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What Explains the Decline of the U.S. Labor Share of Income?
An Analysis of State and Industry Level Data

by Yasser Abdih and Stephan Danninger

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I N T E R N A T I O N A L M O N E T A R Y F U N D

IMF Working Paper

Western Hemisphere Department

**What Explains the Decline of the U.S. Labor Share of Income?
An Analysis of State and Industry Level Data****Prepared by Yasser Abdih and Stephan Danninger¹**

Authorized for distribution by Nigel Chalk

July 2017

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Abstract

The U.S. labor share of income has been on a secular downward trajectory since the beginning of the new millennium. Using data that are disaggregated across both state and industry, we show the decline in the labor share is broad-based but the extent of the fall varies greatly. Exploiting a new data set on the task characteristics of occupations, the U.S. input-output tables, and the Current Population Survey, we find that in addition to changes in labor institutions, technological change and different forms of trade integration lowered the labor share. In particular, the fall was largest, on average, in industries that saw: a high initial intensity of “routinizable” occupations; steep declines in unionization; a high level of competition from imports; and a high intensity of foreign input usage. Quantitatively, we find that the bulk of the effect comes from changes in technology that are linked to the automation of routine tasks, followed by trade globalization.

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Keywords: Routine tasks, offshoring, labor share, unions, import competition.

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I. INTRODUCTION

Since the early 2000s, the share of U.S. national income that accrues to labor, in the form of wages and benefits, has fallen by 3.5 percentage points. Prior to that, while the labor share displayed some ups and downs, there was no notably long-term trend (Figure 1). Indeed, for the aggregate economy, the labor share never strayed too far from 56 percent of GDP or about 64 percent of corporate sector output.

Data broken down by state and industry show the decline is broad based. Its extent, though, has varied (Figures 2 and 3). For states, the labor share drop between 2001 and 2014 ranged from over 8 percentage points in Nebraska, Oregon, and Oklahoma to a mere 0.2 percentage points in New Hampshire and Maine (Figure 2). For industries, the median decline across states over the same period was largest in the more tradable sectors, such as information technology, manufacturing, transportation, mining, and agriculture (Figure 3). The median change in the labor share was very small in the real estate and accommodation and food services sectors, and positive in such sectors as health, education, and other services (See Table 1 for a definition of industry codes).

A falling labor share has implications for the overall distribution of income. Labor income is more evenly distributed across US households than capital income—the latter tend to be more concentrated at the top income households (see Jacobson and Occhino 2012, and Armenter 2015). Hence, a decrease in the labor share—and equivalently an increase in the capital share—makes overall income less evenly distributed and more concentrated at the top of the income distribution. The result has been an increase in overall income inequality. Indeed, the data indicate a negative correlation between the Gini coefficient and the labor share (Figure 4). This income inequality, in turn, entails large social costs. It deprives lower-income households of the ability to stay healthy and

Figure 1. Labor Share: Overall and Corporate Sector
(labor compensation in percent of current-value output)

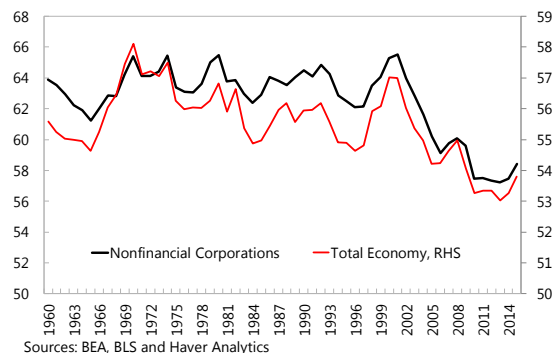


Figure 2. Labor Share by State: Change 2001-2014
(in percentage points)

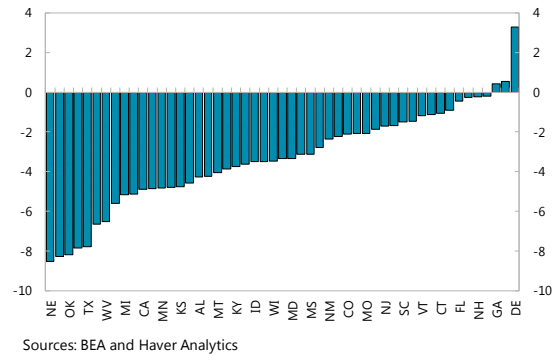


Figure 3. Labor Share by Industry: Median Change Across States
(change over 2001-14 in percentage points; x-axis values are industry codes)

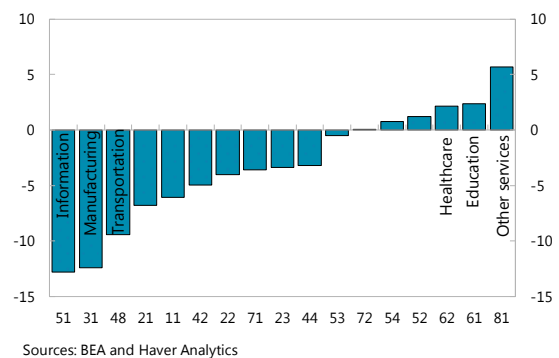
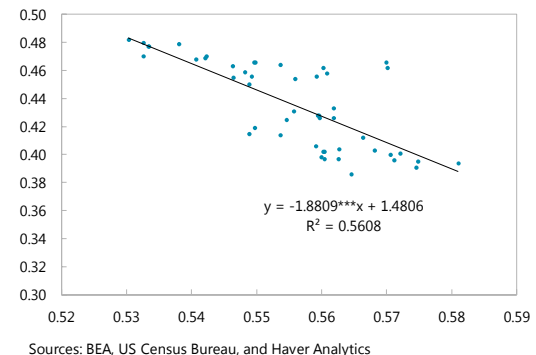


Figure 4. US Labor Share and Income Inequality: 1967-2015
(Y-axis: Gini Index; X-axis: Labor Share)



accumulate physical and human capital (Galor and Moav 2004; Aghion, Caroli, and Garcia-Penalosa 1999), and has been shown to negatively affect the pace and sustainability of economic growth (Berg and Ostry 2011, Ostry and others 2014, and Dabla-Norris and others 2015).

The existing literature suggests that the downward trend in the labor share is a widespread and global phenomenon (for seminal contributions, see IMF 2017, Elsby, Hobijn, and Sahin 2013, and Karabarbounis and Neiman 2014, and Dao, Das, Koczan and Lian 2017). Previous research has focused on three leading drivers: the rapid pace of technological progress, the globalization of trade and capital, and developments in labor market institutions and policies.

Industry	Code
Agriculture	11
Mining	21
Utilities	22
Construction	23
Manufacturing	31
Wholesale trade	42
Retail trade	44
Transportation and warehousing	48
Information	51
Finance and insurance	52
Real estate and rental and leasing	53
Professional and business services	54
Educational services	61
Health care and social assistance	62
Arts, entertainment, and recreation	71
Accommodation and food services	72
Other services, except government	81

Source: US Census Bureau; the North American Industry Classification System (NAICS)

In this paper, we build on this literature and make three main contributions:

- First, we shed light on the key drivers and their relative contribution by exploiting cross-state variation at the industry level. To our knowledge, we are the first to do so. We follow closely the empirical methodology in IMF 2017, which mostly focused on labor share drivers at the global level.
- Second, we carry out the empirical analysis utilizing a data set on the task characteristics of occupations. We exploit the richness of this data and construct indexes of exposure to routinization (automation of routine tasks) and to offshorability (a measure of the potential to relocate occupational tasks) that vary by industry and state. IMF 2017, and Das and Hilgenstock 2017, constructed similar routinization indexes at the cross-country aggregate and sectoral levels.
- Finally, we build bottom up measures of trade integration and labor market institutions by utilizing the wealth of information in the US input-output tables and the Current Population Survey (CPS).

Our key findings are as follows:

- The overall decline in the labor share since the early 2000s mostly reflects declines *within* sectors and states, rather than compositional shifts across sectors or to states with lower labor shares.
- Routinization intensity is the dominant factor underlying the downward trend in the labor share, explaining 44 to 57 percent of the *within* decline since 2001 depending on the empirical specification.

- Offshoring of intermediate products as well as competition from imports facing domestic industry's output and sales, are strongly significant explanatory variables explaining 21-33 percent and 16-21 percent of the decline, respectively.²
- While highly statistically significant, labor market institutions, in particular unionization, play a smaller role relative to that of technology and combined global/international factors.

These results provide important empirical markers for understanding the decline in the labor share. In particular, the findings are consistent with the notion put forward by Autor, Dorn, Katz, Patterson, and Van Reenen 2017 (henceforth, Autor et al. 2017) that technological progress may have facilitated concentration of production in large firms which reap higher profits in equilibrium, thereby reducing the labor share. The paper, however, also identifies an important role of international factors, including rising international competition and intermediate goods trade.

The rest of the paper is organized as follows. Section II discusses key concepts and measurement of the main drivers of the labor share. Section III presents a brief description of the data. Section IV carries out a shift-share exercise, and conducts regression analysis as well as various robustness checks. Section V offers concluding remarks and outlines some considerations for policy.

II. CONCEPTS AND MEASUREMENT

In this section, we very briefly describe—at an intuitive level—the key channels through which the potential drivers affect labor share dynamics (for an extensive discussion on these, see IMF 2017, and Dao et al. 2017) and the measurement of variables used to capture the said effects. In particular, we look at the role of technology (routinization); international forces (offshorability of tasks, import competition facing the output of domestic industries, and intermediate goods import); and institutional factors (unionization).

A. Technology: Routinizability of Occupations

An extensive literature has argued that technological progress—in particular, advancement in information and communication technology (ICT)—displaced labor through the automation of routine tasks (see Autor and Dorn 2013; Goos, Manning, and Salomons 2014; and IMF 2017). The general idea here is because of ICT, capital has become better and cheaper, increasing its demand and reducing labor demand. As capital replaces labor, income gets redistributed from the latter to the former.

A decline in the labor share brought about by routine task automation can occur even at full employment—that is, as a permanent change in equilibrium. This is because the rental rate of capital is permanently higher, increasing income accruing to capital, while workers after

² These numbers are the minimum and maximum contributions of the international factors to the within labor share decline across all empirical models estimated and reported in this paper (see Figures 8 through 10).

adjustment are at the margin less productive, receiving a smaller share of aggregate output (Autor and Dorn 2013). This result holds in models with one or multiple skill levels of workers (Karabarbounis and Neiman 2014).

Routinization Scores

To construct our measure of routinization (and further below of offshoring potential), we exploit data from the U.S. Department of Labor’s Occupational Information Network (O*NET). The O*NET database is a rich source of information on the nature of activities and tasks performed in over 960 occupations, rooted in surveys of a broad range of workers from each occupation.

We follow Autor and Dorn 2013 and Firpo, Fortin, and Lemieux 2011 and capture routinization—that is, the propensity to automate routine tasks—by the following O*NET variables: “degree of automation”; “importance of repeating same tasks”; “structured versus unstructured work”; “pace determined by speed of equipment”; and “spend time making repetitive motions.” Each occupation has a score for each of these variables; we aggregate these to form a composite routinization score. The latter is increasing in the degree of routinizability, and is further normalized to have a zero mean and a cross-occupation standard deviation of unity.

By the above criteria, occupations with the most routine tasks are: tire builders; telephone operators; postal service mail sorters, processors, and processing machine operators; reservation and transportation ticket agents and travel clerks; and textile winding, twisting, and drawing out machine setters, operators, and tenders. Occupations with the most non-routine tasks are: teachers; therapists; clergy; speech language pathologists; door-to-door sales workers, news and street vendors, and related workers; and directors of religious activities and education.

Following the approach introduced in IMF 2017 and Das and Hilgenstock 2017, we weight the routinization scores by employment shares to construct aggregate measures at the industry and state levels. Let $Scor_o$ denote the composite and normalized routinization score for occupation o , as described above. We define an aggregate routinization index/exposure for industry i , in state s , and at time t , RTI_{ist} , as follows:

$$RTI_{ist} = \sum_o w_{oist} Scor_o$$

where w_{oist} is occupation o ’s share of employment in industry i , state s at time t . These shares/employment weights are constructed from the Current Population Survey (CPS). Note that $Scor_o$ is assumed not to vary across industries, states, and time, which is typical in the literature (see, for example, IMF 2017). For example, it seems reasonable to assume that tasks performed by postal service mail sorters are intrinsically automatable while those performed by therapists or teachers inherently non-automatable, always and everywhere. That said, we show in the next section that our key results are robust to relaxing this assumption and allowing the routinization scores to vary, particularly over time.

B. International Factors

There are multiple channels for international factors to shape a country's labor income share. We explore three: offshoring potential of job tasks; offshoring through imports of intermediate goods, and import competition facing domestic industries' output/sales.

Offshorability of tasks

A growing literature studies international offshoring, whereby firms perform specific subcomponents or tasks of their production processes overseas (see, for example, Grossman and Rosii-Hansberg 2008, Blinder 2007, Jensen and Kletzer 2010, Blinder and Krueger 2013, and Firpo, Fortin, and Lemieux 2011). In the U.S. context, it is intuitive to think of firms outsourcing the labor-intensive stages of production or tasks to countries where labor is abundant and cheap. The result is a substitution of foreign labor for domestic labor. As demand for domestic labor declines, real wages fall and with them the labor share.

Unlike trade in goods, offshored tasks are not captured in national accounts and are hard to measure. As such, we follow the standard practice of measuring the potential for an occupational task to be offshored (offshorability), rather than the actual offshoring that takes place (although we do capture one form of actual offshoring below through trade in inputs). To that end, we construct an *index* that incorporates two key criteria for non-offshorability highlighted by the literature: (1) that a job requires direct face-to face interactions with clients; and/or (2) that a job requires direct physical access to the client's working site (or proximity to a specific domestic work location).

Specifically, and following Autor and Dorn 2013 and Firpo, Fortin, and Lemieux 2011, we capture the *face-to-face contact* criterion by the O*NET variables: "face-to-face discussions"; "establishing and maintaining interpersonal relationships"; "assisting and caring for others"; "performing for or working directly with the public"; and "coaching and developing others". We capture the *on-site job* criterion by the O*NET variables: "inspecting equipment, structures, or material"; "handling and moving objects"; "controlling machines and processes"; "operating vehicles, mechanized devices, or equipment"; "repairing and maintaining mechanical equipment"; and "repairing and maintaining electronic equipment".

The above subcomponents have scores, which we aggregate to form a composite non-offshorability score for each occupation. We subtract from this variable its mean value, divide by the cross-occupation standard deviation, and multiply by negative one so that the resulting index is normalized with a mean on zero, a standard deviation of unity, and is increasing rather than decreasing in offshorability.

By this metric, the most offshorable occupations are: proofreaders and copy markers; mathematical science occupations; brokerage clerks; operational research analysts; interviewers (except eligibility and loan); financial analysts; actuaries; and telemarketers. The least offshorable occupations are: emergency medical technicians and paramedics;

elevator installers and repairers; firefighters; manufactured building and mobile home installers; and electrical power-line installers and repairers.

We construct industry/state level offshorability measures in the same way as we did with routinization above—that is, as a weighted sum of the composite and normalized offshorability scores, with employment shares again acting as weights. Like routinization, we show in the next section that our results hold irrespective of whether the offshorability scores are assumed constant or allowed to vary over time.

Imports of intermediates

An alternative way to capture international effects is to measure the intensity with which domestic industries use foreign intermediate inputs in production. This could be the result of either offshoring production steps/stages or by drawing on newly available international supply chains. To the extent that imported intermediates replace labor intensive production processes, they reduce labor demand and the labor share.

We construct a variable capturing the intensity of foreign input usage in two stages. First, we utilize the U.S. input-output tables to construct the variable at the national industry level. We then compute state level equivalents using industry-level relative output data as weights (for examples on this imputation procedure, see Garofalo and Yamarik 2002, and Yamarik 2013).

Specifically, the input-output tables provide information on 206 NAICS industries. These industries produce commodities—each industry produces a primary commodity (or commodities) but may produce other commodities as well. A given industry imports a set of *inputs* that it uses for domestic production. We define the intensity of foreign input usage for industry i at the national level as its imported inputs relative to its output. That is,

$$ForInpInten_i = \frac{\sum_{k=1}^K MI_{ki}}{Y_i}$$

where MI_{ki} = Imports of *input* k by industry i ($k=1, 2, \dots, K$); and Y_i = Gross output (sales) of *all* commodities in industry i . Next, using output weights, we aggregate the 206 foreign input intensity variables into 17 variables corresponding to our 17 NAICS 2-digit industries (that we use in the empirical exercise that follows). Finally, we impute the state level equivalents by multiplying each variable by:

$$Weight_{is} = \frac{Output_{is}}{Output_i}$$

where:

$Output_{is}$ = Output of industry i in state s .

$Output_i$ = Output of industry i nation-wide.

To give an example, the intensity of foreign input usage for manufacturing in California is computed as the intensity of foreign input usage for manufacturing nation-wide times the share of California's manufacturing output in nation-wide manufacturing output.

Import Competition

Finally, foreign goods—final or intermediate— can compete with domestic production. For example, if foreign steel is cheaper than domestically produced steel and transaction costs are low, then one would expect the former to substitute for the latter. As steel imports increase, domestic production and labor demand in the steel industry would most likely fall. So here, through the import channel, U.S. workers face competition from foreign workers, putting downward pressure on wages, and potentially the domestic labor share of the surplus generated from production. And indeed, the empirical evidence does support that: trade with low-wage countries depresses wages and employment in industries, occupations, and regions that are exposed to import competition (Artuc, Chaudhuri, and McLaren, 2010; Autor, Dorn and Hanson, 2013; and Ebenstein et al., 2014).

We utilize the same US input-output tables we used for imported inputs to construct a measure of import competition. Once again, we start with 206 NAICS industries. These industries produce commodities but face competition from abroad—commodities can be imported instead of being bought domestically. Also, recall that a given industry produces one or more primary commodities but may produce other commodities as well; this also implies that a given commodity can be produced by more than one industry.

We define import competition for a given industry as follows:

$$ImportCom_i = \sum_{j=1}^N \left(\frac{M_j}{(M_j + Y_{j.})} \right) \left(\frac{Y_{ji}}{Y_i} \right)$$

where:

i denotes industry; $i = 1, 2, \dots, T$, where $T=206$, the total number of industries;

j denotes commodity $j = 1, 2, \dots, N$, where N is the total number of commodities;

M_j = Imports of commodity j into the economy;

Y_{ji} = Gross output (sales) of commodity j in industry i ;

$Y_{j.}$ = Gross output of commodity j from *all* industries. That is, $Y_{j.} = \sum_{i=1}^T Y_{ji}$;

Y_i = Gross output (sales) of *all* commodities produced by industry i . That is, $Y_i = \sum_{j=1}^N Y_{ji}$.

Intuitively, the above equation implies that competition facing a given industry intensifies when there is an increase in the imports of the primary commodities that this industry produces.

We then aggregate the 206 import competition variables into 17 variables corresponding to our 17 NAICS 2-digit industries; after that we compute the state level equivalents using the same procedure/weights that we used when constructing the foreign input intensity variable above.

C. Institutional Factors: Unionization

An important change to the U.S. labor market institutional structure has been a decline in unionization. For example, in the private sector, the number of employed workers who are union members has dropped by 19 percent since the early 2000s. And the fraction of employed workers who are covered by a collective bargaining agreement has dropped by 2.4 percentage points. At 7.3 percent now, this number is at an all-time low.

Unions' bargaining power is likely to increase workers' share of the income generated in the production process. Estimates by Hirsch (2012), for example, put the union wage premia in the private sector at about 20 percent. This is sizable. As such, a decline in union membership is likely to weigh on the labor share.³

We measure unionization as the percentage of workers who are union members or covered by a union. The data come from the Current Population Survey.

Other forms of institutional differences in labor markets at the state level (e.g. right to work laws) were also assessed as robustness checks.

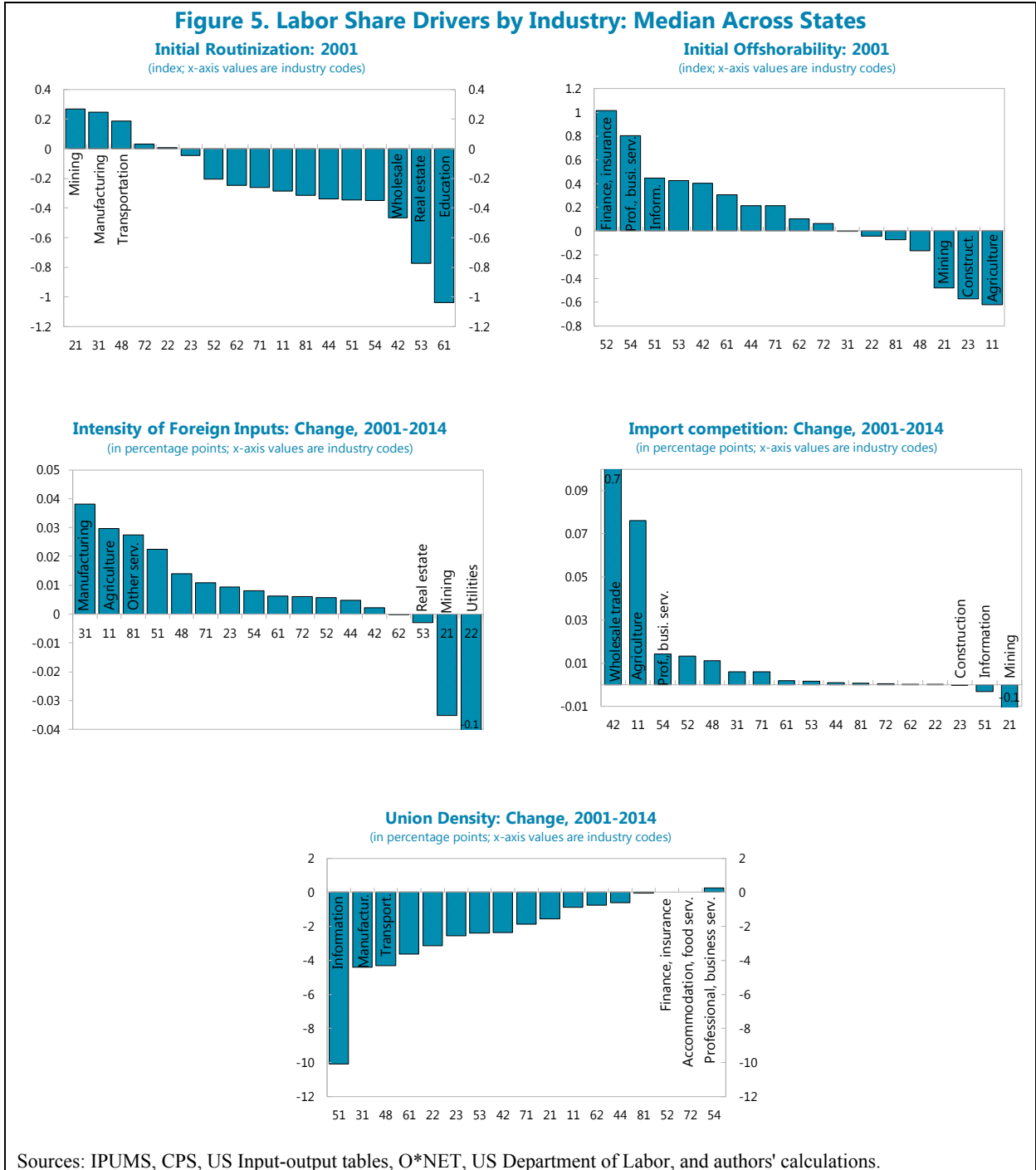
III. KEY DRIVERS: DATA

Unless otherwise specified, data are collected by industry, state, and year. We summarize in Figure 5 data for the key drivers of the labor share discussed above. The data are presented by industry, with the x-axis displaying the NAICS industry codes (for industry description, see Table 1). The y-axis displays the median across states of the key drivers. For reasons that we will discuss in the following section, we display routinization and offshorability in levels at the beginning of the sample period (this is how they will enter the regressions). We show unionization, foreign input usage, and import competition as changes over 2001-14. Several interesting observations emerge:

- Around the turn of the century, the median state's top five industries with the highest exposure to routinization were: mining; manufacturing; transportation and warehousing; accommodation and food services; and utilities. Industries with the lowest exposure included: educational services; real estate, rental, and leasing; wholesale trade; and professional and business services.
- Around the same time, the potential to offshore tasks in the median state was highest in: finance and insurance; professional and business services; and information; and was lowest in: agriculture; construction; mining; and transportation and warehousing.

³ Kramarz (2016) and OECD (2012) provide some evidence that declining bargaining power have contributed to lowering the labor share of national income.

- Manufacturing saw the highest increase in foreign input usage, followed by agriculture, other services, and information, while utilities faced the largest drop, followed by mining and real estate.



- Over 2001-14, import competition in the median state increased the most in wholesale trade and agriculture; it remained broadly constant in several industries— including, other services; accommodation and food services; healthcare; utilities; and construction—and declined in mining.
- Since 2001, unionization declined in virtually all industries, with the largest impact occurring in information, manufacturing, and transportation and warehousing.

IV. EMPIRICAL RESULTS

We begin this section by conducting a shift share analysis to determine whether the decline in the economy-wide labor share reflects an actual labor share decline in individual industries and states or a reallocation of resources from industries and states with a high labor share to those with a lower labor share. This will motivate and help inform the econometric modeling that follows. We conclude this section by carrying out a battery of robustness checks to our baseline regression.

A. Shift-Share Analysis

We decompose the total change in the aggregate labor share over 2001-2014 as follows:

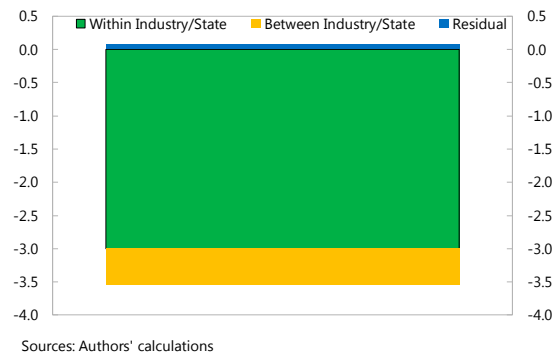
$$\underbrace{LS_T - LS_o}_{Total} \approx \underbrace{\sum_j \sum_i (LS_{ijT} - LS_{ijo}) \times W_{ijT}}_{Within} + \underbrace{\sum_j \sum_i (W_{ijT} - W_{ijo}) \times LS_{ijT}}_{Between}$$

where LS denotes labor share, $T = 2014$, $o = 2001$, i denotes industry, j denotes state, and W_{ij} denotes output of industry i in state j as a share of GDP. The within component holds GDP shares constant at their 2014 values and focuses on the over-time variation of the labor share in individual industries and states. The between component holds the industry/state labor share constant while allowing the GDP shares themselves to vary over time.

The results are depicted in Figure 6. They indicate that 90 percent of the aggregate decline is driven by a fall in the labor share within industries/states. Thus, the drop in the labor share is largely not the result of compositional changes either in industrial structure (e.g., the decline in manufacturing employment) or from a regional redistribution of production.

The dominance of the within labor share decline is in line with the shift share analysis conducted by Elsby, Hobjin, and Sahin, 2013 at the nation-wide industry level, with a sample that starts in the early 1990s. More recently, Author et al. 2017 added one more layer by exploiting firm level data. They showed that much of the nation-wide within industry decline in the labor share is largely due to between-firm rather than a within-firm decline. They

Figure 6. Labor Share Decline: Shift-Share, 2001-14
(in percentage points)



attribute this to rising industry concentration with shifts in output toward “superstar” firms with superior quality, higher profit levels, and lower labor shares. We view this as consistent and complementary to our results. In fact, Autor et al. 2017 further hypothesis that industry concentration could potentially result from technological progress and trade. While firm level data by state and industry do not seem to be available (and hence constructing concentration measures is not feasible), we do encompass empirically in the following section a reduced form empirical relationship of their model where changes in the labor share are modeled as ultimately dependent on measures of technology and trade.

The results here suggest that to understand the overall trend, it is more useful to model the within component of the labor share decline rather than those arising from the reallocation of resources. We do that next.

B. Econometric Analysis

We first conduct regression analysis to help us understand the extent to which the variation at the industry/state level of the potential drivers highlighted in the literature and discussed above can explain the corresponding variation in the labor share. Then we use the estimated coefficients of the econometric model and the actual data of the explanatory variables to decompose the total decline of the within labor share component over 2001-14 into contributions from the various drivers.

Our empirical strategy follows closely IMF 2017. The dependent variable in our empirical model is the change in the labor share for a given industry and state over 2001-14—the period that witnessed the secular decline (see Figure 1)⁴. The explanatory variables include the corresponding changes in import competition, the intensity of foreign input usage, and unionization, as well as the levels in 2001 of the indexes capturing the intensity of routinization and offshoring potential. The reason we include the latter two in levels, rather than changes in the levels, is to mitigate concerns that high initial exposure to routinization and offshorability may themselves lead to actual subsequent automation of routine tasks and actual subsequent offshoring such that by the end of the sample the exposure in both areas becomes less (see Dao et al. 2017 and IMF 2017). Stated differently, if the initial exposure is large to begin with, then the marginal tasks become less routine and less offshorable (Das and Hilgenstock 2017). Indeed, the data do indicate that the higher the initial exposure to routinization and offshorability, the larger is their subsequent decline (Table 2).

⁴ Following the key contributions in the literature (for example, IMF 2017, Elsby, Hobijn, and Sahin 2013, Karabarbounis and Neiman 2014, and Acemoglu and Restrepo 2016), our interest is in understanding the determinants of the *long-term changes* in the labor share rather than its cyclical fluctuations. Also, it takes time to adjust to structural changes in technology, trade, and institutions. Short term changes in the data, or even over few years are likely not to capture such effects. This motivates our choice of looking at changes over a long enough period.

Table 2. Modeling the Change in Routinization and Offshorability: 2001-14		
Explanatory Variables	Dependent Variable	
	Change in Routinization	Change in Offshorability
Initial Routinization	-0.4484*** (0.0392)	
Initial Offshorability		-0.5574*** (0.0411)
Observations	599	599
R-squared	0.5834	0.7063
Source: Authors' estimates		
Notes: Robust Regressions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include a constant, as well as state and industry dummy variables.		

Table 3 contains the results of the regression analysis. Specification (8) includes all variables.⁵ The coefficients of initial routinization intensity and of changes in import competition, foreign input intensity of usage, and unionization have the expected signs and are statistically significant at the one percent level. Intuitively, these results imply that the industries that had a large initial intensity of routinizable occupations; faced a steeper decline in unionization; and saw a greater increase in import penetration, including intermediates, are those that experienced a bigger drop in their labor share.

The coefficient of initial offshorability does not have the expected sign but is statistically insignificant. One might argue that offshorability and routinization maybe measuring something that is very similar and only routinization survives when included together. We believe this interpretation is unlikely for the following reasons. First, offshorability is negatively correlated with routinization across industries and states, and this correlation does not appear to be particularly strong—the correlation coefficient is – 0.38. Second, by

Table 3. Modeling the Change in the Labor Share: Baseline									
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Initial Routinization	-6.9353*** (0.7792)	-6.7081*** (0.7440)	-6.5883*** (0.7973)	-6.9874*** (0.7226)	-6.4922*** (0.7427)	-6.7707*** (0.7732)	-6.3571*** (0.7948)	-6.5578*** (0.7753)	-6.7648*** (0.7268)
Unionization		0.3758*** (0.0571)	0.3707*** (0.0578)	0.3839*** (0.0552)	0.3405*** (0.0569)	0.3765*** (0.0559)	0.3354*** (0.0576)	0.3442*** (0.0560)	0.3525*** (0.0554)
Initial Offshorability			0.2834 (0.6499)			0.4692 (0.6297)	0.3071 (0.6435)	0.4789 (0.6269)	
Import Competition				-2.8816*** (0.5487)		-2.9231*** (0.5506)		-2.6189*** (0.5495)	-2.5927*** (0.5481)
Foreign Input Intensity					-21.0283*** (5.3520)		-21.0746*** (5.3613)	-18.4250*** (5.2287)	-18.3826*** (5.2227)
Observations	599	599	599	599	599	599	599	599	599
R-squared	0.1894	0.2576	0.2571	0.2955	0.2786	0.2949	0.2783	0.3067	0.3069
Source: Authors' estimates									
Notes: Robust regressions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All variables are expressed as changes over 2001-2014, except for measures of routinization and offshorability, which are measured as levels in 2001. All specifications include a constant and state dummy variables.									

⁵ All specifications in Table 3 include state dummy variables. We experimented with including industry dummy variables as well. In running these models, however, we detected a high degree of collinearity of the industry dummies and all explanatory variables which resulted in highly overfitted models. As such, we refrained from including industry dummies. The same argument applies to the specifications in the remaining tables of this paper.

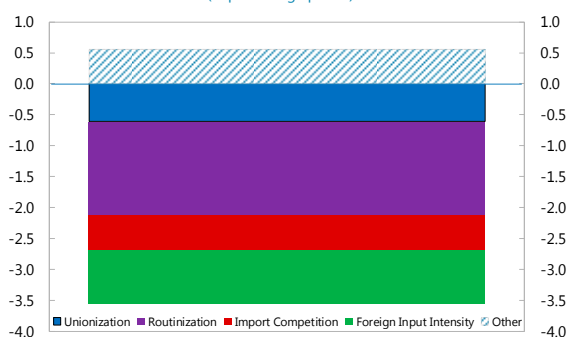
construction, the concepts are different: routinization much more closely approximates technological change and automation, while offshorability measures the potential for cross-border outsourcing. That they are distinct is also corroborated by the stylized facts in sections II and III—occupations and industries that are most exposed to routinization are not necessarily those that are characterized by the highest potential for offshoring.

It is worth mentioning that the insignificance of offshorability is in line with results from a parallel literature on labor market polarization. For example, Autor and Dorn 2013; Goos, Manning, and Salomons 2011; and Michaels, Natraj, and Van Reenen 2014 found that offshorability has a statistically insignificant role when considered alongside other potential explanations—particularly routinization—of cross-commuting zone, cross-industry and cross-national trends in employment and wage polarization. Note that, as shown in Table 3, all the results discussed above are robust to alternative permutations involving subgroups of the five key drivers.

It is also interesting to note that the other two international factors appear to play distinct roles. This is evident conceptually: import competition measures how much is imported of the commodity that a given industry produces—the commodity can be final or intermediate. The foreign input measure looks at the intensity of usage of imported intermediates in the production of that commodity. A given industry may face no competition in what it sells but could rely heavily on importing inputs. In contrast, an industry may buy all its inputs domestically but face high competition to what it sells from abroad. That the concepts are distinct is also evident statistically: the sign and significance of the coefficients of these two variables are unchanged in specifications where they enter separately, jointly, or in combination with other variables. The magnitude of the coefficient of either variable is also broadly the same across specifications. Moreover, the correlation coefficient between them is a mere 0.16.

We next decompose the within labor share decline into contributions from the various determinants. The decomposition is based on specification (9) of Table 3, which retains only the statistically significant variables. Figure 7 contains the results. Initial routinization accounts for about 51 percent of the within labor share decline over 2001-14—in other words, 1.52 percentage points out of the 3 percentage points within drop is due to routinization. The contribution from foreign input usage amounts to 29 percent of the decline and from import competition, 19 percent. The contribution from unionization is roughly the same as that of import competition. It is interesting to note that other factors appear to have pulled in the other direction. For example, as we will show in the next section, these include, most notably, increases in education attainment over 2001-14 which has dampened the decline of the labor share.

Figure 7. Within Labor Share Decline: Contributions—Baseline
(in percentage points)



Sources: Authors' calculations

The dominant role of technological progress is consistent with recent evidence for advanced economies (IMF 2017), and evidence based on firm level data for the U.S. economy (Autor et al. 2017). Here, we also highlight the role of international factors which, although is still less than that of technology even when these factors are taken jointly, is nonetheless significant.

C. Robustness Checks

We conduct here a battery of robustness checks to the baseline model discussed in the previous section. As will be shown below, the key messages conveyed above continue to hold.

Tables 4 through 6 summarize the results. Starting with Table 4:

- Model 1 replicates, for reference, our baseline model (that is, specification 8 of Table 3).
- Model 2 replaces the routinization and offshorability measures of model 1 with alternatives. To explain, recall that in section II, we constructed the routinization and offshorability measures as employment-weighted sums of occupations scores. These scores were assumed not to vary over time. We now test/relax this assumption by constructing occupation scores for 2001 based on the same criteria for routinizability and offshorability that we used for 2014.
- Model 3 adds the initial capital-labor ratio (in logarithm) to model 1 to control for potential cross-industry differences in the intensity of capital in production. (see the Appendix for details on the construction of this variable and others discussed below).
- Model 4 adds to model 1 a labor market deregulation index—with higher values indicating more deregulation. The index measures, among other things, whether a state has: no minimum wage or the minimum wage is the same as federal; a right-to-work law; flexible requirements or regulations for employers to purchase worker’s compensation insurance; no requirement for employers to have short-term disability insurance for their employees; and no provision for paid family leave insurance programs (see the Appendix for more details).
- Model 5 excludes right-to-work from the labor market deregulation index of model 4 to mitigate concerns arising from potential negative correlation with unionization.
- Model 6 combines models 2 through 4; and model 7 replaces the labor market deregulation index of model 6 with the alternative that excludes the right-to-work.

Several interesting results are worth highlighting. First, across all specifications that include our baseline variables, the coefficients of initial routinization, unionization, import competition, and foreign input intensity retain their expected signs, and remain highly statistically significant with magnitudes that do not differ much from the baseline model. Second, the statistical insignificance of offshorability is also robust to virtually all models, including those that use the alternative offshorability measure. Third, technology retains its

Table 4. Modeling the Change in the Labor Share: Robustness Checks I

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial Routinization	-6.5578*** (0.7753)		-5.2586*** (0.8384)	-6.3570*** (0.7482)	-6.3733*** (0.7493)		
Unionization	0.3442*** (0.0560)	0.2923*** (0.0549)	0.3135*** (0.0556)	0.3320*** (0.0509)	0.3346*** (0.0509)	0.2596*** (0.0495)	0.2599*** (0.0495)
Initial Offshorability	0.4789 (0.6269)		1.0498* (0.6364)	0.6636 (0.6053)	0.6548 (0.6063)		
Import Competition	-2.6189*** (0.5495)	-2.8665*** (0.5380)	-2.5395*** (0.5409)	-2.6839*** (0.5234)	-2.6883*** (0.5249)	-2.6623*** (0.5067)	-2.6940*** (0.5069)
Foreign Input Intensity	-18.4250*** (5.2287)	-13.3519** (5.1958)	-21.4763*** (5.1857)	-19.8014*** (4.5070)	-19.7749*** (4.5245)	-15.6339*** (4.3837)	-15.6876*** (4.3900)
Initial Routinization_Alternative		-8.7963*** (0.8677)				-8.1342*** (0.8070)	-8.1666*** (0.8067)
Initial Offshorability_Alternative		-0.2942 (0.6487)				0.1024 (0.6194)	0.1208 (0.6194)
Initial Capital-Labor Ratio			-0.0087*** (0.0025)			-0.0080*** (0.0017)	-0.0081*** (0.0017)
Labor Market Deregulation				-0.8115 (0.8941)		-0.4252 (0.8610)	
Labor Market Deregulation_Alternative					-0.2912 (1.1345)		0.5274 (1.0954)
Observations	599	599	599	599	599	599	599
R-squared	0.3067	0.3342	0.3222	0.2639	0.2628	0.3161	0.3167

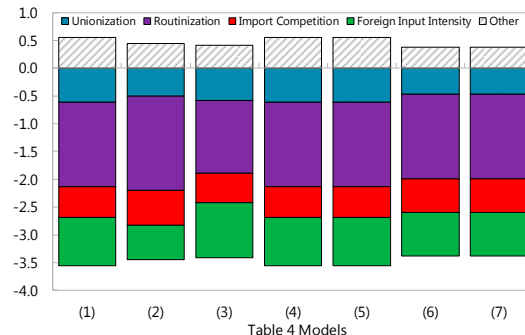
Source: Authors' estimates

Notes: Robust regressions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All variables are expressed as changes over 2001-2014, except for measures of routinization, offshorability, and capital-labor ratio, which are measured as levels in 2001. All specifications include a constant and state dummy variables except for those that include labor market deregulation variables. This is because labor market deregulation variables are observed at the state level only. Hence, inclusion of state dummy variables in regressions that contain labor market deregulation variables would result in model overfitting and collinearity.

statistically significant explanatory power when using the alternative measure of routinization. Fourth, the indexes of labor market deregulation do not appear to exert a statistically significant impact on the labor share. We interpret this result as two effects on the labor share potentially offsetting each other: deregulation could foster employment but may weigh on wages. And fifth, the initial capital-labor ratio persistently enters with a negative and highly statistically significant coefficient, implying high substitutability between capital and labor.

Figure 8 decomposes the within decline in the labor share into contributions from the various drivers for each model in Table 4. Once again, as we did above, in carrying out the decompositions, we retain the statistically significant variables only. The results are broadly the same as those of the baseline model. In particular, technology, as measured by routinization, has the single largest contribution across all specifications, explaining 1.3 to 1.7 percentage points of the 3 percentage points decline in the within component of the labor share. The contributions of

Figure 8. Within Labor Share Decline: Contributions I
(Y-axis: in percentage points; X-axis: Table 4 models)



unionization, import competition, and imported intermediates are roughly like those of the baseline model.

We next carry out another set of robustness checks by estimating models that condition on demographic/human capital variables. Table 5 contains the models' estimates. Once again, for reference, model 1 is our baseline model. Models 2 and 3 augment model 1 with the percentage of workers with a college degree or more, and with a high school degree, respectively. Model 4 combines models 2 and 3. Model 5 augments model 1 with the average years of schooling; and model 6 does so with the average years of experience and its square. Model 7 combines models 5 and 6.

The main results from this exercise are as follows: The significant explanatory power of our baseline variables and the lack of in the case of offshorability carry through all specifications. Also, changes in the labor share are positively related to changes in the human capital or skills of the labor force. For example, specification 7 suggests that, all else held constant, the labor share declined less (or increased more) in industries that experienced a larger increase in the average education and experience of its workforce. This is consistent with a wealth of evidence from microeconomic studies that find education and experience to be key determinants of wages—the Mincer-type wage models.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial Routinization	-6.5578*** (0.7753)	-6.6171*** (0.7717)	-6.5420*** (0.7754)	-6.6888*** (0.7750)	-6.4974*** (0.7638)	-6.0468*** (0.7802)	-6.0929*** (0.7755)
Unionization	0.3442*** (0.0560)	0.3544*** (0.0559)	0.3457*** (0.0561)	0.3533*** (0.0560)	0.3314*** (0.0552)	0.3075*** (0.0557)	0.3057*** (0.0553)
Initial Offshorability	0.4789 (0.6269)	0.0965 (0.6491)	0.4453 (0.6329)	0.0532 (0.6511)	0.5066 (0.6177)	0.4661 (0.6297)	0.4680 (0.6254)
Import Competition	-2.6189*** (0.5495)	-2.5992*** (0.5476)	-2.6281*** (0.5492)	-2.5707*** (0.5495)	-2.5518*** (0.5419)	-2.2092*** (0.5500)	-2.2409*** (0.5462)
Foreign Input Intensity	-18.4250*** (5.2287)	-19.4780*** (5.2167)	-18.6042*** (5.2324)	-19.6225*** (5.2319)	-19.6174*** (5.1658)	-18.7222*** (5.1427)	-19.4446*** (5.1214)
Percent of Labor with College Degree		11.0280** (4.6339)		14.1402** (5.6314)			
Percent of Labor with High School Degree			-3.1101 (4.9808)	5.9719 (6.0276)			
Average Years of Schooling					2.8202*** (0.8224)		2.2645*** (0.8422)
Average Years of Experience						1.7790** (0.8232)	1.5285* (0.8251)
Average Years of Experience-Squared						-0.0500*** (0.0185)	-0.0420** (0.0187)
Observations	599	599	599	599	599	599	599
R-squared	0.3067	0.3179	0.3081	0.3185	0.3236	0.3217	0.3313

Source: Authors' estimates

Notes: Robust regressions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All variables are expressed as changes over 2001-2014, except for measures of routinization, and offshorability, which are measured as levels in 2001. All specifications include a constant and state dummy variables.

We next re-estimate all the models in Table 5, but now using the alternative measures of routinization and offshorability. Table 6 contains the results. All our key conclusions regarding the explanatory power of the core drivers continue to hold. Also, compared to Table 5, the impact of routinization is slightly higher while that of the intensity of foreign input usage is slightly lower. Once again, education matters for the labor share. To give a sense of the order of magnitude, specification 5 implies that, on average, if the structural drag

from routinization is to be completely offset by education, it would require an increase in average schooling equivalent to about 2.5 times that observed since the early 2000s. This is a tall order. As can be seen in models 6 and 7, while the coefficient on experience and its square continue to have the expected signs, they are nonetheless imprecisely estimated.

Table 6. Modeling the Change in the Labor Share: Robustness Checks III

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial Routinization_Alternative	-8.7963*** (0.8677)	-8.4553*** (0.8754)	-8.7064*** (0.8675)	-8.4563*** (0.8776)	-8.7134*** (0.8639)	-8.2455*** (0.9050)	-8.3141*** (0.9050)
Unionization	0.2923*** (0.0549)	0.3008*** (0.0549)	0.2980*** (0.0549)	0.3003*** (0.0550)	0.2806*** (0.0548)	0.2772*** (0.0553)	0.2730*** (0.0552)
Initial Offshorability_Alternative	-0.2942 (0.6487)	-0.5844 (0.6621)	-0.3892 (0.6507)	-0.5820 (0.6637)	0.0001 (0.6510)	-0.0366 (0.6788)	0.1559 (0.6805)
Import Competition	-2.8665*** (0.5380)	-2.8797*** (0.5378)	-2.9137*** (0.5370)	-2.8701*** (0.5395)	-2.7956*** (0.5361)	-2.5609*** (0.5480)	-2.5969*** (0.5467)
Foreign Input Intensity	-13.3519** (5.1958)	-14.2156*** (5.2042)	-13.3653** (5.1905)	-14.2797*** (5.2151)	-14.4517*** (5.1877)	-13.8671*** (5.1897)	-14.5299*** (5.1882)
Percent of Labor with College Degree		10.7825** (4.4668)		11.2317** (5.4657)			
Percent of Labor with High School Degree			-6.5260 (4.8233)	0.8219 (5.9054)			
Average Years of Schooling					2.3696*** (0.8200)		2.1191** (0.8435)
Average Years of Experience						0.7215 (0.8246)	0.4521 (0.8329)
Average Years of Experience-Squared						-0.0232 (0.0186)	-0.0153 (0.0189)
Observations	599	599	599	599	599	599	599
R-squared	0.3342	0.3406	0.3373	0.3401	0.3415	0.3352	0.3408

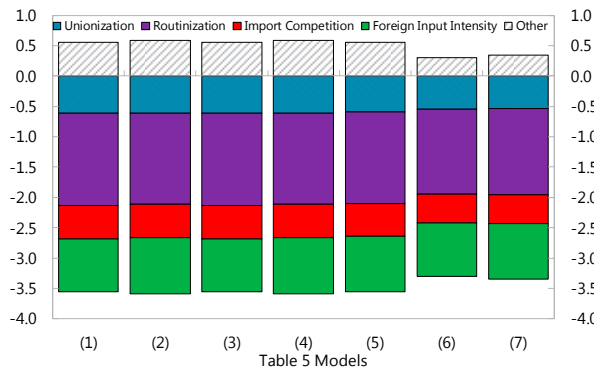
Source: Authors' estimates

Notes: Robust regressions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All variables are expressed as changes over 2001-2014, except for measures of routinization and offshorability, which are measured as levels in 2001. All specifications include a constant and state dummy variables.

In Figures 9 and 10, we once again perform decompositions of the decline in the within labor share component, but now for all the models in Tables 5 and 6, respectively. It is remarkable how robust our baseline results are: across all specifications, technology continues to play the dominant role—explaining 1.4 to 1.7 percentage points of the 3 percentage points decline in the within labor share. Contributions from foreign input intensity are 0.6 to 0.9 percentage points while that import competition and unionization are 0.5–0.6 percentage points, each.

Figure 9. Within Labor Share Decline: Contributions II

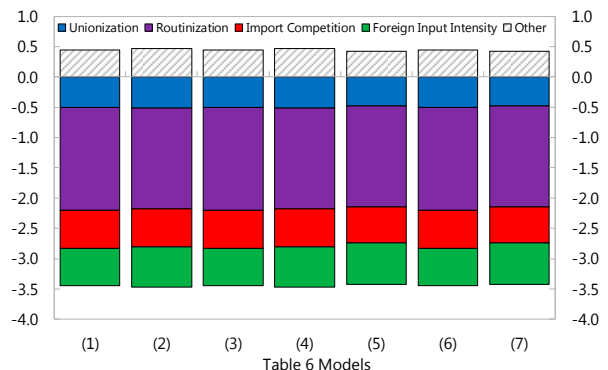
(Y-axis: in percentage points; X-axis: Table 5 models)



Source: Authors' calculation

Figure 10. Within Labor Share Decline: Contributions III

(Y-axis: in percentage points; X-axis: Table 6 models)



Source: Authors' calculation

V. CONCLUSION AND POLICY IMPLICATIONS

In this paper, we aim to explain the reasons behind the secular decline in the labor share since the early 2000s. We care about such a decline because of the strong negative correlation with inequality. The latter has been shown to weigh on investments in human and physical capital, and to hold back economic growth.

We built on the empirical strategy and contributions made by IMF 2017 to shape our thinking regarding the lessons learned from the cross-country experience but introduced a broader set of control variables especially for international factors. We began by documenting key stylized facts. We found the decline in the labor share to be common across most states and industries, with varying degrees. A shift-share exercise showed that much of the fall is *not* the result of structural transformation of states/industries, but rather derives from a fall in individual labor shares in these states/industries. Exploiting a new data set that we built from scratch and the cross-state variation of industry level data, we ran regressions linking changes in the labor share to measures of technology, offshoring potential of occupational tasks, trade, and labor market institutions.

We found technology—as measured by the intensity of routinization of job tasks—to have significant explanatory power and to be the principal driver of state and industry level differences in the labor share. While we found estimates of the impact on the labor share of the potential to offshore occupational tasks to be persistently imprecise, we did consistently find the actual cross-border movement of commodities, including imported inputs, to matter greatly for labor share dynamics. Changes in union density—capturing labor market institutions—are also statistically significant. In terms of magnitudes, we found that technological progress explains 44 to 57 percent of the (within) decline in the labor share when looked at across all estimated empirical specifications. Global/international factors, captured by import competition and usage of foreign inputs, jointly explain between 41 to 51 percent of the decline depending on model specification, but in virtually all specifications, this joint contribution never exceeds that of technology. Unionization matters quantitatively, but it ranks third after technology and combined international factors. We also found human capital, particularly education, to have contributed positively to labor share dynamics, and prevented an otherwise steeper decline.

Our results have important policy implications. Technology and trade have provided substantial benefits to the US economy and elsewhere, so the results here by no means imply that we should stop pursuing progress on both fronts. That said, we must acknowledge that there are unintended consequences and a falling labor share is one manifestation of that. So, what can be done?

Encouraging systems for continuous retooling and skill upgrading appears an important policy area. Although such programs would not immediately address the short-term adjustment costs for affected workers, they could over time enhance the resilience of employment and productivity of labor. Investing in education and training programs outside traditional channels could prepare future workers to keep up with technological progress and

cope with the challenges posed by globalization. But prior to pursuing such a strategy, several questions would need to be researched and addressed. Regarding education, for example, why does the growing skills premia itself not encourage enough people to accumulate more education? Is it the availability of a particular type of education, and hence the need to rethink either secondary or tertiary systems? Or, is it barriers to borrowing to smooth out costs, in which case the focus would be on access and financing (e.g., through student loans policy or future tax supplement to repay education costs)? How much more schooling could the U.S. population absorb and what would be the cost? Is the issue more schooling or better quality of schooling?

At the same time, the effects of de-unionization need to be better understood. Could this be related to the globalization of trade and the threat of external competition? Is it something else? These questions form an important research agenda that should develop in parallel to continued work on understanding the secular changes in the US labor share.

APPENDIX I. VARIABLE CONSTRUCTION

We present here details on the construction and sources of the additional variables used in robustness check regressions of section III. Unless otherwise noted, the data are constructed by industry, state, and year.

Capital-Labor Ratio

The Bureau of Economic Analysis (BEA) constructs capital stock data by industry at the national level. We combine these with employment from the CPS to construct measures of capital-labor ratios. Once again, we impute the state level data in the same way as we did with the imports of intermediates variable in the main text.

Labor Market Deregulation

Our deregulation measure is obtained from the Cato Institute's "Freedom in the 50 States", and is available by state and year. Labor market "freedom" is high (i.e., the labor market has a high degree of deregulation) in states that:

- Have no minimum wage or the minimum wage is the same as federal.
- Have a right-to-work law.
- Have flexible/loose/no requirements or regulations for employers to purchase worker's compensation insurance.
- Provide options for employers to buy worker's compensation insurance from other than a state-run insurance company (e.g., private insurance, or self-insured)—the state run is typically considered more expensive than the alternatives.
- Do not require employers to have short-term disability insurance for their employees.
- Do not provide for paid family leave insurance programs.
- Do not require (all) employers to verify the legal resident status of employees.
- Do not require employment anti-discrimination laws to covering any non-federal category.

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