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Productivity, innovation and economic growth: understanding the embodied and disembodied contributions of factor inputs.

Juan Ricardo Perilla Jiménez*

Abstract

The role of productivity measurement in the assessment of the decoupling hypothesis–which suggests divergent paths between productivity and the labor income share–is investigated using a detailed dataset on quality-adjusted-production-factors across economic sectors in the Colombian economy over 1990-2019. The quality adjustment is found to increase the contribution of production factors, and to attenuate the contribution of productivity to value added growth. Cointegration relationships between alternative productivity indicators and the labor share do not hold at the aggregate level. But they hold for a number of industries. Short-run robust negative relationships arise for all sectors. But comparison between alternative measures of productivity leads to conclude that quality adjusted measures of productivity has the potential to improve model specification on the econometric assessment of the decoupling effect.

Key words: *Productivity, growth accounting, time series cointegration, panel data. (JEL: O22, O23, O40, O47, O57)*

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1 Introduction

The aim of this paper is to provide a better understanding on the interplay between two crucial macroeconomic issues: the contribution of productivity to value added growth, and the ongoing debate on the empirical relationship of productivity growth with the evolution of the labor income share. Despite being naturally interconnected (Atkinson 2009), these issues actually belong to significantly different lines of research related in the first case to the sources of economic growth, and in the second to the distribution of income between those sources. This difference has inevitably led to contrasting views about the role of technology in the economy.

In particular, the advance in *high-tech* sectors, like computer equipment manufacturing, has been found to be the fundamental source of embodied productivity in growth accounting (Jorgenson 2009, 2011, Jorgenson, Ho & Samuels 2012).[1] Yet, precisely because of this spectacular performance applied research has turned toward questions related to the existence of a *wage-productivity decoupling effect* whose essential feature is a decline in the labor share of income driven, apparently and at least in part, by skill biased technological changes (Gollin 2002; Bentolila & Saint-Paul 2003; Feldstein 2008; Arpaia, Pérez, & Pichelmann 2009; Brynjolfsson & McAfee 2013; Karabarbounis & Neiman 2014; Cho, Hwang & Schreyer 2017).

The extent and nature of this hypothesis has been a subject of much debate and controversy (see Schwellnus et al., 2018; Paternesi & Stirati 2022 for extended surveys of the literature). New technologies that are incorporated into advanced machines may, in the first place, expand the range of task automated activities. Thus displacing routine labor and leading to a relative decline in wages for less skilled workers. But, this effect may be offset–partially or completely–by the increase in the demand and compensation of skilled workers. While aggregate decoupling effects may be uncertain, some researchers point to wage inequality as another important implication of technological change (Schwellnus, Kappeler & Pionnier 2017; Criscuolo & Schwellnus 2018; Gil-Alana et al., 2020).

Strikingly, despite extensive efforts to carefully explaining the gap between productivity and wages, researchers into the decoupling effect pay little or no attention to productivity measurement issues. Instead, under the

[1] In the US this is a tiny sector comprising just 0.3% of value added. But it makes up for 25% of productivity growth and 2.7% of economic growth.

classical assumption of competitive markets, they assume that the real wage should equal *mean labor productivity* and fill in the gap by focusing on labor compensation issues: wages, non-wage benefits and relative differences in deflation methods (Feldstein 2008; Pessoa & van Reenen 2013; Bivens & Mishel 2015; Lawrence 2016; Sharpe & Uguccioni 2017). The problem with this approach is that it leads to neglect the non-trivial contributions to value added growth that are embodied in new capital equipment, therefore increasing the weight of productivity contributions. Furthermore, while there is a lack of systematic evidence, using *mean labor productivity* as a proxy for technology change has been found to be associated to poor inference and misspecification problems in econometric approaches to this problem (Bassanini & Manfredi 2014).

A key contribution of this paper is that it provides new evidence to help a better understanding on the implications of productivity measurement for the analysis of factor income shares, and hence the decoupling effect. In particular, by using well established growth accounting techniques (Jorgenson 2009, 2011), a coherent explanation is drawn where economy-wide growth contributions embodied in factor inputs increase and disembodied contributions– accrued to TFP– decrease leading to a strong decline in the size of decoupling at the whole economy level.

There are, however, large differences across economic sectors with some industries exhibiting large positively increasing and other rather small declining TFP to labor share ratios which suggests that decoupling is indeed a sectoral issue. Lastly, the econometric specification lends support to the use of sophisticated productivity measurement in regressions where productivity is set as a proxy to capture the impact of technology on the labor share. In general, the findings in this paper, support the decoupling hypothesis and suggests that is consistent with a reduction in wage inequality at the sectoral–but not at the economy-wide level.

I frame my investigation as a country-case study using data from the Colombian economy over 1990-2019 and rely on high quality statistics from the System of National Accounts (SNA) compiled by the Colombian National Department of Statistics (DANE), and the LAKLEMS project.[2] The data set includes information on value added at the aggregate level and across 9 sectors of activity, worked hours and compensation for 18 types of labor, and volume and compensation for 10 types of capital assets. This rich disag-

[2] www.dane.gov.co (productivity accounts) and www.laklems.net

gregation allows for a detailed discussion about the relationship between the labor share and its determinants than is usually found in related literature.

In the following section, I provide a brief review of the literature related to the subjects of productivity measurement and the decoupling effect. In Section 3, I focus on the economics of labor productivity and growth accounting techniques. In Section 4, I study the implications of those techniques to understand factor contributions and distributional patterns for the Colombian economy throughout the sample period. In Section 5, I use econometric techniques to test the decoupling hypothesis, and discuss the results. Finally, in Section 5, I provide some concluding remarks.

2 Literature review

Research on growth accounting has provided persuasive evidence relating to the use of detailed price and quality attributes which, being neglected, seriously bias the identification and interpretation of the true contributions of productive factors, hence magnifying the role of unknown sources of economic growth, which are consequently allocated to TFP (Stigler 1947; Schultz 1962; Denison 1962; Griliches 1970; Jorgenson 2009).

The *economics of productivity*, as Jorgenson 2009 has famously referred to this line of research, has established standards that are now increasingly adopted internationally both in academic research and in practice by leading statistical agencies (Schreyer 2001, Timmer, OMahony & Van Ark, 2007, Fernández-Arias, Hofman & Gálvez 2021). This has instigated the production of highly dis-aggregated statistics relating to value added across all sectors of the economy, types of employment, hours worked, wages and investment flows in diverse types of assets, which are reported systematically in the National Accounts Statistics of many countries. The rich availability of data has made possible to compute detailed quality adjusted price and volume indicators that are needed to compute the true contribution of each type of input to overall economic growth, thus narrowing *"the size of our ignorance"*.

Because in principle every other source of growth that is embodied in factor inputs is accounted for, researchers in this area have come to the conclusion that TFP is in fact an indicator of innovation (Jorgenson 2009, 2011). Therefore, I refer to this approach as the *innovation based growth accounting framework*.[3]

[3]The argument is that without innovation output would increase in proportion to fac-

Related to this, a natural question of interest is about the distribution of productivity gains across production factors. As mentioned above, the *wage-productivity decoupling hypothesis* suggests a technology-induced departure from classical assumptions of competitive markets that is strongly biased against unskilled workers (Schwellnus, Kappeler & Pionnier 2017; Mishel & Bivens 2021; Paternesi & Stirati 2022).

Attempting to explain whether and through which channels this would have been a key factor leading to the decline in the labor income share experienced in advanced economies since the 1980s—with notable differences across countries and industries, and over time—a line of research has concentrated on accounting for all those other forms of labor compensation benefits that fill in the gap between real wages and *mean labor productivity* (Pessoa & van Reenen 2013; Lawrence 2016). Another group (Bentolila & Saint-Paul 2003; Arpaia et al., 2009; Karabarbounis & Neiman 2014; Autor & Salomon 2018; Archanskaia, Meyermans & Vandeplas 2019), focuses instead on TFP as a proxy to capture capital augmenting technological changes and find that the labor share is negatively and statistically associated to this variable.

More closely related to the approach in this paper, Bassanini & Manfredi 2014 test the relative importance of different approaches to measure productivity. Their findings suggest that using *mean labor productivity* instead of TFP leads to misspecification problems in the econometric approach to test the causal role of productivity on the labor share.

A key advantage of using the *innovation based growth accounting framework* in this context is that it allows for a detailed analysis of growth contributions by production factors that are quite different in quality. This is relevant as long as the evidence suggests that the labor share may be influenced by mixed patterns of factor substitution and complementary effects with heterogeneous implications on factor´s compensation across industries.

Labor-replacement effects would be expected in industries with a high share of low skilled workers as new-design machines are set to perform routine-intensive tasks more efficiently (Lordan & Newmark 2018, Acemoglu & Restrepo 2019). *Capital-labor complementary effects* would be expected in sectors where investments in skill-intensive technologies lead to a higher demand and compensation for qualified workers (Autor & Salomons 2018, Autor et

tor inputs. With innovation, through the introduction of new products and processes, organization structures, altered production systems, and business models, output per unit of input would increase more than proportionally (Jorgenson 2009).

al., 2020).

Typically, labor share declines would be expected in sectors employing mostly less-skilled workers and the contrary would be expected in skill-intensive sectors. But the evidence is still insufficient to establish a convincing pattern. Archanskaia et al., 2019, find strong declines in the labor share for manufacturing and finance, and positive trends for information and communication services, professional activities and business services. Schwellnus et al., 2017, find that the decoupling is smaller if sectors are excluded where labor shares are driven by changes in commodity and asset prices or where labor shares are driven by imputation choices (primary, housing and non-market sectors). Schröder 2020, suggests that the decline would be stronger in export- and manufacturing-orientated activities.

The empirical evidence suggests that there are contributing factors other than embodied / disembodied technology acting as possible determinants of the labor share, namely institutional (minimum wages, union wage bargaining), structural (unemployment, formal versus informal labor composition) and (commercial, financial) globalization associated effects (Arpaia et al., 2009; Karabarbounis & Neiman 2014; Criscuolo & Schwellnus 2018; Schwellnus et al., 2018; Archanskaia et al., 2019; Paternesi & Stirati 2022). Although not actually in the scope of the research here, an important implications of this literature is that even if there is no decoupling it may be possible that technology-induced skilled versus unskilled labor wage inequalities arise (Atkinson 2009; Jacobson & Occhino 2012; Paternesi & Stirati 2022).

Finally, while from a policy perspective, the focus on transitional dynamics seems to be the preferred analytical avenue in empirical research, the relationship between productivity and the labor share is more likely subject to both short and a long-run dynamics. The theoretical equality between these two variables (Kaldor 1961; Gollin 2002; Arpaia et al., 2009) leads to question whether there is a stable cointegration relationship between them. Some research seems to provide support to this argument (Yusof 2008; Chirinko & Mallick 2011). But the evidence is not yet systematic and it remains to be investigated in the context of decoupling. That endeavor seems relevant as, focusing on panel data cointegration, Archanskaia et al., 2019, find that the null hypothesis of no cointegration is rejected for all but the transport and storage (retail) sectors.

In what follows, the purpose is to evaluate whether methodological differences in the approach to measure productivity make a difference in studying the decoupling hypothesis.

3 Productivity measurement

From a methodological viewpoint, *mean labor productivity* assumes that labor is homogeneous across industries and over time. While it has the advantage of being simple, this strategy fails to account for output growth contributions accrued to physical capital and technology progress. This implies a bias in the relationships between labor productivity and workers compensation. After all, workers endowed with better tools are expected to be more efficient, and basic economic principles suggest that productivity gains should be distributed proportionally to the contributions accrued to changes in the quantity and quality of every factor.

Conventional growth accounting partly corrects the above limitations, e.g., accounting for productivity contributions that are embodied in physical capital and labor, and disembodied contributions accumulated in TFP. However, this approach still assumes that capital and labor are homogeneous, failing to account for quality attributes that make these production factors essentially different over time and across economic sectors. Taking into account such differences, the *innovation based growth accounting framework*, in theory, accrues for larger factor embodied contributions and narrowed TFP disembodied contributions to output growth.

Consider the following indicator of *mean real labor productivity* per hour worked

$$mph_t = va_t - h_t \tag{1}$$

where va_t is real gross value added and h_t the total number of hours worked (lowercases are use to denote logarithms of a variable). Conventionally, Total Factor Productivity (TFPC) is computed as follows

$$\Delta tfpc_t = \Delta va_t - \omega_t \Delta h_t - (1 - \omega_t)\Delta k_t \tag{2}$$

where k_t measures physical capital and ω_t is the labor share of income. I follow the standard adjustment to account for income accrued to self-employed workers (Criscuolo & Schwellnus 2018, Fernández-Arias et al., 2021).[4]

$$VA_{Lt} = \frac{H_{TLt}}{H_{Et}} \times WC_{SNA_t}$$

Where VA_L is the part of value added distributed to labor, H_{Et} and H_{Lt} are, respectively, the number of worked hours of employed workers and total labor (including self-employed workers), and WC_{SNA} is labor compensation in the SNA. The labor share is then

$$\omega_t = \frac{VA_{Lt}}{VA_{Lt} + VA_{Kt}}$$

The *innovation based growth accounting framework* assumes a translog production function to obtain TFP. This may be done in two different ways:

i) *Unweighted-approach* (TFPNU): treating every sector and the whole economy in the same way (the whole economy as one sector)[5]

$$\Delta tfpnu_{jt} = \Delta va_{jt} - \overline{\omega}_{jt}\Delta ls_{jt} - \overline{\upsilon}_{jt}\Delta ks_{jt} \tag{3}$$

where ks_t and ls_t are set to denote capital and labor services, as explained below. Let $\overline{\upsilon}_t = 1 - \overline{\omega}_t$ be Thörnqvist - Theil Divisia indices of each factor´s income share.

ii) *Weighted-approach* (TFPNW): total factor productivity is value added weighted at the sectoral level. TFP at the whole economy level is a weighted average.

$$\Delta tfpnw_t = \sum_j \Delta tfpnw_{jt} + \sum_j \overline{tfpnu}_{jt}\Delta\psi_{jt}$$

where $\psi_{jt} = \frac{VA_{jt}}{VA_t}$ and $\overline{\psi}_t = (\psi_t + \psi_{t-1})/2$. This is a *shift-share* decomposition where the *within-sector* contributions to overall productivity are given by the first term on the right hand side and the *between-sector* contributions are given by the second term.

Following the DANE-LAKLEMS approach (Fernández-Arias et al., 2021) sector specific labor services are broken down into 18 categories out of the

[4]The System of National Accounts (SNA) reports only the wages and salaries of registered employees. Thus workers compensation should be adjusted to take into account the compensation of self-employed workers.

[5]This approach is used in the LAKLEMS approach (www.laklems.net).

combination of sex (male, female), age (15-29, 30-49, +50 years), and education (high, medium and basic levels). Labor services are broken down into a *labor composition* (LC) effect and a *change in hours worked* (HW) effect as follows

$$\begin{aligned}\Delta ls_{jt} &= \sum_l \overline{\mathrm{v}}_{ljt} \Delta ln \left(\frac{H_{ljt}}{H_{jt}}\right) + \Delta h_{jt} \\ &= \Delta lc_{jt} + \Delta h_{jt}\end{aligned}$$

The *labor composition* effect captures the contributions of the change in hours worked by each type of labor times their specific cost share. The second term captures the contribution of the change in *hours worked* by all types of workers.

In a similar fashion, capital services are calculated from sector specific stocks using the perpetual inventory method for each of nine asset types, specific price (user cost share and user cost of capital) and depreciation rates.

$$\Delta ks_{jt} = \sum_k \overline{\mathrm{v}}_{kjt} \Delta \mathrm{K}_{kjt}$$

As long as the decoupling literature is mostly concerned with the impact of technology-induced changes in productivity, capital services are broken down into the contributions of *High-Tech* (information and technology, computing equipment, software, machines, transport equipment) and *Non-High-Tech* assets (residential and non residential structures, cultivated assets, R&D and intellectual property).[6]

The weighted contribution of *High-Tech* assets is obtained as

$$\Delta htk_{jt} = \sum_j \overline{\mathrm{v}}_{\mathrm{HT}jt} \Delta \mathrm{K}_{\mathrm{HT}jt}$$

Analogously, the contribution related to *Non-High-Tech* assets is obtained as

$$\Delta nhtk_{jt} = \sum_j \overline{\mathrm{v}}_{\mathrm{NHT}jt} \Delta \mathrm{K}_{\mathrm{NHT}jt}$$

Thus, overall capital services may be written as

$$\Delta ks_{jt} = \Delta htk_{jt} + \Delta nhtk_{jt}$$

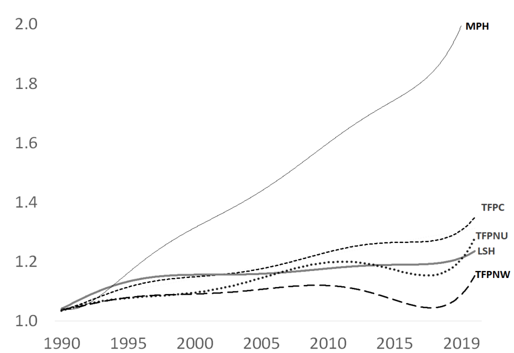
[6] See Appendix for further details.

4 The Colombian Economy

In Figure 1, panel (a), the wide gap between mean labor productivity (MPH) and the labor share (LSH) lends graphical support to the idea of decoupling as it suggest that over 1990-2019 labor productivity was increasing at a much faster pace than real wages. Using conventional growth accounting (TFPC) leads to a huge reduction of the gap highlighting the substantial contributions of capital services to VA growth over the 30 years period. Using the *innovation based growth accounting framework* (weighted and unweighted) leads to a further reduction in the gap. In fact, the unweighted version of this variable (TFPNU) suggests almost no decoupling, while the weighted version (TFPNW) suggests that the labor share was increasing even slightly faster than productivity.

This graphical analysis seems consistent with the central argument in this paper that mean labor productivity and, to a lesser extent, conventional growth accounting overstate the role of productivity. Therefore, it supports the case for a refinement of productivity measurement to account for quality attributes in factor inputs that would otherwise be counted as part of TFP.

Panel (b) plots the ratio of TFPNW to the labor share for each of nine



(a) *TFP and labor share.*

(b) *TFP/ labor share ratio.*

Figure 1: *Panel (a) plots the labor share, mean real labor productivity per hour worked (MPH), conventional (TFPC), innovation based unweighted (TFPNU) and value added weighted (TFPNW) measures of productivity. Panel (b) plots sectoral ratios of TFPNW to the labor share. All lines are sixth order polynomial trends (1990=1). Labor shares are adjusted for self-employment.*

sectors. Thus, upward trends indicate sectors where quality adjusted productivity contributions in factor inputs was increasing more rapidly than labor compensation. Conversely, trends in the opposite direction show up in sectors where compensations was increasing faster. Notice that for agriculture and construction the average outcome over the 30-year period is roughly a balance (TFP≈labor share).[7]

In order to better understand the implications of alternative approaches to measure productivity, growth accounting results for the whole economy are reported in Table 1. Note that by omitting every other contribution accrued to capital services the average (unweighted) growth of *mean labor productivity* (per hour worked) leads to overstate the role of productivity contributions. This may be calculated simply by subtracting the average growth of hours worked from the VA growth: 2.68-0.49=2.19 over 1990-1999; 3.45-1.38=2.07 over 2000-2009; and 3.61-1.44=2.17 over 2010-2019.

Using instead TFPC leads to a strong reduction in the assessment of productivity, from 2.19 to 0.79 in the 1990s, from 2.07 to 0.79 in the 2000s, and from 2.17 to 0.78 in the 2010s. Consistent with the graphical analysis, the numerical result in the table shows that the strong decline in productivity under TFPC is driven by (subtracting) the contribution of capital services. In fact, including capital services leads also to a reduction in the contribution of hours worked: from 0.49 to 0.27 in the 1990s, from 1.38 to 0.87 in the 2000s and from 1.44 to 0.94 in the 2010s. This is because $\omega = 1$ in Eq. (1) but $\omega < 1$ in Eq. (2).

As expected, the *innovation based growth accounting framework* leads to reduce further the role of productivity, particularly under the weighted (TFPNW) approach. Although to varying degrees both labor composition (in the first and last decades) and hours worked (in the last couple of decades) play a meaningful role in the declining role of productivity contributions to VA growth. The decline has been associated mostly to an increasing role of Non-High-Tech rather than High-Tech capital assets. This, however,

[7] Professional services (including a broad range of public administration, entertainment, education, and health activities) and the retail sector (including wholesale and retail trade, hotels and restaurants) exhibit very large labor shares, in many cases exceeding total income (which implies negative capital shares). This is a well known but rather difficult to solve *mismeasurement* problem (Criscuolo & Schwellnus 2018, Fernández-Arias et al., 2021). Some authors opt to subtract these sectors from the aggregate for the whole economy, which seems somewhat odd. Since the SNA is plagued with mismeasurement issues, a similar correction would be needed in all sectors. I apply no such correction here.

seems consistent with the shrinking share of the last type of assets in capital investments of the Colombian economy during the sample period.

Note, lastly, that the *shift-share* decomposition reveals large and increasing contribution of the *within-sector* component to overall changes in TFP: 0.29/0.45 over 1990-1999, 0.62/0.73 over 2000/2009 and 0.56/0.50 over 2010-2019. This suggests that for the Colombian economy in the period under study, relevant productivity drivers have been industry specific rather than driven by structural patterns shifting factors from less to more productive activities.

The decomposition in Table 2 provides further support for the *innovation based growth accounting framework* as a way to disentangle the true contributions of factor services and productivity to VA growth. Over 1990-1999, labor composition (LC) is an essential element to explain the contribution of labor services (LS). Jointly with the contribution accrued to capital services (KS with Non-High-Tech and High-Tech collapsed in one variable), both factor services suggest that the contribution of productivity was indeed negative in all but three sectors (mining, construction and professional services).

There is substantial heterogeneity across economic activities and over the decades in Table 2 that makes it difficult to establish empirical generalizations. Even so, there are some worth noting patterns: First, after a widespread decline over 2000-2009, LC continues playing an important role in the last decade, particularly in sectors where TFPNW contributions are relatively large (professional services, finance, transport and retail). This explains the upward trends found for the same activities in the graphical analysis.

Except during the last decade, some economic sectors with the largest labor shares (Retail, Transport, Finance, agriculture over the 1990s, Mining over the 2000s) exhibit also very large factor contributions and negative or relatively lower contributions of productivity. For instance, in the Finance sector, over 1990-1999 LS (0.28) and KS (0.59) largely exceeded TFPNW (-0.09), and these two factor contributions related positively with the labor share (0.28). Over 2000-2009 LS (0.34) and KS (0.81), are again associated to a negative contribution of TFPNW (-0.57) and a positive labor share (0.14). In contrast, over the last decade, the LS (0.42) and KS (0.26) are associated to a positive TFPNW (0.18) and a negative labor share (-0.05).

Indeed, the fact that only in the last decade there are three economic sectors (Retail, Transport, Finance) exhibiting labor contributions that are larger than capital contributions, and that they are associated with positive

	1990-1999				2000-2009				2010-2019			
	mph	tfpc	tfpnu	tfpnw	mph	tfpc	tfpnu	tfpnw	mph	tfpc	tfpnu	tfpnw
VA Growth	2.68	2.68	2.68	2.68	3.45	3.45	3.45	3.45	3.61	3.61	3.61	3.61
Contribution of:												
Labor services	0.49	0.27	1.07	1.11	1.38	0.87	0.91	1.10	1.44	0.94	1.94	1.93
—Labor Hours	0.49	0.27	0.27	0.03	1.38	0.87	0.87	1.37	1.44	0.94	0.94	1.11
—Labor Composition			0.80	1.08			0.04	-0.27			1.00	0.82
Capital services		1.62	1.38	1.29		1.79	1.43	1.74		1.89	1.96	2.24
—HT-Capital services			0.21	0.19			-0.07	-0.06			0.19	0.16
—Non-HT Capital services			1.16	1.09			1.49	1.79			1.77	2.08
Within Effect				0.29				0.62				-0.56
Between effect				0.16				0.11				0.06
PTF	2.19	0.79	0.24	0.45	2.07	0.79	1.12	0.73	2.17	0.78	-0.29	-0.50

Table 1: *Growth accounting decomposition for conventional and innovation based unweighted and value added weighted measures of productivity.*

SECTOR	va	hw	lc	ls	ks	within	between	tfpnw	lsh
				1990-1999					
WHOLE ECONOMY	2,68	0,03	1,08	1,11	1,29	0,29	0,16	0.45	0.72
AGRICULTURE	0.11	0.13	0.04	0.17	0.11	-0.17	-0.00	-0.17	0.06
MINING	0.20	-0.05	0.08	0.03	0.09	0.08	0.03	0.11	-0.12
MANUFACTURING	-0.16	0.03	0.16	0.18	0.00	-0.34	-0.00	-0.34	-0.16
UTILITIES	0.04	-0.01	0.10	0.09	0.07	-0.12	0.01	-0.11	-0.02
CONSTRUCTION	0.07	-0.12	0.09	-0.03	0.06	0.04	0.03	0.07	-0.17
RETAIL	0.26	0.09	0.08	0.17	0.19	-0.10	-0.00	-0.10	0.03
TRANSPORT	0.20	0.06	0.08	0.14	0.14	-0.08	0.00	-0.08	0.03
FINANCE	0.76	0.10	0.18	0.28	0.59	-0.11	0.02	-0.09	0.28
PROF. SERVICES	1.20	-0.20	0.28	0.07	0.03	1.10	0.07	1.17	0.79
				2000-2009					
WHOLE ECONOMY	3.45	1.37	-0.27	1.10	1.74	0.62	0.11	0.73	0.32
AGRICULTURE	0.14	-0.13	-0.08	-0.21	0.11	0.24	0.00	0.24	-0.03
MINING	0.19	0.15	-0.02	0.13	0.25	-0.19	0.04	-0.15	0.05
MANUFACTURING	0.76	0.15	0.03	0.18	0.20	0.38	0.01	0.39	-0.31
UTILITIES	0.11	0.00	-0.07	-0.07	0.06	0.12	0.00	0.12	-0.03
CONSTRUCTION	0.44	0.11	-0.05	0.06	0.07	0.31	0.06	0.38	0.15
RETAIL	0.55	0.42	-0.07	0.35	0.11	0.10	0.00	0.11	0.31
TRANSPORT	0.52	0.37	-0.03	0.33	0.13	0.05	0.00	0.05	0.28
FINANCE	0.58	0.57	-0.22	0.34	0.81	-0.58	0.01	-0.57	0.14
PROF. SERVICES	0.17	-0.27	0.25	-0.02	0.03	0.17	-0.02	0.16	-0.25
				2010-2019					
WHOLE ECONOMY	3.61	1.11	0.82	1.93	2.24	-0.56	0.06	-0.50	-0.28
AGRICULTURE	0.20	-0.01	0.02	0.01	0.06	0.12	0.00	0.12	-0.05
MINING	0.30	0.02	0.08	0.10	0.51	-0.31	0.04	-0.28	-0.12
MANUFACTURING	0.25	0.04	0.08	0.13	0.37	-0.24	0.01	-0.23	-0.14
UTILITIES	0.07	0.02	0.01	0.03	0.10	-0.06	-0.00	-0.07	-0.00
CONSTRUCTION	0.24	0.14	0.05	0.19	0.21	-0.16	0.01	-0.15	-0.06
RETAIL	0.51	0.23	0.10	0.33	0.08	0.10	0.03	0.13	-0.08
TRANSPORT	0.35	0.06	0.08	0.14	0.09	0.12	-0.00	0.12	-0.11
FINANCE	0.86	0.30	0.12	0.42	0.26	0.18	0.00	0.18	-0.05
PROF. SERVICES	0.84	0.31	0.27	0.58	0.05	0.21	0.00	0.21	0.35

Table 2: *All figures are measured in percentage points summing up to the overall change (constructed as weighted averages using time-average sectoral shares in value added). va=ls+ks+within; tfp=within+between; ls=lc+hw.*

contributions of productivity and negative labor shares is a finding that lends support to earlier research according to which decoupling is a sectoral and time-varying issue.

Summing up, the outcomes discussed above suggest meaningful differences in the assessment of productivity between *mean labor productivity*, conventional growth accounting and the *innovation based growth accounting framework*. As expected, those differences are associated to labor and capital composition effects. Failing to account for these contributions, the first two approaches tend to overstate labor productivity.

Given the rather heterogeneous outcomes found for factor inputs and productivity contributions across economic activities and periods of time, and given also the different outcomes reported in the alternative approaches to measure productivity, it seems reasonable to question whether there is econometric evidence to support the decoupling hypothesis and whether the productivity measuring approach plays a role in this assessment.

5 Econometric approach

The *decoupling* hypothesis suggests that there is a significant negative association between productivity and the labor share. The econometric approach to this issue typically includes productivity as a proxy to capture the impact of technical change. I have shown above that there are meaningful accounting differences regarding productivity measures that are based on the MPH, $TFPC$ and $TFPN$ (weighted and unweighted) and, additionally, that the results are highly heterogeneous across economic activities and over time. In this section, I conduct inference on the decoupling hypothesis using time series and panel data techniques, and investigate whether the annotated differences in the strategies to measure productivity lead to statistically significant differences in the results.

A first line of inquiry is whether, as the theory suggests, there is a stable long-run relationship between productivity and the labor share. The classical assumption of constant factor shares suggests that the labor share and productivity are I(1) and cointegrated. The decoupling hypothesis, on the other hand, suggests that there is a negative long-run relationship between these two series. To assess the adequacy of these assumptions, using Johansen Cointegration (1991) techniques, the following vector error-correction model may be written

$$\Delta lshw_t = \alpha^i \Big(lsh_{t-1} - \beta^i x(i)_{t-1} + \gamma + \rho\tau \Big) + \sum_{p=1}^{P} \Delta lshw_{t-p} + \sum_{q=1}^{Q} \Delta x(i)_{t-q} + \epsilon_t$$

where $x(i)$ denotes an element i from the array $x \in \{mphw, tfpcw, tfpnw\}$, $\alpha^i \beta^{i\,\prime}$ are the corresponding *speed of adjustment* and cointegrating parameters, τ is a linear trend. All series are value added weighted and converted into logarithms of an index number such that each series is equal to $ln(100)$ at the beginning of the period. Weighting the series has proved useful to address the huge disparities observed between sectoral variables and their aggregate at the whole economy level improving the precision of the estimated results. The lag length is chosen such that P=Q for sectoral regressions.

The null hypothesis that the series of interest are unit root cannot be rejected at conventional levels.[8] The cointegration vector estimates are normalized with respect to the labor share ($lshw = 1$). Probability values associated to the null hypothesis that the *speed of adjustment* parameter (α) and the cointegrating parameter (β) are equal to zero are reported jointly with overall fit results (*stability* and *normality*). Note that the presence of decoupling requires $\beta > 0$ in the long-run equation.

The results presented in Table 3 are generally consistent with the underlying economic theory that labor share and productivity exhibit a cointegration relationship. With a couple of exceptions, the three alternative measures of productivity analyzed here ($mphw, tfpcw, tfpnw$) render similar results regarding the direction of the long-run association between both time series. But there are sizable differences in the magnitude of the estimated coefficients depending on how productivity is measured.

Notice that, almost in general, the *innovation based growth accounting framework* ($tfpnw$) leads to more parsimonious models and yields a better model specification in terms of parameter significance and overall fit criteria. A remarkable exception is in *retail* where the resulting values for the best fit under *tfpnw* contains eight lags while those under alternative model specifications contain only one. While estimated coefficients are still significant one would need to be wary of estimated models with a sample of 30 observations and very long lags as is the case here. Lastly, though exogeneity restrictions are not in the scope of this investigation, the analysis of

[8] Results of the unit root test are available from the author.

the *speed of adjustment* parameters shows that they are generally consistent with convergence toward a long run equilibrium. The decoupling hypothesis posits that the cointegration vector of interest should have the form $lshw_{t-1} + \beta^i x(i)_{t-1}$ to be consistent with a stable long run equilibrium relationship $lshw_{t-1} = -\beta^i x(i)_{t-1}$ that changes only in response to stochastic shocks. Accordingly to this theory, from the results in Table 3, decoupling seems not to be an issue at the whole economy level in the Colombian economy in the period under study. But it seems to be a relevant issue at the sectoral level although with a couple of exceptions (*transport, professional services*) and some disparity between alternative measures of productivity (in *mining* and *retail*). Noticeably, these results are consistent with the findings of Archanskaia et al., 2019 that were discussed above.

Summing up, while the findings of the cointegration approach are quite robust to alternative measures of productivity, the results for some coefficient estimates (such as size and direction) and in some instances the performance statistics (stability and normality) are sufficiently different across alternative specifications to deserve comparison. This lends support to the contention that the methodological approach to productivity measurement matters when researchers seek to test the statistical relationship posited by the decoupling hypothesis. Even if the results may not be still very accurate, the *innovation based growth accounting framework* seems to lead to better model fit than other alternatives.

Consider now a more traditional formulation of the econometric model to test the decoupling hypothesis using panel data techniques. A general specification of the model is

$$\Delta lsh_{st} = c_0 + \sum_{p=0}^{P} \beta_p \Delta lsh_{st-p-1} + \sum_{p=0}^{P} \beta_p^i \Delta x(i)_{st-p} + \sum_{p=0}^{P} \beta_q^z \Delta z_{st-p} + \tau_t + gap_{st} + D1 + D2 + C99 + \mu_s + \epsilon_{st} \tag{4}$$

Where s is the economic sector and t is time. I include all sectors but the aggregate for the whole economy. Thus, this is a balanced panel with 9 sectors and 30 yearly periods over 1990-2019. The focus is on short-run dynamics which seems to be more interesting from a policy-making point of view. The year-over-year (logarithmic) change of the labor share is regressed over lagged changes of the labor share, contemporaneous and lagged changes of alternative productivity measures and other covariates of interest. The model specification includes time and sector specific effects (τ_t, μ_s), two dummy variables to capture decade specific events over the 2000s and 2010s (D1, D2) and a dummy to capture the *end of millennium* crisis that affected

	lag	$Coint.Vector$ $\alpha(1+\beta x(i)+\gamma+\tau)$	$Prob(\alpha)>\|z\|$	$Prob(\beta)>\|z\|$	$Stability$	$Normality$
WHOLE ECONOMY						
$tfpnw$	2	-0.48(1 - 0.58 - 1.97 - 0.1E-4)	0.00***	0.09*	Yes	Yes
$tfpcw$	2	-0.25(1 - 1.93 + 4.30 + 0.01)	0.00***	0.00***	Yes	Yes
$mphw$	2	-0.29(1 - 1.55 + 2.53 - 0.038)	0.00***	0.00***	Yes	Yes
AGRICULTURE						
$tfpnw$	3	-0.36(1 + 1.49 - 11.44 - 0.2E-3)	0.08*	0.00***	Yes	Yes
$tfpcw$	4	-0.87(1 + 1.61 - 12.05 - 0.2E-3)	0.00***	0.00***	Yes	Yes
$mphw$	4	-0.93(1 + 0.08 - 4.97 - 0.3E-3)	0.00***	0.00***	Yes	Yes
MINING						
$tfpnw$	1	-0.78(1 + 1.88 - 13.54 + 0.5E-3)	0.00***	0.00***	Yes	Yes
$tfpcw$	2	-0.70(1 + 1.06 - 9.73 - 0.4E-3)	0.00***	0.05**	Yes	Yes
$mphw$	2	-0.66(1 - 0.43 - 2.80 + 0.3E-3)	0.00***	0.06*	Yes	Yes
MANUFACTURING						
$tfpnw$	3	0.79(1 + 1.16 - 10.09 + 0.2E-3)	0.01***	0.00***	Yes	Yes
$tfpcw$	2	0.58(1 + 1.35 - 10.90 + 0.1E-3)	0.03**	0.00***	Yes	Yes
$mphw$	2	0.27(1 + 2.59 - 16.00 - 0.5E-3)	0.00***	0.00***	Yes	No
UTILITIES						
$tfpnw$	3	0.12(1 + 4.36 - 24.93 + 0.2E-3)	0.03**	0.00***	Yes	Yes
$tfpcw$	3	0.36(1 + 2.18 - 14.81 + 0.1E-3)	0.00***	0.00***	Yes	Yes
$mphw$	3	-0.17(1 + 0.99 - 9.22 + 0.6E-4)	0.54	0.00***	Yes	No
CONSTRUCTION						
$tfpnw$	2	-0.21(1 + 0.76 - 8.08)	0.04**	0.00***	Yes	Yes
$tfpcw$	2	-0.23(1 + 0.88 - 8.64)	0.08*	0.00***	Yes	Yes
$mphw$	2	-0.49(1 + 0.64 - 7.55)	0.02**	0.00***	Yes	Yes
RETAIL						
$tfpnw$	8	-0.25(1 - 3.41 + 11.05)	0.02**	0.06*	Yes	Yes
$tfpcw$	1	-0.77(1 + 1.73 - 11.94 - 0.4E-3)	0.00***	0.00***	Yes	Yes
$mphw$	1	-0.58(1 + 1.83 - 12.33 - 0.4E-3)	0.02**	0.00***	Yes	Yes
TRANSPORT						
$tfpnw$	4	-0.40(1 - 2.15 + 5.35 - 0.3E-4)	0.01***	0.00***	Yes	Yes
$tfpcw$	3	-0.22(1 - 2.17 + 5.19 + 0.1E-3)	0.03**	0.00***	Yes	Yes
$mphw$	3	-0.13(1 - 2.08 + 4.85 + 0.7E-4)	0.07*	0.02**	Yes	Yes
FINANCE						
$tfpnw$	7	0.45(1 + 2.72 + 18.28 + 0.6E-3)	0.01***	0.00***	Yes	Yes
$tfpcw$	7	0.55(1 + 1.64 - 12.80 + 0.3E-3)	0.00***	0.00***	Yes	Yes
$mphw$	7	0.24(1 + 1.29 - 9.58 - 0.5E-3)	0.05**	0.06*	Yes	Yes
PROFESSIONAL SERVICES						
$tfpnw$	5	-0.17(1 - 0.58 - 1.85)	0.00***	0.00***	Yes	Yes
$tfpcw$	5	-0.34(1 - 0.17 - 3.78)	0.00***	0.00***	Yes	Yes
$mphw$	5	-0.31(1 - 0.18 - 3.74)	0.00***	0.00***	Yes	Yes

Table 3: *Johansen Cointegration.*

the Colombian economy over 1999-2002 (C99). It includes also a variable to capture the business cycle gap measured as deviations of the cycle with respect to its sectoral trend using a *Hodrick-Prescott* filter.

The array $z \in \{htk, nhtk, hwsk, hwnsk, lcsk, lcnsk, rwsk, rwnsk\}$, where all variables are logarithmic transformations, includes *High-Tech* and non *High-Tech* capital $(htk, nhtk)$ and a set of labor covariates split between skilled and non skilled workers: hours worked $(hwsk, hwnsk)$, labor composition $(lcsk, lcnsk)$ and real wages $(rwsk, rwnsk)$.

It is expected that the more substitute (complementary) capital is with labor will impact negatively (positively) the labor share. Since coefficient estimates with the same (opposite) sign may reasonably deemed complementary (substitutes) among them, it is expected that the coefficients of *High-Tech* capital and skilled labor have the same sign as these factors have been found to be highly complementary with each other (Arpaia et al., 2009, Bassanini & Manfredi 2014). On the contrary, is expected that the coefficients of *High-Tech* and unskilled labor will have opposite signs.

The nature of the variables included in the array suggests the need to identify patterns of linear dependency among them. The correlation matrix in the appendix suggests that this is not an issue here. In general, within sector changes in the covariates are only slightly correlated. The highest correlation coefficients are between labor composition and between hours worked of skilled versus non skilled workers (-0.43 and 0.39).

Interestingly, mean labor productivity exhibits higher correlation with the conventional measure of total factor productivity (correlation coefficient of 0.92) than the productivity measure obtained from the *innovation based growth accounting framework* (0.84). This seems intuitively right. Consistent with the graphical evidence presented earlier, the evolution of mean labor productivity is very different from the conventional and the *innovation based growth accounting framework* measures of this variable, which in turn are different between them (correlation coefficient of 0.91). Also notice that mean labor productivity is less correlated with the labor share than the other productivity alternatives.

Decoupling is a problematic relationship to test econometrically given the presence of measurement errors, simultaneity bias and other statistical issues. As noticed above, mismeasurement is rather difficult to solve as long as the national accounts system, where the data set used here originates, is plagued with this problem. Therefore, caution is needed in the interpretation of estimated coefficients. Simultaneity bias is a somewhat less challenging issue. While idiosyncratic shocks may simultaneously affect the labor share and productivity, or the latter might somehow be a function of the labor share, consistent estimation of the parameters in the model is possible by using appropriate estimation techniques.

I estimate Equation (4) using two types of panel-data regression techniques that are robust to cross sectoral heteroskedasticity, contemporaneous and serial correlation in models with many time periods and short cross sections. Beck & Katz 1995, show that the so-called Panel Correlated Standard Errors (PCSE) technique leads to consistent and more conservative estimates compared to the more typical approach based on Feasible Generalized Least Squares (FGLS).[9] As a check of robustness, I also run the model using a two-stage instrumental variables approach with fixed effects and clustered errors, using lagged values of relevant variables as instruments (Balestra & Varadharajan-Krishnakumar 1987). Taking advantage of the strong correlation between conventional and *innovation growth accounting framework* measures of productivity with mean labor productivity and the low correlation of the latter with labor share, I use the contemporaneous and lagged values of mean labor productivity as instruments in regressions that include the other productivity measures. I also use as an instrument lagged values of the own productivity variable which by construction are uncorrelated with the contemporaneous error term. As a rule of thumb, all regressions include two lags of the explained and explanatory variables.[10]

Given space constraints, the results presented in Table 4 focus on the model based on the *innovation growth accounting framework* and report only the results on contemporaneous relationships. Comparison with other productivity measures will be presented later in this paper.

In general, the econometric evidence supports the claim of a statistically significant negative relationship between changes in productivity and the labor share posited by the decoupling hypothesis. An increase of 1% in $tfpnw$ leads to reduce the labor share between 0.32 and 0.82 percentage points depending on the model specification and regression technique. The negative association between productivity and the labor share is robust to

[9]Beck & Katz 1995 note that the asymptotic theory in the FGLS leads to more efficient estimates with the disadvantage that it tends to be too "optimistic" (anti conservative) when the data is not large.

[10]SBC and AIC criteria selects between 1-5 lags depending on the economic sector. Nevertheless, the two-lag models yield results that are very similar to those with a longer lag length specification.

	FGLS				PCSE				IV			
Coeff.	A	B	C	D	A	B	C	D	A	B	C	D
$\Delta tfpnw_t$	-0.32*** (0.04)	-0.41*** (0.07)	-0.40*** (0.09)	-0.62*** (0.07)	-0.39*** (0.07)	-0.46*** (0.11)	-0.48*** (0.11)	-0.68*** (0.10)	-0.38*** (0.12)	-0.35** (0.16)	-0.32** (0.15)	-0.82*** (0.13)
$\Delta nhtk_t$		-0.19*** (0.04)	-0.18*** (0.04)	-0.17*** (0.03)		-0.26*** (0.06)	-0.27*** (0.06)	-0.21*** (0.05)		-0.26*** (0.06)	-0.26*** (0.06)	-0.22*** (0.05)
Δhtk_t		-0.27* (0.17)	-0.28* (0.17)	-0.22** (0.11)		-0.45* (0.26)	-0.49* (0.26)	-0.32* (0.19)		-0.44* (0.25)	-0.45* (0.26)	-0.29 (0.21)
$\Delta hwsk_t$		-0.12*** (0.03)	-0.11*** (0.04)	-0.09*** (0.03)		-0.12** (0.05)	-0.12** (0.05)	-0.09** (0.04)		-0.10** (0.07)	-0.09* (0.05)	-0.11*** (0.04)
$\Delta hwnsk_t$		0.02 (0.03)	0.004 (0.04)	0.09** (0.04)		0.03 (0.05)	0.02 (0.05)	0.08* (0.05)		0.06 (0.06)	0.07 (0.06)	0.05 (0.05)
$\Delta lcsk_t$			-0.004* (0.002)	-0.002 (0.002)			-0.003 (0.003)	-0.002 (0.03)			-0.001 (0.004)	-0.003 (0.004)
$\Delta lcnsk_t$			-0.01 (0.01)	-0.03** (0.01)			-0.005 (0.03)	-0.04** (0.02)			-0.003 (0.03)	-0.04** (0.02)
$\Delta rwsk_t$				0.20*** (0.02)				0.20*** (0.03)				0.21*** (0.03)
$\Delta rwnsk_t$				0.21*** (0.03)				0.22*** (0.03)				0.23*** (0.03)
R^2					0.16	0.33	0.34	0.60	0.13	0.27	0.28	0.60
AR(1)	0.09	0.04	0.04	0.07	0.09	0.04	0.05	0.07				
Sargan-Hansen Chi-sq(3) P-Value									0.79 (0.85)	1.83 (0.61)	2.69 (0.44)	5.22 (0.16)
$corr(u_i, Xb)$									-0.04	-0.20	-0.19	0.03
Sector effects	yes	yes	yes	yes	yes	yes	yes	yes	no	no	no	no
Time effects	no	no	no	no	no	no	no	no	no	no	no	no
Wald chi2 Prob> chi2	131.50 0.00	169.63 0.00	138.70 0.00	420.49 0.00	49.57 0.00	117.49 0.00	116.21 0.00	277.79 0.00	95.04 0.00	52.40 0.00	37.38 0.00	253.9 0.00
N Grupos	243 9	243 9	243 9	243 9	243 9	243 9	243 9	243 9	243 9	243 9	243 9	243 9

Table 4: *All regressions use the value added weighted* innovation based growth accounting framework *measures of productivity ($tfpnw$) and value added weighted changes of relevant variables. The instrumental variables approach use as instruments contemporaneous and twice lagged values of mean labor productivity and the second lag of $tfpnw$.*

the sequential addition of covariates that account for the impact of capital and labor services (Column B) and labor composition (C) differences between skilled and non skilled workers. In fact, adding these covariates appears to increase the explanatory power of $tfpnw$. This effect is particularly large in column D, where real wages of skilled and unskilled labor are included.

As discussed in Beck & Katz 1995, PCSE coefficient estimates are more conservative exhibiting, in general, larger standard errors and lower Wald test statistics than estimates under FGLS. This may be appropriate given the small sample properties of the data available to this research. The estimated coefficients under the instrumental variables approach reconfirm the robustness of this general result. Although the Sargan-Hansen test of overidentification tends to lose power as additional covariates are included, even in the last column (column D) the test fails to reject, at conventional significance values, the null hypothesis that the model is over-identified.

Including the other covariates shows that there is a negative association between increases in capital and the labor share which is larger in magnitude but less statistically significant in the case of *High-Tech* assets. A 1% increase in *High-Tech* (non *High-Tech*) is associated with a decrease in the labor share between 0.22 - 0.49 (0.17 - 0.26) percentage points. The negative sign of these coefficients seems to suggest that decoupling is likely to be driven by a capital augmenting (or labor replacing) process of technical change and is consistent with earlier findings in Arpaia et al., 2009 and Bassanini & Manfredi 2014. The large impact of *High-Tech* assets is somewhat puzzling given the small and declining share of this type of assets in the capital stock of the Colombian Economy.[11]

The evidence also shows a small but statistically significant negative association between the increase in hours worked by skilled workers and the labor share. A 1% increase in hours worked by this type of workers reduces the labor share between 0.09-0.12 percentage points. On the contrary, a change in hours worked by non skilled workers appears to be positively associated with the labor share. But this effect is less statistically significant. Taken together, the last couple of results suggest that the process of technical change in the Colombian economy has been accompanied by a mild substitutability between skilled and non skilled workers. Remarkably, given the results found

[11]The share of *High-Tech* assets was 23% in the 1990s and decline to 17% in the 2010s at the national level. In this period the only increase was in Transport Equipment (1.5% and 4.9%). In comparison non *High-Tech* assets kept growing at an increasing pace (19% and 31%)

for the two types of capital assets, the evidence also suggest a strong complementary relationship between both *High-Tech* and non *High-Tech* assets with skilled workers, and reconfirms the likely substitution effect between both types of capital and non skilled workers.

Including labor composition seems to have little effect on the labor share. Particularly in the case of skilled workers, the estimated coefficients are rather small and not statistically significant. In the case of non skilled workers the estimates are a bit larger, but they are statistically significant only under the instrumental variables approach. The lack of robustness in this case, however, is not surprising given the fact that the Colombian economy has experienced only little and sluggish changes in the composition of the labor market over the sample period.[12]

Another interesting result arise from the inclusion of real wages. The estimated coefficient for both, skilled and non skilled types of labor have positive, very similar in size and statistically significant effects on the labor share. This is not something implausible given the wage adjustment process in the country that typically takes the increase in the *minimum wage* as the reference point to increase other wages. The slightly smaller magnitude found for the coefficient of skilled workers seems consistent with the findings of declining wage inequality documented in earlier research for the Colombian economy over a similar period of time as in this investigation (Galvis et al., 2021). It remains puzzling, however, that contrary to the substitutability effect found in the estimated coefficients of hours worked, relative wages suggest instead a complementary relationship between skilled and non skilled workers.

To summarize, the results presented in Table 4 are highly consistent with empirical findings in the literature on the decoupling effect and fit reasonably well the known facts of the Colombian economy through the sample period under investigation. While they are not shown in the table, the results obtained are quite robust to the sequential elimination of control variables included in the model, and also to the elimination of economic sectors one-by-one from the sample. This additional check of robustness seems relevant, as suggested by Bassanini & Manfredi 2014, to ensure that aggregate estimates are not entirely dominated by some specific sector in the sample. The largest enlargement in all cases is obtained by dropping *professional services*. The

[12]More that 3/4 of the labor force is made of workers with less than secondary education. This structure has had only little changes from the 1990s to the 2010.

smallest is obtained by dropping the *retail* sector. However, the differences are not statistically different from the coefficient estimates presented in the table.[13]

As mentioned above, the focus of the results presented in Table 4 is on the relationship between changes in the labor share and the value added weighted *innovation based growth accounting framework* measure of productivity. It remains to be seen if the results obtained are robust to the other two alternative measures of productivity that have been analyzed in this section. Thus, for comparison purposes, I re-estimate the specification for the full model presented in column D by sequentially replacing the productivity variable in the array $x \in \{mphw, tfpcw, tfpnw\}$.

In the results presented in Table 5, point estimates of productivity and non *High-Tech* capital assets become smaller but remain highly statistically significant when using $tfpcw$ and much more when using $mphw$. The somewhat large differences in the productivity parameter (from -0.82 to -0.71 under IV and from -0.68 to 0-0.46 under the PSCE approach) do not contradict the evidence found under $tfpnw$ in support of a decoupling effect. Similarly, the smaller impact of non *High-Tech* assets under the alternative measures of productivity still provide suggestive evidence to the thesis that decoupling in Colombia has been driven by a capital-augmenting (labor-replacing) process of technical change.

Interestingly, the coefficient estimates of other co-variates that are key in the *innovation based growth accounting framework* (*High-Tech*, hours worked and labor composition of skilled and non skilled workers) also become smaller and, with a couple of exceptions, not significant in the regressions that use the alternative measure of productivity. It seems to suggests that overlooking the role of these components affects the statistical inference concerning the role of productivity and other factors affecting the labor share. Based on this reasoning, the model using the *innovation based growth accounting framework* should be a preferred specification to conduct inference on the relationship between productivity and the labor share.

Another interesting result indicates a highly robust positive effect of a change in real wages (for both skilled and non skilled workers) on the labor share. This still implies a rather complementary relationship between both types of workers that is puzzling as I have argued above. It is also noticeable that using $tfpcw$ and $mphw$, regression results appear to contradict the ear-

[13] Results of these regressions are available under request.

lier finding about the declining trend in wage inequality that was discussed above for the Colombian economy through the sample period. In particular, the estimated coefficients for skilled workers appear now equal or slightly larger, not smaller, than the corresponding estimates for non skilled workers which seems inconsistent with the evidence found by Galvis et al., 2021 for the Colombian economy.

Taken them together, the regressions using other than the *innovation based growth accounting framework* measure of productivity do not appear to fit the data well. The poor performance of the alternative models indicates some sort of misspecification problem. In fact, the Sargan-Hansen test results shows that, at the 10% level of significance, the model is better specified when using the *innovation growth accounting framework* than any of its alternatives. As a robustness check, I also compare the four version of the IV regression model in columns A-D of Table IV using the Sargan-Hansen test and found similar results confirming a better fit of the model using the *innovation growth accounting framework* measure of productivity.

6 Concluding remarks

The aim of this paper has been to draw the attention of the profession on issues of productivity measurement and the concerns associated to the decoupling hypothesis as, in spite of its relevance, this issue has been typically overlooked in the literature.

Theoretical justifications and empirical results suggest that taking into account detailed quality and price attributes of all production factors can matter for the enhanced assessment of the contribution of production factors thereby enhancing the assessment on the disembodied contribution of productivity to value added growth.

The growth accounting evidence presented in this paper lend support to two salient arguments: i) the failure to take into consideration capital and labor quality and price attributes leads to overestimate the role of productivity contributions to value added growth, therefore leading to misleading conclusions about the extent of the decoupling effect; and ii) even if well-defined productivity measurement is possible and it leads to close the overall decoupling gap, highly heterogeneous results across economic sectors provide a justification for using more rigorous econometric tools in order to test the statistical inference on the decoupling hypothesis.

	FGLS			PCSE			IV		
Coeff.	tfpnw	tfpcw	mphw	tfpnw	tfpcw	mphw	tfpnw	tfpcw	mphw
$\Delta x(i)_t$	-0.62***	-0.61***	-0.50***	-0.68***	-0.67***	-0.46***	-0.82***	-0.79***	-0.71***
	(0.07)	(0.07)	(0.06)	(0.10)	(0.10)	(0.09)	(0.13)	(0.12)	(0.10)
$\Delta nhtk_t$	-0.17***	-0.16***	-0.13***	-0.21***	-0.21***	-0.18***	-0.22***	-0.22***	-0.18***
	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Δhtk_t	-0.22**	-0.18	-0.09	-0.32*	-0.30	-0.19	-0.29	-0.27	-0.09
	(0.11)	(0.11)	(0.11)	(0.19)	(0.18)	(0.20)	(0.21)	(0.21)	(0.23)
$\Delta hwsk_t$	-0.09***	-0.02	0.0003	-0.09**	-0.01	0.008	-0.11***	-0.02	0.003
	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
$\Delta hwnsk_t$	0.09**	0.03	0.01	0.08*	0.008	0.01	0.05	-0.04	-0.10*
	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
$\Delta lcsk_t$	-0.002	0.002	0.003	-0.002	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.03)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
$\Delta lcnsk_t$	-0.03**	-0.01	-0.008	-0.04**	-0.04*	-0.03	-0.04**	-0.04*	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\Delta rwsk_t$	0.20***	0.20***	0.21***	0.20***	0.22***	0.24***	0.21***	0.22***	0.26***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\Delta rwnsk_t$	0.21***	0.20***	0.23***	0.22***	0.21***	0.22***	0.23***	0.21***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
R^2				0.60	0.60	0.57	0.60	0.59	0.55
AR(1)	0.07	0.08	0.07	0.07	0.08	0.07			
Sargan-Hansen							5.22	7.57	5.99
Chi-sq(3) P-Value							(0.16)	(0.06)	(0.11)
$corr(u_i, Xb)$							0.03	-0.05	0.06
Sector effects	yes	yes	yes	yes	yes	yes	no	no	no
Time effects	no	no	no	no	no	no	no	no	no
Wald chi2(6)	420.49	425.87	401.80	277.79	286.59	254.51	253.9	254.32	236.64
Prob> chi2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	243	243	243	243	243	243	243	243	243
Grupos	9	9	9	9	9	9	9	9	9

Table 5: *In each block $x(i)$ stands for $tfpnw$ in the first column, $tfpcw$ in the second column and $mphw$ in the third column. All variable changes are value added weighted. Instruments under $tfpnw$ and $tfpcw$ are contemporaneus and twice lagged values of mean labor productivity and the second lag of the own variable. Under $mphw$ the instruments are contemporaneous and twice lagged values of $tfpnw$ and the second lag of the own variable.*

The results of the cointegration approach show that decoupling is not an issue at the whole economy level in the Colombian economy over the 30-year period in this investigation. But it seems to be hugely relevant for some economic activities, even if ambiguities arise from the results based on alternative measures of productivity. Remarkably, inference conducted on the innovation based growth accounting framework for productivity measurement seems to provide a better fit of the data.

Regressions based of short run dynamics under the panel data approach provide convincing statistical support to the decoupling hypothesis at the sectoral level. It also provides strong evidence to the thesis that decoupling has been driven by a process of technical change that is capital augmenting (or labor replacing) with strong complementarity between *High-Tech* and non *High-Tech* capital assets and skilled workers, less strong (or at least not statistically significant) substitutability between both types of capital and non skilled labor, and ambiguous evidence on the complementarity/substitutability relationship between skilled and non skilled workers. While there are conflicting results between different specification of the regression model, the preferred specification based on the *innovation based growth accounting framework* fits reasonably well the declining trend in wage inequality between skilled and non skilled workers in the Colombian economic through the sample period.

Remarkably, using the *innovation based growth accounting framework* seems, in general, to lead to better model specifications and improves the econometric estimation of the effect of variations on the components of production factors over the labor share. Apparently, by disentangling the sources of productivity, this line of research helps to improve the understanding on the relationship between changes in productive factors and the disembodied contribution of productivity and the evolution of the labor share. Yet, certainly, further research effort would be needed before deriving more general conclusions.

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Appendix A

Innovation Based Growth Accounting

Consider the conventional neo-classical approach where value added is produced using a standard Cobb-Douglas technology across all sectors of activity. At the aggregate level, value added for the whole economy is obtained as an unweighted sum as follows

$$VA_t = \sum_j VA_{jt} = \sum_j A_{jt} KS_{jt}^{\upsilon_{jt}} LS_{jt}^{\omega_{jt}} \tag{1A}$$

Where A_{jt} represents multi factor or Total Factor Productivity (TFP), KS_{jt} denotes capital services, LS_{jt} labor services, measured in hours of work, and υ_{jt}, ω_{jt} are sector specific time changing factor shares.

$$\upsilon_{jt} = \frac{VA_{Ljt}}{VA_{jt}} = \frac{i_{jt} \times KS_{jt}}{VA_{jt}} \tag{2A}$$

$$\omega_{jt} = \frac{VA_{Kjt}}{VA_{jt}} = \frac{\mathrm{w}_{jt} \times LS_{jt}}{VA_{jt}} \tag{3A}$$

where i_{jt} is the use nominal cost of capital and w_{jt} the nominal wage per hour.[14]

Using logarithmic changes on both sides of Eq. (1A) TFP contributions are conventionally obtained as follows

$$\Delta tfpc_{jt} = \Delta va_{jt} - \overline{\upsilon}_{jt}\Delta ks_{jt} - \overline{\omega}_{jt}\Delta ls_{jt} \tag{4A}$$

Following Fernández-Arias et al., (2021), labor services are broken down into 18 categories resulting from the combination of sex (male, female), age (15-29, 30-49, 50 or more years), and education (high, medium and basic levels). Labor services growth contributions are calculated as a Thörnqvist - Theil Divisia index of the growth of hours worked by each category of labor weighted by its nominal share in value added.

$$\Delta ls_{jt} = \sum_l \overline{\mathrm{v}}_{ljt}\Delta h_{ljt} \tag{5A}$$

[14] Under conventional assumptions of perfect competition and constant returns to scale $\upsilon_{jt} A_{jt} KS_{jt}^{\upsilon_{jt}-1} LS_{jt}^{\omega_{jt}} = i_{jt}$, $\omega_{jt} A_{jt} KS_{jt}^{\upsilon_{jt}} LS_{jt}^{\omega_{jt}-1} = \mathrm{w}_{jt}$, and $\upsilon_{jt} = 1 - \omega_{jt}$.

where

$$\mathrm{v}_{ljt} = \frac{\mathrm{w}_{ljt} H_{ljt}}{\sum_l \mathrm{w}_{ljt} H_{ljt}} = \frac{\mathrm{w}_{ljt} H_{ljt}}{VA_{Ljt}} \tag{6A}$$

is the labor type specific cost share in the total sectoral value of the same variable. The labor type specific nominal wage per hour worked is calculated as

$$\mathrm{w}_{ljt} = \frac{VA_{ljt}}{h_{ljt}} = \frac{WC_{SNA,ljt}}{H_{E,ljt}} \tag{7A}$$

Further decomposition into contributions accrued to *labor composition* and *hours worked* are obtained as follows

$$\begin{aligned} \Delta ls_{jt} &= \sum_l \overline{\mathrm{v}}_{ljt} \Delta h_{ljt} - \Delta h_{jt} + \Delta h_{jt} \\ &= \sum_l \overline{\mathrm{v}}_{ljt} \Delta \left(\frac{H_{ljt}}{H_{jt}} \right) + \Delta h_{jt} \end{aligned}$$

where $\Delta h_{jt} \approx \sum_j \overline{\mathrm{v}}_{ljt} \Delta h_{jt}$ is used in the second row. This equation may be written more compactly as

$$\Delta ls_{jt} = \Delta lc_{jt} + \Delta h_{jt} \tag{8A}$$

where the first term on the right hand side represents the contribution of *labor composition* and the second the contribution of hours worked.

Similarly, capital services are calculated from sector specific stocks using the perpetual inventory method

$$\Delta ks_{jt} = \sum_k \overline{\mathrm{v}}_{kjt} \Delta \mathrm{K}_{kjt}$$

where

$$K_{kjt} = K_{kjt-1}(1 - \delta_{kjt}) + I_{kjt} \tag{9A}$$

$$\mathrm{v}_{kjt} = \frac{i_{kjt} K_{kjt}}{\sum_k i_{kjt} K_{kjt}} = \frac{i_{kjt} K_{kjt}}{VA_{Kjt}} \tag{9B}$$

where I_{kjt}, δ_{kjt}, v_{kjt} and i_{kjt} are asset (k) and sector (j) specific investment, depreciation, user cost shares and user cost of capital. For every sector $VA_{Kjt} = VA_{jt} - VA_{Ljt}$ holds.

The user nominal cost of capital, specific for each asset type and sector, is captured by the following equation

$$i_{kjt} = p_{Ikj,t-1}(1 + \bar{i}_{jt}) - p_{Ikjt}(1 - \delta_{kj}) \tag{10A}$$

where p_{Ikjt} is the SNA investment price index, $\bar{i}_{jt}$ is the sector specific nominal rate of return on capital, and δ_{kj} a time invariant asset-specific rate of depreciation. The nominal rate of return is calculated as

$$\bar{i}_{jt} = \frac{VA_{K,jt} + \big(p_{Ikjt}(1 - \delta_{kj}) - p_{Ikj,t-1}\big)K_{kjt}}{p_{Ikj,t-1}K_{kjt}}$$

As explained in the main text, the growth contribution of *High-Tech* assets (information and technology, computing equipment, software, machines, transport equipment) is obtained as

$$\Delta htk_{jt} = \sum_{j} \overline{\mathrm{V}}_{\mathrm{HT}jt} \Delta \mathrm{K}_{\mathrm{HT}jt}$$

and the growth contribution of capital services related to non-*High-Tech* assets (residential and non residential structures, cultivated assets, R&D and intellectual property)

$$\Delta nhtk_{jt} = \sum_{j} \overline{\mathrm{V}}_{\mathrm{NHT}jt} \Delta \mathrm{K}_{\mathrm{NHT}jt}$$

Thus, the growth rate of capital service may be written as

$$\Delta ks_{jt} = \Delta htk_{jt} + \Delta nhtk_{jt} \tag{11A}$$

Appendix B

Correlation matrix

	Δlsh	Δmph	$\Delta tfpn$	$\Delta tfpc$	$\Delta knit$	Δkit	$\Delta hwsk$	$\Delta hwnsk$	$\Delta lcsk$	$\Delta lcnsk$	$\Delta rwsk$	$\Delta rwnsk$
Δlsh	1											
Δmph	-0.0787	1										
$\Delta tfpn$	-0.1751	0.8442	1									
$\Delta tfpc$	-0.1817	0.9188	0.9061	1								
$\Delta knit$	-0.0280	-0.0507	-0.1202	-0.1621	1							
Δkit	0.1176	0.0101	-0.0276	-0.0044	0.0324	1						
$\Delta hwsk$	0.0021	-0.3180	-0.6135	-0.3290	0.0061	0.0250	1					
$\Delta hwnsk$	-0.0041	-0.6657	-0.5352	-0.6548	0.0723	-0.0325	0.3875	1				
$\Delta lcsk$	0.0109	0.0107	-0.1000	0.0179	0.0008	0.0836	0.0909	-0.0994	1			
$\Delta lcnsk$	-0.0378	0.0499	0.0379	0.0075	-0.0320	-0.1062	-0.0438	0.0824	-0.4295	1		
$\Delta rwsk$	0.3996	0.3091	0.2117	0.2415	-0.0713	0.1012	-0.0548	-0.1423	-0.0109	0.1390	1	
$\Delta rwnsk$	0.3533	0.5604	0.5706	0.4888	-0.0441	0.0325	-0.3715	-0.2857	-0.0882	0.0420	0.2092	1

All varriables are value added weighted.