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India's Development Aspirations: A Macroeconomic Perspective

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Keywords: India, macro-development, 2047 GDP target

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July 3, 2026

Abstract

The paper reviews India's macro-development experience since 1980 and conducts a growth decomposition exercise. Our analysis reveals that the post-liberalization growth pick-up in India was mostly due to capital accumulation. Total factor productivity (TFP) growth remained tepid throughout and actually becoming negative post-2016. We show that at comparable levels of economic development countries like China and Korea grew much faster which was mostly sparked by rapid TFP growth. To understand India's growth challenge better we formalize a three-sector model with factor market and output market distortions. Using counterfactual exercises on the calibrated model, we find that labor market wedges significantly reduced aggregate output in India by distorting production away from Industry and Services. The measured output loss due to labor market wedges is over 30 percent. We also conduct projections for India in 2047. Unfortunately, even under the most optimistic TFP growth assumptions, the projected GDP of India falls well short of the $30tn target. Our results underscore the importance of ushering in labor market reforms and easing business conditions urgently.

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1 Introduction

India completed 75 years as an independent republic in 2022. Milestones such as these are often moments of self-examination: how well has India done economically? Were there areas that they should have done better? What are the headwinds that proved to be the biggest obstacles to faster growth and development? Are there specific policies that need to be prioritized in order to accelerate India's economic development? This paper addresses these questions.

We first conduct an empirical review of India's recent development history from 1980 onwards. This exercise mostly reveals familiar patterns of a growth pick-up in the 1990s, a consolidation of the growth process through the Great Financial Crisis (GFC) episode of 2008, and the more recent investment and growth slowdown. We then use the KLEMS data to conduct a growth decomposition exercise and show that the Indian growth pick-up was mostly accounted for by capital accumulation rather than productivity growth. In the post-2016 period, total factor productivity (TFP) growth actually turned negative. Growth in this recent phase would have declined even further but for India's demographic dividend which put more labor to work. Of the 5.20% annual growth in Gross Value Added (GVA) during 2016-2024, a full two percentage points were due to additions to India's labor supply.

We then conduct a comparative analysis of India's performance from 2000-2022 onward with Brazil, China and Korea by examining their GDP and TFP growth for the 22 year period after the per capita incomes of these countries were at the same level as India in 2000. This normalized comparison shows that India has grown way more slowly and its TFP growth too has been an order of magnitude lower than China and Korea at a comparable stage of their economic development. Even Brazil, whose per capita income growth during a similar stage of development was lower, experienced faster TFP growth than what India has managed from 2000-2022.

In order to conduct a deeper analysis of India's macroeconomic performance, we formalize a dynamic, three-sector model with distortions in factor markets and goods markets. We measure the distortions (wedges in our terminology) from the data and the model's optimality conditions. The calibrated model matches the Indian aggregate and sectoral output and factor usage data for 1980-2022. We then use the model to conduct a sequence of counterfactual exercises.

The first set of counterfactuals involve removing the factor market wedges and recomputing the model solution. We find that the factor market wedge that has the biggest impact on aggregate and sectoral outcomes is the labor market wedge. Removing the labor market wedge raises aggregate output by around 30 percent. Clearly, this friction is quantitatively significant. In addition, we show that removing the labor market wedge generates a significant increase in India's TFP due to a pure composition effect as resources get reallocated towards higher productivity sectors.

Our second set of counterfactuals use the model to project India's GDP to 2047 by freezing all the factor and output market wedges at their 2022-23 levels and assuming different scenarios for the annual sectoral TFP growth between 2023 and 2047. Here our findings are sobering. Even under the most optimistic TFP growth projections, India's GDP falls well short of the oft-stated national target of India becoming a $30tn economy by 2047. Indeed, the difficulty of that task is best illustrated by the fact that TFP needs to grow at over 6% annually for the next 20 years for India to achieve this target. No country in modern economic history has come close to achieving such stratospheric TFP growth.

A more optimistic result emerges from another counterfactual exercise in which we combine the removal of all labor market wedges with the optimistic projection of sectoral TFP growth between 2023 and 2047 being the average of the ten highest sectoral TFP growth rates observed since 1980. This exercise delivers a $27tn economy by 2047, the closest to our target that any of the counterfactuals deliver.

Our assessment of the results is that the two major challenges facing the Indian economy are tepid productivity growth and labor market frictions. There are other issues naturally, but these two appear to be quantitatively the most consequential. Policy initiatives that address factor market distortions can potentially address both of these simultaneously. We illustrate these through the lens of our model with some quantitative and stylized examples.

Our paper is related to two distinct strands of work. There is, of course, a long list of papers that have analyzed India's development experience over the years. Relevant work in this area, amongst others, are Kotwal et al. [2011], Kochhar et al. [2006], Rodrik and Subramanian [2005] and Aghion et al. [2008]. Relative to this literature, our analysis provides an updated empirical analysis upto 2022-23. We also provide a quantitative structural macroeconomic perspective to the issue along with counterfactual scenarios, both of which, we believe, are new.

The paper is also related to a voluminous literature on market distortions and factor misallocations in emerging economies. Work along these lines can be found in Hsieh and Klenow [2009], Restuccia and Rogerson [2017] and Duarte and Restuccia [2010], amongst others. Our methodology using wedges to study distortions builds on the work of Chari et al. [2007].

The next section presents our empirical review of India's performance since 1980 and the growth accounting exercises. Section 3 formalizes the model and discusses its quantitative fit to the data. Section 4 uses the model to conduct dynamic projections till 2047 while Section 5 analyzes counterfactuals where we study the effects of the individual wedges. Section 6 provides a conceptual discussion about what the wedges represent and provides a quantitative mapping of the labor wedge to credit constraint. Section 7 discusses the implications of our model for explaining India's low productivity. The last section concludes.

2 The Empirical Record: 1980-2023

We begin our analysis with an empirical review of the macroeconomic record of India since 1980. Our primary data sources are the National Accounts Statistics (NAS), KLEMS India and the Penn World Tables (PWT) 11.0. We express ratios of variables relative to GDP at market prices while all real values are measured in constant 2011-12 prices.

2.1 Growth facts

Table 1 shows the aggregate and per capita growth of real Gross Value Added (GVA) during 1980-2025 broken into four phases: (I) the pre-reform 1980s (1980–91); (II) liberalization and the boom (1991–2008); (III) the recovery phase after the Great Financial Crisis (GFC) (2008–16); and (IV) the recent inflation-targeting and COVID period (2016 to latest). The table also reports decadal averages.

Table 1: Growth and per-capita growth (average annual log-growth, %)

Period	Real GVA growth	Per-capita GVA growth	Population growth
I: 1980-81 to 1990-91	5.39	3.26	2.13
II: 1991-92 to 2007-08	5.99	4.20	1.79
III: 2008-09 to 2015-16	6.18	4.68	1.50
IV: 2016-17 to 2025-26	5.64	4.63	1.02
Full: 1980-81 to 2025-26	5.81	4.15	1.65
1980s	5.41	3.28	2.13
1990s	5.66	3.69	1.97
2000s	6.13	4.57	1.56
2010s	6.18	4.82	1.36
2020s (to 2025-26)	5.54	4.57	0.96

While annual GVA growth during this entire period averaged 5.8 %, there was significant variation across the phases and decades. The 1980s witnessed the lowest aggregate growth, the period 2008-16 saw the fastest aggregate growth during the sample period. The other takeaway from Table 1 is that per capita GVA received a major boost from declining population growth which declined from 2.13% in the 1980s to an estimated rate if less than 1% during the 2020s.

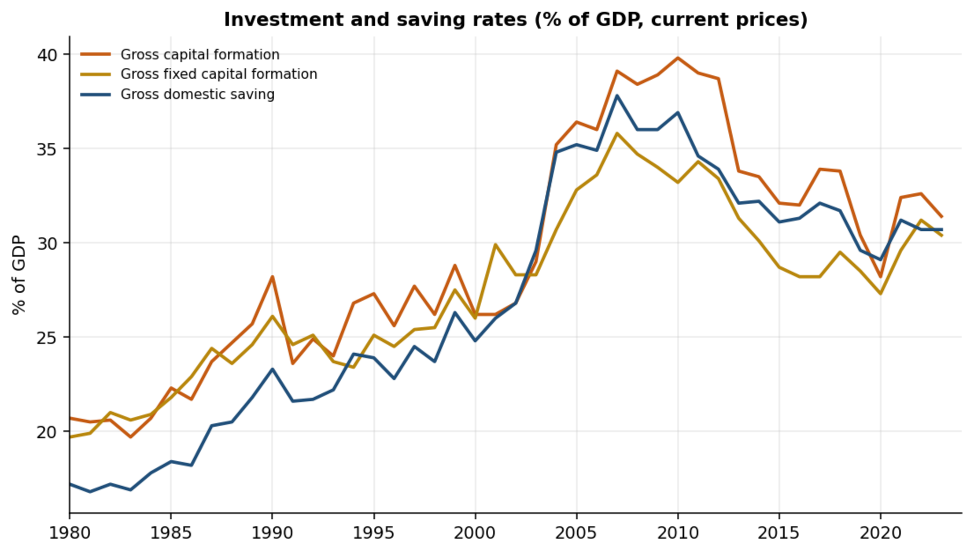
To get a perspective on the evolution of the demand side of the Indian economy during this period, Table 2 shows the breakdown of GDP into various expenditure components as well as the evolution of saving and investment.

Table 2: Demand composition and investment, phase averages (% of GDP, net ICOR (lagged))

Phase	PFCE	Govt cons.	Invest. (GCF)	Net exports	Saving rate	Public GFCF	Net ICOR
I (1980–91)	71.5	10.9	22.6	-1.0	18.9	10.9	2.52
II (1991–2008)	62.1	10.8	28.8	-1.8	27.1	8.0	3.2
III (2008–16)	56.2	10.6	36.8	-4.0	34.1	7.7	5.55
IV (2016–latest)	56.7	9.8	31.8	-2.2	30.8	6.9	5.49

Two features of the Table are noteworthy: (a) the consumption share of GDP declined sharply in India during this period, which is standard in emerging economies; (b) the net Incremental Capital-Output Ratio (ICOR) rose sharply after 2008, indicating a decline in investment efficiency.

Figure 1: Expenditure composition of GDP (current prices).



2.2 Investment dynamics

To dig deeper into the non-monotonic investment and saving rate indicated in Table 2, Figure 1 shows the investment and saving rates for the entire 1980-2025 period. Clearly, both investment and saving rates rose to peaks of around 38-40% of GDP around 2007-08 but then have mostly declined down towards 30-31%.

The investment slowdown in the Indian economy after 2010 is a puzzling phenomenon in an economy that has been growing relatively fast over the past three decades. A better understanding of this requires a sense of who invests in India and whose behavior has changed since 2010. Table 3 use the NAS institutional accounts to report the breakdown of Gross Fixed Capital Formation

(GFCF) in India by sector for selected years from 2007-08 onwards.

Table 3: Gross fixed capital formation by broad sector (% of GDP), selected years.

	2007–08	2011–12	2015–16	2023–24
Public sector	8.1	7.3	7.4	7.7
Private corporate	15.4	11.2	11.9	10.1
Households (+NPISH)	12.3	15.7	9.4	12.7
Total GFCF	35.8	34.3	28.7	30.4

The main insight from the table is that the investment slowdown in India since 2010 has been almost entirely due to a 5 percentage point reduction in private corporate investment since 2007-08, which is the entire decline in the overall GFCF rate. Public investment has actually been fairly constant over this period. The question then becomes "why did private corporates reduce their domestic investment?"

2.3 Structural transformation

Alongside these aggregate dynamics, the Indian economy has also been undergoing a sharp structural transformation during this period [on the standard patterns of sectoral reallocation, see Herrendorf et al., 2014]. Agriculture's share of value-added output fell from about 36% in 1980 to under 18%. The gap was filled by *services* (rising from 44% to above 60%) rather than by industry, whose share has remained flat near 20%; manufacturing in particular never exceeded its earlier share and has drifted down toward 14%.[1] The sectoral employment shares behaved similarly except that that agriculture's share fell more slowly than its output share. Figures 2 and 3 show these structural transformation trends.

A summary of these trends is that India's structural transformation process has been unfolding as one would expect in any developing economy except that it's sectoral labor adjustment, especially the movement of labor out of agriculture has been rather tepid. This potentially reflects frictions in the labor market in the other two sectors, an issue that we will focus on later. India's transformation is also atypical in its composition: the services-heavy, skill-intensive path documented by Kochhar et al. [2006] and analyzed structurally by Verma [2012] and Duarte and Restuccia [2010].

[1] Manufacturing is classified as Industry minus Mining/Quarrying, Construction and Electricity, Gas and Water Supply.

Figure 2: Sectoral composition of GVA (NAS)

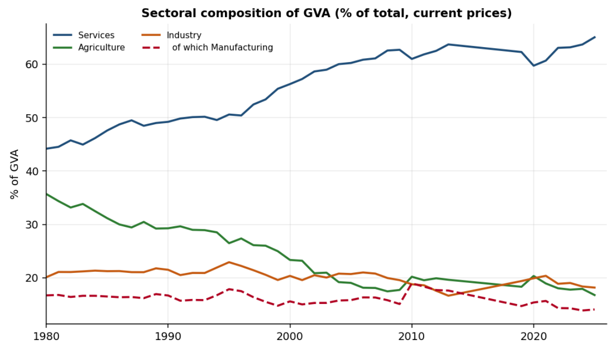
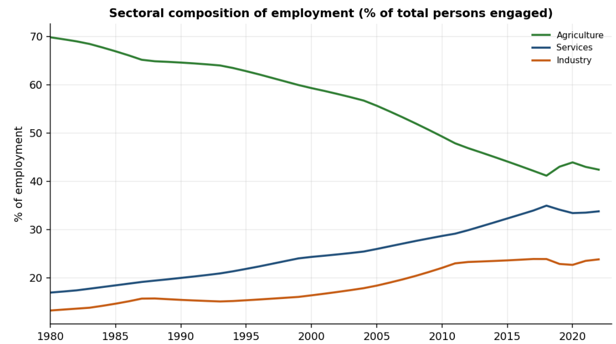


Figure 3: Sectoral employment shares (KLEMS)



2.4 Growth accounting

What have been the key forces driving economic growth in India? We examine this by subjecting the Indian output data to a standard growth accounting exercise [in the tradition of Bosworth and Collins, 2008, for the India-China comparison]. Our main exercise uses the KLEMS dataset, whose methodology and India-specific implementation are documented in Goldar et al. [2017]. We decompose growth into the contributions of physical capital, human capital, labour and TFP. With quality-adjusted inputs the aggregate identity is

$$\Delta \ln V = \bar{s}_K \big(\Delta \ln K + \Delta \ln Q_K\big) + \bar{s}_L \big(\Delta \ln L + \Delta \ln Q_L\big) + \Delta \ln A,$$

where K is the capital stock, Q_K capital composition, L persons employed, Q_L labour quality, and $\bar{s}$ are two-year-average income shares.[2] Table 4 reports the growth decomposition. The key point to note from the Table is that out of the 5.8% annual growth in value added during 1980-2022, total factor productivity (TFP) contributed just 0.55 percentage points, which is just 9.4% of the overall growth. The majority of value added growth was due to composition-adjusted physical capital growth which contributed 3.5 percentage points to value added growth, or over 60%.

[2]KLEMS calculates Q_K by using the user cost of capital for each capital asset which then becomes the weight attached the value of the physical capital asset in question when calculating the total physical capital stock. Similarly, Q_L is the human capital quality adjustment factor that is computed using factors such as gender, age and education attainment levels of the workforce.

Table 4: Growth accounting, aggregate: avg. annual contributions to VA growth (pp).

Period	VA growth	Physical capital	Human capital	Labour	TFP	TFP share
I: 1980-81 to 1990-91 (pre-reform)	5.69	2.61	0.35	1.66	1.07	18.8%
II: 1991-92 to 2007-08 (liberalization & boom)	6.09	3.72	0.28	1.40	0.68	11.2%
III: 2008-09 to 2015-16 (post-GFC)	6.24	4.59	0.24	0.96	0.45	7.1%
IV: 2016-17 to 2023-24 (recent)	5.20	3.26	0.19	2.00	-0.24	-4.6%
Full: 1980-81 to 2023-24	5.84	3.53	0.27	1.50	0.55	9.4%
Decadal:						
1980s	5.67	2.54	0.35	1.65	1.13	19.8%
1990s	5.69	3.05	0.27	1.42	0.96	16.8%
2000s	6.29	4.39	0.30	1.39	0.20	3.2%
2010s	6.20	4.16	0.20	1.21	0.62	10.0%
2020s (to 2023-24)	4.50	2.81	0.19	2.28	-0.78	-17.3%

Two other features of the growth accounting results are noteworthy. First, the pick-up in growth after the 1991 reforms was mostly due to faster capital accumulation rather than TFP growth — a reading that qualifies the productivity-transition narrative of Rodrik and Subramanian [2005] and complements the reforms surveys of Kotwal et al. [2011]. Second, the recent period post-2016 has seen a sharp reduction of 1.04 percentage points in annual growth relative to the 2008-09 to 2015-16 period. The decrease is on account of a 1.03 percentage point fall in the annual contribution of physical capital growth and a 0.69 percentage point decrease in the annual contribution of TFP growth. Indeed, the only feature that prevented the growth slowdown post-2016 from being much larger was a 1.04 percentage point increase in labor growth. This is the demographic transition helping the growth process in India by adding to productive workers.

The growth contribution of this demographic transition can be seen more starkly through a decomposition exercise of per capita value added. The same growth accounting in *per-capita* terms adds a labour-utilisation term, $\Delta \ln(L/N)$ (workers per head): $\Delta \ln(V/N) = \Delta \ln(V/L) + \Delta \ln(L/N)$. Table 5 shows the decomposition.

The table shows that per capita value added grew 4.2% per year over 1980-2024, of which labour utilization contributed 1.2 percentage points. This is India's demographic dividend. Strikingly, this channel is doing *more* of the work recently: in the latest phase post-2016, of the 4.2 percent annual per-capita growth, 2.8 percentage points are due to rising workers per capita.

Table 5: Growth accounting, **per capita**: avg. annual contributions to per-capita VA growth (pp).

Period	VA/capita growth	Capital deepening	Human capital	TFP	Labour utilisation
I: 1980-81 to 1990-91	3.57	1.21	0.35	1.07	0.94
II: 1991-92 to 2007-08	4.32	2.33	0.28	0.68	1.02
III: 2008-09 to 2015-16	4.74	3.60	0.24	0.45	0.45
IV: 2016-17 to 2023-24	4.16	1.40	0.19	-0.24	2.81
Full: 1980-81 to 2023-24	4.18	2.12	0.27	0.55	1.24

2.5 An international comparison

The preceding results have shown that TFP growth in India has been weak for over three decades now. More worryingly, in the most recent phase since 2016 it has actually turned negative. India's growth story in fact has mostly been sustained by its demographic transition adding to the number of workers in the economy. This though is, at best, a temporary phase. In the long run, sustained growth requires productivity growth.

To put this statement and India's development challenge in some perspective, we now compare India with some other recent international success stories – China and Korea. Specifically, we us the PWT dataset to identify the year in which each country's real per-capita income was closest to India's in 2000. This happens to be **1992 for China and 1969 for Korea**. We then track the next 23 years, rebasing each country's TFP to 100 in its own start year. Figure 4 plots the resulting normalized per capita income paths for the three countries.

From the *same* starting income, China more than doubled its TFP over the next 23 years and Korea raised it by about half. India's TFP has risen only about 19% since 2000 (+0.8%) during this phase. More disturbingly, its TFP path flattens and dips at the end . The income trajectories mirror this (Figure 5): from a near-identical ∼\$2,350 starting point, Korea reached 8.0× and China 6.1× their initial per-capita income after 23 years, against India's 3.8×. A middle-income comparator sharpens the point from the other side — Brazil, starting from the same income in 1957, managed only 2.6× over its next 23 years, *below* India's pace. It is worth noting that even Brazil's TFP growth during this comparable period of development was higher than India's.

In summary, the Indian growth experience over the last 45 years has been one of a growth pick-up post liberalization in 1991. Most of the growth increase was due to faster capital accumulation and increasing labor participation due to the demographic transition. Worryingly, the contribution of TFP growth to India's growth story during 1980-2022 has been tepid. More concerning is the

Figure 4: TFP from a common starting income level

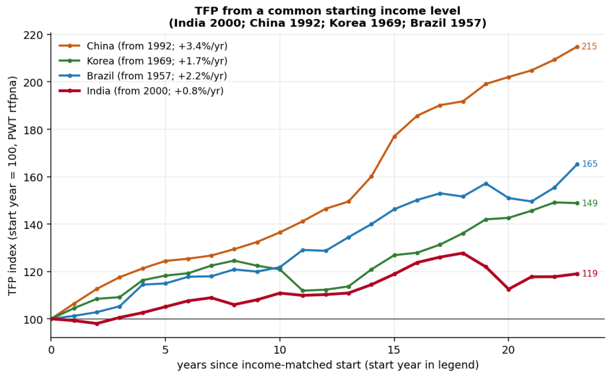
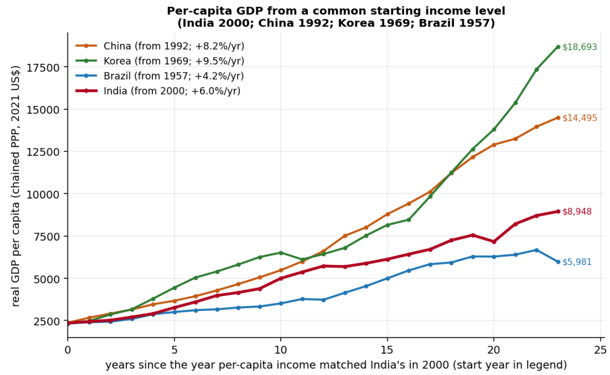


Figure 5: Per-capita GDP from the same start (adds Brazil, 1957).



fact that TFP growth has turned negative in the recent post-2016 phase.

As is well recognized, sustaining long-run growth requires productivity growth. Our growth decomposition exercise highlights that this has become an even bigger challenge for India recently. Indeed, achieving national policy targets such as a $30tn economy by 2047 would become much more feasible with even a partial closing of the TFP differential with China. Precisely for this reason, we now turn our attention to structural impediments to attaining productivity and allocative efficiency.

3 A Macroeconomic Model with Distortions

We now formalize a macroeconomic environment for the Indian economy which we shall then use to simulate different possibilities for the dynamic evolution of India over the next two decades. Our baseline approach is to formalize a three-sector model where households make saving and consumption decision while firms choose capital and labor to maximize profits.

A key feature of the model that we build is that it allows for tax wedges which potentially distort economic decisions by households and firms. In combination with the identified sectoral productivities, these wedges allow the model to reproduce the macroeconomic data for India. Our wedge-accounting approach follows Chari et al. [2007] by applying it across three intermediate sectors. Our approach complements the establishment-level misallocation lens of Hsieh and Klenow [2009] and Restuccia and Rogerson [2008] by tracing the aggregate consequences of sectoral factor-market distortions. We then use the model to conduct counterfactual exercises involving factor market reforms as well as future paths for the economy under different productivity scenarios.

Our model features three intermediate goods – agriculture, manufacturing and services – and one final good. The economy is inhabited by a representative household. The final good is used as the numeraire good throughout.

3.1 Households

The household has l units of labor time that it allocates to work across the three sectors. The household chooses its optimal consumption at each date and saves by accumulating capital. The capital is rented out to firms in exchange for rental income. The three sectors are agriculture, manufacturing and services. The goods produced by these three sectors are combined into a final good by a representative final good firm. All firms are owned by the household. The household maximizes lifetime utility

$$V = \sum_{t=0}^{\infty} \beta^t U(c_t)$$

where c denotes consumption. We will proceed by assuming that $U(c) = \log c$ for convenience. The periodic budget constraint for the representative household is

$$\tau_t c_t + k_{t+1} = \sum_{i=a,m,s} (r_{it} k_{it} + w_{it} l_{it} + \pi_{it}) + \pi_{ft} + (1-\delta) k_t$$

where r_{it} denotes the rental rate in sector i at date t, w_{it} is the corresponding wage rate, π_{it} are profits received as dividends from sector i firms and π_{ft} are dividends received from the final good firm at date t. τ is a tax wedge on consumption that potentially varies with time.

The sectoral capital and labor allocations by households at all points in time must satisfy

$$k_t = k_{at} + k_{mt} + k_{st} \quad (3.1)$$

$$l_t = l_{at} + l_{mt} + l_{st} \quad (3.2)$$

The first-order conditions for maximizing utility of the household are

$$r_{it} = r_t \text{ for } i = a, m, s \quad (3.3)$$

$$w_{it} = w_t \text{ for } i = a, m, s \quad (3.4)$$

$$\frac{c_{t+1}}{c_t} = \beta \left(r_{t+1} + 1 - \delta \right) \tau^e_{t+1} \quad (3.5)$$

The first two optimality conditions say that wages and rental rates must be equalized across sectors while the third condition is the intertemporal Euler equation for optimal saving and investment. If factor prices were different, factors would be reallocated by the household to the sectors with higher rates until these conditions were reestablished.[3] Note that $\tau^e_{t+1} \equiv \frac{\tau_t}{\tau_{t+1}}$ is the intertemporal Euler equation wedge which varies based on the time variation on the consumption tax. It captures distortions in the market for savings and consumption.

3.2 Final goods sector

The competitive final good producer's problem is to combine sectoral output taking sectoral prices as given. The final goods technology is

$$y_t = \left(\sum_{i=a,m,s} \lambda_i y_{it}^{\rho} \right)^{1/\rho} \tag{3.6}$$

where λ_i is weight of sector i in the final goods technology.[4] The final goods firms maximize profits:

$$\pi_{it} = \tau_t^F y_t - \sum p_{it} y_{it} \tau_{it} \qquad i = a, m, s$$

where τ^F is a tax wedge faced by producers in the final goods sector which changes the producer price while τ_i is a tax wedge on the intermediate good i which changes the effective cost of buying good i for the final goods firm.

The first order conditions for this problem are the inverse demand functions:

$$\tau_t^F \lambda_i \left(\frac{y_t}{y_{it}} \right)^{1-\rho} = p_{it} \tau_{it}, \qquad i = a, m, s \tag{3.7}$$

where τ_{it} is a potential wedge in the first order condition which we shall estimate from the data. $\tau_{it} = 1$ if the first order condition holds exactly in the data.

Substituting these conditions into the final goods production function gives

$$\left(\tau^F\right)^{\frac{-\rho}{1-\rho}} = \sum_{i=a,m,s} \left(\frac{\lambda_i}{(p_{it}\tau_{it})^{\rho}} \right)^{\frac{1}{1-\rho}} \tag{3.8}$$

[3] As will become apparent later, we amalgamate all distortions in the factor market into wedges from the firms side.

[4] We also considered variants of this production technology to allow for a minimum level of the agricultural in producing the final good: $y_t = [\lambda_a (y_{at} - \bar{y})^{\rho} + \lambda_m y_{mt}^{\rho} + \lambda_s y_{st}^{\rho}]^{\frac{1}{\rho}}$. This specification allows productivity growth to endogenously induce structural transformation due to the non-homothetic aggregator. However, our baseline results and takeaways were mostly unaffected by this change, hence we omit discussions about it here

If the final goods wedge were one then this condition would give the effective price index since the final good price has been normalized to one. As we shall show below, the final goods wedge τ^F allows one to match the aggregate real rental rate r in the data. Consequently, we shall infer it directly from the data when we calibrate the model.

3.3 Intermediate goods

Intermediate goods sectors are characterized by competitive firms who produce by combining capital and labor using a constant returns to scale technology. We assume that the production technology for these firms is

$$y_{it} = \Gamma_{it} k_{it}^{\alpha} l_{it}^{1-\alpha} \tag{3.9}$$

The firms maximize

$$\pi_{it} = p_{it} \Gamma_{it} k_{it}^{\alpha} l_{it}^{1-\alpha} - \tau_{it}^{k} r_{it} k_{it} - \tau_{it}^{l} w_{it} l_{it}$$

where $\tau_{it}^{j},\ j = k, l,\ i = a, m, s$ are wedges in the intermediate firms' first order conditions for capital and labor. We shall describe below how we estimate these wedges to make the first order conditions hold exactly in the data. This will allow the model to match the data closely.

The first order conditions for this problem are

$$\alpha p_{it} y_{it} = r_{it} k_{it} \tau_{it}^{k} \qquad i = a, m, s \tag{3.10}$$

$$(1-\alpha) p_{it} y_{it} = w_{it} l_{it} \tau_{it}^{l} \qquad i = a, m, s \tag{3.11}$$

Equations (3.10) and (3.11) describe 6 equations that must hold for optimality of intermediate goods firms' input choices.

3.4 Equilibrium

Any competitive equilibrium requires that all markets clear. Combining the household budget constraint with the intermediate and final goods firms' profit functions gives

$$c_t + k_{t+1} = y_t + (1-\delta) k_t \tag{3.12}$$

The equilibrium for this economy is fully described by equations 3.1, 3.2,3.33.4,3.5,3.6, 3.7, 3.8, 3.9, 3.10, 3.11 and 3.12 which describe a system of 24 equations that jointly solve for the 24 endogenous variables $c, k, y, \tau^e, y_a, y_m, y_s, k_a, k_m, k_s, l_a, l_m, l_s, p_a, p_m, p_s, r_a, r_m, r_s, r, w_a, w_m, w_s, w$.

3.5 Wedge and parameter identification

Note that the first order conditions of the final goods firm imply two sectoral relative demand relationships and three sectoral demand growth rates over time. Holding the λ's constant, these are

$$\frac{\lambda_i}{\lambda_j}\left(\frac{y_{it}}{y_{jt}}\right)^{\rho-1} = \frac{\tau_{it}}{\tau_{jt}}\frac{p_{it}}{p_{jt}}, \qquad i \neq j, \tag{3.13}$$

$$\left(\frac{y_{it}}{y_{i,t+1}}\right)^{\rho-1} = \frac{\tau_{it}}{\tau_{i,t+1}}\frac{p_{it}}{p_{i,t+1}}. \tag{3.14}$$

We index the price-wedge distortions by setting $\tau_i = 1$ in 1980. The cross-sector condition (3.13), evaluated at 1980 with $\tau_i = 1$, uncovers the implied λ_i while the within-sector condition (3.14) then traces out the wedge over time.

For the factor wedges, the first-order conditions (3.10)–(3.11) identify τ^k_{it} and τ^l_{it} directly, given the common rental r_t and wage w_t that the household conditions (3.3)–(3.4) impose. We use the aggregate rental and wage rates in the data as (r_t, w_t), and measure the wedges as

$$\tau^k_{it} = \frac{\alpha\, p_{it}\, y_{it}}{r_t\, k_{it}}, \qquad \tau^l_{it} = \frac{(1-\alpha)\, p_{it}\, y_{it}}{w_t\, l_{it}}, \tag{3.15}$$

The aggregate factor prices are taken directly from the KLEMS data as

$$r_t = \frac{Ksh_{\text{agg},t}\, Y_t}{K_t}, \qquad w_t = \frac{(1-Ksh_{\text{agg},t})\, Y_t}{L_t}, \tag{3.16}$$

where $Y_t = \sum_g p_{gt} y_{gt}$ is aggregate real value added, $K_t = \sum_g k_{gt}$ and $L_t = \sum_g l_{gt}$ are the aggregate KLEMS real capital stock and persons engaged, and $Ksh_{\text{agg},t}$ is the aggregate capital income share (the value-added-weighted average of the sectoral Ksh_{gt}). The numerator of τ^k_{it} is the sectoral marginal revenue product of capital and the denominator is what that same physical stock would earn at the common rental r_t; analogously for τ^l_{it}. We set $\alpha = 0.4$ in all sectors. Lastly, the sectoral TFP terms Γ_{it} are identified directly from the KLEMS sectoral data via (3.9).[5]

[5] The sectoral prices we recover from current- and constant-price sectoral value added in KLEMS are price indices, not price levels. Consequently the *growth rates* of p_i have independent informational content while the *levels* are subject to the base-year normalisation. The KLEMS constant price series use a 2011-12 base, so each sectoral deflator equals one in 2011-12. We work throughout with the relative price $p_g = P_g/P$ where P is the aggregate GVA deflator. The same $P = 1$ normalisation in 2011-12 therefore carries through to the relative-price series as well.

We identify the final goods wedge τ^F by using the model to exactly target the aggregate rental rate in the data. More specifically, the intermediate firm's first-order condition for capital gives

$$p_{it} = r_t \frac{\tau_{it}^k k_{it}}{\alpha y_{it}}$$

Substituting this into equation (3.8) and rearranging the result gives

$$r_t = \tau_t^F \left[\sum_{i=a,m,s} \left(\frac{\lambda_i (\alpha y_{it})^\rho}{(\tau_{it}^k k_{it} \tau_{it})^\rho} \right)^{\frac{1}{1-\rho}} \right]^{\frac{1-\rho}{\rho}} = \tau_t^F r^* \tag{3.17}$$

Since r^* is generated solely by endogenous variables in the model and the exogenously measured capital wedge and the price wedges which are measured (independently of the rental rate) from equations ((3.13)) and ((3.14)), we can estimate τ^F from equation (3.17) to exactly target the aggregate real rental rate r in the data.

Since the KLEMS dataset reports industry level data but no consumption or government sector, we have an issue in matching that data to our macro model which includes consumption. Moreover, our consumption data comes from the National Accounts Statistics (NAS) while our sectoral output, capital and investment is computed from the KLEMs data. In order for the resource constraint to hold in every period in the data counterpart of the model, we introduce an expenditure wedge in the aggregate resource constraint. Specifically, for our dynamic simulations we specify the resource constraint to be

$$c_t + k_{t+1} + g_t = y_t + (1 - \delta) k_t$$

where g_t is the expenditure wedge that balances the resource constraint. We estimate this directly from the data as a residual.

There are four parameters that need to be quantified for the calibration exercise.

- Discount factor: $\beta = 0.96$
- Capital exponent: $\alpha = 0.4$
- Elasticity parameter: $\rho = 0.5$. This implies an elasticity of substitution $\frac{1}{1-\rho} \equiv \sigma = 2$
- Depreciation rate parameter: $\delta = 0.05$.

These values are standard in the calibration literature. We have experimented with variations on these values and found the results to be quite robust to changing these values.

The above describes a model with nine sectoral wedges: $\tau_i, \tau_i^k, \tau_i^l$, and three aggregate wedges τ^e, τ^F, g. We measure $\tau_i, \tau_i^k, \tau_i^l, g$ directly from the data. We choose τ^F to match the aggregate real rental rate while τ^e is chosen every period to exactly match the consumption growth rate in the data.

We solve for the perfect foresight equilibrium path of this economy for the period 1980-81 to 2022-23 by using the time-paths of the sectoral TFPs along with the nine sectoral wedges as exogenous drivers, all measured directly from the KLEMS data, as exogenous drivers. We initialize the model with the initial sectoral capital stocks in 1980-81 as reported in KLEMS.

For measurement of the wedges and for the calibration exercise, we use the India KLEMS dataset, which provides data for 27 industries over 1980-81 to 2022-23. The dataset includes data on sectoral and aggregate value added at current prices (VA) and at constant 2011-12 prices (VA_r), and the labour and capital income shares of value added (Lsh, Ksh). The two shares sum to unity in every industry, so $Ksh_{it} = 1 - Lsh_{it}$. Each industry's raw output deflator is $P_{it} = VA_{it}/VA_{r,it}$ and its real output is $y_{it} = VA_{r,it}$.

To map the 27-industry KLEMS dataset to our three-sector environment, we define Agriculture = industry 1, Industry = industries 2–17, and Services = industries 18–27 with the industries as defined in KLEMS.

3.6 Results

Labour and capital wedges. Figures 6–7 report the sectoral wedges (3.15). To interpret the figure recall that a wedge greater than one indicates the marginal product of the factor exceeds its rental cost. The main takeaway from the figure then is that labour is paid above its marginal revenue product in Agriculture and below it in Industry and Services, with the under-payment in non-agricultural sectors diminishing over time.

Figure 6: Labour wedge by sector

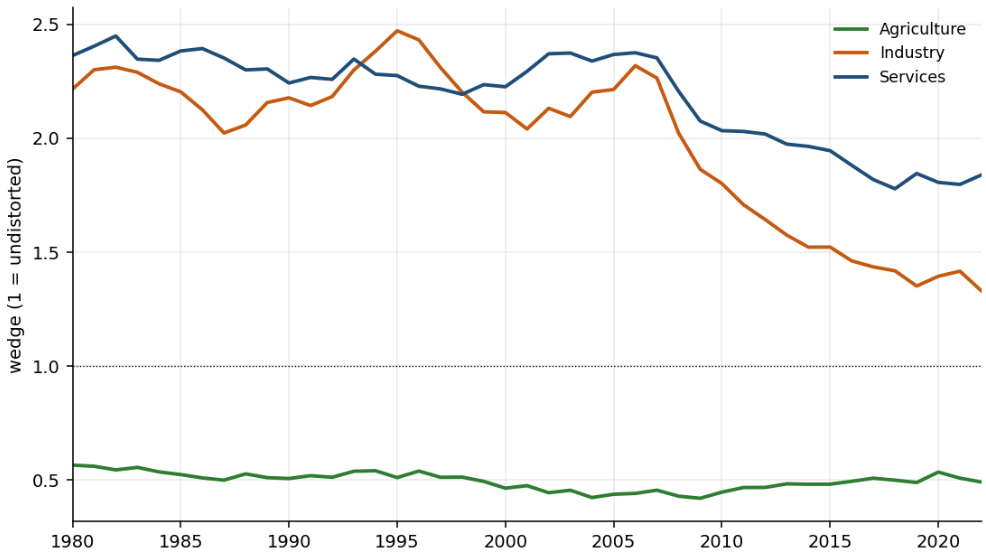
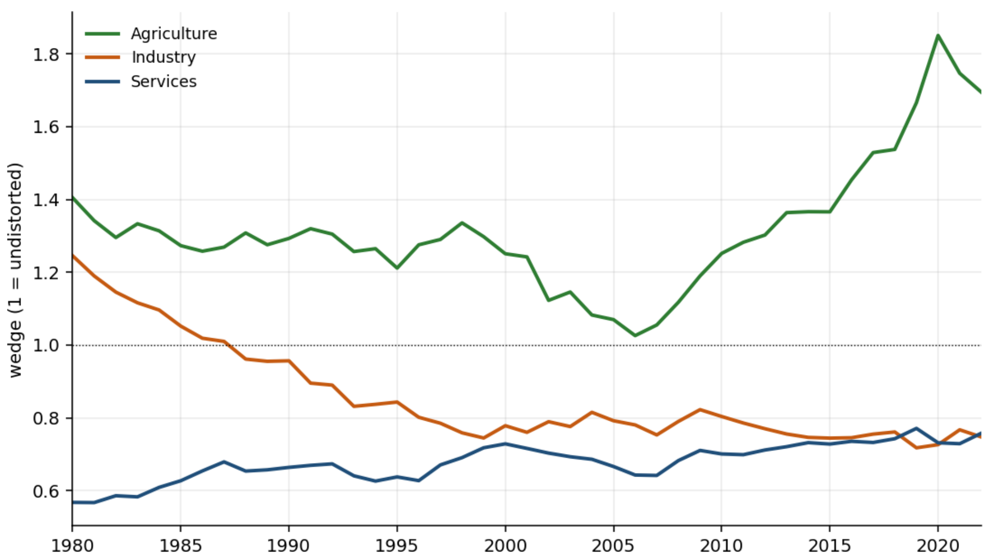


Figure 7: Capital wedge by sector



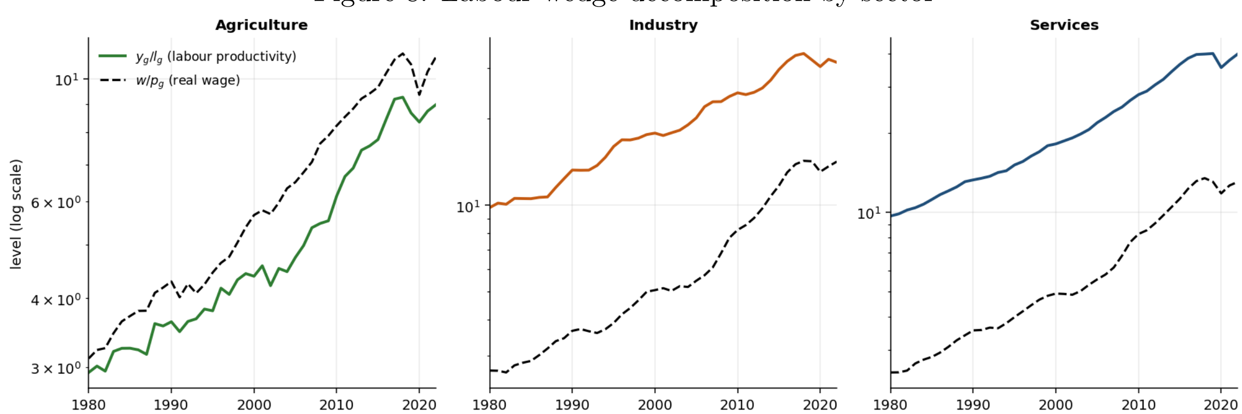
The capital wedge exhibits crucial differences relative to the labor wedges in terms of both the cross-sectional and time series patterns. First, the wedge ranking across sectors is the *reverse* of the labour wedge ranking: Agriculture has the highest capital wedge while Services has the lowest. Second, the movements in the capital wedges in Industry and Services are much smaller than the corresponding sectoral movements in the labor wedge during the sample period. The only sector that actually shows sharp changes in the sectoral capital wedge is Agriculture after 2006. By contrast, the agricultural labor wedge barely moves between 1980 and 2023.

Since the labor wedges in Industry and Services exhibit significant time series movements, one might wonder about the drivers of these movements. To examine this more closely, note that the labor wedge can be decomposed as

$$\tau_g^l \;=\; (1-\alpha)\,\frac{y_g/l_g}{w/p_g}$$

where y_g/l_g is the sectoral real average product of labour and w/p_g is the common aggregate wage. The labor wedge then is the ratio of sectoral labor productivity to the sector's own real factor price, up to the constant $(1-\alpha)$. Figure 8 plots the four components by sector. The figure shows that the long-run decline in the labour wedges in Industry and Services is driven by the real wage rising faster than sectoral labour productivity.[6]

Figure 8: Labour-wedge decomposition by sector

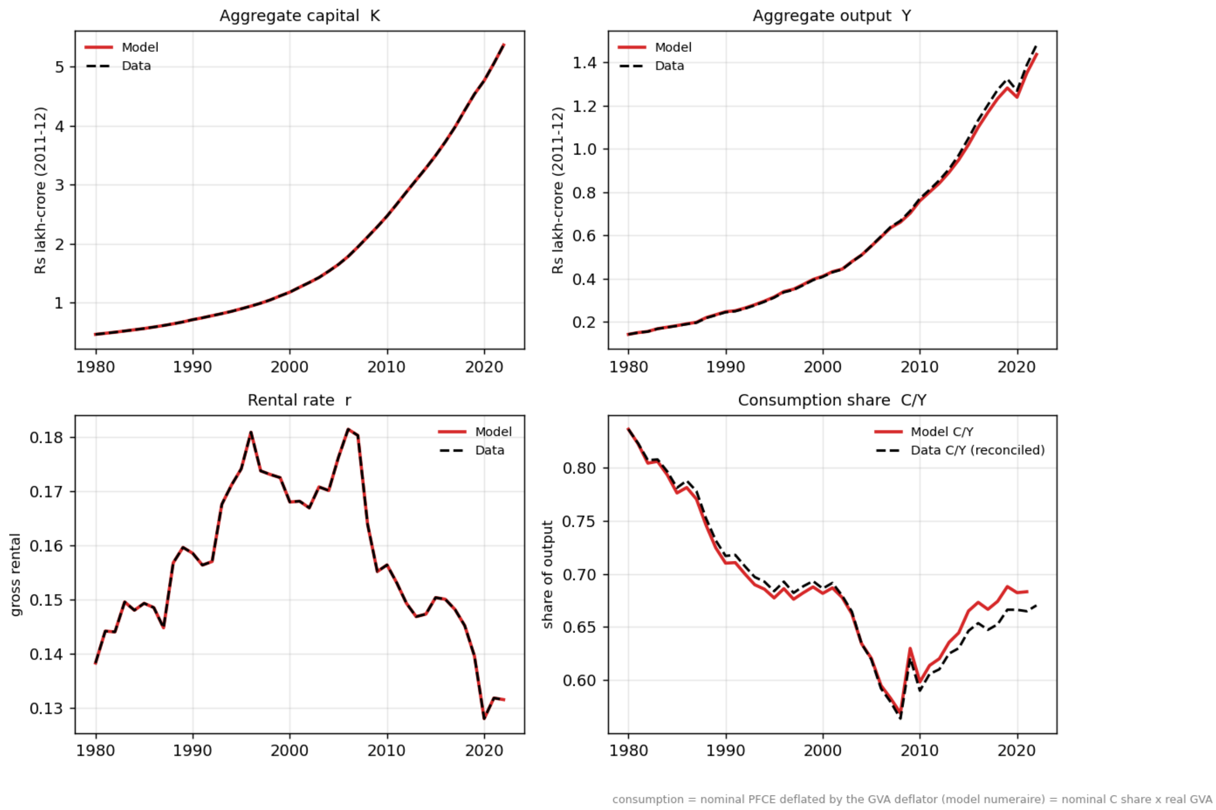


3.7 Dynamic simulation results: 1980-81 to 2022-23

How well does the model fit the data for the period 1980-2023? Figure 9 shows the data and the model counterparts of aggregate capital, aggregate output, the aggregate real rental rate and the consumption-output ratio during this period. Clearly, the model matches the aggregate behavior of the Indian economy quite well.

[6]The estimated intermediate goods price wedges (τ_{it}), the final goods wedge (τ_t^F), and the intermediate goods sectoral weights (λ_i) in the final goods technology are reported in the Appendix.

Figure 9: Dynamic-simulation: Aggregate variables fit



In our dynamic simulations we allowed the Euler equation wedge τ^e to adjust endogenously in order to match the consumption growth rate in the data. One might wonder as to how the estimated euler wedge behaved over the sample. Figure 10 shows the implied Euler wedge. The recovered series stays in $[0.93, 1.11]$ throughout the sample, i.e. the household intertemporal margin is essentially undistorted in our dynamic simulation.

Next, we examine the fit of the sectoral dynamics generated by the model to their data counterparts. Figure 11 show the evolution of the output, capital and labor shares of the three sectors in the model and the data. The figure shows that the sectoral output, capital, and labour shares track the data to machine precision and so coincide visually.

In summary, the results from the dynamic simulations of the model show that the model equilibrium reproduces the aggregate and sectoral dynamics of the Indian economy for the period 1980-2023 very well.

Figure 10: Implied Euler wedge τ^e under the baseline calibration, 1980-2022

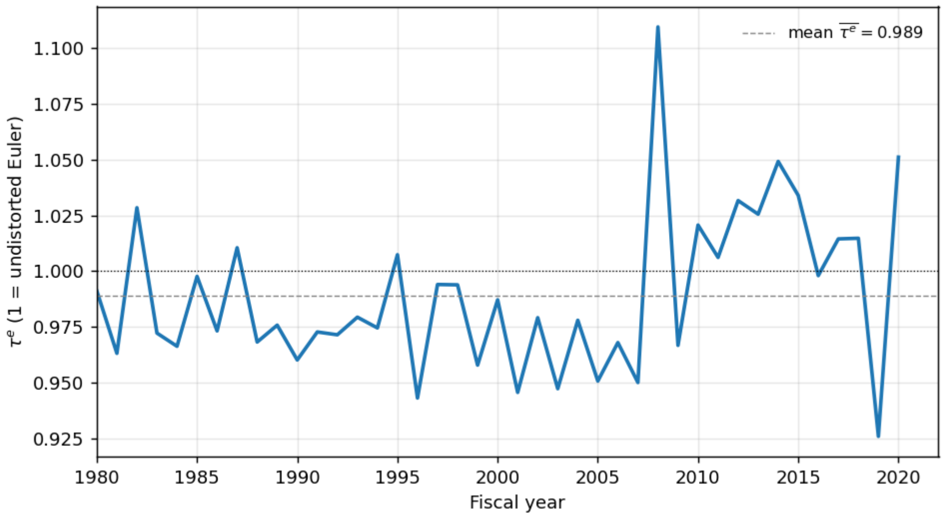
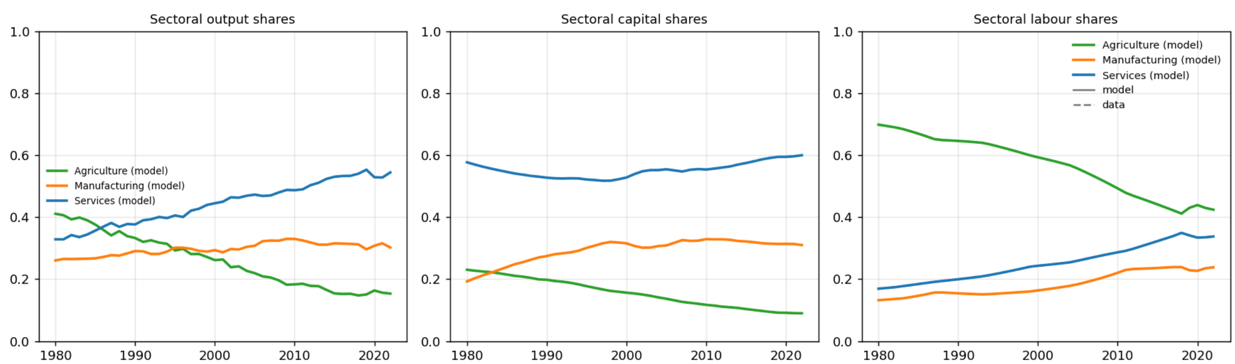


Figure 11: Sectoral composition: model and data



4 Projections for 2046–47

Having established that our three-sector wedge model reproduces the data patterns of both aggregate and sectoral variables, we now use the model to project aggregate economic outcomes till 2046-47 under a few different scenarios for TFP growth during the next twenty years.

All the projections are based on freezing the wedges $\tau^l, \tau^k, \tau_i,$ and τ^F at the 2022-23 levels. We also freeze the Euler equation consumption tax wedge τ^e at its 2016-2022 average level. Given that this average was one, the Euler equation in these projections is essentially undistorted. Lastly, we freeze the expenditure wedge g also at its 2016-2022 average. We then feed various scenarios for annual sectoral TFP growth from 2023-24 onwards and solve for the perfect foresight equilibrium path of the model subject to a terminal condition given by the steady state of the model which is achieved at some long-horizon future date.

In conducting the projections we assume that aggregate labor in the Indian economy will grow at 0.522% annually. This is based the projected 14.5% cumulative growth of the working age population over the next twenty years.[7] We assume that the unemployment rate in India will remain at the 2023-24 level of 3.2%.

We examine four different scenarios for TFP growth between 2023 and 2047:

1. **Recent sectoral TFP trends:** Under this scenario, we assume that sectoral TFP in India between 2023-24 and 2046-47 would grow at the average annual sectoral TFP growth of 2016-23. The observed sectoral TFP growth rates (as reported in KLEMS) during 2016-23 in India were 0.74% in Agriculture, -0.81% in Industry and -0.35% in Services.

2. **Top-20 growth rates**: This scenario computes the mean of each sector's twenty highest historical year-on-year growth rates over 1980–2022 and projects the economy till 2046-47 based on this average of the top-20 TFP growth rates will occur every year till 2046-47.

3. **Top-10 growth rates**: This scenario is identical to the top-20 scenario except that we compute the average of the ten highest year-on-year sectoral TFP growth rates and project the 2046-47 outcome based on this top-10 growth rate being observed every year till 2047.

4. **Requisite TFP growth for $30tn GDP in 2047:** This scenario solves for the annual TFP growth rate (common across sectors – so this is an aggregate TFP growth) that would cause the economy to achieve a GDP of $30 trillion dollars in 2046-47. This is a GDP target that has often been cited in India. The year 2047 is momentous because India will complete 100 years of independence that year.

Table 6 contrasts the four exercises side by side. The table reports the annual output growth under each scenario, the aggregate GVA level that the model projects for 2047 under each scenario. The projections are quite stark. for one, the recent trends in sectoral TFP growth were quite dire. Consequently, a continuation of that pattern for the next 24 years has a rather minuscule effect on GDP by 2047.

[7] See the 2024 revision of the United Nations Department of Economic and Social Affairs' (UNDESA) World Population Prospects.

Table 6: Projections to 2046–47

	Recent trends	Top-20	Top-10	\$30tn target
Aggregate output growth (%/yr)	0.69	6.71	8.19	9.61
Aggregate GVA, 2046–47 (\$tn, mkt)	3.62	14.58	20.29	27.78
Aggregate GDP, 2046–47 (\$tn, mkt)	3.91	15.75	21.91	30.00

Note: The assumed annual sectoral TFP growth rates under the four scenarios are: "Recent trends" $a : 0.74$, $m : -0.81$, $s : -0.35$; "Top-20" $a : 5.08$, $m : 4.05$, $s : 4.01$; "Top-10" $a : 7.30$, $m : 5.45$, $s : 4.55$; "\$30tn target" $a = m = s = 6.09$

The scale of the development challenge facing India is that even the top-10 historical TFP growth rates misses the \$30tn GDP target by \$8tn. The last column shows that to achieve the \$30tn target by 2047, the economy has to grow annually at 9.6% which can be achieved if aggregate TFP growth averages 6.1% per year for 24 years. Given that such growth rates have not been achieved in India save for periods of recovery after big output contractions, the target seems difficult to achieve.

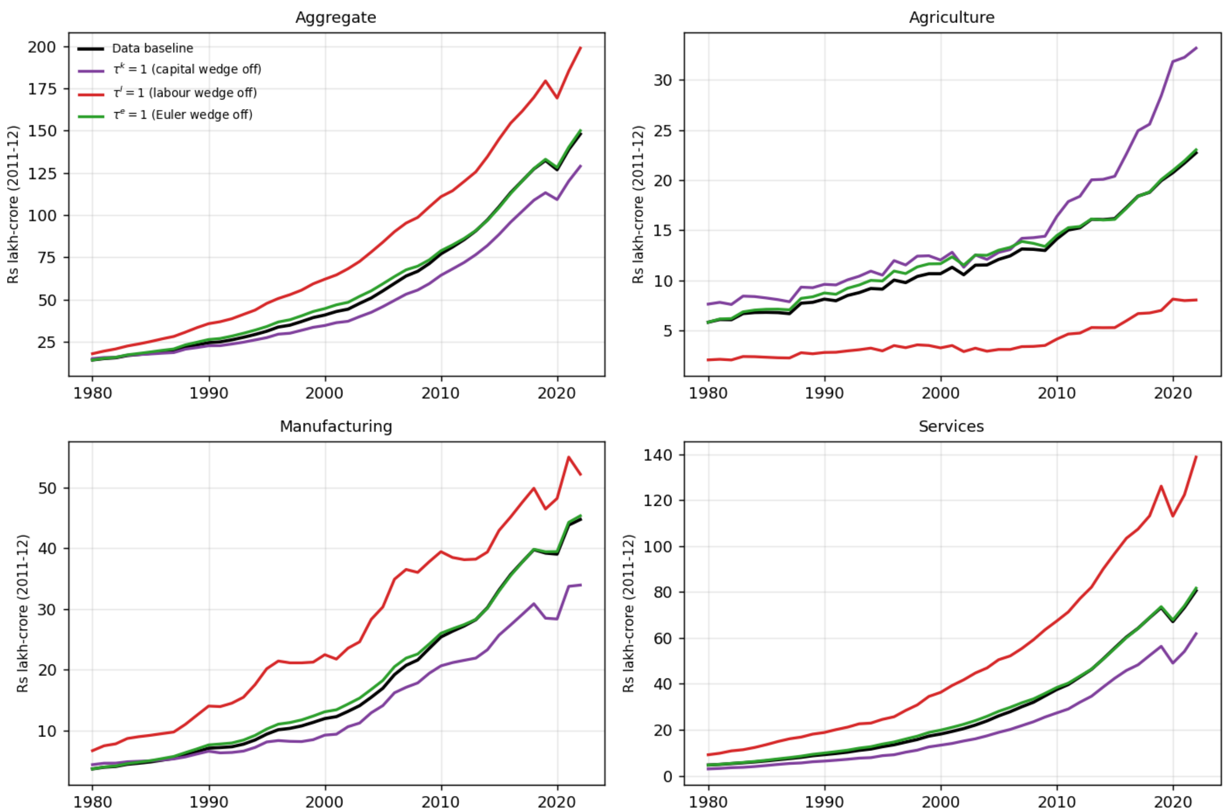
5 Wedges and Potential Gains from Policy Reforms

Our wedge approach to modelling the economy allows for sectoral and market distortions which were then quantified in the calibration and dynamic simulations that we have presented above. The key follow-up questions that this structure allows one to address are: (a) which of these wedges has the largest quantitative impact on the economy? (b) which wedge, if removed, would make the 2047 \$30tn target easiest to achieve? (c) what do these wedges stand for? and (d) can one quantify the gains from specific policy reforms that would operate through a reduction in the wedges? We address these questions in this section.

There are three main factor market wedges in the model: the sectoral capital market wedges τ_i^k, the sectoral labor market wedges τ_i^l, and the Euler equation wedge τ^e. While all the wedges were generated within the model as tax wedges, they potentially reflect a broader set of distortion that include regulatory compliance costs, regulatory forbearance, regulatory frictions, as well as quantitative restrictions. Hence, a stand-in for policy reforms within the model is to eliminate these wedges by setting them to one.

To examine the quantitative importance of these wedges, we conduct a sequence of counterfactual exercises. We quantitatively estimate the effect of each wedge by eliminating it and then re-running both the dynamic simulation of the model from 1980-2022 (shown in Figure 9) as well as the projection exercise for 2047 (reported in Table 6) with all other wedges and parameters unchanged relative to the baseline case. Figure 12 shows the counterfactual dynamic output paths..

Figure 12: Dynamic output paths under the three counterfactuals, 1980–2022



The main insight from Figure 12 is that eliminating the labor wedge is the only reform that raises aggregate output. Eliminating the other two wedges either leaves aggregate output unchanged or lowers it somewhat. Eliminating the labor wedge primarily benefits Industry and Services; Agricultural output actually declines in the absence of the labor wedge.

To understand these sectoral effects of removing the labor wedge, recall from Figure 6 that the labor wedge is above one throughout for Industry and Services (value marginal product above the wage). Hence, the labor wedge acts as a tax for Industry and Services which depresses employment in those sectors. Removing it therefore causes Industry and Services to expand. The opposite dynamics come into play in Agriculture when the labor wedge is removed.

The second set of policy counterfactuals that we conduct is with regard to the model projections for 2047. Specifically, we re-do our projections for 2047 by sequentially eliminating the three wedges, one at a time. We re-do the projections for three scenarios for annual sectoral TFP growth between 2023 and 2047: the last 20 years average TFP growth ("Last-20 TFP"), the the average of the 20 highest annual sectoral TFP growth rates during 1980-2022 ("Top-20 TFP"), and the average of the ten highest annual sectoral TFP growth rates during 1980-2022 ("Top-10 TFP").

Table 7: Single-wedge counterfactuals under different historical-mean TFP variants

	Last-20 TFP		Top-20 TFP		Top-10 TFP	
Counterfactual	reformed	distorted	reformed	distorted	reformed	distorted
CF1: $\tau_g^k = 1$	6.8	7.8	14.2	15.7	21.2	21.9
CF2: $\tau_g^l = 1$	10.3	7.8	20.4	15.7	**27.0**	21.9
CF3: $\tau^e = 1$	7.8	7.8	15.7	15.7	21.9	21.9

Note: "Distorted" is the 2046–47 GDP from a projection that starts at the actual 2022–23 data state with the variant TFP path; "reformed" starts from the 2022–23 state of the indicated single-wedge counterfactual and projects forward at the indicated TFP path.

Table 7 reports the resulting 2046–47 GDP in constant-2023 USD at market rates. The table shows that while no single reform achieves the $30tn target, removing the labor wedge has the biggest impact and gets to within touching distance of the target in the "Top-10 TFP" case. This is reiteration of the main message of Figure 12 that sectoral labor markets may be the most promising targets of policy reforms.

6 What are these labor market wedges?

The previous section highlights the importance of reducing the distortions captured in the labour market wedge. In this section, we discuss the sources of these distortions.

A number of studies have pointed out that regulations that limit the ability of firms to respond to economic conditions by changing the size of their labour force, can lead to inefficiencies [Besley and Burgess, 2004, Aghion et al., 2008]. For example, a firm that faces declining demand for its product or higher costs, might wish to down-size but is unable to because of limits on the firing of workers. Conversely, a firm may not increase its labour force in order to remain below a size threshold beyond which new constraints apply. The large presence of informal sector firms in India also interacts with regulatory frictions since informal sector firms are smaller and less subject to oversight and regulations. In addition, informal sector firms may be able to avoid or reduce their taxes, including payroll taxes and this may incentivize them to remain smaller than their optimal size.

A different class of distortions that would also show up as a labour wedge involve monopoly power in the product or labour markets [for a taxonomy, see Restuccia and Rogerson, 2017]. In product markets, market power allows the firm to limit production and keep prices above marginal costs. The ensuing markup would also show up as part of the labour wedge. Similarly, monopsony power in the factor market would lead to wages being lower than the marginal revenue product of labour, a situation that would show as a labour wedge above one.

Frictions in the access to credit may be yet another reason for the existence of a labor wedge different from one [Buera et al., 2011]. Most small and medium scale enterprises tend to obtain financing from banks. To the extent that inefficiencies in credit markets limit the availability of business credit financing, it can show up as a labor wedge in firm optimality conditions.

To illustrate the relationship between credit conditions and labor wedges, consider the same model that we developed above but with one twist. Assume that intermediate firms need to pay a fraction of their wage bill before the revenues for the period are realized, following the working-capital device of Neumeyer and Perri [2005]. To make these payments they borrow from banks. Specifically, the firms need access to loans n from banks which can be represented by a wage-in-advance constraint:

$$n_t \geq \phi_i w_t l_t$$

To keep the notation simple and the firm's problem static, assume that the bank loans are intra-period loans which the firm repays at the end of the period. The firm's periodic profit funciton then becomes

$$\pi_{it} = p_{it}\Gamma_{it}k_{it}^{\alpha}l_{it}^{1-\alpha} - r_{it}^{L}n_t - r_t k_{it} - w_t l_{it}$$

where r_{it}^L is the loan rate facing firm i at date t. As is well known, as long as $r^L > 0$, the wage-in-advance constraint will exactly bind. Under a binding wage-in-advance constraint, the firm's first-order-condition for optimal labor demand becomes

$$(1-\alpha)\frac{p_{it}y_{it}}{l_{it}} = (1+\phi_i r_{it}^L)w_t$$

This condition can be rewritten as

$$\frac{\phi_i w_t l_{it}}{p_{it}y_{it}} = \frac{n_{it}}{p_{it}y_{it}} = \frac{\phi_i(1-\alpha)}{(1+\phi_i r_{it}^L)w_t}$$

where the second term follows directly from the wage-in-advance condition given above.

Two observations follow directly this equation. First, assuming that all firms in sector i face a common wage-in-advance constraint, sector i's credit-in-advance parameter ϕ_i can be identified if one has the sectoral credit-GDP ratios along with the sectoral average lending rates. Second, the mapping between the labor wedge in our model and this credit market friction is direct: $\tau^l_{it} = 1 + \phi_i r^L_{it}$. Since the wage rate is common across sectors, $\frac{n_{it}}{p_{it}y_{it}} = \frac{\phi_i(1-\alpha)}{(1+\phi_i r^L_{it})w_t}$ implies that the labor wedge and the credit-GDP ratio in Industry should be negatively correlated.

The prediction about the negative correlation between the labor wedge and the credit-GDP ratio is easy to test since the RBI makes available data on sectoral allocation of credit. Table 8 reports the correlations. As our small illustrative example predicts, the correlations of the sectoral labor wedges and sectoral credit-GDP ratios are strongly negative.

Table 8: Correlations of sectoral labor wedges with own-sector bank-credit-to-GVA ratio, 1980-2022

	vs own-sector credit/GVA		
Wedge	Agriculture	Industry	Services†
τ^l_g	−0.56	−0.77	−0.81
τ^k_g	+0.31	−0.56	+0.68

†Services own-sector credit-to-GVA is constructed as the residual non-food bank-credit series (non-food − Agriculture − Industry) divided by sectoral nominal GVA, since the explicit RBI Services line exists only from 2007; the residual series therefore bundles the explicit Services line with Personal Loans and a small unclassified remainder over the 1980–2006 portion of the sample.

As we suggested above, credit frictions is just one of many sources of labour market wedges. These results are suggestive of the relevance and importance of addressing labor market frictions in a comprehensive fashion since quantitatively they have the largest impact on both aggregate and sectoral outputs.

7 What Ails Productivity?

Our empirical analysis identified two broad speed-breakers in the Indian economy: labor market wedges and TFP. While we have flagged possible policy-actionable frictions that could impact labor market wedges, we have been silent on the reasons for tepid TFP growth. We turn to this issue now.

A first-order reason for TFP to be low in economies subject to factor market distortions is that they can lead to factor misallocations across firms and sectors: low productivity firms can gain access to resources that are better used by higher productivity firms which consequently remain small. The overall effect is for a more distorted economy to have low TFP due to this composition effect. This is a widely studied mechanism going back to Hsieh and Klenow [2009]. We haven't fully exploited this mechanism in this paper partly because it is well studied but also because we haven't focused on firm heterogeneity. The mechanism however does exist in our structure due to sectoral heterogeneity. In as much as factor market wedges distort sectoral allocations, reforms would induce aggregate productivity gains here too.

We can quantify this sectoral misallocation channel directly. Using the model's simulated aggregates under the baseline and under the counterfactual where the labor w in each case:edges are eliminated ($\tau^l = 1$), we can compute an aggregate Cobb-Douglas TFP residual

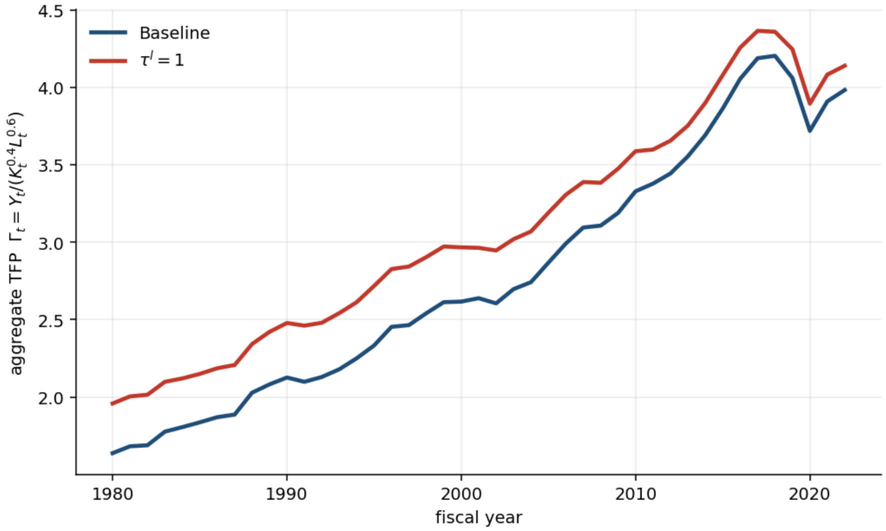
$$\Gamma_t \;=\; \frac{Y_t}{K_t^{\alpha}\, L_t^{1-\alpha}}, \qquad \alpha = 0.4,$$

in each year from 1980 to 2022. The sectoral productivities Γ_{it} are identical across the two configurations by construction, so any gap between the two aggregate Γ_t paths reflects pure allocative efficiency. Figure 13 plots the two paths. The counterfactual residual (when $\tau^l = 1$) lies above the baseline throughout the sample, by 19.6% in 1980, shrinking to 3.9% by 2022, with a sample mean gap of 12.0%. The narrowing of the gap mirrors the observed decline in τ^l over the sample: as the labour market has become less distorted, the potential gain from eliminating what remains has shrunk correspondingly.

The exercise also yields a striking growth-accounting decomposition. Baseline aggregate Γ_t grows at 2.14% per year over 1980–2022, whereas the counterfactual aggregate Γ_t grows at only 1.80% per year. Roughly one-third of a percentage point per year of India's measured aggregate TFP growth — about 16% of the total — is therefore accounted for by *declining labour-market misallocation* rather than by underlying technological progress. India's already-modest baseline TFP growth is in part a misallocation-relief story: a portion of the residual we measure as productivity is really the labour wedge eroding on its own.

We also want to highlight a different, possibly simpler, impact of regulatory or business conditions frictions that could impact TFP more directly. Consider our environment where intermediate goods firms who produce using capital and labor. But now suppose, they face regulatory compliance costs. Gross output production requires not just capital and labor but also requires some

Figure 13: Aggregate Cobb-Douglas TFP $\Gamma_t = Y_t/(K_t^{0.4}L_t^{0.6})$: baseline versus $\tau^l = 1$ counterfactual, 1980–2022.



employing regulatory compliance capital s which comes at a rental cost of b per unit. The gross output function of the firm is

$$Q_{it} = k_{it}^{\alpha} l_{it}^{\beta} s_{it}^{\gamma}$$

The optimal employment of regulatory capital services is

$$s_{it} = \left(\frac{b_{it}}{\gamma k_{it}^{\alpha} l_{it}^{\beta}} \right)^{\frac{1}{\gamma-1}}$$

Substituting this into the gross output function and expanding it yields the value added production function

$$y_{it} = \Gamma_{it} k_{it}^{\hat{\alpha}} l_{it}^{\hat{\beta}}$$

where $\Gamma_{it} \equiv \left(\frac{\gamma}{b_{it}}\right)^{\frac{\gamma}{1-\gamma}}$, $\hat{\alpha} \equiv \frac{\alpha}{1-\gamma}$, $\hat{\beta} \equiv \frac{\beta}{1-\gamma}$. If we set $\beta = 1 - \alpha$ then this specification is isomorphic to the value added production function that we used for intermediate goods. The crucial insight though is that sectoral TFP Γ_{it} is *decreasing* in the regulatory compliance cost b_{it}.

The primary message of this little example is that regulatory compliance costs faced by businesses can induce reduced valued added TFP since firms have to spend resources on navigating the regulatory space. This is a deadweight loss. Difficulty in doing business and burdensome compliance norms may be a simple explanation for India's TFP challenges.

8 Conclusions

The goal of this paper was to help understand the macroeconomic history of India since 1980 and to map out through 2047 potential paths towards the oft-state development targets of $30tn GDP To that end, we began by discussing the broad macroeconomic picture of recent decades to lay down the empirical context of our exercise. Our review of the evidence highlighted low productivity growth, which has actually turned negative in recent years, as one of the major challenges to future growth. We found that TFP growth in India has been much lower than the corresponding TFP growth rates in Brazil, China and Korea when they were at similar stages of their development.

To understand the macro challenges better, we developed a three-sector dynamic macroeconomic model capable of replicating the path of labour, capital, sectoral output and prices in India from 1980 to 2022-23. The model included wedges in key efficiency conditions and constraints to capture the distortions present in the Indian economy in a parsimonious way. We used the model to explore which type of reform would have the biggest impact on GDP by sequentially removing each distortion in 1980 and allowing the model to trace out counter-factual time paths. We found that removing the labour wedge leads to a substantially higher path for GDP (+35%) above actual 2023 levels. This increase is mainly driven by the movement of labour away from agriculture and into industry and especially into services. The extra labour would have also raised the marginal return to capital and induced more investment in these sectors than observed in the data.

We also used the model to conduct projections for the Indian economy from 2023 to 2047. Our key finding was that aggregate TFP would have to grow at 6.1% annually for this entire period in order for India to hit the $30tn GDP target in 2047, if the distortions in the economy are frozen at their 2023 levels. This extremely high level of TFP growth is outside even the average associated with the best ten years in the sample. It is also way higher than the TFP growth rates experienced by comparator nations such as China. So, the $30tn target seems difficult to achieve.

As one might expect from the above discussion, we show that reducing labour market distortions can significantly reduce the TFP growth required to hit the $30tn GDP target. Given the importance of the labour wedge, we discuss various underlying market distortions that may be relevant for India and in particular show that credit financing to cover a firm's wage bill could be a part of the observed labour wedge. Consistent with model predictions, we show that movements in measured sectoral credit to GVA are negatively correlated with the sectoral labour wedges, suggesting that reforms which increase firm's access to credit could play an important role in reducing these distortions.

The paper also documented the importance of sectoral misallocations induced by the labor wedges. As per our model-based identification, about 0.34 percentage points out of India's average TFP growth of 2.14% was due to declining labor wedges inducing better sectoral factor allocations. We also showed that if firms have to use resources for regulatory compliance costs, the value added TFP becomes a decreasing function of these expenses. We believe these types of firm expenses can be a powerful explanation for the anemic TFP growth observed in India.

We leave for future work an important question. Why has India's private sector investment slowed down in recent years and if domestic savings cannot provide resources, can international investment flows make up for the domestic shortfall?

A Appendix

A.1 Sectoral price wedges

Figure 14 below shows the sectoral price wedges while Figure 15 shows the growth rate of the price wedges. The price wedges are sensitive to the elasticity of substitution σ between intermediate goods in the final goods technology. The figures show the wedges for three different values of σ.

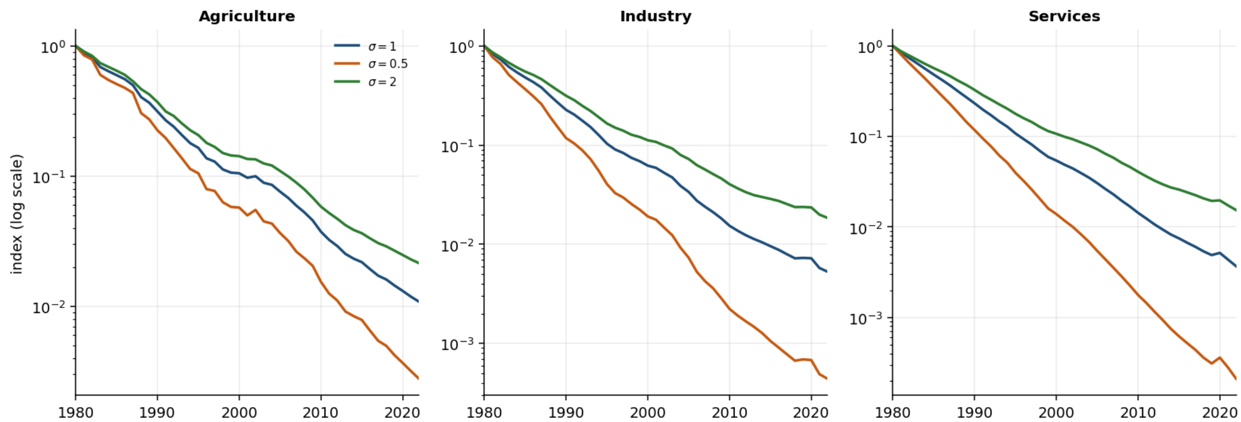


Figure 14: Price-wedge index (1980 = 1, log scale), three elasticities $\sigma \in \{1, 0.5, 2\}$.

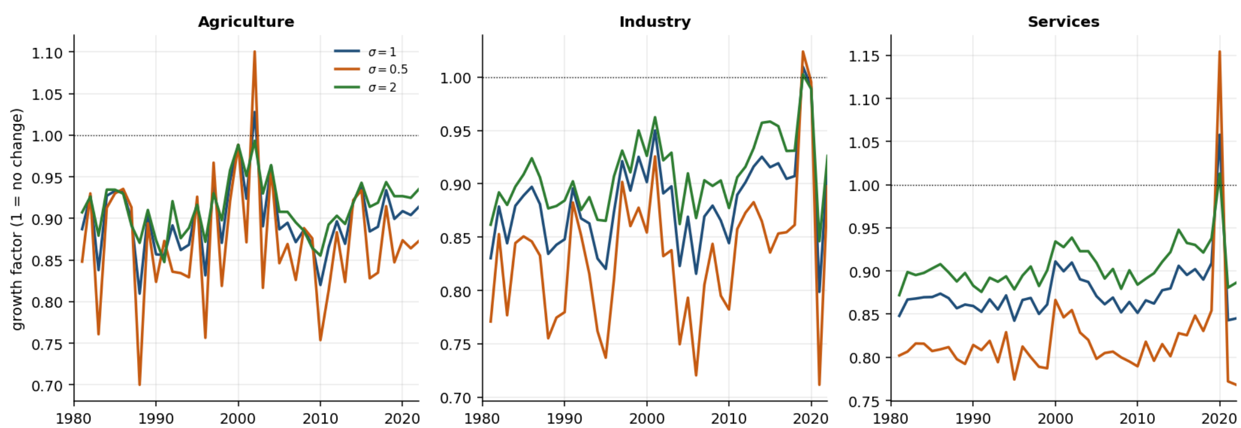


Figure 15: Price-wedge growth factor (year on year). A value of one means the wedge is unchanged from the previous year.

A.2 Final goods wedge

Figure 16 shows the measured final goods wedge τ^F that allows the model to match the real rental rate in the data.

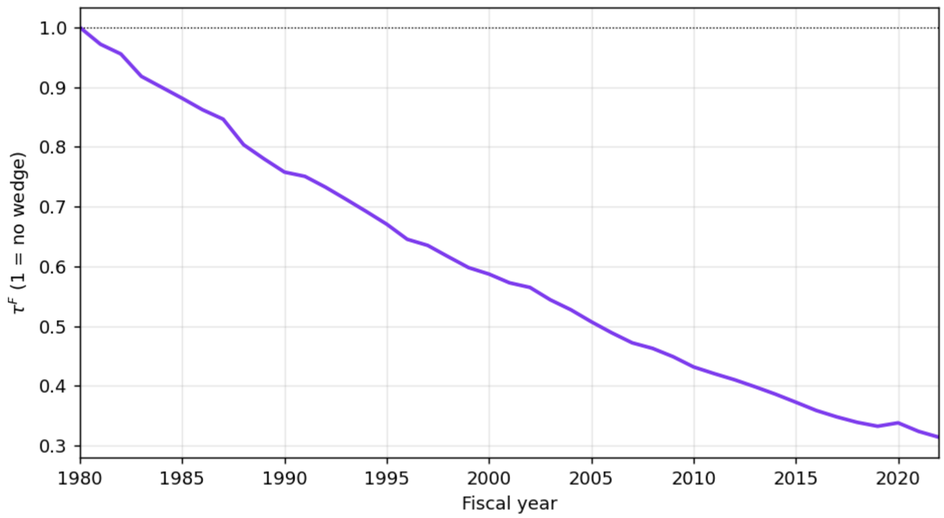


Figure 16: Final-good wedge τ^F implied by pinning the model rental to the data rental, 1980–2022.

A.3 Final goods weights

Table 9 reports the three-sector λ's (the output-weighted mean of the constituent industry weights, and the group total). The weights are sensitive to the elasticity of substitution between intermediate goods in the final goods technology, σ.

Table 9: Three-sector final-good weights λ (normalised across 27 industries). "wt-mean" is the real-VA-share-weighted mean of the constituent industry weights; "sum" is the group total (the totals sum to one across the three sectors).

	$\sigma = 1$		$\sigma = 0.5$		$\sigma = 2$	
Sector	wt-mean	sum	wt-mean	sum	wt-mean	sum
Agriculture	0.3630	0.3630	0.8227	0.8227	0.1218	0.1218
Industry	0.0294	0.2693	0.0085	0.0422	0.0338	0.4865
Services	0.0745	0.3676	0.0356	0.1350	0.0589	0.3917

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