COVID Scarring and Sustainable Recovery Challenges: A Production Function Approach

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Abstract

We use the India KLEMS database to classify industries into four sub-sectors based on their energy and labour intensities. To estimate the heterogeneous scarring effects due to the pandemic we use a model-generated output assuming away the pandemic effects as a counterfactual and compare it with projected growth paths from a hybrid dataset. Our findings suggest that scarring was least in green industries. Furthermore, our empirical findings indicate that these sectors are intertwined with technological dependence on the brown industries. This may result in short-run transition costs while adapting to sustainable methods of production. Therefore, the adoption of greener technology and a path towards more sustainable and equitable growth will necessitate calibrated policy interventions tuned to the diverse requirements of all sub-sectors.

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1 Introduction

The COVID-19 pandemic has disrupted global economy due to supply-side limitations, and it has spread to the demand side via job losses, health risks, and heightened future uncertainty. Anecdotal evidences suggest that with the ongoing pandemic, contact sensitive sectors have been impacted more than non-contact sensitive sectors, notwithstanding the relative importance of demand vs. supply amplifications. With the expansion of the immunisation programme and advancements in medical care, economies are gradually rebounding. It is also of policy relevance to remind ourselves of the objective to follow a sustainable growth path (see Acemoglu, Aghion, Bursztyn, and Hemous (2012)). Given the backdrop of COVID pandemic, therefore, the challenges are two-fold: the economy must not only revive but also must follow a sustainable path which is consistent with the expansion of the green economy. In this vein, we make an attempt to highlight new evidence using KLEMS dataset.

We examine the heterogenous impact of the COVID shock on several industry groups using a supply-side partial equilibrium framework. We use the KLEMS dataset to aggregate industries in terms of contact sensitivity compared to non-contact sensitivity subsectors. Additionally, as part of recent policy initiatives toward environmentally friendly production methods, it may be necessary to be aware of structural changes, physical dangers, and transitional risks to brown industries relative to their greener equivalent. Therefore, we further classify industries into green and brown industries - green being the environment-friendly, whereas brown being the polluting industries.

For our analysis, we make use of the KLEMS-India dataset. KLEMS data for India provides estimates of total factor productivity (TFP) and sectoral labour productivity that are comparable internationally. Our sample period roughly corresponds to the time when India adopted complete current account convertibility starting in 1993 as a result of the economic liberalisation process started in 1991, during which time the country enjoyed a consistent market-determined exchange rate policy. We start by defining our method for classifying industries as contact-sensitive or non-contact based on the average of the inverse of labour productivity for the years 2010–19. Furthermore, we divide industries into green and brown industries using the average energy cost share in gross output for the years 2010 to 2019.

We need a counterfactual without the pandemic to quantify the scar due to COVID. To predict the output trajectories in the absence of the pandemic, we build a theoretical model for the situation using parameters inferred from India-KLEMS data. Then, in order to assess and gauge the size of the pandemic blemish, we extend our research to include the post-COVID period. Since the KLEMS data is only available until 2019, we use the perpetual inventory approach to acquire the series on capital in order to extend the data for the COVID period, or 2020 and 2021, by obtaining recent investment data from CMIE prowess. Then, using the concordance approaches, we map the Prowess industries to the KLEMS industries. Additionally, we map information on industry-wise employment to obtain recent labour statistics on employment from the CMIE Consumer Pyramids (CMIE-CP) Databases.

Understanding the connections between various groups is important when evaluating the growth revival of various industries, particularly in the wake of a disastrous epidemic. COVID resulted in two different kinds of disruptions: direct and indirect. These indirect effects cascaded across industry groups as a result of upstream and/or downstream linkages. We assess sectoral linkages by using the most recent Input-Output Matrix (I/O matrix) to quantify the indirect effects, while our methodology for creating projections as indicated above captures the direct effect.

The four sectors which are important for our purpose are Green Contact Sensitive (GCS), Brown Contact Sensitive (BCS), Green Non-Contact Sensitive (GNCS), Brown Non-Contact Sensitive (BNCS). Our results show that since the 1990s, the rise in value-added of green non-contact sensitive (GNCS) has been rather slow. The value-added growth of the brown non-contact sensitive (BNCS) sector was essentially stable. After 2010, all four industries had a slowdown in employment and capital, which was made worse by the pandemic. Our findings reveal that the pandemic caused a deeper scar in the brown sectors and the contact-sensitive sectors as against the green sectors and the non-contact sensitive sectors.

We also evaluate the inter-linkages between the four sectors by constructing an input share matrix. This matrix reveals that the GNCS sector has the highest input share usage from BNCS products, as against inputs from the other three sectors. Furthermore, the largest portion of GNCS output is used as input for the BCS sector. This is significant circularity when considering the inputs because the requirements of the BCS sector are evenly distributed across all four sectors. As we move closer to Netzero, interdependence could provide a significant obstacle to the transition of the brown to green industries. This also necessitates the implementation of carefully calibrated public regulation.

The remainder of the paper is structured as follows: Section 2 describes the broad industry metrics classification based on energy and labour intensity for production. Section 3 shows the data trend observed in pre-pandemic time. Section 4 presents a model that enables us to comprehend a hypothetical growth path in the absence of the pandemic. Section 5 quantifies the impact of the pandemic on the output growth for each subsector by using a concordance between KLEMS, CMIE-Prowess, and CMIE-CP databases. Section 6 evaluates the nature of the policy for achieving a sustainable growth path after taking into account the cascading effects of the green and brown industries, and finally, Section 7 concludes.

2 Classification of Sectors

KLEMS India provides data for 27 sectors from 1980-81 to 2018-19. That includes manufacturing, services, and agricultural sectors. Gross output is given in the data series and from there, energy, material, and services are net out to get the gross value added. For each of the sectors, the KLEMS India provides data on labour employment, cost of labour, cost of capital, energy cost, material cost, and cost of other services in real terms. To throw light on the overall economy the data set aggregates the sectors and bring down the number of sectors to three sectors, namely Manufacturing, Services, and Agriculture & Allied sectors. However, we need to frame new classifications according to our aim described in section 1.

Using the average energy cost share in gross output for the period 2010-19, we rank the 25 KLEMS industries (excluding Agriculture, Hunting, Forestry & Fishing, and Public Administration & Defense). We then classify industries that have energy cost share above the median level as “Brown” industries, or else the industry is “Green”. Moving to the definition of contact sensitive and non-sensitive we take an innovative turn. Labour productivity in KLEMS data shows the output produced per unit labour. The inverse of that implies the number of workers required to produce one unit of output. Therefore, larger this inverse value means higher worker congestion in that sector.

Using the average of the inverse of labour productivity for the period 2010-19 as a measure for contact sensitivity, we again rank the 25 KLEMS industries and thereafter classify industries that have contact sensitivity above the median level as "Contact Sensitive" industries. Similarly, those below are categorized as "Non-Contact Sensitive" industries. Contact sensitive sectors in the list shown in table 1 consists of those services which are anecdotally understood as sectors that are highly ranked as either employment generation or in terms of serving to dense customer base.[1] On the other hand in manufacturing the contact-sensitive industries are ranked low in terms of their capital augmentation. This observation provides justification for our definition of "Contact Sensitive" and "Non-contact Sensitive".

For each of the 25 industries, we get the value of factor inputs and GVA from KLEMS data. We aggregate the factor inputs and GVA of the relevant industries to generate the input and GVA for $\{\text{Green, Brown}\} \times \{\text{Contact Sensitive, Non-Contact Sensitive}\}$ sectors. We try to understand the features and trends of these sectors pre-Covid period using the above-mentioned compiled data set.

3 Pre-Covid Data Trends

In this section, we focus on trends in output growth, productivity, and growth in labour and capital for the four sub-sectors, prior to the COVID-19 pandemic. Figure 1 plots the pre-covid HP-Filtered trends in Gross Value Added for all four sub-sectors. On average, for the entire period of study (i.e., 1980-81 to 2018-19), both brown sectors – contact sensitive and non-contact sensitive – grew faster than the green sectors. It is, however, observed that there is a broad-based slowdown in the value-added growth rates of all four sub-sectors starting almost a decade prior to the Covid-19 pandemic. Growth in the value added of green non-contact sensitive subsector (GNCS) remained subdued since the 1990s. On the contrary, for the Brown non-contact

[1] It may be mentioned that our industry classification is along the lines of the energy input contributions as listed in the Energy Intensity Tables of the latest IPR report. See Chapter 7 of IPR (2022).

Table 1: Classification of Industries

KLEMS Industry Description	Category by Energy Use	Category by Employment Share	Complete Classification
Textiles, Textile Products, Leather and Footwear	Brown	Contact sensitive	Brown and contact sensitive
Pulp, Paper,Paper products,Printing and Publishing	Brown	Contact sensitive	Brown and contact sensitive
Other Non-Metallic Mineral Products	Brown	Contact sensitive	Brown and contact sensitive
Transport and Storage	Brown	Contact sensitive	Brown and contact sensitive
Food Products,Beverages and Tobacco	Green	Contact sensitive	Green and contact sensitive
Wood and Products of wood	Green	Contact sensitive	Green and contact sensitive
Manufacturing, nec; recycling	Green	Contact sensitive	Green and contact sensitive
Construction	Green	Contact sensitive	Green and contact sensitive
Trade	Green	Contact sensitive	Green and contact sensitive
Hotels and Restaurants	Green	Contact sensitive	Green and contact sensitive
Education	Green	Contact sensitive	Green and contact sensitive
Health and Social Work	Green	Contact sensitive	Green and contact sensitive
Mining and Quarrying	Brown	Non-contact sensitive	Brown and non-contact sensitive
Chemicals and Chemical Products	Brown	Non-contact sensitive	Brown and non-contact sensitive
Rubber and Plastic Products	Brown	Non-contact sensitive	Brown and non-contact sensitive
Basic Metals and Fabricated Metal Products	Brown	Non-contact sensitive	Brown and non-contact sensitive
Electrical and Optical Equipment	Brown	Non-contact sensitive	Brown and non-contact sensitive
Transport Equipment	Brown	Non-contact sensitive	Brown and non-contact sensitive
Electricity, Gas and Water Supply	Brown	Non-contact sensitive	Brown and non-contact sensitive
Post and Telecommunication	Brown	Non-contact sensitive	Brown and non-contact sensitive
Business Service	Brown	Non-contact sensitive	Brown and non-contact sensitive
Coke, Refined Petroleum Products and Nuclear fuel	Green	Non-contact sensitive	Green and non-contact sensitive
Machinery, nec.	Green	Non-contact sensitive	Green and non-contact sensitive
Financial Services	Green	Non-contact sensitive	Green and non-contact sensitive
Other services	Green	Non-contact sensitive	Green and non-contact sensitive

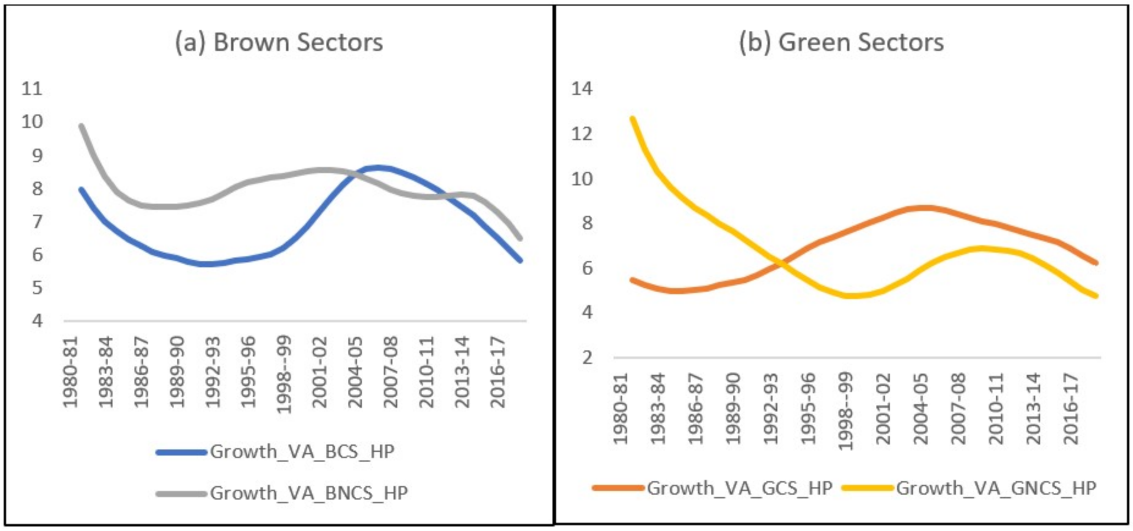

Figure 1: Green and Brown Sectors: Pre-Covid Trends in GVA

sensitive (BNCS) sector, value-added growth was largely stable. However, after 2000 the growth in Green contact-sensitive (GCS) took over and the average growth rate starting form 2000-01 to 2018-19 surpassed both BCS and GNCS sub-sectors.

With regards to employment, all four sectors showed experienced a slow-down in HP-Filtered growth since 2010 (see Figure 2). Contact sensitive sectors, both brown and green, experienced a sharp fall in employment growth from 2000-01 till 2018-19. Therefore, employment growth in contact-sensitive sectors was suffering even prior to the pandemic. With regards to the non-contact sensitive sectors, the green subsector experienced stable, yet low growth since the late 1990s, while the brown subsector witnessed the highest growth in employment compared to all other sectors. This was consistently true even post-2008-09. As observed, the growth of employment in the contact and non-contact sensitive sectors, within the green sector, in terms of employment growth on average has remained slim. However, after the Global Financial Crisis (GFC) the trend growth rate of employment in the green non-contact sensitive overtook the green contact sensitive sector.

In Figure 3 we plot the trend growth rate in capital in all four sub-sectors. As expected, there is a broad-based slowdown in the growth, from around 2008-09, which is in line with the well-known investment slowdown

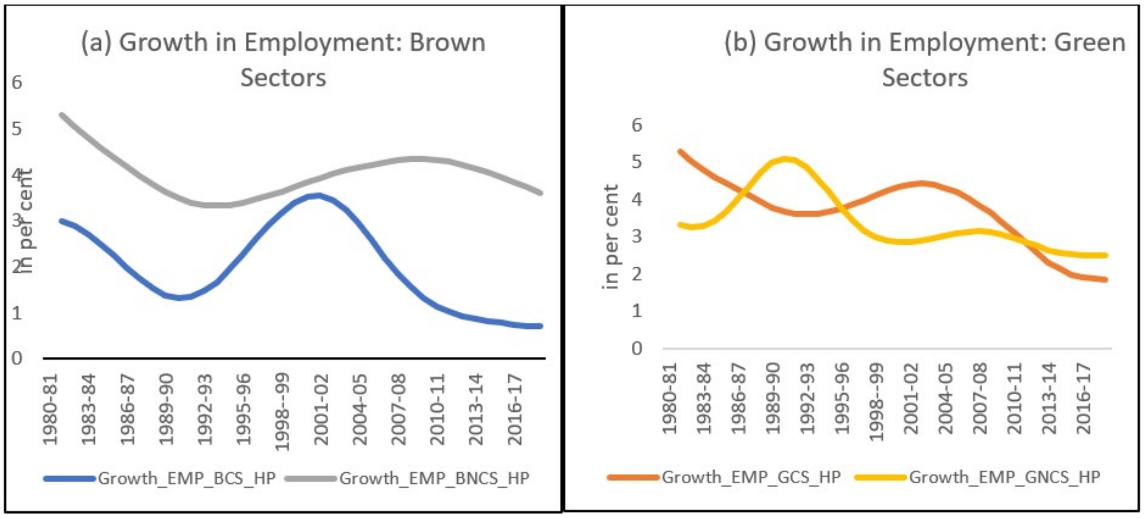

Figure 2: Green and Brown Sectors: Pre-Covid Trends in Employment

story. However, the trend growth in capital in the green non-contact sensitive sector started slowing down even earlier – during the early 2000s. Interestingly, within the brown sector, capital growth was dominated by the non-contact sensitive sub-sector over the contact-sensitive sub-sector. In the green sector, however, capital growth was relatively stronger in the contact-sensitive sub-sector. In general, the growth rate in capital for the green sector, overall, did not outweigh the brown sectors' capital growth.

Broad trends, therefore, suggest that value-added growth and growth in factors slowed down in the brown sub-sectors since 2008. This slowdown, however, was not compensated for, by the green sub-sectors as these sectors have been experiencing even lower growth rates.

3.1 Pre-Covid Trends in Productivity

To analyse COVID scar we need a benchmark or counterfactual. Suppose we wish to obtain the pre-covid trends in productivity growth. For doing this, we assume that the production function of value added is given by the following Cobb-Douglas functional form:

$$Y_{i,j,t} = F\left(K_{ijt}, L_{i}j; \mathcal{A}_{jt}\right) = \mathcal{A}_{jt} K_{ijt}^{1-\alpha} L_{ij}^{\alpha} \tag{1}$$

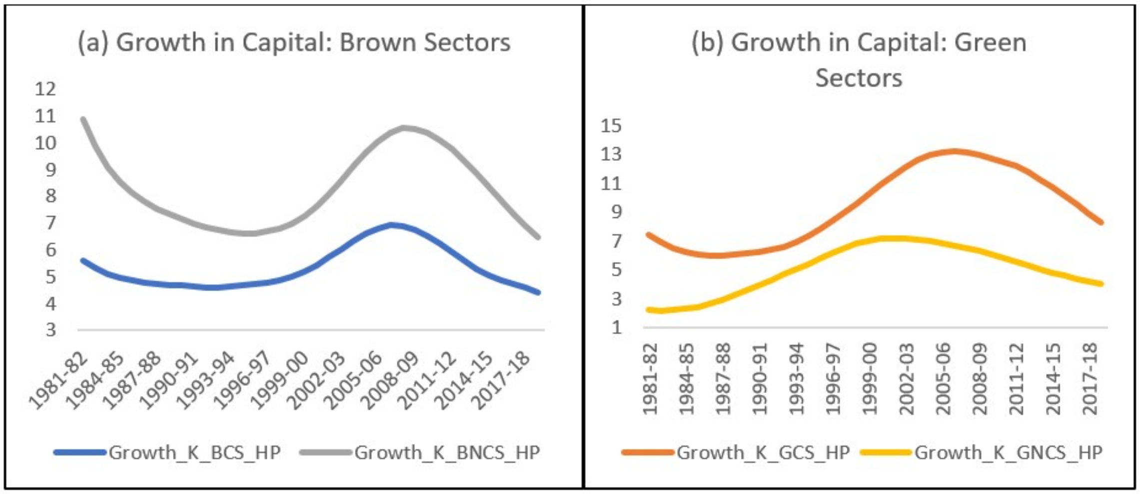

Figure 3: Green and Brown Sectors: Pre-Covid Trends in Capital

where $i = \{CS, NCS\}$ and $j = \{G, B\}$. Here K_{ijt} represents the aggregate capital input after augmenting capital quality and H_{ijt} is the aggregate labour input after augmenting labour quality for the $\{i,j\}^{th}$ industry sub-category at period t. Y_{ijt}, on the other hand, denotes the gross value added of the $\{i,j\}^{th}$ sector, and A_{ijt} is the corresponding Total Factor Productivity. We followed the KLEMS approach to estimate the α_{ij} by using the cost share of each input. We obtain the productivity of the $\{i,j\}^{th}$ sector as follows,

$$\mathcal{A}_{jt} = \frac{Y_{i,j,t}}{K_{ijt}^{1-\alpha} L_{ij}^{\alpha}} \tag{2}$$

Using eq. (2), we plot trends in TFP and TFP growth in Figures 4-5. In terms of levels, Figure 4 shows that the trend TFP of the green contact sensitive subsector dominated all the other sectors' TFP. In the green sub-sectors, TFP was on average higher than the brown sectors' TFP. However, post 2008-09, the brown contact sensitive subsector showed a sharp rise in TFP and surpassed the levels of TFP trend in the green non-contact sensitive subsector.

The slowdown which was visible in GVA, Employment, and Capital growth after 2009-10 was, however, largely absent in TFP growth, except for the brown contact sensitive sectors where the slowdown in TFP growth started from 2011-12. TFP growth in brown sectors on average remained higher than the green sectors' TFP growth after 2008-09. We see this in Figure 5.

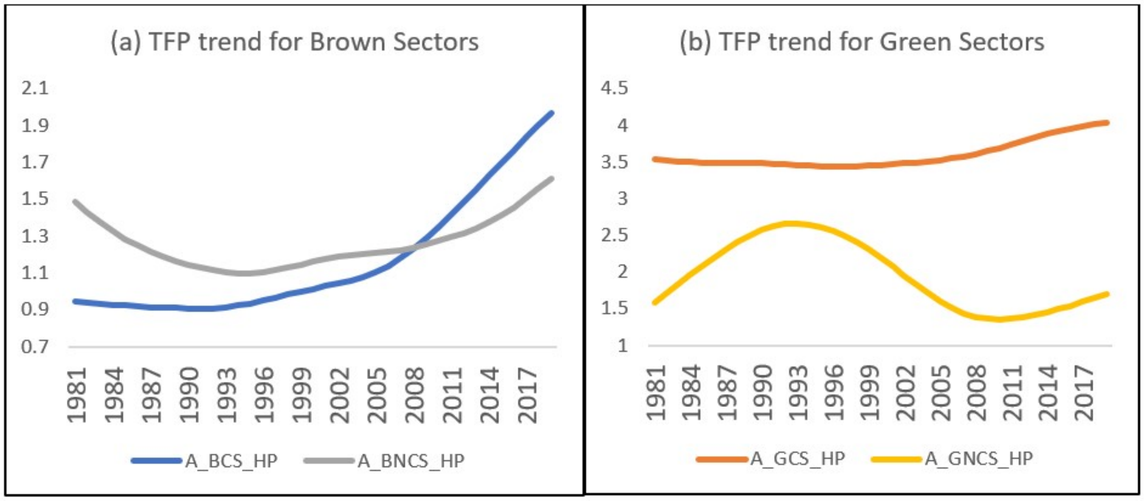

Figure 4: Green and Brown Sectors: Pre-Covid Trends in TFP

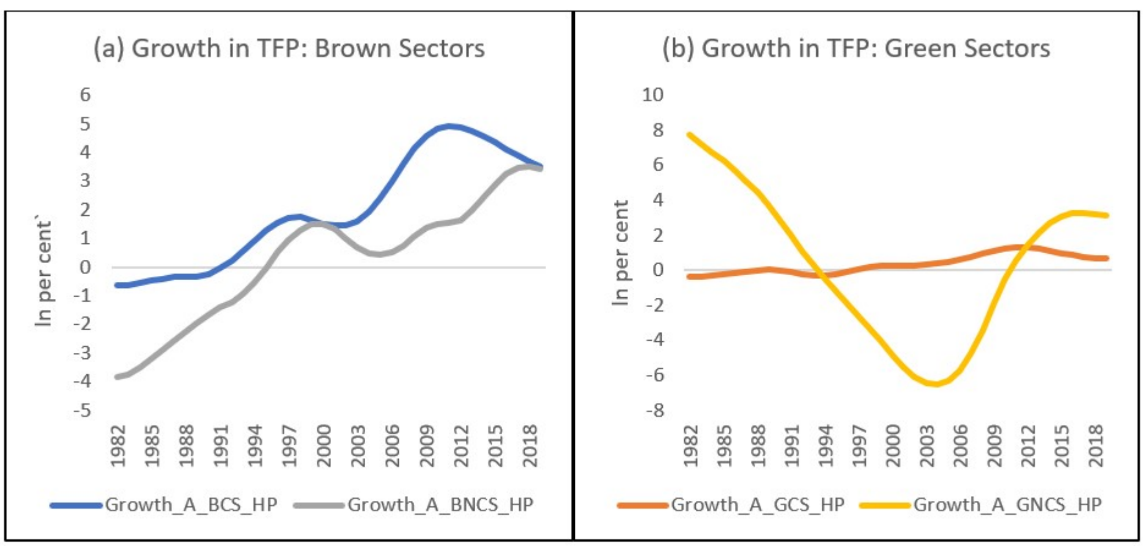

Figure 5: Green and Brown Sectors: Pre-Covid Trends in TFP Growth

4 Model Prediction in Pre-Pandemic Scenario

In this section, we explore the possible paths for $\{GCS, BCS, GNCS, BNCS\}$ if there was no Covid-19 pandemic. Following Barro and Sala-i Martin (1992), Alogoskoufis, Kalyvitis, et al. (1996) and the model presented in Chapter VI of Report on Currency and Finance (RCF) 2022 published by Reserve Bank of India [2], we reestimate and assign parametric values suitable to this analysis. Thereafter, we simulate the hypothetical growth path of the four sectors. The growth model of Chapter VI in RCF 2022.

The production function is

$$Y_{i,j,t} = F\left(K_{ijt}, L_i j; \mathcal{A}_{jt}\right) = \mathcal{A}_{jt} K_{ijt}^{1-\alpha_j} L_{ij}^{\alpha_j} \tag{3}$$

where i represents firms. Firms use the production function F with inputs: effective labour (L) and capital (K). It follows constant returns to scale. The four sector $\{GCS, BCS, GNCS, BNCS\}$, are indexed with j. $\alpha_j \in (0,1)$ is denoted as the labour income share. $\mathcal{A}_{jt}$ which is given to the firms, and is the effective TFP level for the firm in sector j. Firms face the wage bill and adjustment cost of investment and the total cost of investment is $I\left(1 + \frac{b}{2}\left(I/K\right)\right)$, where b>0. Additionally, firms pay tax, at the rate T_y to the government. The government spends the tax revenue to meet the expense of its own consumption, and on building public capital stock.

In our model, the TFP, $\mathcal{A}_{jt}$ constitutes two components. First is an exogenous technology level $A_{0,j}$ and second is the public capital or infrastructure $(K_{G,t})$ which benefits all the firms without the problem of congestion externality. More precisely, $\mathcal{A}_{j,t} \equiv A_{0,j} K_{G,t}^{\alpha_j}$. Therefore, a rise in public infrastructure stock increases the productivity of private capital and labour. Government spending is financed by tax revenue. So, the balanced budget condition says,

$$T_Y Y_t = g Y_t + I_{G,t} \tag{4}$$

where $I_{G,t}$ shows additional capital invested for building public capital by Government. Y_t is the aggregate output of the economy, and g is the share of government consumption expenditure to aggregate output. The

[2] https://rbi.org.in/Scripts/PublicationsView.aspx?id=21040

Table 2: Parameter Specifications

Sl. No.	Parameters	GCS	BCS	GNCS	BNCS	Source
1	Labour Income Share (α)	0.60	0.47	0.44	0.33	Estimated from KLEMS
2	Depriciation (δ)	0.1	0.1	0.1	0.1	Banerjee and Basu (2019)
3	Marginal adjustment cost of investment (b)	5.45	5.45	5.45	5.45	RCF (2021)
4	Tax to GDP (T_y)	0.25	0.25	0.25	0.25	Estimated
5	Depriciation of public capital (δ_g)	0.14	0.14	0.14	0.14	RCF (2021)
6	Revenue Expenditure to GDP ratio (g)	0.16	0.16	0.16	0.16	Estimated
7	Real rate of return (r)	1.01	1.01	1.01	1.01	Behera, Wahi, and Kapur (2017)
8	$A_{0,j}$	3.98	1.72	1.556	1.405	Estimated from KLEMS
9	Effective Labour (L^{α})	0.64	1	1.06	1.17	Calibrated

flow of the public capital is governed by the following rule,

$$\dot{K_G} = I_{G,t} - \delta_G K_{G,t}. \tag{5}$$

$\dot{K_G}$ represents the change in K_G over time and δ_G is the rate of public capital depreciation. A representative firm, Firm i of sector j maximizes its present discounted value of the lifetime profit by choosing its labour input and investment level for each period subject to the private capital flow rule

$$\dot{K_{ijt}} = I_{ijt} - \delta K_{ijt} \tag{6}$$

where $\dot{K_{ijt}}$ is the change in private capital for firm i in sector j and δ is the rate of depreciation of the private capital stock.

Given this framework, we solve the steady state equilibrium growth for each sector and log-linearize the model to simulate the dynamic paths. Here, we report only the simulation results given the parameters which are declared in Table (2). We estimate the labour income share and TFP for $\{GCS, BCS, GNCS, BNCS\}$ sectors from the KLEMS data for the purpose of the current paper (the description of that are in subsequent sections). We keep the other macro-economic parameters according to RCF 2022.

The simulation results are given in the following figure (6). The simulated growth paths for GVA of $\{GCS, BCS, GNCS, BNCS\}$ converge to the steady state level of $\{6.34\%, 5.79\%, 4.35\%, 6.14\%\}$, respectively.

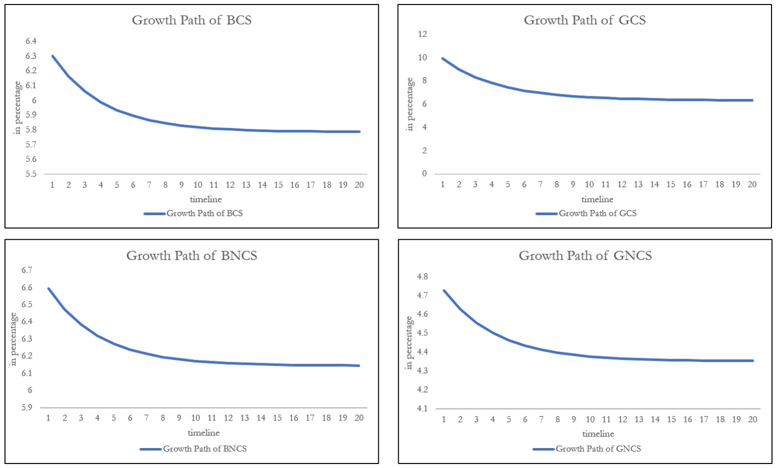

Figure 6: Simulated growth path of GVAs of $\{GCS, BCS, GNCS, BNCS\}$

These growth rates show the possible long-run average growth rates of the four sectors given the parameters were assigned pre-pandemic values.

5 Growth Projections

The official KLEMS data ends in 2019. To make for the pandemic period, we build a concordance between KLEMS database and two major CMIE databases – Prowess and Consumer Pyramids (CP) – to map micro-data from these databases into KLEMS industry classifications. This enables us to obtain data for the years 2020 and 2021. In this section, we begin our discussion with how we compile the data for capital and labour for 2020 and 2021, and hence how we make output projections for the same period.

5.1 Compiling the data for Capital

There are three steps involved in obtaining the subsectoral numbers for capital for the years 2020 and 2021. To begin with, we construct a concordance between the KLEMS database and the Annual Consolidated Accounts from the CMIE Prowess database. We exploit the NIC code listing information given in the official

KLEMS and the NIC code of operation given at the firm level in CMIE Prowess database.[3]

Next, at the annual firm level, we use define net investments as in eq. (7):

$$I = GFA - Deductions - Depreciation. \tag{7}$$

where I is net investments, GFA is the addition to Gross Fixed Assets by the firm. We subtract Deductions and Depreciations to GFA to finally obtain I. Thereafter, take the aggregate sum of firm-level net investments to arrive at industry-level investments. To this, we apply the perpetual inventory method assuming a standard depreciation rate of 10% to arrive at industry-level capital. This method enables us to arrive at a long time series for capital by industry, which we then aggregate to our major four sub-sectors - BCS, BNCS, GCS, and GNCS as shown in Table 1.

The correlations between aggregate capital obtained from the Prowess database and the aggregate Gross Capital from KLEMS database for the period 2009-2019 is very high at 0.94. We, therefore, use the growth rates for capital by subsector from the Prowess database for the years 2019-20 and 2020-21, to project capital for 2020 and 2021 in the KLEMS database.

5.2 Compiling the data for Labour

A concordance between CMIE Consumer Pyramids (CP) database and KLEMS is used to make projections for labour (see Appendix: Table 3 for concordance). The CP database has a rich panel database on employment where survey respondents indicate the "industry of occupation" for each survey wave from January 2016 to December 2021. We match the industry of occupation with the KLEMS industry and compute the annual average number of people employed for the period 2016-2021. Since the correlation between labour for the period 2016 to 2019 is strong at 0.76, we obtain growth rates for the period 2019-20 and 2020-21 for each subsector (BCS, BNCS, GCS, and GNCS) from CP, and project the labour for the KLEMS database for each

[3]See Appendix A in RBI KLEMS Report, 2021 for the concordance between KLEMS industry listing and NIC code listing. From the Prowess database, we obtain the NIC Product Code at the firm level and match it with the NIC Code listing in Appendix A in the KLEMS report which enables us to match the firms with their respective KLEMS industry.

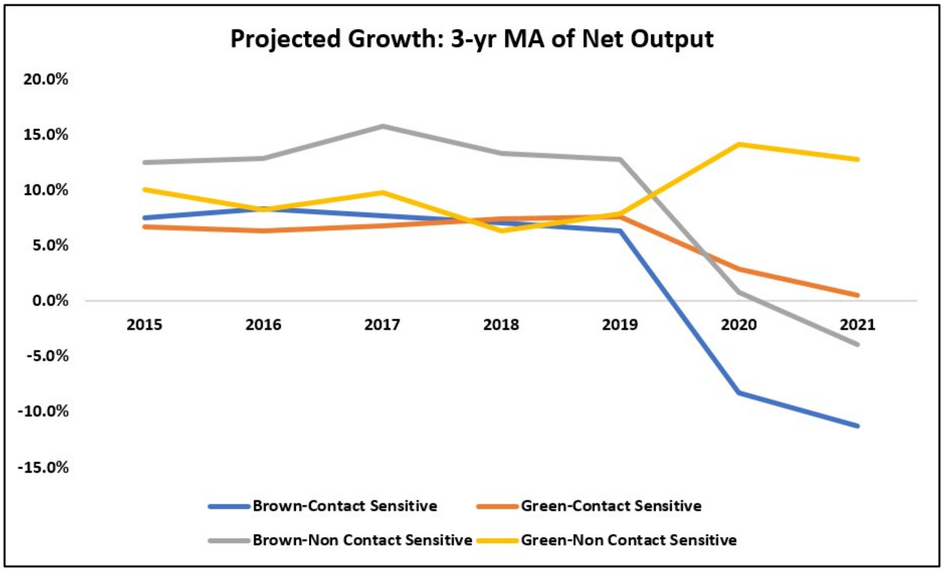

Figure 7: Green and Brown Sectors: Post-Covid Growth Projections

subsector for the period 2020 and 2021.

5.3 Simulation vs. Projection

We make projections of output and hence output growth using the concordance. For computing output, we use net output using the production function approach given in eq. (1) for the period 2020 and 2021. Growth rates are then computed and smoothed for a 3-yr moving average. This enables us to compare the projected output growth using the data and the model-simulated counterfactuals that assume absence of the pandemic shock. By doing so, we are able to quantify the scar of the pandemic on the four subsectors.

The projected 3-yr MA output growth path is shown in Figure 7. We observe that there is a broad-based contraction among all sectors during the pandemic years. Specifically, the brown sectors are projected to have contracted more than the green sectors. Also, as expected, contact-sensitive sectors have contracted more than the non-contact sensitive sectors. This indicates the resilience of the green sectors and it has important policy implications.

If we now compare these estimates for output growth with the steady state growth rates for the four sectors as discussed in Section 4 and Figure 6, we can compute the extent of the scarring.[4] Our comparisons yield that the GCS sector contracted by more than 6% due to COVID from its projected steady state growth rate. GNCS on the other hand, improved, compared to its projected growth rates, which was calculated based on the pre-pandemic parameters.

For the brown sectors, however, the scarring due to the pandemic is more pronounced. In the BCS sector, the dip from its steady state projections in 2021 was the highest and the extent is -17%. The contraction in the BNCS sector in 2021 is nearly 10% from its steady state growth rate.

For the purposes of assessing what is the right policy intervention, however, for reviving the economy and bringing it back to an inclusive and sustainable growth path, it is imperative to consider the potential spillovers from and within different subsectors. This requires a way of quantifying the inter-linkages between each subsector, commonly referred to in the literature as the "Cascading Effect".

6 Cascading Effects

According to a recent interim report published by the Financial Stability Board (FSB 2022), there is a need to construct and disclose cross-industry metrics which help understand the true impact and spillovers of climate-related risks on different segments of the economy. Along these lines, we use the latest available Input-Output (IO) matrix released in 2003 assuming the structural relation between sectors remains unchanged over time.

We convert the IO matrix for our purpose in two stages of concordance. First, we collapse the IO matrix of 130 sectors into 27 industries according to the KLEMS database. By doing this, we obtain a 27×27 IO matrix in accordance with the KLEMS industry classification. [5] We then use our pre-constructed concordance from KLEMS to B,G$\times$CS, NCS, provided in Table 1 to collapse and obtain a 4×4 IO matrix for our purpose. This enables us to understand the input and output inter-linkages between the subsectors and help create

[4]Note that Figure 7 captures 3-yr MA numbers, which broadly capture trends, and hence these numbers are comparable with our simulations.

[5]See https://m.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=ID=936APE for the official KLEMS industry classification

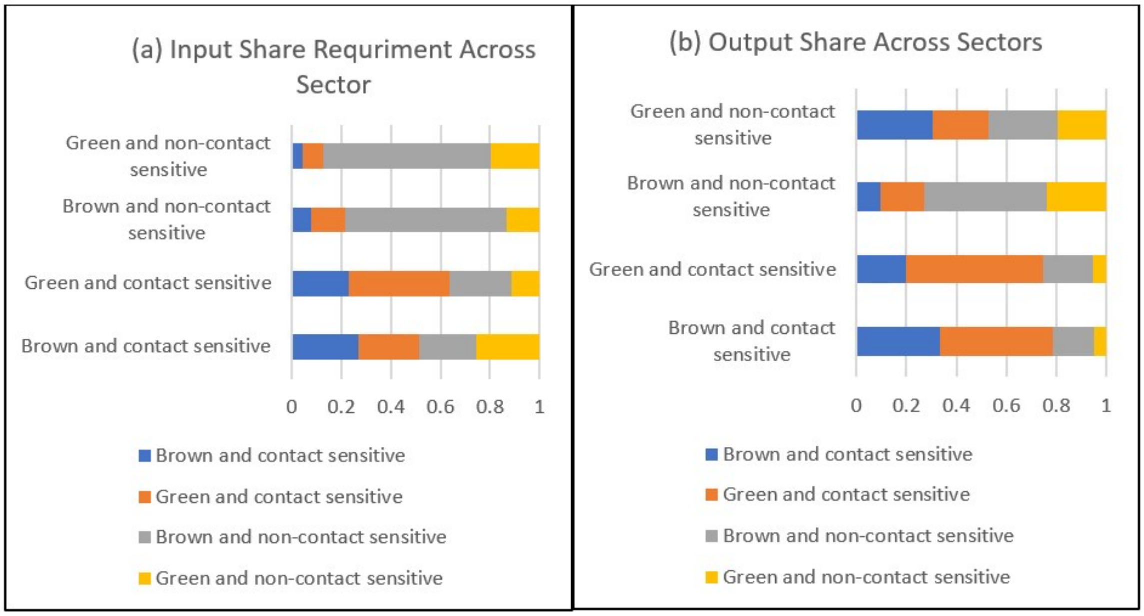

Figure 8: Input and Output Share Matrices for the Green and Brown Sectors

a structure to quantify the transition and physical risks while projecting the future aggregate and sectoral growth path for the economy.[6]

Figure 8 (a) provides the input share matrix between the four subsectors. We observe that the GNCS sector uses 67% of BNCS products as inputs. In terms of input dependence, this is much higher than the rest of the three products. Typically the BNCS sector includes industries that produce equipment and other related capital products (see Table 1), and a high share of these as capital inputs implies greater serviceability of capital and a more productive labour force (see IPR 2022). Therefore, if the BNCS sector faces significant transitional risk, this would pose a significant dent in the recovery of the GNCS sectors which contributes to over 20% of the total value added of the economy. The GCS sector, on the other hand, is self-reliant in terms of input dependence, with about 41% of all inputs coming from within the sector. However, it uses inputs from the BCS and BNCS sectors amounting to about 22.7% and 24.7%, respectively. This again suggests that even if growth in the GCS and GNCS sectors are to be our top policy priority for a green-sustainable

[6]To make the input share matrix for these 4 sectors, we divide each cell by the column sum of the 4×4 matrix. Similarly, to make the output share matrix each cell is divided by the row total of the 4×4 matrix.

and inclusive growth path, spillovers policy needs to take cognizance of supply linkages brown sectors, the bottlenecks that may arise from abrupt changes in this sector.

The BNCS sector, again, is self-reliant as its production depends significantly on inputs from its own sectors (of over 60 %). The BCS sector depends on over 50% of the inputs coming from the brown sectors. Turning to the sectoral output, for an emerging economy such as India, a crucial factor for growth is also output interdependence. Figure 8 (b) indicates the output composition, which represents a snapshot of a given subsector's importance in terms of the technological dependence on output production by other subsectors. It may be mentioned that adopting new technologies is costly, and it is difficult to change an existing production technology in the short run. For instance, as we see from Figure 8 (b), the largest portion of GNCS output goes towards producing output in the BCS sector (about 30%). On the contrary, 45.2% of total output produced by the BCS sector goes to of GCS sector as input. This evidence, along with the input share requirement as shown in Figure 8 (a), the output cascade across different segments.

7 Conclusion

The pandemic scar has engulfed the world over the past two years, and India is not an exception. There are several challenges for an emerging economy to recover from the scars of the pandemic, especially during times when the policy priority is to have a sustainable, green, and inclusive growth trajectory. With highly inter-related production technologies and with a slow-growing green sector, the Indian economy faces two-fold challenges that include reviving the hard-hit economy and moving towards a greener economy. In this paper, using KLEMS dataset we first segment the Indian economy into four segments, namely brown and green and contact sensitivity and non-contact sensitive industries. In our analysis of the pre-pandemic trends, we find the key factors of production - i.e., capital and labour have been slowing down since 2010 - way before the pandemic.

Furthermore, to have an estimate of the pandemic scarring, we estimate the counterfactual using a parsimonious model in the four sub-sectors. Thereafter, we extend the labour and capital stocks using appropriate data from different sources and estimate pandemic time decline in sectoral output. Our findings indicate that the pandemic scarring was lower for the green segment, which highlights its resilience.

As the next step for effective policy design, we evaluate the interdependence between green and brown industries using the KLEMS data-set and Input-Output matrix, which clearly indicate considerable interdependence and circularity among the sub-segments. Therefore, as we move toward sustainable growth and Netzero-related policies, sectoral interdependence could be a binding constraint. It is indeed the friction that brown industries are paying the market prices of fossil energy that do not include its social costs or costs of the negative externality, which has to be addressed with an appropriate incentive-penalty mechanism. It underlines the room for public policy, to push to economy toward an efficient and sustainable output growth trajectory with a greener economy as our policy priority.

Our findings indicate that the transition of the brown to green industries would necessitate the implementation of carefully calibrated public regulation to promote the implementation of greener technologies, by explicitly taking into account this transitional cost. We must emphasize the importance of output composition and the need for appropriate incentives, and technology transfer for a gradual transition towards a greener future.

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8 Appendix

Table 3: Concordance Between CMIE-CP and KLEMS Industries

INDUSTRY OF OCCUPATION [CMIE CP]	**KLEMS INDUSTRY**
Real Estate & Construction	Construction
Retail Trade	Trade
Public Administrative Services	Public Administrative Services
Education	Education
Defence Services	Public Administrative Services
Automobiles and Other Transport Equipment Manufacturers	Transport Equipment
Pharmaceutical Manufacturer	Chemicals and Chemical Products
Health Care	Health and Social Work
Food Industries	Food Products,Beverages and Tobacco
Wholesale Trade	Trade
Personal Professional Services	Business Service
Personal Non-Professional Services	Business Service
Textile Industries	Textiles, Textile Products, Leather and Footwear
Footwear and other Leather Industries	Textiles, Textile Products, Leather and Footwear
Metal Industries	Basic Metals and Fabricated Metal Products
Mines	Mining and Quarrying
Agriculture- allied activities	Agriculture- allied activities
Financial Services	Financial Services
Hotels and Restaurants	Hotels and Restaurants
Cement, Tiles, Bricks, Ceramics, Glass and other construction materials	Other Non-Metallic Mineral Products
Handicraft Industries	Textiles, Textile Products, Leather and Footwear
Machinery Manufacturers	Machinery, nec.
Travel and Tourism	Other services
IT & ITES	Post and Telecommunication
Gems & Jewellery	Manufacturing, nec; recycling
Chemical Industries	Chemicals and Chemical Products
Soaps, Detergents, Cosmetics, Toiletries	Chemicals and Chemical Products
Communication, Post & Courier	Post and Telecommunication
Utilities	Electricity, Gas and Water Supply
Crop Cultivation	Crop Cultivation
Plantation Crop Cultivation	Plantation Crop Cultivation
Fruits and Vegetable Farming	Fruits and Vegetable Farming
Media and Publishing	Pulp, Paper,Paper products,Printing and Publishing
Entertainment and Sports	Other services
Poultry Farming, Animal Husbandry and Vermiculture	Poultry Farming, Animal Husbandry and Vermiculture
Fishing	Fishing
Forestry including Wood Cutting	Wood and Products of wood