_{j',t}^{1-\theta} (1-\theta) \left(\frac{s_{j',t}}{n_{j',t}} \right)^\theta h_t^{1-\theta} k_t^\theta}{\hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta h_t^{1-\theta} k_t^\theta}. \quad (\text{C.24})$$

Using the relationship in Equation (C.21), Equation (C.24) becomes

$$\frac{p_{j,t}}{p_{j',t}} = \frac{\hat{a}_{j',t} a_{j',t}^{1-\theta}}{\hat{a}_{j,t} a_{j,t}^{1-\theta}}. \quad (\text{C.25})$$

Taking Good 0 as the numeraire good, it follows that

$$\frac{p_{j,t}}{p_{0,t}} = \frac{\hat{a}_{0,t} a_{0,t}^{1-\theta}}{\hat{a}_{j,t} a_{j,t}^{1-\theta}}. \quad (\text{C.26})$$

Substituting Equation (3.2) and Equation (C.26) into Equation (3.9) gives

$$\begin{aligned} y_t &= \sum_{j=0}^{m-1} \frac{p_{j,t}}{p_{0,t}} \hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^\theta n_{j,t}^{1-\theta} k_t^\theta h_t^{1-\theta} = \sum_{j=0}^{m-1} \frac{\hat{a}_{0,t} a_{0,t}^{1-\theta}}{\hat{a}_{j,t} a_{j,t}^{1-\theta}} \hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^\theta n_{j,t}^{1-\theta} k_t^\theta h_t^{1-\theta} \\ &= \sum_{j=0}^{m-1} \hat{a}_{0,t} a_{0,t}^{1-\theta} \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta n_{j,t} k_t^\theta h_t^{1-\theta}. \end{aligned} \quad (\text{C.27})$$

Applying $\sum_{j=0}^{m-1} n_{j,t} = 1$ and $s_{j,t} = n_{j,t}$ on Equation (C.27) leads to Equation (3.14).

Equation (3.7) is the law of motion of capital, and Equation (3.15) is the resource constraint, respectively. Importantly, we see that the set of Equations (3.11) (3.12) (3.13) (3.14), and (3.15) do not contain any sector-level variables, and can be used to track the aggregate economy without any reference to the sector-level dynamics.

C.2.2 Proposition 7

Here, we show the proofs that lead to the relationships in the disaggregated economy. These proofs are similar to what was shown in the proof of Proposition 2 in Chapter 1.

Multiplying Equation (3.10) by $\frac{c_{0,t}}{c_{0,t}}$, and noting that Good 0 is the numeraire good gives

$$c_t = c_{0,t} \sum_{j=0}^{m-1} \frac{p_{j,t}}{p_{0,t}} \frac{c_{j,t}}{c_{0,t}}. \quad (\text{C.28})$$

From the first and second relationships in Equation (C.15), we can write the following:

$$\frac{p_{j,t}}{p_{0,t}} = \frac{\beta^t \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_j c_{j,t}^{\frac{-1}{\varepsilon}}}{\beta^t \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_0 c_{0,t}^{\frac{-1}{\varepsilon}}} = \frac{\omega_j c_{j,t}^{\frac{-1}{\varepsilon}}}{\omega_0 c_{0,t}^{\frac{-1}{\varepsilon}}} . \quad (\text{C.29})$$

Rearranging Equation (C.29) to solve for $\frac{c_{j,t}}{c_{0,t}}$ and multiplying both sides by $\frac{p_{j,t}}{p_{0,t}}$ produces

$$\frac{c_{j,t} p_{j,t}}{c_{0,t} p_{0,t}} = \left(\frac{w_j}{w_0} \right)^\varepsilon \left(\frac{p_{j,t}}{p_{0,t}} \right)^{1-\varepsilon} = z_{j,t} . \quad (\text{C.30})$$

Substituting Equation (C.26) into Equation (C.30) produces Equation (3.18).

Substituting Equation (C.30) into Equation (C.28) together with the definition in Equation (3.19) gives

$$c_t = c_{0,t} Z_t . \quad (\text{C.31})$$

Rearranging Equation (C.31) to solve for $c_{0,t}$ and putting it into Equation (C.30) yields

$$\frac{p_{j,t} c_{j,t}}{p_{0,t}} = \frac{c_t}{Z_t} z_{j,t} . \quad (\text{C.32})$$

Substituting in Equation (C.26) and Equation (3.6) into Equation (C.32) and utilizing Equation (C.21) gives the following:

$$\left(\frac{s_{0,t}}{n_{0,t}} \right)^\theta n_{j,t} k_t^\theta h_t^{1-\theta} \hat{a}_{0,t} a_{0,t}^{1-\theta} = \frac{c_t z_j}{Z_t} . \quad (\text{C.33})$$

Rearranging Equation (C.33) to solve for $n_{j,t}$, and using the definition of aggregate output from Equation (3.14) leads to Equation (3.17).

Moreover, since the shares sum to 1 and using Equation (3.17), we have

$$1 = n_{0,t} + \sum_{j=1}^{m-1} n_j = n_{0,t} + \sum_{j=1}^{m-1} \frac{c_j Z}{y Z} = n_{0,t} + \frac{c}{y} \frac{Z - 1}{Z} . \quad (\text{C.34})$$

Rearranging Equation (C.34) leads to Equation (3.16).

Similarly, since capital shares sum to 1, we can write

$$1 = s_{0,t} + \sum_{j=1}^{m-1} \frac{s_{0,t}}{s_{j,t}} \frac{n_{j,t}}{n_{0,t}} s_{j,t} = s_{0,t} + \frac{s_{0,t}}{n_{0,t}} \sum_{j=1}^{m-1} n_{j,t} = s_{0,t} + \frac{s_{0,t}}{n_{0,t}} \sum_{j=1}^{m-1} \frac{c_t}{y_t} \frac{z_{j,t}}{Z_t} = s_{0,t} + \frac{c_t}{y_t} \frac{s_{0,t}}{n_{0,t}} \frac{Z_t - 1}{Z_t}.$$

Plugging in for $n_{0,t}$ from Equation (3.16) and solving for $s_{0,t}$ we find $s_{0,t} = n_{0,t}$. Moreover, from this and Equation (C.21), we arrive at

$$s_{j,t} = n_{j,t}, \forall j. \quad (\text{C.35})$$

C.3 Derivation of system of equations with adjustment cost

With adjustment costs, the maximization problem is

$$\begin{aligned} L = & \max_{\Omega_t, k_{t+1}} E_t \sum_{t=0}^{\infty} \beta^t \left(\ln \phi_t - \frac{\psi h_t^{1+\frac{1}{\eta}}}{1+\frac{1}{\eta}} \right) \\ & + \lambda_{c,j,t} \left(\hat{a}_{j,t} a_{j,t}^{1-\theta} s_{j,t}^{\theta} n_{j,t}^{1-\theta} q_{n,j,t}^{1-\theta} h_t^{1-\theta} k_t^{\theta} - c_{j,t} \right) \quad (\forall j > 0) \\ & + \lambda_{c,0,t} \left(\hat{a}_{0,t} a_{0,t}^{1-\theta} s_{0,t}^{\theta} n_{0,t}^{1-\theta} q_{n,0,t}^{1-\theta} h_t^{1-\theta} k_t^{\theta} - i_t - c_{0,t} \right) \\ & + \lambda_{n,t} \left(1 - \sum_{j=0}^{m-1} n_{j,t} \right) \\ & + \lambda_{s,t} \left(1 - \sum_{j=0}^{m-1} s_{j,t} \right) \\ & + \lambda_{k,t} \left(k_{t+1} - \left(1 - \delta - \frac{\psi k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 \right) k_t - i_t \right) \end{aligned}$$

where $\Omega_t \equiv \{c_{i,t}, n_{i,t}, s_{i,t}, h_t\} \quad i \in \{0, 1, \dots, m-1\}$.

The first order conditions are

$$c_{j,t} : \quad \lambda_{c,j,t} = \beta^t \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_j c_{j,t}^{-\frac{1}{\varepsilon}} \quad (\forall j) \quad (\text{C.36})$$

$$n_{j,t} : \quad \lambda_{c,j,t} (f_{n,j,t} + f_{q,t} q_{n,j,t}^{n_t}) + E_t (\lambda_{c,j,t+1} f_{q,t+1} q_{n,j,t+1}^{n_t}) = \lambda_{n,t} \quad (\text{C.37})$$

$$s_{j,t} : \quad \lambda_{c,j,t} f_{s,j,t} = \lambda_{s,t} \quad (\text{C.38})$$

$$i_t : \quad \lambda_{c,0,t} = \lambda_{k,t} \left(\psi_k \left(\frac{i_t}{k_t} - \delta \right) - 1 \right) \quad (\text{C.39})$$

$$h_t : \quad \beta^t \psi h_t^{\frac{1}{\eta}} = \sum_{n=0}^{n-1} \lambda_{c,j,t} f_{h,j,t} \quad (\text{C.40})$$

$$k_{t+1} : \quad \lambda_{k,t} = E_t \left[\lambda_{k,t+1} \left(1 - \delta - \frac{\psi_k}{2} \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right)^2 + \psi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \frac{i_{t+1}}{k_{t+1}} \right) - \sum_{n=0}^{n-1} \lambda_{c,j,t+1} f_{k,j,t+1} \right] \quad (\text{C.41})$$

where $f_{n,j,t}$, $f_{s,j,t}$, $f_{h,j,t}$, $f_{k,j,t}$, and $f_{q,t}$ are the marginal productivities with respect to $n_{j,t}$, $s_{j,t}$, k_t , and q_t respectively, while $q_{n,j,t}^{n_t}$ and $q_{n,j,t+1}^{n_t}$ are the derivatives of the adjustment cost function with respect to $n_{j,t}$. These are defined below

$$\begin{aligned} f_{s,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} \theta \left(\frac{s_{j,t}}{n_{j,t}} \right)^{\theta-1} q_{n,j,t}^{1-\theta} h_t^{1-\theta} k_t^\theta \\ f_{n,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta q_{n,j,t}^{1-\theta} h_t^{1-\theta} k_t^\theta \\ f_{k,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} \theta \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta n_{j,t} q_{n,j,t}^{1-\theta} h_t^{1-\theta} k_t^{\theta-1} \\ f_{h,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta n_{j,t} q_{n,j,t}^{1-\theta} h_t^{-\theta} k_t^\theta \\ f_{q,j,t} &\equiv \hat{a}_{j,t} a_{j,t}^{1-\theta} (1-\theta) \left(\frac{s_{j,t}}{n_{j,t}} \right)^\theta n_{j,t} q_{n,j,t}^{-\theta} h_t^{1-\theta} k_t^\theta \\ q_{n,j,t}^{n_t} &= -\psi_n (n_{j,t} - n_{j,t-1}) \\ q_{n,j,t+1}^{n_t} &= \psi_n (n_{j,t+1} - n_{j,t}) . \end{aligned}$$

Using Equation (C.16) and the marginal productivities $f_{h,j,t}$ and $f_{s,j,t}$ to clean Equa-

tion(C.40) gives

$$\psi h_t^{\frac{1}{\eta}+\theta} = \frac{1}{c_t} (1-\theta) \hat{a}_{0,t} \hat{a}_{0,t}^{1-\theta} \left(\frac{s_{0,t}}{n_{0,t}} \right)^{\theta-1} q_{n,0,t}^{1-\theta} k_t^\theta. \quad (\text{C.42})$$

Using Equation (C.16) and Equation (C.38), the last term of the Euler equation in Equation (C.41) can be written as

$$\sum_{n=0}^{n-1} \lambda_{c,j,t+1} f_{k,j,t+1} = \frac{\beta^{t+1}}{c_{t+1}} \hat{a}_{0,t+1} a_{0,t+1}^{1-\theta} \theta \left(\frac{s_{0,t+1}}{n_{0,t+1}} \right)^{\theta-1} q_{n,0,t+1}^{1-\theta} h_{t+1}^{1-\theta} k_{t+1}^{\theta-1}. \quad (\text{C.43})$$

Using Equation (C.43) and Equation (C.39), the Euler equation in Equation (C.41) can be written as

$$\begin{aligned} 1 = E_t & \left(\frac{\beta c_t}{c_{t+1}} \left[\frac{1 - \left(\psi_k \left(\frac{i_t}{k_t} - \delta \right) \right)}{1 - \left(\psi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \right)} \left(1 - \delta - \frac{\psi_k}{2} \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right)^2 + \psi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \frac{i_{t+1}}{k_{t+1}} \right. \right. \right. \\ & \left. \left. \left. + \left(1 - \psi_k \left(\frac{i_t}{k_t} - \delta \right) \right) \hat{a}_{0,t+1} a_{0,t+1}^{1-\theta} \theta \left(\frac{s_{0,t+1}}{n_{0,t+1}} \right)^{\theta-1} q_{n,0,t+1}^{1-\theta} h_{t+1}^{1-\theta} k_{t+1}^{\theta-1} \right] \right). \end{aligned} \quad (\text{C.44})$$

Combining Equation (C.36) and Equation (C.37) gives

$$\begin{aligned} \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_0 c_{0,t}^{\frac{-1}{\varepsilon}} (f_{n,0,t} + f_{q,t} q_{n,0,t}^{n_t}) + E_t \left(\beta \phi_{t+1}^{\frac{1-\varepsilon}{\varepsilon}} \omega_0 c_{0,t+1}^{\frac{-1}{\varepsilon}} f_{q,t+1} q_{n,0,t+1}^{n_t} \right) = \\ \phi_t^{\frac{1-\varepsilon}{\varepsilon}} \omega_j c_{j,t}^{\frac{-1}{\varepsilon}} (f_{n,j,t} + f_{q,t} q_{n,j,t}^{n_t}) + E_t \left(\beta \phi_{t+1}^{\frac{1-\varepsilon}{\varepsilon}} \omega_j c_{j,t+1}^{\frac{-1}{\varepsilon}} f_{q,t+1} q_{n,j,t+1}^{n_t} \right). \end{aligned} \quad (\text{C.45})$$

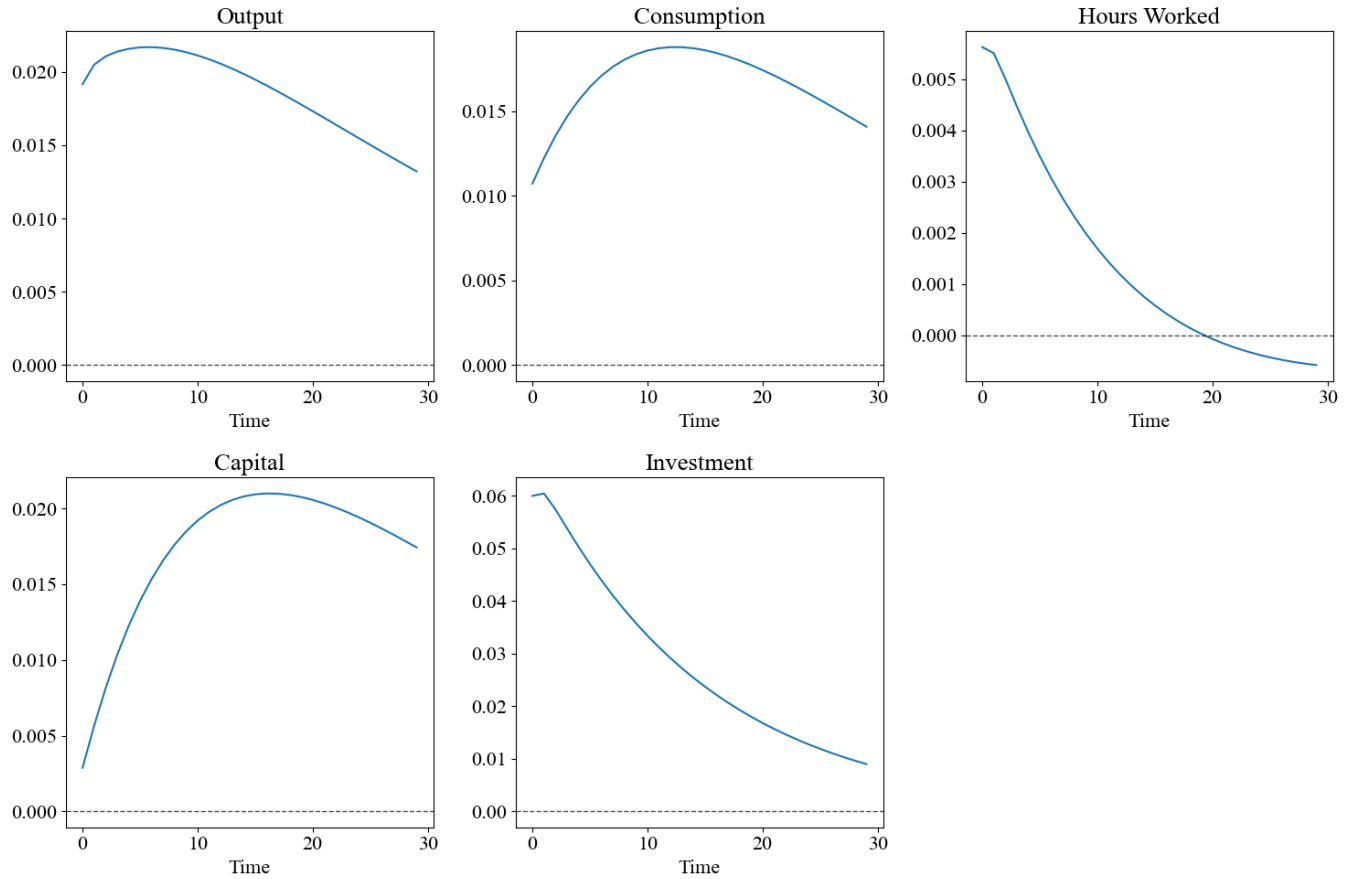
Similarly, combining Equation (C.36) and Equation (C.38) gives

$$\omega_0 c_{0,t}^{\frac{-1}{\varepsilon}} f_{s,0,t} = \omega_j c_{j,t}^{\frac{-1}{\varepsilon}} f_{s,j,t}. \quad (\text{C.46})$$

Equations (C.43), (C.44), (C.45), and (C.46) form the system of equations needed to solve the model with adjustment costs.

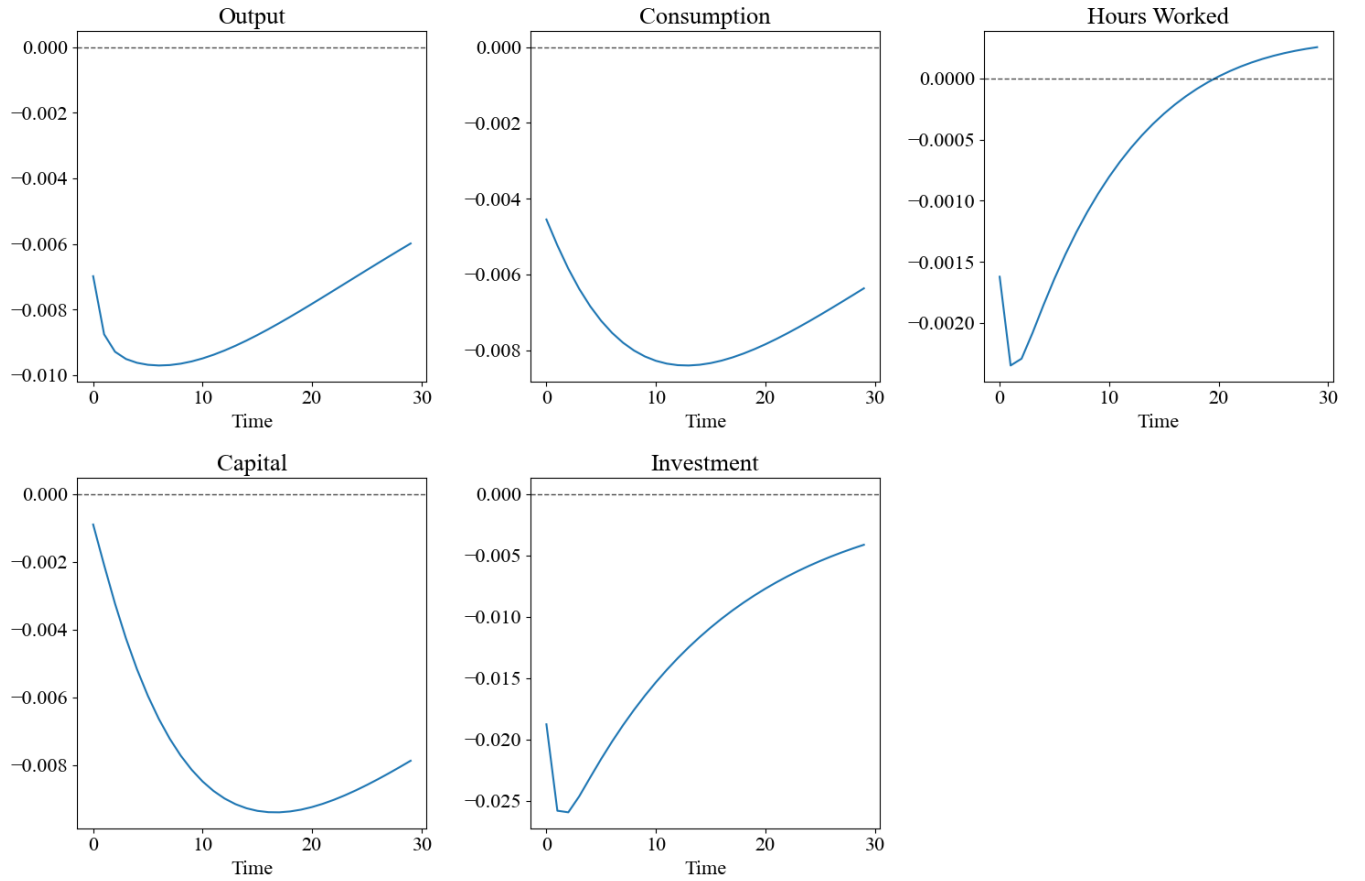
C.4 Impulse response to sector-specific TFP shocks with high substitutability and varying sector TFP levels

Figure C.1: Aggregate economy response to a TFP shock to agriculture (Good 1) ($\psi_n > 0$, $\varepsilon = 1.5$, $a_{1,t} > a_{0,t} = a_{2,t}$)



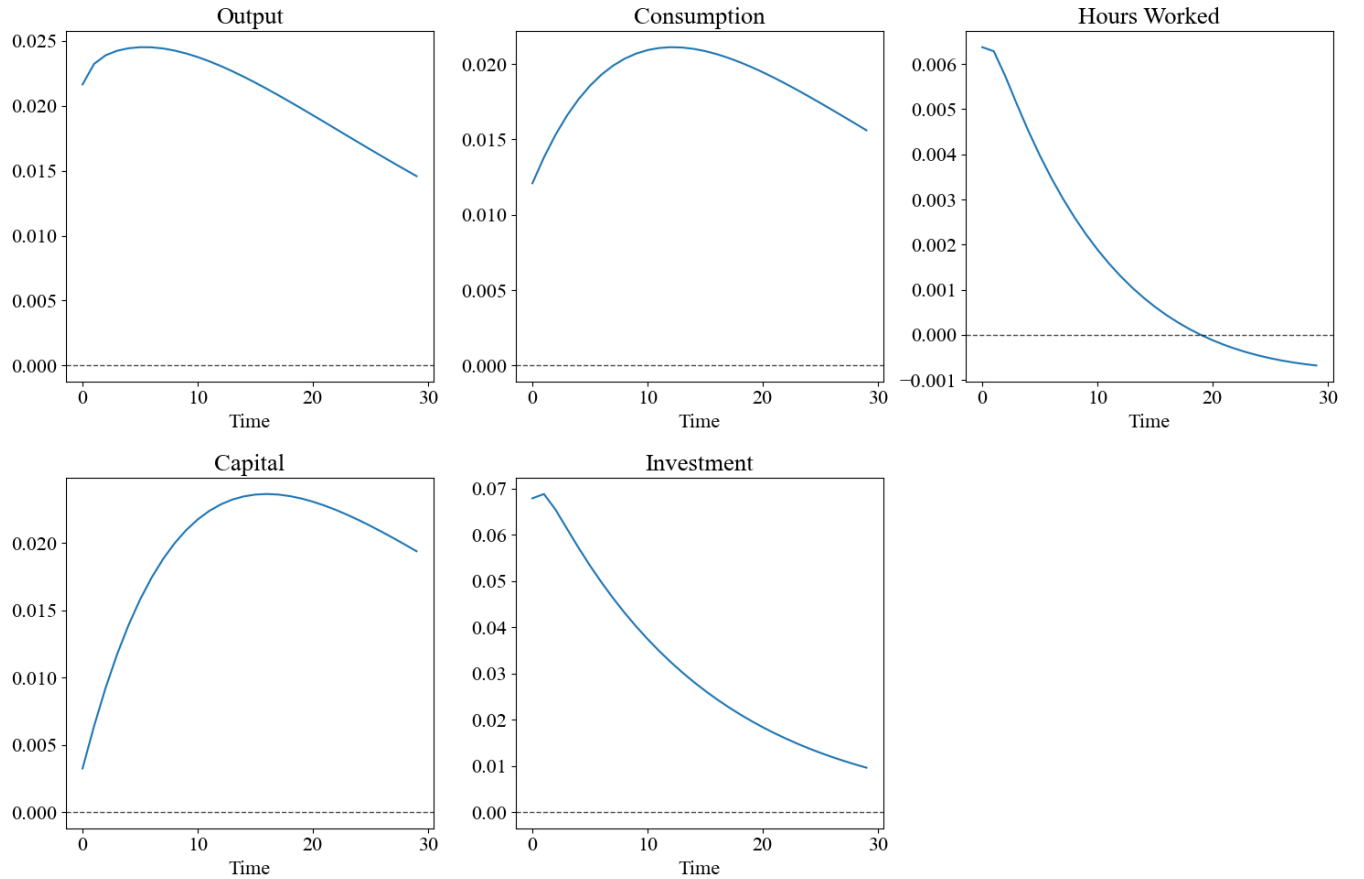
Note: Figure C.1 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the agricultural sector, in the model with adjustment costs, high substitutability, and a more productive agricultural sector.

Figure C.2: Aggregate economy response to a TFP shock to services (Good 2) ($\psi_n > 0$, $\varepsilon = 1.5$, $a_{1,t} > a_{0,t} = a_{2,t}$)



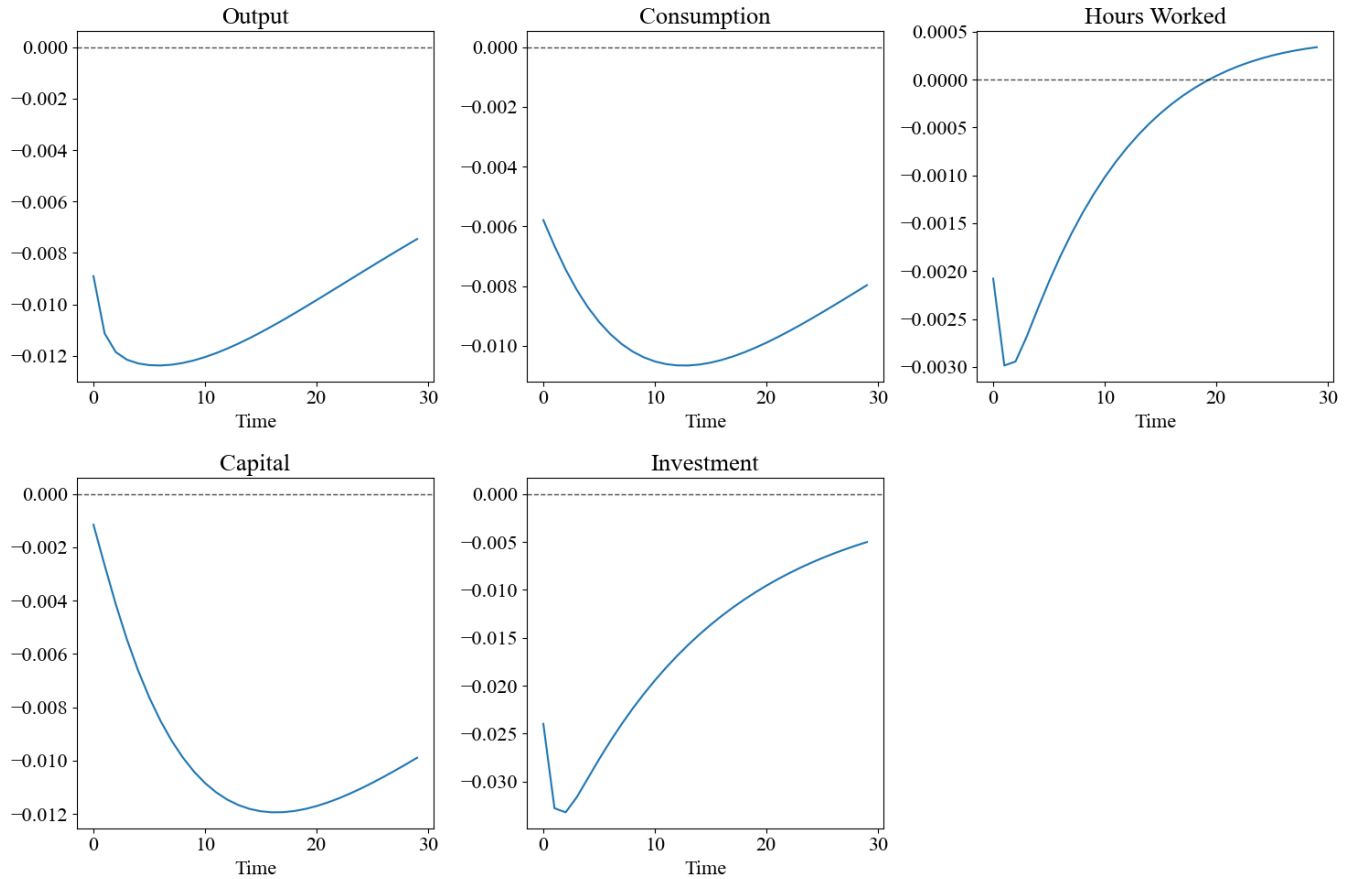
Note: Figure C.2 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the service sector, in the model with adjustment costs, high substitutability, and a more productive agricultural sector.

Figure C.3: Aggregate economy response to a TFP shock to agriculture (Good 1) ($\psi_n > 0$, $\varepsilon = 1.5$, $a_{1,t} > a_{0,t} > a_{2,t}$)



Note: Figure C.3 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the agricultural sector, in the model with adjustment costs, high substitutability, and a more productive agricultural sector, and a less productive service sector.

Figure C.4: Aggregate economy response to a TFP shock to services (Good 2) ($\psi_n > 0$, $\varepsilon = 1.5$, $a_{1,t} > a_{0,t} > a_{2,t}$)



Note: Figure C.4 shows the impulse responses of the aggregate variables to a positive total factor productivity (TFP) shock in the service sector, in the model with adjustment costs, high substitutability, and a more productive agricultural sector, and a less productive service sector.