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Detecting technological progress in Russia: Intersectoral approach or the aggregate economy

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Abstract

We pioneer the estimation of technological progress parameters for Russia in the framework of the neoclassical theory. Implementing the CES production function (CES PF hereafter) as an instrument of output description, we construct a system of cointegrated time series which guarantee no spurious interpretations. Our analysis follows a logical transition from an aggregate to a sectoral level and is based on two convergent datasets of different length. For the aggregate economy most of our accepted models generally forecast a slight labor income share increase under capital-augmenting technical progress biased to labor. Selected models with structural break in 2008–2009 show below-unity elasticity of substitution between labor and capital. Sectoral estimates stand in support of labor income share (LS) growth across six of the eight analyzed economic sectors. We empirically illustrate the rule for LS direction in response to joint values of labor-to-capital elasticity of substitution and a combination of the relative factor intensity and the average growth rate of labor-to-capital ratio. The fact that the values of relative labor intensity in the Mining and Energy & Waste management sectors are less than the growth of labor-to-capital ratio provide no grounds for labor share rise. While our reduced-form evidence suggests that broad capital tax relaxations in these two sectors are unlikely to raise LS, this should be read as a hypothesis for future causal work rather than a policy prescription.

Keywords: labor income share, factor-augmenting technical progress, labor-augmenting technical change, capital-augmenting technical change, relative labor intensity, elasticity of substitution, sectoral decomposition of technological progress.
JEL classification: C00, E00, E01, E13, E17, J01.

1. Introduction

Labor income share (LS) dynamics is a controversial issue. On the one hand, labor share decline (triggered by the economy's digitalization) is a stylized fact appli-

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cable to a majority of developed countries, which is justified both by its downward trend over the last several decades and empirical estimates of factors influencing LS (Berg et al., 2018; Freeman, 2015; Manyika et al., 2019). On the other hand, even if in general digitalization leads to LS decline, it is important to outline the detailed mechanism for this. For instance, a long-term equilibrium should be maintained in the labor market in case new jobs emerge en masse (Acemoglu and Restrepo, 2018, 2019, 2020). Nevertheless, both research venues are designed to outline the drivers for labor income share dynamics or to make predictions about it.

In the current paper we pioneer the estimation of technological progress parameters for Russia on the aggregate and sectoral levels and hope to produce reliable forecasts of labor income share. Sectoral analysis is vital to interpret how the economy adapts to digitalization and automation in terms of its structure. Put another way, it answers whether the economy develops homogenously or if the changes that take place in one economic sector (i.e., industry—used interchangeably), inevitably compensate the lack of change in the other sector. In addition, sectoral decomposition of technological progress parameters may enlighten the problem of capital to seize the power over labor in a particular industry.

The remainder of the paper is organized as follows. Literature review section describes the theoretical framework of the paper and initiates the discussion on the interference of technical progress and labor income share. Methods section describes in detail the mathematics of CES production function and its properties regarding substitution elasticity of labor with capital and relative labor intensity. Data and preliminary facts section clearly states data sources and limitations associated with data availability for Russia and draws a connection to the analyzed variables. Next, results are presented. On the aggregate economy level, the elasticity of substitution is estimated, and the relative factor intensity is compared to capital-labor ratio growth rate. In addition, the labor income share forecasts are produced. Sectoral decomposition included the estimation of technological progress parameters only. Both bunches of results are simultaneously covered with real economic background.

2. Literature review

Labor income share decline is analyzed profoundly in a lot of countries. On the global level, the low price of investment (mainly induced by new technologies) explains roughly a half of the labor income share decline, which is robust to capital augmentation effects and professional skills evolution of the workforce (Karabarbounis and Neiman, 2014). In addition, pessimistic opinions cast doubts on the prevalence of the long-term revival of the labor market over its short-term shrinking—e.g., Berg et al. (2018) state that “real wages fall in the short run and eventually rise, but “eventually” can easily take generations.” However, the assumption of the economy balanced growth path (BGP[1]) implies the equilibrium in which new technologies may initially reduce labor costs, making technologies relatively more expensive and, subsequently, should increase the demand for labor, which is shown in theoretical papers by Acemoglu (2003) and Acemoglu and Restrepo (2018).

[1] Balanced growth path—is an equilibrium path towards which the economy strives to holding the growth rates of consumption, output, and capital stock the same.

In the frame of BGP several parameters are estimated to specify future labor share dynamics. First, the elasticity of substitution, commonly used in previous research, is designed to capture the level of interchangeability of labor with capital keeping all other factors unchanged. Here, an overview of substitution elasticity should be noted — a meta-regression analysis of 77 papers published between 1961 and 2017 determined the elasticity ranging from 0.45 to 0.87 for the aggregate economy with no significant deviations for the sectoral level analysis (Knoblach et al., 2020). Next, the relative factor intensity indicator parameterizes the direction of factor-augmenting technical progress (FATP or F-A — hereafter) (Acemoglu, 2003) to represent the influence of automation and digitalization on the economy. Ceteris paribus, the relative factor intensity is assumed to be constant over time and is analyzed in a tight connection with growth rates of capital-labor ratio (Acemoglu and Restrepo, 2018; Akaev et al., 2021). This helps to track the influence of technical change (in terms of its direction to labor or capital augmentation) on the economy and, therefore, to derive reliable estimates of LS dynamics.

Technical progress is required to be analyzed via its respective representation, intrinsic to a particular economy. The form of technical progress, implicitly assigned for a certain economy, should be empirically tested. For instance, Hicks-neutral technological progress (H-N — hereafter) is usually opposed to FATP, which implies clarifying the values of the parameters mentioned above, i.e., elasticity of substitution and the relative factor intensity — the second equals zero within H-N technical change. The Hicks-neutral technical change is better suited for a between-analysis exploiting panel data, i.e., intercountry or sectoral comparisons (Akaev et al., 2021; Karabarbounis and Neiman, 2014), whereas FATP is used for the analysis on the aggregate or the sectoral level with time series data to illustrate technical progress (Klump et al., 2007; Young, 2013). In addition, despite widely accepted skepticism about the credibility of Cobb–Douglas production functions in describing economic processes (e.g., the literature review Gechert et al., 2022, Havranek et al., 2019, other papers — Chilarescu, 2018, Knoblach and Stöckl, 2020, Pilnik and Radionov, 2022; Ziesemer, 2021), they should not be automatically swept aside in the future analysis but rather properly checked for applicability, e.g., Pilnik and Radionov (2022) point out analytical tractability and convenience in DSGE models construction (Pilnik and Radionov, 2021).

For the sake of consistency, technological progress should be interpreted on the sectoral level — this captures heterogeneity in development of economic sectors, which are different in several metrics. Initially such sectoral estimates were obtained by Young (2013) having estimated f.o.c. of CES production function in the design developed by Antras (2004). Technological progress is proved to be labor-augmenting in a significant percentage of KLEMS-classified U.S. economic sectors, which is in line with the same results on the aggregate level — the labor-to-capital elasticities of substitution are significantly below unity in both studies (Antras, 2004). However, similarly designed studies of R&D effects on sectoral technological progress in OECD countries (Smeets Kristkova et al., 2017) report that the existing large capital accumulation may induce capital-augmentation (labor-saving), meaning no Hicks-Neutrality. These results also refute Cobb–Douglas production function form as labor-to-capital elasticities of substitution are significantly below unity. Still, the revealed complementarity of manufacturing to R&D services makes the labor augment, i.e., R&D may increase the labor use in other non-R&D sectors.

Finally, speculating on a suitable production function for the Russian economy first, it is important to state that in principle the building of production functions was possible during the transitionary period of the 1990s (Bessonov, 2002). Second, there were quite a lot of attempts to describe the Russian economy with Cobb–Douglas production function trying to account for different factors such as high-quality education (Ovchinnikova, 2010) or oil prices and innovation (Kirilyuk, 2013). The latter paper also concerns the time series cointegration issue (however, it does not take it into account due to data insufficiency as the author reports) which is considered in our paper in great detail. In Kopoteva and Chyorniy (2011) the authors model post 2008-crisis development of the Russian economy via the modified Cobb–Douglas production function allowing for constant-rate-innovations. To contrast this with our paper, we also estimate the velocity of technological progress but we apply it to the sectoral decomposition of labor income share. All these issues are further investigated in our paper using CES- and Cobb–Douglas production functions.

3. Methods

The class of constant elasticity of substitution (CES) production functions (PF—hereafter) imposes that the substitution between capital and labor is constant. This includes the cases of Cobb–Douglas and Leontief PF with unity or zero substitution elasticity respectively. Here the CES-production function (see equation 1) allows not only to decide on the correct form of production function but also to incorporate FATP (in terms of its parameters) into the proposition of the balanced growth trajectory. In other words, similarly to (Antras, 2004; León-Ledesma et al., 2010; León-Ledesma and Satchi, 2019) the f.o.c. of CES production function (2) are used to estimate the elasticity of substitution (σ) and relative factor intensity (λ) parameters—(3) and (4) are the f.o.c. in the logarithmic form.

$$Y(L, K) = C\left(\alpha(A_t L)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(B_t K)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where A_t and B_t are the indexes of labor- and capital augmenting efficiency respectively; α is a distribution parameter; σ is the elasticity of substitution between capital and labor; $Y(L, K)$—value added; L—labor input in thousands of employees; K—capital stock.

$$\text{F.O.C.: } \frac{w}{r} = \frac{\alpha}{1-\alpha}\left(\frac{K}{L}\right)^{\frac{1}{\sigma}}\left(\frac{A_t}{B_t}\right)^{\frac{\sigma-1}{\sigma}} \text{ or } \frac{K}{L} = \left(\frac{1}{\alpha}-1\right)\left(\frac{w}{r}\right)^{\sigma}\left(\frac{A_t}{B_t}\right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where w—wage rate (total labor cost divided by L); r—rental rate of capital (see the explanation of its calculation in the Data and preliminary facts section).

As soon as the relative factor intensity is designed to be an instrument for the labor income share prediction, having postulated that the economy is on a balanced growth path, it evaluates the effect of technical progress on the economy by adding a respective parameter into the regarded CES production function. Relative labor intensity parameter $\lambda_L - \lambda_K$ (denotes $\lambda_L - \lambda_K = \lambda_{LK}$) becomes evident in the transition from equations (2) to equations (3) and (4) meaning that multipliers A_t and B_t set the development of technological progress in terms of labor and capital augmentation. Therefore, one can describe $A_t = e^{t\lambda_L}$ and $B_t = e^{t\lambda_K}$, where λ_L and λ_K should be interpreted as growth rates of labor and capital intensity. The parameter λ_{LK} is the aggregate growth rate of technical progress, which is the difference between the rate of labor-augmenting technical change and capital-augmenting technical change (LATC and CATC respectively). Next, considering equations (3) and (5) λ_{LK} may be rewritten in terms of parameters estimates β_{KL}, β_t as $\lambda_{LK} = \beta_t/(1-\beta_{KL})$ for linear time trend. Furthermore, nonlinearity in time modifies the relative factor intensity parameter as $\lambda_{LK_t} = (\tau_{t_i} - \tau_{t_{i-1}})\beta_t/(1-\beta_{KL})$—see the respective regression equations (7) and (8).

$$\ln\left(\frac{w}{r}\right) = \ln\left(\frac{\alpha}{1-\alpha}\right) + \frac{1}{\sigma}\ln\left(\frac{K}{L}\right) + \frac{\sigma-1}{\sigma}(\lambda_L - \lambda_K)t, \tag{3}$$

$$\ln\left(\frac{K}{L}\right) = \ln\left(\frac{1}{\sigma} - 1\right) + \sigma\ln\left(\frac{w}{r}\right) + \frac{\sigma}{\sigma-1}(\lambda_L - \lambda_K)t, \tag{4}$$

$$\ln\left(\frac{w}{r}\right) = \beta_0 + \beta_{KL}\ln\left(\frac{K}{L}\right) + \beta_t t + \varepsilon, \tag{5}$$

$$\ln\left(\frac{K}{L}\right) = \delta_0 + \beta_{wr}\ln\left(\frac{w}{r}\right) + \delta_t t + \varepsilon, \tag{6}$$

$$\ln\left(\frac{w}{r}\right) = \beta_0 + \beta_{KL}\ln\left(\frac{K}{L}\right) + \beta_t \tau(t) + \varepsilon, \tag{7}$$

$$\ln\left(\frac{K}{L}\right) = \delta_0 + \beta_{wr}\ln\left(\frac{w}{r}\right) + \delta_t \tau(t) + \varepsilon. \tag{8}$$

Equations (7) and (8) relax the linearity assumption imposed on the time trend in (5) and (6) with possible $\tau(t)$ time components, which stands either for time functional form in trend component (a–h) or for the same but with partial structural break (i–k).

The following $\tau(t)$ modifications are considered in this paper (m is iteratively chosen):

(a) $\tau(t) = 0$—Hicks-neutrality
(b) $\tau(t) = t$—linear trend
(c) $\tau(t) = \ln(t)$—logarithmic trend
(d) $\tau(t) = \ln(1 - e^{-t})$—logarithmic logistic trend
(e) $\tau(t) = \dfrac{m}{t}$—inverse function time trend
(f) $\tau(t) = e^{mt}$—exponential trend
(g) $\tau(t) = t^m$—trend component incorporating nonlinearity as power function
(h) $\tau(t) = \dfrac{1}{1+e^{mt}}$—logistic function trend
(i) $\tau(t) = \sum_{i=1}^{N+1}\beta_{t_i} t_i$—partial structural break on linear trend
(j) $\tau(t) = \sum_{i=1}^{N+1}\beta_{t_i} \ln t_i$—partial structural break on logarithmic trend
(k) $\tau(t) = \sum_{i=1}^{N+1}\beta_{t_i} e^{mt_i}$—partial structural break on exponential trend
(l) $\tau(t) = \sum_{i=1}^{N+1}\beta_{t_i} t_i^m$—partial structural break on power function time trend.

Regressions (9) and (10) are designed to capture full structural break abandoning time invariance of the substitution elasticity, i.e., $\varphi(\,)$ stands for the structural break in $\ln\left(\frac{K}{L}\right)$ or $\ln\left(\frac{w}{r}\right)$.

$$\ln\left(\frac{w}{r}\right) = \beta_0 + \beta_{KL}\,\varphi\left(\ln\left(\frac{K}{L}\right)\right) + \beta_t\,\tau(t) + \varepsilon, \tag{9}$$

$$\ln\left(\frac{K}{L}\right) = \delta_0 + \beta_{wr}\,\varphi\left(\ln\left(\frac{w}{r}\right)\right) + \delta_t\,\tau(t) + \varepsilon. \tag{10}$$

Regressions (7)–(8) and (9)–(10) both are cointegrating equations and include a time trend. Consequently, to avoid spurious regression the residuals must be tested for stationarity. Cointegration analysis requires to be relatively more strict in terms of critical values for ADF-test (MacKinnon, 1990; MacKinnon, 2010).

$$\theta = \frac{wL}{wL + rK}, \tag{11}$$

Regressions (5), (7), (9) are designed to calculate the forecasted $\ln(w/r)$ and to obtain the forecast for the labor income share denoted θ in formula (11). Our forecast procedure implied modelling all the variables included in the production function including the right-hand side of the regressions (5), (7), (9), i.e. capital and labor. Capital stock (K) growth is obtained as an average of the absolute yearly growth of capital stock weighted by GVA (Y) in each historical year, i.e., $\Delta K/Y$. Capital stock growth is calculated over the period after a possible structural break. The forecasted values of capital stock are calculated as the product of forecasted below-mentioned GVA (Y) and the above-mentioned weighted-by-GVA-capital-stock growth ($\Delta K/Y$). The growth rates for labor stock (L) and GVA (Y) are calculated as an average of their respective growth rates over the historical period after possible structural break. Then, the respective forecasted values of labor stock (L) and GVA (Y) are calculated using their own growth rates.

4. Data and preliminary facts

Two different datasets used in this paper are constructed on data from multiple sources. The first dataset stands for estimations on the aggregate economy level and covers the time period from 1990 to 2016. Real GVA, capital stock at constant national prices, and number of persons engaged are taken from PWT 10.0 database (Feenstra et al., 2021) holding the methodology described in (Feenstra et al., 2015). Labor compensation is calculated as a product of the value of the labor income share reported in PWT 10.0[2] and GVA in constant prices,[3] whereas capital compensation is the difference between GVA and labor compensation. Average wages are calculated as a ratio of labor compensation and the number of persons engaged; real interest rates on capital are capital compensation divided by capital stocks.

The second dataset is shorter (2004–2016) and is designed for panel data estimations on the sectoral level. The following indicators are used — value

[2] They calculate LS with variables at current national prices.
[3] All constant prices indicators are stated in 2017 national prices reported in U.S. dollars.

Table 1
KLEMS-classified decomposition of economic sectors.

Code	Sector name	Code	Sector Name
A	Agriculture, hunting, forestry and fishing	F	Construction
B	Mining and quarrying	GJ	Business services except real estate
C	Manufacturing	K	Real estate activities
DE	Electricity, gas and water supply	LQ	Community and social services

Source: Compiled by the authors.

added, labor compensation, number of FTE jobs (HSE, 2019) and balances of fixed assets (EMISS, 2018a), which is a proxy of net capital stocks in current prices (Voskoboynikov, 2012). In the absence of sectoral data for capital stock deflators balances of fixed assets (EMISS, 2018a) were recalculated into constant prices using capital volumes (EMISS, 2018b) and the growth rates of capital in current prices. Rosstat publishes capital indicators in later years but special corrections of labor compensation for hidden wages and self-employed are made in (HSE, 2019), which obstructs using the raw Rosstat data for wages without such corrections. The structure of the sectoral decomposition (see Table 1) mainly outlines the difference between services and production and is required to provide data convergence taken from the above-mentioned sources.

The International labor organization assigns Russia to the quadrant of countries with the rising or constant labor income share and the rising inequality measured with the Gini index — see graph in (ILO, 2015). Indeed, looking at the relationship between relative wages and relative factor supply, an almost identical change of relative wage can be noted in response to a change in relative factor supply (see 1.02 trend coefficient on Fig. 1). Fig. 1 also reveals that the ratio of relative

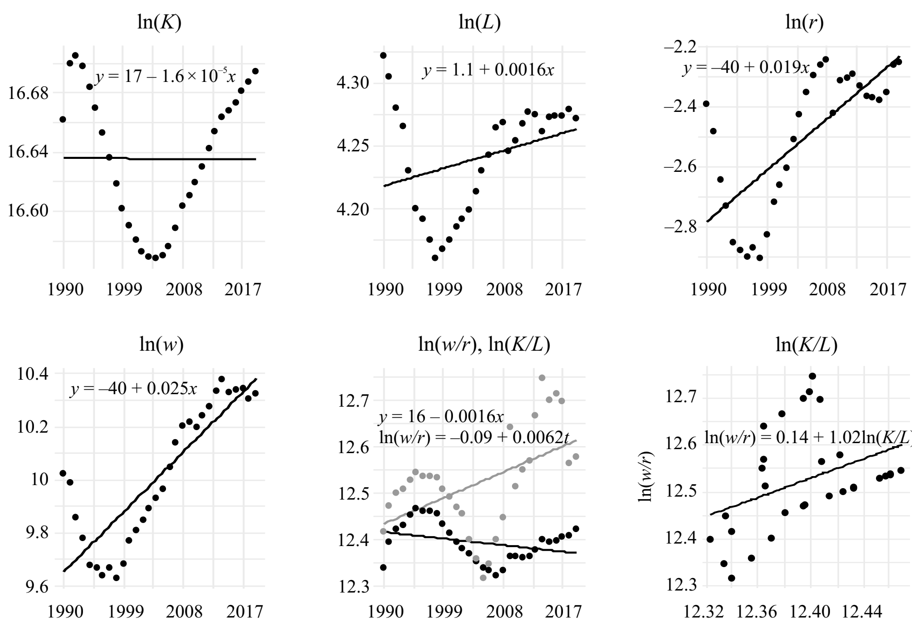

Fig. 1. Assembling $w/r \sim K/L$ scatterplot from its components for the aggregate Russian economy.

Source: Authors' calculations.

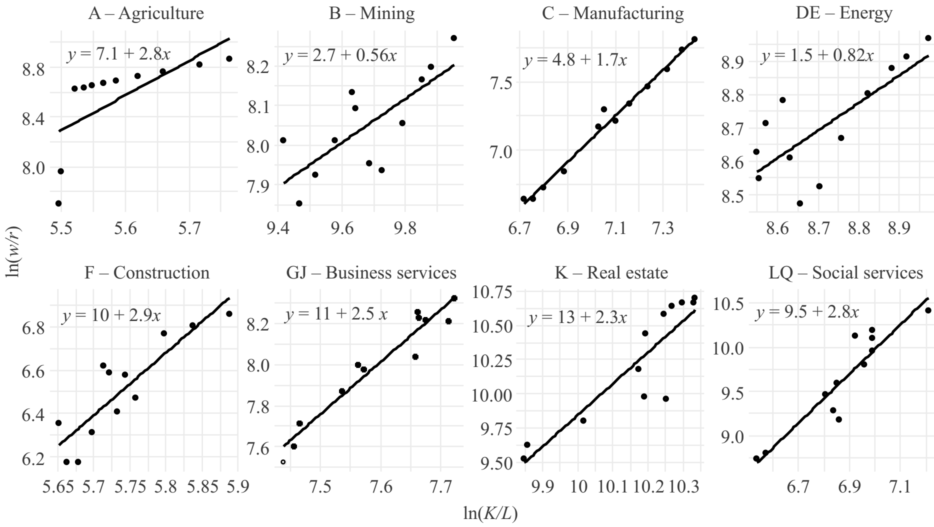

Fig. 2. Relative wages against relative factor supplies: sectoral decomposition.

Source: Authors' calculations.

wages ln(*w/r*) trend is positive (+0.62% a year), which in absolute value is higher than the negative trend of the relative factor supply ratio ln(*K/L*) (–0.16% a year). This is because wages grow 1.3 times quicker than the interest rate on capital (judging by the average annual growth rate 2.5% a year as opposed to 1.9% a year respectively), whereas capital stock is almost constant along with the labor supply increase by 0.16% a year.

A closer look at *w/r* to *K/L* trends (for the later period 2005–2016 and decomposed into 8 economic sectors — see Fig. 2) clarifies that in all sectors relative wages unsurprisingly grow in response to the growth of the rental rate of capital. The relative factor supply increases in all sectors and its growth is faster than relative wages in all sectors but B and DE (see the central graph in Fig. A1 in Supplementary material 1). The growth of labor-to-capital ratio originates from the fact that capital stock growth (even slight growth) exceeds labor supply growth (see Fig. A1 in Supplementary material 1 that the slope coefficients of trend regressions for ln(*K*) exceed the same metrics for ln(*L*)). The relative wages ratio also grows in all sectors. However, in sectors B and DE the absolute real wages fall, which is a reason for a slower growth of relative wages than the growth rate of relative factor supplies in these two sectors and therefore, the acute angle of the trend for ln(*w/r*) and ln(*K/L*). This may explain the increased labor substitution in these two sectors, which potentially is a harmful factor for the labor income share.

5. Estimations for the aggregate economy

First, H-N and F-A technical progress models were investigated (see Table 2 for the regression (7) estimation with H-N or different specifications of FATP). Introducing a trend component $\tau(t)$ into the initial model with H-N technical change (thereby moving to FATP) has not improved the model in terms of cointegration between relative wages ln(*w/r*) and relative labor supply ln(*K/L*) and

Table 2
Parameters estimates for regression 7 with various trend specifications (a-g).

Time trend specification	β_0	β_{KL} (*s.e.*)	β_t	R^2_{agj}	Cointegration test, ADF statistic, lag = 1[a)]	Autocorrelation test, D–W, *p*-value
$\tau(t) = 0$	–0.137	1.022 (0.451)		0.12	–1.92	3.091E–11
$\tau(t) = t$	–7.634	1.615 (0.338)	0.009***	0.56	–2.04	1.10E–07
$\tau(t) = \ln(t)$	–4.549	1.364 (0.404)	0.065**	0.35	–1.83	1.03E–09
$\tau(t) = \ln(1 + e^{-t})$	0.752	0.950 (0.462)	–0.261	0.11	–1.41	3.24E–11
$\tau(t) = \frac{m}{t}(m = -0.196)$	0.029	1.010 (0.442)	0.725	0.16	–1.47	8.02E–11
$\tau(t) = e^{mt}(m = 0.05)$	–5.795	1.464 (0.320)	0.075***	0.59	–1.95	3.72E–07
$\tau(t) = t^m(m = 1.9)$	–5.879	1.478 (0.312)	3.92E–04***	0.61	–1.96	6.62E–07
$\tau(t) = \frac{1}{1 + e^{mt}}(m = 0.01)$	–5.902	1.618 (0.338)	–3.521***	0.56	–2.04	1.07E–07

Note: Significance level of β_0, β_t: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; for β_{KL} standard errors are given in parentheses; for cointegration test McKinnon (2010) critical value calculated at 10% significance level is –3.74 (–3.19 for H-N model); autocorrelation tests are reported only with *p*-values for better guidance.
[a)] Maximum significant lag of PACF of residuals from each of the models reported.
Source: Authors' calculations.

autocorrelation in residuals. To fulfil the cointegration requirement, the residuals of regression 7 must satisfy that the ADF statistics is less than the critical values for the Engle–Granger test developed by MacKinnon (1990, 2010).[4] Autocorrelation of the first order in residuals may be checked with the Durbin–Watson test (H_0: No autocorrelation). Yet, the conditions for cointegration or absence of residuals autocorrelation are not fulfilled for both H-N and FATP models, reported in Table 2 (see two columns on the right-hand side of Table 2). Hence, these models cannot reliably reflect the nature of technological development in Russia.

Recalling the Fig. 1 the dots for $\ln(w/r)$ and $\ln(K/L)$ are poorly approximated with a straight line, which is supported by a relatively low $R^2_{adj} = 0.12$ (see the first row in Table 2). Hence, a polyline with break would better fit the data. This provides grounds for further structural break analysis.

Table 2 contains the estimated models with partial structural breaks found in the trend component at 2008 or 2009 (immediately after financial crisis) via the Sup F test, the χ^2 distribution critical values (Andrews, 1993; Zeileis et al., 2002). Owing to the insignificance of β_{t_1} we additionally reestimated each model without the before-break trend component. This has not significantly affected the estimates of β_{KL} and β_{t_2}. Allowing for structural breaks has improved cointegration in case of the logarithmic trend (see lines 3–4 in Table 3 that the ADF-test statistics is less

4 According to McKinnon (1990, 2010), critical value in Engle–Granger test depends on sample size, test specification (with or without trend), the number of cointegrating equations N. Hence, we report critical values at 10% level of significance for two cointegrating equations ($N = 2$) with linear trend case for F-A models as –3.74 for 30-year sample (MacKinnon, 2010) and with No Trend case (MacKinnon, 2010) for H-N models as –3.19.

Table 3
Regression 7 parameters estimates — partial structural breaks.

$\tau(t)$	β_0	β_{KL} (s.e.)	β_{t_1}	β_{t_2}	SB year Sup F	Cointegration test			Autocorrelation tests	
						ADF (lag)	McKinnon (2010) critical values[a]	Durbin–Watson	Breusch–Godfrey, order 1	Breusch–Godfrey, order 2
$\sum_{i=1}^{2}\beta_{t_i}t_i$	–2.618	1.218 (0.260)	–0.003	0.006***	2008 14.01**	–3.46 (0)	–3.74 / –4.35	0.005	0.119	0.257
$\beta_{t_2}t_2$	–4.046	1.331 (0.237)		0.007***		–3.13 (0)		0.002	0.053	0.134
$\sum_{i=1}^{2}\beta_{t_i}\ln t_i$	–2.448	1.204 (0.235)	–0.010	0.050***	2009 19.65***	–4.58 (2)	–3.74 / –4.46	1.37E.–05	0.002	4.39E–04
$\beta_{t_2}\ln t_2$	–2.962	1.244 (0.224)		0.056***		–4.45 (2)		3.44E.–05	0.002	0.001
$\sum_{i=1}^{2}\beta_{t_i}e^{0.05t_i}$	–2.039	1.175 (0.252)	–0.042	0.030*	2008 12.76**	–3.59 (0)	–3.74 / –4.35	0.008	0.144	0.282
$\beta_{t_2}e^{0.05t_2}$	–3.619	1.297 (0.244)		0.049***		–2.91 (0)		0.001	0.030	0.081
$\sum_{i=1}^{2}\beta_{t_i}t_i^{1.9}$	0.788	0.944 (0.291)	–3.38E–04	2.96E–04***	2008 10.38**	–3.25 (0)	–3.74 / –4.35	0.002	0.070	0.154
$\beta_{t_2}t_2^{1.9}$	–2.434	1.202 (0.256)		3.62E–04***		–1.78 (1)		1.75E.–04	0.008	0.025

Note: Significance level of β_0, β_t: $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$; for β_{KL} standard errors are given in parentheses; for cointegration test McKinnon(2010) critical values are calculated at 10% significance level and stated with '/' for full sample and after-break subsample; autocorrelation tests are reported only with *p*-values for better guidance.
[a] For the full 30-year sample the 10% critical value equals –3.74 whereas for the truncated after-break subsample –4.35 or –4.46 for after-2008 or after-2009 sample respectively (MacKinnon, 2010).
Source: Authors' calculations.

than minus 3.74 — the above-mentioned McKinnon critical value for F-A models) and removed autocorrelation in residuals of all other models.[5] Akaev and Rogachev (2022) also confirmed viability of the model with partial SB and logarithmic trend over a similar timespan based on the research for 12 European countries.

In the extension of structural breaks analysis models with a full structural break in 2008 and 2009 were estimated, which means that β_{KL} and consequently the elasticity of substitution (σ) before and after the breaking point may be different. Table 4 contains the respective estimates of the H-N model and the FATP models previously reported in Table 3 with partial SB estimates. In comparison to the H-N model from Table 2 (line 1) the H-N model with SB fulfils cointegration and autocorrelation conditions and has two significantly different[6] β_{KL} parameters. For the FATP models the estimators β_{KL_1} and β_{KL_2} mainly converge in value to β_{KL} of the models with partial SB in Table 3 and the models without SB — see Table 2 (lines 2–3, 5–6). However, these β_{KL_1} and β_{KL_2} in all four instances are not significantly different from 1, which added to the insignificance of β_{t_1} and β_{t_2} cast doubts on the relevance of full SB in models with FATP. The cointegration requirement under FATP holds in the models with the logarithmic trend (–4.58 is less than –4.46 — the critical value for the after-break subsample), the exponential trend (–3.80 < –3.74 - critical value for full sample only), and the power function trend (–3.78 < –3.74) whereas only the models with linear and exponential trend (lines 2 and 4 in Table 4) have no autocorrelation in residuals according to both Durbin–Watson and Breusch–Godfrey tests.

In summary, none of the models without SB demonstrated cointegration and no autocorrelation in the residuals, whereas the models with SBs performed better. The H-N model with a break fulfilled cointegration and its residuals are free from autocorrelation. Models with full SB and a logarithmic, exponential or power function trend showed cointegration but failed to reject autocorrelation in the residuals. Partial SB was effective in terms of cointegration only for the model with logarithmic trend.[7]

The aggregate economy elasticity of substitution (σ) has similar estimates across regarded models with different trend components, which amount to an average of 0.78 (see Table 5). The estimates of the best models (depicted with superscript "+") vary between 0.67 and 0.83 as only five models fulfilled selection criteria mentioned in previous paragraph.

It is remarkable that Cobb–Douglas PF should not be falsely admitted for the models with FATP depic ted in Table 3 and Table 4 (lines 2–5) under the excuse of failing to reject the null hypothesis $\beta_{KL} = 1$.[8] First, β_{t_2} are significant in Table 3. Second, presumable dropping of insignificant β_{t_1} and β_{t_2} from the models with full SB depicted in Table 4 would result in the H-N model (see line 1 of Table 4), in which $\beta_{KL_1} \neq 1$ or $\beta_{KL_2} \neq 1$. Thus, Cobb–Douglas PF form is empirically rejected.

5 We have empirically noticed a peculiar tradeoff between cointegration and absence of residuals autocorrelation.

6 Apart from the significance of structural breaks confirmed with supF test statistic (conducted during the estimation of models) we judge on the difference of β_{KL_1} and β_{KL_2} by the fact that both of them are significantly different from unity, which having been true would imply Cobb–Douglas PF.

7 In pursuit of getting rid of autocorrelation we additionally estimated VECM model (see Fig. A3 in Supplementary material 1) but we believe that the timespan of 30 years is exceptionally short to consider the presence of autocorrelation as a strict filter for model selection.

8 See the respective β_{KL} parameters estimates and their standard errors in parentheses in Tables 3 and 4.

Table 4

Regression 9 parameters estimates with breaking point in $\ln(K/L)$ and trend $\tau(t)$.

$\varphi(\ln(K/L))$, $\tau(t)$	β_0	$\beta_{KL_1}(s.e.)$	$\beta_{KL_2}(s.e.)$	β_{t_1}/β_{t_2}	R^2_{adj}	SB year Sup F	Cointegration test			Autocorrelation tests	
							ADF (lag)	Critical value[a)]	Durbin–Watson	Breusch–Godfrey, order 1	2
$\tau(t) = 0$ (H–N)	–5.878	1.479 (0.235)	1.493 (0.235)		0.77	2008 12.36^{**}	–3.75(0)	–3.19 / –3.45	0.013	0.141	0.271
$\tau(t) = \sum_{i=1}^{2} \beta_{t_i} t_i$	–4.200	1.345 (0.312)	1.353 (0.318)	–0.002 / 0.002	0.76	2008 12.66^{**}	–3.72(0)	–3.74 / –4.35	0.004	0.163	0.293
$\tau(t) = \sum_{i=1}^{2} \beta_{t_i} \ln t_i$	–3.071	1.254 (0.251)	1.276 (0.264)	–0.009 / –0.033	0.78	2009 19.79^{***}	–4.58(2)	–3.74 / –4.46	4.13E–06	0.002	2.99E–04
$\tau(t) = \sum_{i=1}^{2} \beta_{t_i} e^{0.05 t_i}$	–4.604	1.379 (0.335)	1.389 (0.342)	–0.017 / 0.005	0.76	2008 13.30^{**}	–3.80(0)	–3.74 / –4.35	0.005	0.169	0.277
$\tau(t) = \sum_{i=1}^{2} \beta_{t_i} t_i^{1.9}$	–4.409	1.361 (0.364)	1.373 (0.368)	–9.65E–05 4.12E–05	0.76	2008 12.48^{**}	–3.78(0)	–3.74 / –4.46	2.28E–05	0.004	0.003

Note: Significance level of β_0, β_i: $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$; for β_{KL} standard errors are given in parentheses; for cointegration test (McKinnon, 2010) critical values are calculated at 10% significance level and stated with '/' for full sample and after–break subsample; autocorrelation tests are reported only with p-values for better guidance.

[a)] For F-A models the full 30-year sample the 10% critical value equals –3.74 whereas for the truncated after-break subsample –4.35 or -4.46 for after-2008 or after-2009 sample respectively (MacKinnon, 2010 p. 14); for H-N model 10% critical value equals –3.19 for full sample and –3.45 for after-2008 subsample (MacKinnon, 2010 p. 13).

Source: Authors' calculations.

Table 5
Estimates of labor-to-capital elasticity of substitution—aggregate economy.

	H-N technical progress	F-A technical progress			
		t	Nonlinear time		
			$\ln(t)$	$e^{0.05t}$	$t^{1.9}$
No SB	0.98	0.62	0.73	0.68	0.68
Partial SB	–	0.82	0.83^{+}	0.85	1.06
Partial SB with t_2 only	–	0.75	0.80	0.77	0.83
Full SB (σ_2 are reported)	0.67^{+}	0.74	0.78^{+}	0.72^{+}	0.73^{+}

Note: $^{+}$ denotes models that meet the selection criteria described in Section 5.
Source: Authors' calculations.

5.1. Discussion on relative labor intensity (λ_{LK}).

Let us recall that relative labor intensity parameter (λ_{LK}) is the difference between the rates of labor and capital intensity—λ_L and λ_K. As was mentioned in the Methods section these parameters constitute $A_t = e^{t\lambda_L}$ and $B_t = e^{t\lambda_K}$ of CES production function and should be interpreted as growth rates of labor and capital intensity and λ_{LK} as the aggregate growth rate of technical progress. In other words, it reflects the direction of technical change, i.e., whether LATC is expected to prevail the CATC. Not unexpectedly, for Hicks-Neutral technical change $\lambda_{LK} = 0$, as both capital and labor growth are assumed to equally add to economic growth, keeping capital and labor shares in national income constant. Therefore, $\lambda_{LK} > 0$ should indicate the tendency for approaching labor-augmenting technical change with an increase in labor income share. However, empirical estimates on relative labor intensity show that this is not always true. Within their simple exercise, Akaev et al. (2021) show that the increase in the λ_{LK} parameter may be conditioned not only on labor-intensive innovations but on monopoly power of a capitalist, which causes a slowdown or a decrease in the growth of relative wages. For instance, given that the substitution of labor with capital is not flexible ($\sigma < 1$) even if $\lambda_{LK} > 0$ the labor share decreases in case $\lambda_{LK} > d\ln(K/L)$ (in case relative labor intensity exceeds the growth rates of capital-labor ratio) and increases if vice versa. Otherwise, when $\sigma > 1$, the labor share is expected to decrease if $\lambda_{LK} < d\ln(K/L)$. We further would refer to a rather general statement of this problem adding to the excessive monopoly power of capitalists also the weakened bargaining power of labor. Discerning between these issues lies beyond the scope of the current macro-based research and leaves space for a separate paper stated on micro-level data.

For each of the selected models of the regression 7 (H-N model with full SB, three versions of CES PF with full SB, and one model with partial SB in logarithmic time trend) forecasting procedure included 1000 imitations for the LS level and confidence interval. Figs. 3 and 4 illustrate[9] the above-mentioned rule that provided $\sigma < 1$ LS decreases upon $\lambda_{LK} > d\ln(K/L)$ (see historical data on graphs before 2008) and increases when $\lambda_{LK} < d\ln(K/L)$ (see historical data after 2008 and LS forecasts of model with partial SB and logarithmic trend, of model with full SB and exponential or power function trend. Table 6 contains the produc-

[9] Figs. A2.1–A2.5.2 in Supplementary material 1 depict in discrete manner the forecasts of LS and λ_{LK} compared with $d\ln(K/L)$

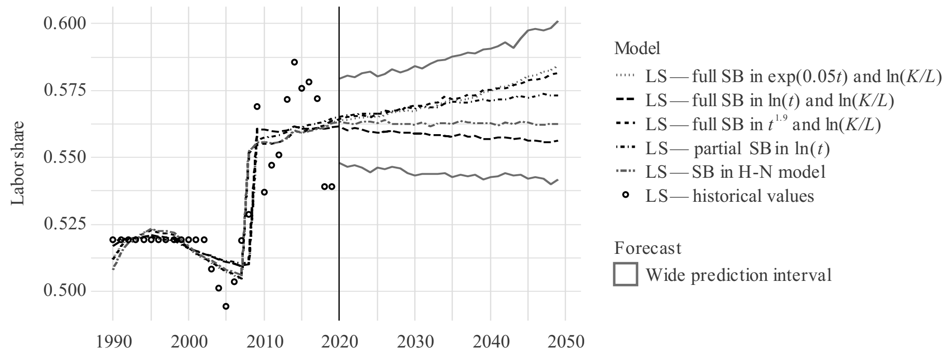

Fig. 3. LS forecasts for aggregate economy (five selected models).

Source: Authors' calculations.

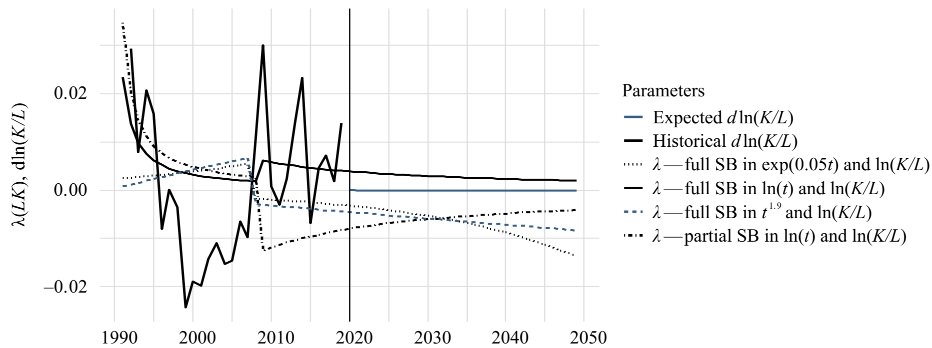

Fig. 4. The relative labor intensity λ_{LK} compared with labor-to-capital growth ratio — $d\ln(K/L)$.

Source: Authors' calculations.

tion function parameters which determine LS dynamics on the forecast horizon. As soon as $\lambda_{LK} < 0$ in the three aforementioned models (providing evidence for slight capital-augmentation), the expected direction of the LS trend for the Russian economy is imperceptibly increasing — see Fig. 3 (0.8, 2, and 2.2 pp respectively for the three above-mentioned models over the forecast period).

However, Hicks-neutral model and FATP model with full SB and logarithmic trend are not so optimistic (see the respective lines on Fig. 4). Hicks-neutral model, which is the sole to fulfil both autocorrelation and cointegration conditions for model quality, states LS to be constant at 56.3% over the forecast horizon. The second model shows 0.4 pp LS decrease from 56% to 55.6% over a 30-year-forecast (this fact is not unexpected owing to $\sigma < 1$ and $\lambda_{LK} > d\ln(K/L)$).

The prediction interval depicted on Fig. 3 is obtained through the union of prediction intervals of all five above-mentioned models. Hence, such an interval adjusted with the greatest minimum and the greatest maximum frontiers among all models has an amplitude of variation 3.6 pp in the beginning and 5.9 pp at the end of the forecast (ranging from 54.6% to 58% and from 54.0% to 59.9% respectively).

In summary, the Russian economy on the aggregate level may be described with the five selected models, which allow producing respective LS forecasts. CES PF with partial SB in logarithmic trend or with full SB and exponential or

Table 6
LS forecast and parameters for the aggregate Russian economy.

Technical progress bias to	CATC or LATC	LS gauging parameters					Forecast dynamics		
		λ_{LK}	$\overline{d\ln\left(\frac{K}{L}\right)}$	σ	LS is expected to…	Model	2020	2050	Change
labor $\lambda_{LK} < 0$ $\sigma < 1$	CATC	–0.008 ↗ –0.004	0.001	0.83	***grow*** $\lambda_{LK} < d\ln\left(\frac{K}{L}\right)$ $\sigma < 1$	Logarithmic trend with partial SB	56.6	57.4	+0.8
capital $\lambda_{LK} > 0$ $\sigma < 1$	LATC	0.004 ↘ 0.002	0.001	0.78	***fall*** $\lambda_{LK} > d\ln\left(\frac{K}{L}\right)$ $\sigma < 1$	Logarithmic trend with full SB	56.0	55.6	–0.4
labor $\lambda_{LK} < 0$ $\sigma < 1$	CATC	–0.003 ↗ –0.014	0.001	0.72	***grow*** $\lambda_{LK} < d\ln\left(\frac{K}{L}\right)$ $\sigma < 1$	Exponential trend ($e^{0.05t}$) with full SB	56.4	58.4	+2.0
labor $\lambda_{LK} < 0$ $\sigma < 1$	CATC	–0.005 ↘ –0.008	0.001	0.73	***grow*** $\lambda_{LK} < d\ln\left(\frac{K}{L}\right)$ $\sigma < 1$	Power function trend ($t^{1.9}$) with full SB	56.4	58.2	+2.2
Hicks-Neutral	H-N	–	0.001	0.67	Constant	H-N	56.3	56.2	–0.1

Note: CATC—capital-augmenting technical progress; LATC—labor-augmenting technical progress.
Source: Authors' calculations.

power function trend indicates an up to 2.2 pp LS growth under CATC ($\lambda_{LK} < 0$) but technological progress is biased to labor (because relative marginal product MP_L/MP_K is inclined towards labor[10]). CES PF with full SB and logarithmic trend forecasts a miniscule 0.4 pp LS decline under LATC ($\lambda_{LK} > 0$) and technological progress is biased to capital[11]. H-N model with SB shows LS stability over the next 30 years. Hence, Fig. 4 contains a set of forecast lines, which range from 55.6% to 58.4%, and the cloud of prediction intervals of these forecasts varies from 54.2% to 59.9% at the end of the forecasts. As soon as the five selected models provide controversial conclusions on the LS trend in future (though the generalized trend for them is slightly upward), LS requires further clarification in sectoral analysis to outline the direction of technical change on the sectoral level for Russia.

6. Sectoral analysis

Historical LS calculated with labor compensation and current GVA taken from (HSE, 2019) has an increasing trend and reaches 65.6% of GVA in 2016 for the aggregate economy. This contrasts with the level of aggregate LS discussed above, which approaches only 58–59% in 2015–2016. Such a distortion is explained by the adjustment for shadow economy and the self-employed made in NRU HSE (2019).

The sectoral approach exploits panel data represented with 8 economic sectors for 12 years (2005–2016). Unfortunately, such a short time span is conditioned on the availability of sectoral statistics for labor compensation, available only up to 2016 at (HSE, 2019) with all necessary adjustments for the self-employed and "hidden" wages and the absence of deflators for capital.[12] First, the year 2005 is a viable starting point for sectoral analysis not only due to capital stocks sectoral data availability from 2005, but also due to the detected structural break in historical data around the year 2008 (see graphs in Fig. 1, 3 and Fig. A.1 in Supplementary material 1). Second, sectoral decomposition shows compliance with the estimates for the aggregate economy in terms of LS trend, despite the different combination of technological parameters (joint values of σ and λ_{LK} with $d\ln K/L$). In a further part of this section sectoral estimation is illustrated as a logical extension of the aggregate economy analysis.

Table 7 outlines models with Hicks-neutral and Factor-augmenting technical progress implying variability in parameter aggregation by sectors (either the intercept

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[10] Considering technical progress (TP) bias to labor or capital implies tracking the influence of only TP parameters (σ and λ_{LK}) on marginal product $\frac{MP_L}{MP_K}$ and may not correspond to LS growth or fall as the latter should take into account labor-to-capital ratio $\left(\frac{K}{L}\right)$. Recall that FATP CES PF in its f.oc. implies $\frac{MP_L}{MP_K} = \frac{\alpha}{1-\alpha}\left(\frac{K}{L}\right)^{\frac{1}{\sigma}}\left(\frac{A_t}{B_t}\right)^{\frac{\sigma-1}{\sigma}}$.

Therefore if $\left.\begin{matrix} \lambda_{LK} < 0\ (CATC) \Rightarrow \frac{A_t}{B_t} = e^{t\lambda_{LK}} < 1 \\ 0 < \sigma < 1 \Rightarrow \frac{\sigma-1}{\sigma} < 0 \end{matrix}\right\}$ then $\left(\frac{A_t}{B_t}\right)^{\frac{\sigma-1}{\sigma}} > 1$. Thus, $\lambda_{LK} < 0\ (CATC)$ and $0 < \sigma < 1$ result in bias of TP toward labor.

[11] In this case TP "remunerate" capital more.

[12] As soon as Rosstat does not publish deflators for capital, we had to manually recalculate into constant prices the capital stock published by Rosstat (in Russian) in current prices (https://fedstat.ru/indicator/40442) using capital volumes (https://fedstat.ru/indicator/36733#) and the growth rates of capital in current prices (https://fedstat.ru/indicator/40442).

Table 7
Regression 7 parameters estimates across 8 economic sectors.

Regression parameter	Sector	Hicks–neutral		Factor–augmenting	
		(1)	(2)	(3)	(4)
Common β_0		-6.015^{***}		2.784	
β_0	A		-7.084^{**}		50.172^{***}
	B		2.663		–31.513
	C		-4.768^{***}		–12.027
	DE		1.528		–13.897
	F		-9.988^{**}		–3.704
	GJ		-11.273^{***}		–1.987
	K		-13.137^{***}		3.922
	LQ		-9.496^{***}		4.035
β_{KL}	A	2.605^{***}	2.796^{***}	0.970^{***}	-7.737^{***}
		(0.168)	(0.541)	(0.366)	(1.730)
	B	1.453^{***}	0.557^{*}	0.545^{**}	4.203^{*}
		(0.097)	(0.286)	(0.213)	(2.209)
	C	1.869^{***}	1.693^{***}	0.555^{*}	2.788^{**}
		(0.133)	(0.198)	(0.301)	(1.313)
	DE	1.688^{***}	0.823^{**}	0.677^{***}	2.650^{**}
		(0.108)	(0.325)	(0.236)	(1.066)
	F	2.182^{***}	2.874^{***}	0.598^{*}	1.751^{*}
		(0.164)	(0.679)	(0.354)	(0.927)
	GJ	1.845^{***}	2.537^{***}	0.639^{**}	1.282
		(0.124)	(0.472)	(0.269)	(0.865)
	K	1.598^{***}	2.298^{***}	0.674^{***}	0.560
		(0.093)	(0.284)	(0.201)	(0.361)
	LQ	2.276^{***}	2.782^{***}	0.891^{***}	0.701^{*}
		(0.137)	(0.263)	(0.303)	(0.370)
β_t	A			0.055^{***}	0.267^{***}
				(0.014)	(0.043)
	B			–0.001	–0.171
				(0.014)	(0.104)
	C			0.076^{***}	–0.075
				(0.023)	(0.089)
	DE			0.003	-0.077^{*}
				(0.014)	(0.044)
	F			0.045^{***}	0.025
				(0.012)	(0.018)
	GJ			0.055^{***}	0.038
				(0.013)	(0.025)
	K			0.091^{***}	0.095^{***}
				(0.013)	(0.017)
	LQ			0.111^{***}	0.119^{***}
				(0.017)	(0.019)
R^2_{adj}		0.98	0.98	0.99	0.99
F		500.53^{***}	$16\,634.71^{***}$	564.21^{***}	$26\,717.84^{***}$

Source: Authors' calculations.

or β_{KL} is decomposed by sectors in regression output). There are no low values in determination indexes for these models, hence, none of them can be counted as inappropriate by default. To overcome uncertainty regarding these models, the best one should be chosen with attention and in compatibility with estimates on aggregate economy.

Hicks-neutral sectoral β_{KL} estimates (see columns 1–2 in Table 7) are mostly greater than one, which is in line with β_{KL} = 1.022 previously estimated in Hicks-neutral model for the aggregate economy. Slacking the restriction for a single (unified) constant term in each sector has not affected β_{KL} estimates except for sectors B and DE in which introducing an individual intercept has switched β_{KL} from 1.453 to 0.557 and from 1.688 to 0.823 respectively. Individual intercepts are supposed to contain characteristics intrinsic to a particular industry. However, standard errors of β_{KL} as well as their values in models with individual sectoral intercepts (columns 2, 4 in Table 7) tend to be higher than those in models with restricted common intercept (columns 1, 3 in Table 7). Moreover, for instance, for the FATP models the respective sectoral β_{KL} values in columns 3–4 of Table 7 differ from each other significantly. These issues indicate that decomposing a common constant term may introduce multicollinearity into the model's estimates for each sector.

Hicks-neutral technological progress model with SB has proven to be viable for the aggregate economy. In sectoral decomposition H-N model with individual intercepts (column 2 of Table 7)[13] shows cointegration only in sectors C, DE and K (in DE and K autocorrelation is present as H_0 in Durbin–Watson test is failed to be rejected at 5% level of significance) — see Table 8. The sectoral factor-augmenting technical progress model with individual intercepts (column 4 in Table 7) illustrates that cointegration holds and residual autocorrelation is absent only in sectors C and DE (in sector C $\beta_t = -0.075$ is not significant). Thus, among sectoral estimates with individual intercepts, only Hicks-neutral model for sector C and factor-augmenting model for sector DE are viable.

The above-mentioned multicollinearity issue and fulfilling the cointegration-autocorrelation requirement only for sectors C, DE and K in models with individual intercepts necessitate models with a restricted constant term to outline parameters for other sectors (columns 1, 3 in Table 7). Unfortunately, it is not possible to test cointegration and autocorrelation for these models as the common constant term may be obtained only in panel estimation but not in the independent estimation of sectoral time series as has been done for the model depicted in columns 2 and 4 of Table 7.

Table 9 contains labor-to-capital substitution elasticities for models from Table 7 reported in the same order. For models with individual intercepts (columns 2 and 4 in Table 7) σ-s are reported only for sectors C, DE and K, which have been proven to be viable in terms of cointegration and autocorrelation (see Table 7 and above). H-N model with common intercept reveals $\sigma < 1$, whereas FATP model with common intercept shows $\sigma > 1$. In the latter case σ are not significantly different from unity for all sectors except (B) Mining. This would indicate Cobb–Douglas PF unless sectoral β_t are significant. Thus, only in sector DE simultaneous conditions for H_0: $\beta_{KL} = 1$ failed to be rejected and β_t not significant at 5% level are fulfilled but in "viable" H-N model for sector DE H_0: $\beta_{KL} = 1$ is rejected. This generally rejects Cobb–Douglas PF form on the sectoral level, which converges with the results of the same test for aggregate economy.

[13] We re-estimated the eight sectors as 8 independent models to test cointegration and autocorrelation in the residuals.

Table 8
Cointegration and autocorrelation tests for models from columns 1 and 3.

Sector	Hicks-neutral model					Factor-augmenting model				
	ADF stat.	D-W *p*-value	B-G *p*-value, order = 1	B-G *p*-value, order = 2	B-G *p*-value, order = 3	ADF stat.	D-W *p*-value	B-G *p*-value, order = 1	B-G *p*-value, order = 2	B-G *p*-value, order = 3
A	–2.78	2.49 E.–04	0.11	0.140	0.26	–2.55	0.011	0.32	0.18	0.30
B	–2.49	0.03	0.32	0.190	0.13	–3.89	0.14	0.94	0.36	0.10
C	–3.34	0.37	0.91	0.540	0.59	–5.04	0.87	0.13	0.17	0.31
DE	–3.79	1.08 E.–03	0.03	0.011	0.03	–5.53	8.84E–04	0.16	0.06	0.06
F	–2.15	0.03	0.19	0.18	0.33	–3.54	0.02	0.24	0.06	0.13
GJ	–2.39	0.03	0.24	0.08	0.12	–2.30	0.006	0.24	0.10	0.15
K	–4.51	0.00	0.03	0.03	0.06	–3.59	1.38E–05	0.02	0.006	0.02
LQ	–1.92	0.02	0.11	0.09	0.15	–0.53	8.99E–04	0.006	0.02	0.03
					H–N	FATP				
McKinnon critical values				5%	–3.89	–4.66				
				10%	–3.42	–4.13				

Source: Authors' calculations.

Table 9
Sectoral elasticities of labor-to-capital substitution.

Economic sector		H-N		FATP	
		Common intercept	Individual intercepts	Common intercept	Individual intercepts
A	Agriculture	0.38		1.03 = 1	
B	Mining	0.69		1.83	
C	Manufacturing	0.54		1.80 = 1	0.36 = 1
DE	Energy waste	0.59	1.22 = 1	1.48 = 1[a)]	0.38
F	Construction	0.46		1.67 = 1	
GJ	Business services	0.54		1.56 = 1	
K	Real estate	0.63	0.44	1.48 = 1	
LQ	Social services	0.44		1.12 = 1	

Note: [a)] Only in sector DE simultaneous conditions for H_0: $\beta_{KL} = 1$ failed to be rejected and β_t not significant at 5% level are fulfilled.
Source: Authors' calculations.

Table 10 illustrates that different combinations of parameters σ and λ_{LK} and the estimated average $d\ln(K/L)$ predict identical LS direction in the frame of the above-mentioned rule. Though there is no surprise in this as according to the rule of the labor income share trend direction in response to simultaneous values of parameters,[14] labor share is expected to increase when $\sigma < 1$[15] and $\lambda_{LK} > d\ln(K/L)$ or $\sigma < 1$ and $\lambda_{LK} < d\ln(K/L)$. Consequently, labor share in all sectors except B and DE is expected to increase as the LATC ($\lambda_{LK} > 0$) model with common intercept estimates $\lambda_{LK} > d\ln(K/L)$ and $\sigma < 1$ under labor-biased technological progress or alternatively $\lambda_{LK} < d\ln(K/L)$ and $\sigma < 1$ under capital-biased technological progress in sector C (see Table 10). In sector B CATC ($\lambda_{LK} < 0$) model with common intecept shows LS fall ($\lambda_{LK} < d\ln(K/L)$ and $\sigma < 1$) under capital-biased technical progress. In sector DE LS decrease is forecasted by LATC model with common intercept, which estimates $\lambda_{LK} < d\ln(K/L)$ under capital-biased technological progress. In sector DE LS decrease is forecasted by LATC model with common intercept, which estimates $\lambda_{LK} < d\ln(K/L)$, $\sigma > 1$ under labor-biased technological progress, and by LATC model with individual intercept, which estimates $\lambda_{LK} > d\ln(K/L)$ and $\sigma < 1$ under capital-biased technological progress (see Table 9).

The discussion on the direction of factor-augmenting technological progress in the eight mentioned economic sectors seems to be viable. Hicks-neutral and FA models correlate with the results of aggregate economy analysis (LS forecasted growth). Still, the very short sample makes it possible to provide only short-term sectoral forecasts and reference.

Despite the increasing trendlines between $\ln(K/L)$ and $\ln(w/r)$ depicted in Fig. 2 for all sectors, the central graph in Fig. A1 in Supplementary material 1 reveals a slower growth of relative wages than capital-labor ratio in sectors B and DE. This was logically confirmed by the fact that calculated from the model with common intercept λ_{LK} in these sectors are the lowest among all other sectors and is lower than the respective $\ln(K/L)$ rates, which is a sign of falling LS. Apart from LS fall this fact may characterize the higher monopolists'

[14] See 5.1 (λ_{LK}) section.
[15] Recall that $\beta_{KL} = 1/\sigma$ from equations 3 and 5.

Table 10
Technical change parameters, type and bias compared to growth rates of labor-to-capital ratio: The connection to LS dynamics.

Technical progress…		LS gauging parameters			Sector	LS is expected to…
type	bias to	λ_{LK}	$\overline{d\ln\left(\frac{K}{L}\right)}$	σ		
H-N				0.38	Agriculture [A]	***grow*** $\sigma^{A} < 1$
LATC	***labor*** $\lambda_{LK}^{[A]} > 0,\ \sigma^{A} > 1$	1.82	0.02	1.03		***grow*** $\lambda_{LK}^{[A]} > d\ln\left(\frac{K}{L}\right)^{A},\ \sigma^{A} > 1$
H-N				0.69	Mining [B]	***grow*** $\sigma^{B} < 1$
CATC	***capital*** $\lambda_{LK}^{[B]} < 0,\ \sigma^{B} > 1$	–0.001	0.05	1.83		***fall*** $\lambda_{LK}^{[B]} > d\ln\left(\frac{K}{L}\right)^{B},\ \sigma^{B} > 1$
H-N				0.54	Manufacturing [C]	***grow*** $\sigma^{C} < 1$
LATC (common intercept)	***labor*** $\lambda_{LK}^{[C]} < 0,\ \sigma^{C} > 1$	0.17	0.07	1.80		***grow*** $\lambda_{LK}^{[C]} > d\ln\left(\frac{K}{L}\right)^{C},\ \sigma^{C} > 1$
LATC (individual intercept)	***capital*** $\lambda_{LK}^{[C]} > 0,\ \sigma^{C} < 1$	0.04	0.07	0.36		***grow*** $\lambda_{LK}^{[C]} < d\ln\left(\frac{K}{L}\right)^{C},\ \sigma^{C} < 1$
H-N				0.59[a)] 1.22[b)]	Energy waste [DE]	***inconclusive*** $\lambda_{common\ \beta_0}^{[DE]} < 1,\ \sigma_{individual}^{[DE]} > 1$
LATC (common intercept)	***labor*** $\lambda_{LK}^{[DE]} > 0,\ \sigma^{DE} > 1$	0.01	0.04	1.48		***fall*** $\lambda_{LK}^{[DE]} < d\ln\left(\frac{K}{L}\right)^{DE},\ \sigma^{DE} > 1$
LATC (individual intercept)	***capital*** $\lambda_{LK}^{[DE]} > 0,\ \sigma^{DE} < 1$	0.05	0.04	0.38		***fall*** $\lambda_{LK}^{[DE]} > d\ln\left(\frac{K}{L}\right)^{DE},\ \sigma^{DE} < 1$
H-N				0.46	Construction [F]	***grow*** $\sigma^{F} < 1$
LATC	***labor*** $\lambda_{LK}^{[F]} > 0,\ \sigma^{F} > 1$	0.11	0.02	1.67		***grow*** $\lambda_{LK}^{[F]} > d\ln\left(\frac{K}{L}\right)^{F},\ \sigma^{F} > 1$
H-N				0.54	Business services [GJ]	***grow*** $\sigma^{GJ} < 1$
LATC	***labor*** $\lambda_{LK}^{[GJ]} > 0,\ \sigma^{GJ} > 1$	0.15	0.03	1.56		***grow*** $\lambda_{LK}^{[GJ]} > d\ln\left(\frac{K}{L}\right)^{GJ},\ \sigma^{GJ} > 1$
H-N				0.63 0.44	Real estate [K]	***grow*** $\sigma^{K} < 1$
LATC	***labor*** $\lambda_{LK}^{[K]} > 0,\ \sigma^{K} > 1$	0.28	0.04	1.48		***grow*** $\lambda_{LK}^{[K]} > d\ln\left(\frac{K}{L}\right)^{K},\ \sigma^{K} > 1$
H-N				0.44	Social services [LQ]	***grow*** $\sigma^{LQ} < 1$
LATC	***labor*** $\lambda_{LK}^{[LQ]} > 0,\ \sigma^{LQ} > 1$	1.02	0.06	1.12		***grow*** $\lambda_{LK}^{[LQ]} > d\ln\left(\frac{K}{L}\right)^{LQ},\ \sigma^{LQ} > 1$

Note: [a)] H-N model with common intercept for all sectors; [b)] H-N model with individual intercepts for each sector.
Source: Authors' calculations.

bargaining power than the same of labor. Thus, corrupt and inefficient state monopolies in sectors B and DE (mining and quarrying; electricity, gas, and water supply) restrain innovative technologies[16] (Prokopenko, 2018), which hampers sound development of labor market though holding it in stagnation. This negatively affects the economy[17] and truly demands updating the antitrust legislation in Russia that conforms to new realities of the digital economy (Svechnikov, 2021).To connect the current results to the literature, several papers should be mentioned. Young (2013) reports U.S. sectoral elasticities of substitution be significantly below unity and technological progress uncertainly be labor-augmenting as in a significant percentage of industries λ_{LK} is negative.[18] Similarly, in the current paper, with a higher level of aggregation most sectors follow LATC. In line with (Young, 2013) and (Smeets Kristkova et al., 2017), the aggregate σ for Russia does not exceed unity but in contrast to these papers the short-term sectoral estimates provided by the model with an intercept common for all sectors are different ($\sigma > 1$).[19] The approach to σ as an endogenous variable (Knoblach & Stöckl, 2020) may help to connect short term trends in sectoral data (Fig. A1 in Supplementary material 1) to the factors that influence σ. Low values of λ_{LK} in sectors B and DE may be associated with capital accumulation exceeding labor supply growth (see Fig. A1 in Supplementary material 1), i.e., with the increase in K-to-L ratio. This converges with OECD research (Smeets Kristkova et al., 2017) regarding the impact of capital accumulation on the labor-saving direction of technical change.

The above-mentioned drivers should be considered in order to save the substitution elasticity from explosion on the asymptotic path of economic growth. In the instance of restricting further K-to-L ratio growth (i.e., control for the fact that labor supply growth is not less than capital accumulation) the demand for capital may be regulated through tax-based change in the cost of capital. According to Chirinko (2002), the heterogeneity of economic sectors (industries) cannot be neglected for the sake of proportionate tax effect on capital demand in a particular industry (tax income is heavier when the elasticity of substitution is relatively higher. In the current paper, the elasticity of substitution is also a marker for policymakers — Table 9 suggests that in the frame of FATP σ is not significantly different from unity in all sectors except B (Mining), in which it exceeds one and a “viable” H-N model shows $\sigma > 1$ for sector DE. Therefore, these two economic sectors may be considered as those where no tax discounts for capital gains should be introduced. In our opinion, taxation should be relatively more severe for large and stable enterprises, but relaxation of taxes for small and medium enterprises (SMEs) should be continued. The latter fact would be helpful for labor income share stability as SMEs are able to make the economy more efficient in comparison to large and usually state-regulated companies or even harmful (not natural) monopolies which inevitably impose distribution of wealth in favor of capitalists.

[16] Here LATC with $\lambda_{LK} > d\ln(K/L)$ would improve the forecasted LS trend (currently in sector B CATC is present whereas in sector DE LATC is present but $\lambda_{LK} < d\ln(K/L)$, which is insufficient for LS to grow).

[17] We further do not immerse into the methods and empirical testing of the tradeoff of capital and labor bargaining power as it goes beyond the purpose of the current paper.

[18] 35 industries are analyzed.

[19] In sectors C and DE the estimates of σ are available and $\sigma < 1$ in these cases.

7. Conclusion

The Russian economy on the aggregate level is generally characterized with LS increase over the coming 30 years and the elasticity of substitution below unity ($\sigma < 1$). CATC biased to labor has been justified by the three of five viable models. These models predict LS increase by 1–2 pp from the current 56.4%, whereas H-N model shows absolute LS stability in the next 30 years. LATC biased to capital has been revealed by one model with less than 1 pp LS decline on the forecast horizon. Under the FATP model with common intercept sectoral decomposition has proven labor-to-capital elasticity of substitution to be above unity ($\sigma > 1$) and technological progress mostly labor-augmenting ($\lambda_{LK} > d\ln(K/L)$, $\lambda_{LK} > 0$) which according to the mentioned pattern for LS, σ, λ_{LK}, and $d\ln(K/L)$ also constitutes LS increase in six of the eight industries. No precise figures on its severity for these sectoral LS may be derived due to the short-term estimation time span.

According to Acemoglu (2003), with the elasticity of substitution exceeding unity, the asymptotic path of the economy does not follow BGP, which may result in explosive growth rates on capital and negatively affect LS. However, in later papers Acemoglu and Restrepo (2018) and a literature review paper by Gechert et al. (2022) LS is described to grow under $\sigma > 1$ and CATC, which is the case described in the current paper in detail for Russia. For all Russian economic sectors, the tax policy for capital should be cautious in order to balance the relative labor supply by regulating the relative factor intensity, i.e., restrain the effectiveness of labor or capital depending on which factor becomes more effective (the goal of policymakers is to control for $\lambda_{LK} > d\ln(K/L)$ if $\sigma > 1$). Simultaneously, in case of using Hicks-neutral model ($\lambda_{LK} = 0$), which was also proven viable, a policymaker should control for σ to be less than unity to hold LS undecreasing.

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Supplementary material 1

Description of variables, descriptive statistics and model estimates

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Data type: Text

Explanation note: Appendix.

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