Investigating Global Labor and Profit Shares*

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Abstract

This paper investigates labor and profit share trends across Advanced Economies. It shows that growth in the Real Estate sector is the primary driver of declining labor shares outside the US. Excluding the Real Estate sector, non-US labor and profit shares have remained relatively stable since the 1970s. By contrast, the US labor share declined and the profit share increased across virtually all industries. The divergent US patterns appear to be explained by declining competition (in the form of rising mark-ups and rising concentration).

Much research indicates that aggregate labor shares, defined as the ratio of labor compensation to nominal value added, have declined in the past decades (e.g., Karabarbounis and Neiman [2013], Elsby et al. [2013], OECD [2015]). Figure 1 illustrates this decline, with the fall present across most advanced economies. Labor shares dropped first in the 1980s, and then again in the 2000s. For the US, the labor share remained stable until 2000 and then dropped dramatically.

Despite the broad consensus around the labor share decline, there remains substantial controversy on its causes.[1] This paper presents systematic cross-country, cross-industry evidence of the labor and profit share trends. The main contributions of the paper are: (i) to show that labor share

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[1]Some authors emphasize rising returns to housing capital [Rognlie, 2015]; while others emphasize capital-biased technical change and automation (e.g., Acemoglu and Restrepo [2016]). Yet others argue that increased concentration is the driving force, either because of increased rents and market power (e.g., Barkai [2017], De Loecker and Eeckhout [2017], Caballero et al. [2017a]), or because technological change has led to an increase in the efficient scale of operation, so that more productive firms account for a larger share of industry output (e.g., the 'superstar' firm hypothesis of Autor et al. [2017a,b]). Last, some authors have emphasized the treatment of intangible capital [Koh et al., 2015]; the decline in the relative price of capital [Karabarbounis and Neiman, 2013]; capital accumulation [Piketty, 2014, Piketty and Zucman, 2014]; import competition and globalization [Elsby et al., 2013]; and a decline in the bargaining power of labor [Blanchard and Giavazzi, 2003].

declines are concentrated in Real Estate in virtually all countries, except the US. (ii) To show that the decrease in US labor share is pervasive across all industries; and is coupled with a rise in profits and concentration – again a pattern unique to the US. (iii) To show that declining US labor shares and rising US profit shares are explained by rising mark-ups and concentration.

I begin by studying aggregate- and industry-level labor and profit share trends across Advanced Economies. I show that the global decline in (gross) labor shares is concentrated in the Real Estate sector: excluding Real Estate (as well as Finance and non-business sectors), the global labor share has remained largely stable since the 1970s. It dropped from 1975 to 2007, but has since recovered above its 1970's level. This is true for nearly all countries – except the US, where the labor share decreased drastically. Similarly, profit shares[2] remained relatively stable for all countries except the US, where they increased drastically (from ∼10% of value added in 1988 to more than 20% in 2015). The rise in profits and decline in labor share is pervasive across US industries; compared to mixed labor and profit share patterns in other countries.

The uniqueness of US patterns poses a challenge for most explanations of declining labor shares. Declining capital prices, automation, technical change, network/winner-take-all effects, import competition and the rise of intangibles would all presumably have similar effects across Advanced Economies. Instead, I propose that divergent levels of competition can explain the differences; and show that Herfindahls and the share of sales going to the top 4/10 firms are rising in the US, yet stable or falling in Europe.[3]

My conclusions on labor share patterns relate to those of Rognlie [2015], and contrast with those of Karabarbounis and Neiman [2013]. The main difference is that I exclude the Real Estate sector entirely, while Rognlie [2015] separates the Housing sector and Karabarbounis and Neiman [2013] studies the Corporate sector. Excluding the Real Estate sector better controls for rising returns to Real Estate assets and, as a result, yields drastically different conclusions. This is particularly true in Europe where Non Financial Corporates hold between 10 and 30 percent of fixed assets in residential property (compared to under 1% in the US).

The US is the odd man out – so I study its behavior in detail for the remainder of the paper. I start by reviewing six theories that (could) explain a decrease in the labor share: (i) declining price of capital; (ii) import competition; (iii) rising returns to housing capital; (iv) rising intangibles; (v) rising efficient scale of operation; and (vi) increased market power. I argue that aggregate patterns are inconsistent with most theories – except for market power and (potentially) an increase in the efficient scale of operation. Nonetheless, I proceed to test most theories empirically in two (complementary) ways:

First, I use empirical proxies for each theory to test them non-parametrically via regression.

[2] Profit shares are defined as the ratio of profits to nominal value added. I follow Barkai [2017] and estimate profits as the capital compensation above the required return on capital. For cross-country analyses, I assume the cost of capital is equal to the sum of country-specific risk-free rates and US BBB corporate bond spreads. Conclusions are robust to estimating equity premia based on country-specific dividend-price and price-earnings ratios. See Section 1.1 for additional details.

[3] Other measures of product market competition such as the OECD's PMR index exhibit similar trends. Concentration measures for Canada and Japan are not available. See Dottling et al. [2017] for additional evidence.

Only measures of concentration and mark-ups appear to jointly explain the decline in (gross and net) labor shares and the rise in profit shares. Other theories explain some or none of these patterns in the cross-section.

Second, I use a simple accounting framework in the spirit of Barkai [2017] and Caballero et al. [2017b] to disentangle the effect of alternate theories for declining labor shares. This framework requires estimates of the Equity Risk Premia (ERP), which are notoriously difficult to generate. I consider 16 different estimates and select the approach of Claus and Thomas [2001]. This approach appears conservative, consistent with the ERP lower bound of Martin [2017], and can be estimated at the industry-level. I then use the corresponding ERP estimates for most of my analyses, and perform thorough sensitivity analyses to ensure conclusions are robust to reasonable variation in ERP estimates. The results of the framework suggest that rising mark-ups (linked to rising concentration) are critical to jointly explaining the decreasing labor shares and stable/increasing returns to productive capital in the presence of falling interest rates. Absent increases in mark-ups, the equity premia would need to exceed 15% to explain the observed patterns for the Non-Financial Corporate (NFC) sector. Increases in automation and capital-biased technical change are relevant for some industries (mainly Manufacturing, Mining and Retail Trade), but cannot independently explain aggregate trends.[4]

The remainder of this paper is organized as follows: Section 1 discusses the data sources and results from cross-country comparisons of labor and profit share trends. Section 2 discusses six explanations put forth in the literature for declining labor shares – particularly as they relate to the US. Last, Section 3 outlines the data sources and tests used to disentangle the alternate theories using US data. Section 4 concludes. The appendix provides (i) additional background and evidence for declining competition in the US, including a comparison of three mark-up estimates; (ii) more detailed results on labor and profit share trends; and (iii) more details on the estimation of the ERP.

1 Cross-country evidence

This section discusses the evolution of country-level labor and profit shares across Advanced Economies. It begins by introducing the dataset and definitions; and then discusses aggregate and industry-level results. It shows that labor (profit) shares remained stable outside the US yet decreased (increased) drastically in the US.

[4] Barkai [2017] and Caballero et al. [2017a] include similar analyses on US profit shares. Barkai [2017] shows that the profit share of the US non financial corporate sector has increased drastically since 1985. Caballero et al. [2017a] develop a simple framework to study the evolution of the labor share along with three secular macro-trends: the decline in interest rates, stable or rising product of capital and declining earnings yield. They argue that the decline in the labor share can be rationalized by a mixture of rising mark-ups, rising risk premia and increased automation/capital-biased technical change. I use the framework of Caballero et al. [2017a] for part of my analyses; but constrain most estimates to using market-implied risk premia to reach more decisive conclusions. Compared to Barkai [2017] and Caballero et al. [2017a], I also study a broader and more detailed sample – including a longer history; a broader set of countries; as well as industry- and aggregate-level results. The results vary widely across countries, which can inform the validity of alternate explanations in the literature.

1.1 Framework

1.1.1 Accounting

I assume that the true model of accounting, in current dollars and for a particular country is[5]

$$Y_t = W_t N_t + R_t^{K,tot} K_{t-1}, \tag{1}$$

$$= W_t N_t + R_t^{K,req} K_{t-1} + \Pi_t \tag{2}$$

W_t denotes wages, N_t denotes labor, Π_t denotes profits, and K_{t-1} denotes the real stock of capital put in place at $t-1$ and used at time t.

Equation (1) provides the 'standard' labor and capital share decomposition, where the capital share includes profits. In other words, $R_t^{K,tot}$ equates the *ex post* return on capital to the total capital compensation. Equation (2) decomposes the capital compensation into a 'required' compensation (the rental cost of capital) and profits (returns above and beyond the rental cost of capital).

The labor, capital and profit shares are then given by:

$$s_t^N = \frac{W_t N_t}{Y_t} = \left(\frac{1}{\mu_t}\right)\left(\frac{W_t N_t}{W_t N_t + R_t^K K_{t-1}}\right), \tag{3}$$

$$s_t^K = \frac{R_t^{K,req} K_{t-1}}{Y_t} = \left(\frac{1}{\mu_t}\right)\left(\frac{R_t^{K,req} K_{t-1}}{W_t N_t + R_t^K K_{-1}}\right), \tag{4}$$

$$s_t^\Pi = \frac{\Pi_t}{Y_t} = 1 - \frac{1}{\mu_t} \tag{5}$$

where μ_t denotes the average mark-up. As usual, $s_t^N + s_t^K + s_t^\Pi = 1$.

1.1.2 Rate of Return

In line with Barkai [2017], the required return on capital is estimated following the standard neo-classical theory of investment introduced by Jorgenson [1963]. Under this theory, investor indifference between buying a unit of capital at relative investment price ζ_{t-1}, collecting a rental fee $R_t^{K,tot}$ and then selling the depreciated asset for $\zeta_t(1-\delta)$ in the next period vs. earning a nominal rate of return i_t on another investment implies:

$$R_t^{K,tot} = \zeta_{t-1}(1+i_t) - \zeta_t(1-\delta_t), \tag{6}$$

$$= \zeta_{t-1}\left(i_t + \delta_t - (1-\delta_t) g_{\zeta,t}\right) \tag{7}$$

[5] In the data, nominal gross value added includes taxes on production and imports less subsidies. This information is not available in KLEMS, however, so I implicitly include taxes in the profit share. Conclusions for the US are robust to excluding taxes.

where we assume no taxes. We can decompose i_t to split the required return on capital and the nominal profit rate PR_t:

$$i_t = r_t^f + KRP_t + PR_t$$

where r_t^f and KRP_t denote the risk-free rate and a capital risk premia, respectively. Substituting i_t into equation 7, we obtain

$$\begin{aligned} R_t^{K,tot} =& \zeta_{t-1}\left(r_t^f + KRP_t + \delta_t - (1-\delta_t)g_{\zeta,t}\right) + \zeta_{t-1}PR_t, \\ =& R_t^{K,req} + \zeta_{t-1}PR_t. \end{aligned}$$

To compute $R_t^{K,req}$ in cross-country analyses, I first define the relative price of capital as the ratio of industry-specific investment price index (KLEMS IP_GFCF) to each country's CPI price index (PCE index for the US). Then, I compute the required rate of return as

$$R_t^{K,req} = \zeta_{t-1}\left(r_t^f + BBB\,spread_t - (1-\delta_t)g_{\zeta,t} + \delta_t\right)$$

δ_t is computed as the weighted average industry depreciation rate by lagged capital; and $g_{\zeta,t}$ is the realized change in the relative price of capital from time $t-1$ to t.[6]

1.2 Global Data

Data for cross-country analyses is primarily sourced from KLEMS 2012 and KLEMS 2016; except for US profit shares which rely on BEA data.

KLEMS 2012 provides industry-level measures of value added, labor and capital compensation; as well as estimates of the *ex post* internal rate of return. Compared to KLEMS 2016, it provides a broader coverage across countries and time-periods. I use data for 12 Advanced Economies (Austria, Canada, Finland, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, United Kingdom and United States[7]), from about 1980 to 2009. Following the KLEMS methodology, each country's statistical office uses consistent assumptions to impute labor income for the self-employed.

Unfortunately, KLEMS 2012 does not include measures of the capital stock (which are needed to compute profit shares) and data series end in 2009. To mitigate these limitations, I use KLEMS 2016. KLEMS 2016 is available over a shorter period (1995 -2014 for most countries; and only after 2001 for Germany) and covers only European economies – but it provides all of the necessary data. In particular, KLEMS 2016 provides series up to 2014; includes measures of capital (current-cost and chained values for the net stock of capital, depreciation and investment) consistent with each country's National Accounts; and incorporates intangible capital other than software. As discussed in Koh et al. [2015], intangible capital can have material implications for the labor and profit share.

[6] I use the realized $g_{\zeta,t}$ for consistency with profit rate estimates based on KLEMS 2012, which are reported in the Appendix.

[7] Belgium is also covered by KLEMS 2012 but I exclude this country from all analyses because the available data is not sufficient to compute profit shares or profit rates.

To summarize, the following datasets are used for each analysis:

1. **Labor shares** are primarily based on KLEMS 2012; but they are filled in after 2009 using KLEMS 2016.[8]

2. **Profit shares** are based on KLEMS 2016 for all countries except the US, for which BEA data is used.[9]

3. **France and Sweden:** I use KLEMS 2016 data for France and Sweden because neither profit shares nor profit rates can be computed using the data available in KLEMS 2012. Fortunately, data for France is available in KLEMS 2016 since 1980.

4. **Profit Rates:** KLEMS 2016 covers a shorter period and sample than KLEMS 2012. To ensure my conclusions are robust, I also estimate and report results based on Profit Rates in the appendix. These estimates are primarily based on the internal rates of return reported in KLEMS 2012.[10]

KLEMS 2012 and 2016 provide data at the sector level (19 groups) following the ISIC Rev. 4 hierarchy. Data for some sectors is further broken out (e.g., manufacturing is split into 11 groups) leading to 34 categories. However, capital measures are not available for some of these groupings. I use the most granular segmentation for which data is available, which corresponds to 31 KLEMS categories.[11] To focus on the non-financial business sector, I then exclude Financials (KLEMS segment K); Public administration and defence (O); activities of households as employers (T); and activities of extraterritorial organizations (U). This leaves 27 industry groupings for cross-country analyses. All other datasets – including BEA segments – are mapped to these 27 groupings.[12]

Macro-data. Computing profit shares requires estimates of the risk-free rate, the capital risk premia, and the relative price of investment goods. And a common currency is needed to aggregate across countries. I gather CPI indices, 10-year government bond rates and USD exchange rates from

[8]In particular, I fill in post-2009 values while holding constant the industry-level average gap between KLEMS 2012 and KLEMS 2016. Let x_t^{12} and x_t^{16} denote a given measure of industry labor shares, profit shares and profit rates based on KLEMS 2012 and KLEMS 2016, respectively. Also let $\bar{x}_{00-09}$ denote the average gap between KLEMS 2012 and KLEMS 2016 from 2000 to 2009$\left(\bar{x}_{00-09} = \frac{1}{10}\sum_{t=2000}^{2009} x_t^{12} - x_t^{16}\right)$. The filled-in value for $t \in \{2010, 2014\}$ is then $x_t^{12} = x_t^{16} + \bar{x}_{00-09}$. Compared to KLEMS 2012, KLEMS 2016 exhibits a slightly lower labor share because of the addition of intangible capital other than software (as emphasized in Koh et al. [2015]). But the industry-level trends are very similar. The imputation is expected to introduce limited error, especially at the aggregate level. See Figure 18 in the Appendix for a comparison of KLEMS 2012 and KLEMS 2016 labor share series.

[9]I use BEA data because the US is not covered by KLEMS 2016. BEA segments are mapped to ISIC Rev. 4 segments following the mapping in the US KLEMS methodology document. Importantly, BEA data is only used for US profit share analyses. For US labor share analyses, I use KLEMS 2012 which ensures a consistent treatment of labor income for the self-employed across countries. I also confirm that US labor shares decline in other labor share series (see Figure 23 in Appendix), including the BEA.

[10]With two exceptions. Profit rates for for France, Sweden and the US are based on KLEMS 2016 and BEA data as noted above. And profit rates are filled in after 2009 using KLEMS 2016. See Appendix B for details on the implementation; and the associated results; and the rest of the text for discussion.

[11]For select countries and sectors, available data combines some categories leading to fewer segments (IT in Canada and Trade in Spain)

[12]A more granular segmentation following the BEA categories is used for US analyses in Section 3.1.

the OECD (tables MEI_PRICES, KEI and SNA_TABLE4, respectively) for all countries except the US. For the US, I instead gather data from FRED. In particular, I gather the PCE implicit price deflator (DPCERD3A086NBEA) and 10 year treasury rate (GS10). I also gather the Moody's Seasoned Baa Corporate Bond Yield from FRED, which is used to compute the corporate bond spread.

Last, for sensitivity analyses, I gather dividend-price and price-earnings ratios on each country's major stock market indices from Datasteam. These ratios are used to estimate country-specific Equity Risk Premia which are then converted to Capital Risk Premia assuming a Debt-to-Equity ratio of 0.5 (which roughly matches the average Debt-to-Equity ratio of the Non-financial Corporate sector of all countries).[13]

1.3 Cross-Country Results

1.3.1 Labor Share

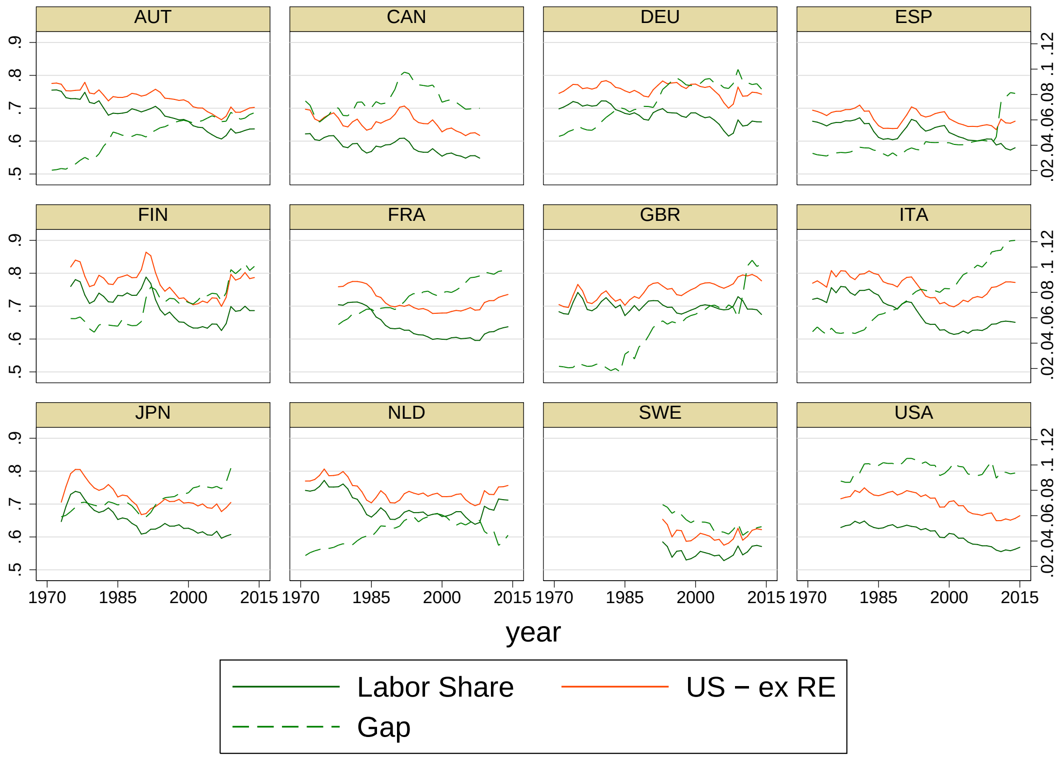
The Labor Share (including Real Estate) Declined Across Most Countries. Figure 1 shows the evolution of the labor share excluding financial services and non-business sectors but including Real Estate for the 12 Advanced Economies in my sample. As shown, labor shares declined in the 1980s (most notably in France, Italy, Japan and the Netherlands), and then again in the 2000s (most notably in Austria, Spain and the US). Only Great Britain and Sweden exhibit rising or stable labor shares over the entire period. The declining labor share trend either reversed or stabilized across most countries since the financial crisis.

The Labor Share Decline is Driven by Real Estate. Figure 2 shows the weighted average labor share across all countries except the US; including and excluding Real Estate. As discussed in a variety of papers, the labor share including Real Estate peaked in the mid 1970s and declined consistently thereafter; until the financial crisis, when it exhibits a slight increase. The peak to trough decline totaled 10% of value added; and the labor share today is nearly 7% lower than in 1970.

The evolution excluding Real Estate (red dotted line) is very different, however. The series again peaked in the 1970s but declined more slowly through 2007. It increased substantially after the financial crisis and today exceeds its level in 1970. It is only slightly below the mid-1970s peak. The dotted line shows the gap between labor shares including and excluding real estate, which rises rapidly from 4% to 9%. It accounts for the entire drop in the world labor share.

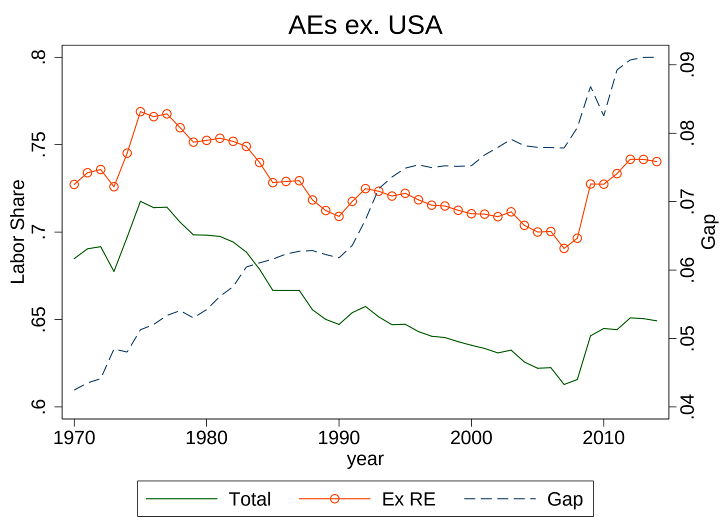
[13] I also gathered balance sheet and income statement data for the non-financial corporate sector of each country. However, I only use these data for exploratory analyses because they are available over a limited time period and cannot be adjusted to exclude Real Estate.

Figure 1: Labor share by country: Including Real Estate



Notes: Figure shows country-level labor shares excluding financials, public administration and defence, activities of households as employers, and activities of extraterritorial organizations. Annual data primarily from KLEMS 2012. KLEMS 2016 used for France and Sweden, and to fill-in labor shares after 2009.

Figure 2: Labor shares including and excluding Real Estate: Advanced Economies ex. US



Notes: Figure shows the weighted average labor share across 11 Advanced Economies including and excluding Real Estate (as well as the sectors listed in Figure 1). Dashed line plots the gap between series. Annual data, primarily from KLEMS 2012.

Table 1: Real Estate Share of VA and effect on Aggregate Labor Share

	RE share of VA			**2014 Labor share**			**Effect on**
Country	**75**	**14**	$\Delta\%VA$	**RE**	**Ex RE**	ΔLS	**Agg LS**
GBR	3.8	14.5	10.7	7.2	77.7	70.5	-7.6
ITA	6.6	16.2	9.6	2.6	77.2	74.6	-7.2
ESP	5.1	13.5	8.4	6.1	66.1	60.0	-5.0
FRA	8.1	14.8	6.6	7.0	73.6	66.5	-4.4
AUT	4.3	10.9	6.6	9.8	70.3	60.5	-4.0
FIN	7.8	13.5	5.7	4.3	78.7	74.4	-4.3
JPN*	8.8	13.9	5.2	6.5	70.5	64.0	-3.3
DEU	7.7	12.2	4.5	4.9	74.3	69.4	-3.1
USA	12.5	16.2	3.7	7.8	65.6	57.9	-2.1
CAN*	9.8	11.8	2.0	3.1	61.7	58.7	-1.2
NLD	5.1	6.9	1.8	11.0	75.7	64.7	-1.2

Notes: Table shows the share of value added for the Real Estate Sector as of 1975 and 2014 (2008 for Canada and 2009 for Japan); as well as the level of the labor share as of 2014 for the Real Estate sector and the remaining sectors in my dataset. Effect on LS computed as $\Delta\%VA\times\Delta$LS. Annual data primarily from KLEMS 2012.
***** 2008 for Canada and 2009 for Japan.

Given the impact of Real Estate, I exclude it in the remainder of the paper. In particular, I exclude Real Estate by subtracting the corresponding value added and labor quantities from the labor share calculation:[14]

$$LS\,ex\,RE = \frac{W_t N_t - W_t^{RE} N_t^{RE}}{Y_t - Y_t^{RE}}$$

How can Real Estate have such a sizable effect? Due to a substantial rise in its share of value added. Table 1 shows the Real Estate share of value added in 1975 and 2014 (2008 for Canada and 2009 for Japan); along with the labor share for the Real Estate sector and the remaining sectors in my dataset. As shown, the Real Estate share of value added increased by 5-10% in most countries (primarily due to rising home prices); and Real Estate has a labor share 60-70% lower than the rest of the economy. This simple shift corresponds to a reduction in aggregate labor share of 3-8% for most countries.

Why exclude Real Estate? To focus on the "real output"-producing sectors of the economy, because most theories of declining labor shares are likely to affect only these sectors. In particular, theories such as technical change, capital accumulation and globalization argue that declining labor shares are driven by changes to each sector's production technology. By contrast, the value added of the Real Estate sector is primarily driven by residential real estate prices – not technology. It is unlikely to be explained by technological change or changes to the industry structure.

In particular, the Real Estate sector is composed of three NACE groups:

- Buying and selling own real estate (Group 68.1)

[14]Similar calculations are done to exclude Finance and all other omitted sectors.

- Renting (to third parties) and operating own or leased residential and non-residential real estate, including both furnished and unfurnished property; the development of building projects for own operation is also included (Group 68.2)

- Appraising real estate; providing real estate agency services as an intermediary; managing property as an agent (Group 68.3)

Table 2 provides a breakdown of the composition of Real Estate activity by country and activity. It shows that nearly 75% of Real Estate value added is composed of actual and imputed rents. Importantly, Real estate activities do not include facilities management (which are part of administrative and support services), development of building projects for later sale (which are part of construction), nor short-stay letting of accommodation (which are part of accommodation and food services). Real Estate also excludes Rental and Leasing services of non-Real Estate assets, which are part of the business services sector.

Table 2 also shows that the vast majority of Real Estate activity is concentrated in residential property. In particular, column 5 shows that imputed rents on owner-occupied properties account for over 60% of Real Estate Value Added in most countries. And column 6 shows that actual rents on tenant-occupied properties are approximately 30% of imputed rents on owner-occupied properties. Combined, actual and imputed rents on residential property account for the vast majority of Real Estate activity. The remaining activity includes property rental for businesses and fee- or contract-based activities. The former are again mainly driven by Real Estate prices, while the latter may actually be affected by technological change.[15]

Importantly, studying the Corporate Sector does not suffice to control for the growth of Real Estate. As shown in the last column of Table 2, the corporate sector holds material residential assets outside the US. European NFCs, for instance, hold between 10% and 30% of fixed assets in residential property. US NFCs are the outlier, holding 1% of their fixed assets in residential property.

The results in this section relate to those of Rognlie [2015] and Karabarbounis and Neiman [2013]. But they differ in important ways.

First, Rognlie [2015] argues that the decline in the (global) net labor share is explained by rising returns to housing capital. He does not study gross labor shares in detail, beyond showing a sharply decreasing gross labor share in Figure 2. My results focus on gross labor shares and show that – when excluding the entire Real Estate sector – the gross labor share has remained stable outside the US yet declined drastically in the US.[16]

Second, Rognlie [2015] separates the Corporate and Housing sector; and finds similar conclusions for the evolution of Corporate labor shares across advanced economies. However, as noted above, separating the housing sector is not sufficient to control for rising returns on Real Estate

[15] Ideally, fee-based activities would be included in the sample. However, this this cannot be achieved due to data limitations.

[16] Rognlie [2015] argues that the net labor share may be the more relevant measure. I focus on the gross labor share because it is available over a longer period; and it is less affected by depreciation estimates. I discuss results using the Net labor share for the US in the following section.

Table 2: Real Estate Share of VA and effect on Aggregate Labor Share

Country	**Composition of RE activities (% of VA)**			**Housing share of RE**		**RE in NFCB**
	Renting and Operating of RE	Activities on a fee or contract basis	Buying and Selling of own RE	Imputed rents on Own-Occ properties as % of RE VA	Ratio of Actual to Imputed Rents in Housing Sector	% Res. RE in NFCB K
AUT	78	18	4	55	33	11
DEU	82	13	5	37	80	17
ESP	89	13	-2	73	17	NA
FRA	70	21	8	62	30	29
ITA	75	11	14	66	15	18
NLD	73	16	11	23	54	22
FIN	NA	NA	NA	63	34	15
GBR	63	35	1	73	35	12
SWE	91	8	0	42	63	27
JPN	NA	NA	NA	NA	NA	6
CAN	NA	NA	NA	66	34	11
USA	NA	NA	NA	59	32	1

Notes: Table shows the average values from 2005 to 2015, when available. Columns 2-4 show the composition of Real Estate activities in European economies from Eurostat. Columns 5-6 show the housing share of Real Estate VA and the ratio of household expenditures on actual and imputed rents for housing (from SNA Tables 5 and 6A sourced from the OECD). Column 6 shows the share of residential assets as a percent of total produced fixed assets in each country's NFCB sector.

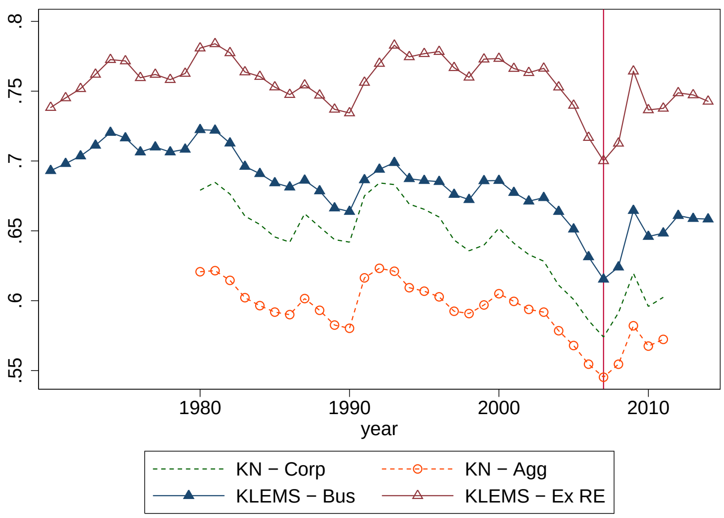
– particularly in Europe. I separate the entire Real Estate sector and find drastically different conclusions.[17] This observation is also relevant when comparing my results to Karabarbounis and Neiman [2013], as it implies that Corporate sector labor shares are also affected by the rise of Real Estate. Figure 3 illustrates this fact by plotting four measures of the labor share for Germany – two based on KLEMS and two from Karabarbounis and Neiman [2013]. As shown, all series including Real Estate behave very similarly – with perhaps a slightly faster drop in the Corporate series. By contrast, the series excluding Real Estate is far more stable.

Last, my results cover the post-Great Recession period, which exhibits a rapid and persistent increase in the labor share. Rognlie [2015]'s series end in 2010; while industry-level analyses in Karabarbounis and Neiman [2013] end on 2007. As shown in Figure 2, 2007 corresponds to the trough in the global labor share, leading to overly negative labor share trends.[18]

[17]Note also that Rognlie [2015] relies on data from National Accounts, gathered by Piketty and Zucman [2014]. These data are based on the pre-2013 BEA revision, which incorporated intangible capital other than software [Koh et al., 2015].

[18]Other advantages from using KLEMS are the broader coverage of countries and periods (relative to Rognlie). For instance, data for Italy and Germany starts in 1970, compared to 1990 for Rognlie [2015]. KLEMS also relies on more granular – and consistent – assumptions to allocate labor income for the self employed; rather than high-level assumptions such as imputing the labor share in the non housing, non corporate sector to be the same as in the corporate sector (although some authors have criticized the granular estimates [Elsby et al., 2013]). The availability of industry data also allows us to compare trends at a more granular level, and leverage the cross-sectional variation in regression analysis. Last, KLEMS allows me to exclude Financial Services (in addition to Real Estate), which is a notoriously difficult segment for which to estimate labor shares – and one that exhibited very unique patterns prior

Figure 3: Alternate labor shares measures for Germany



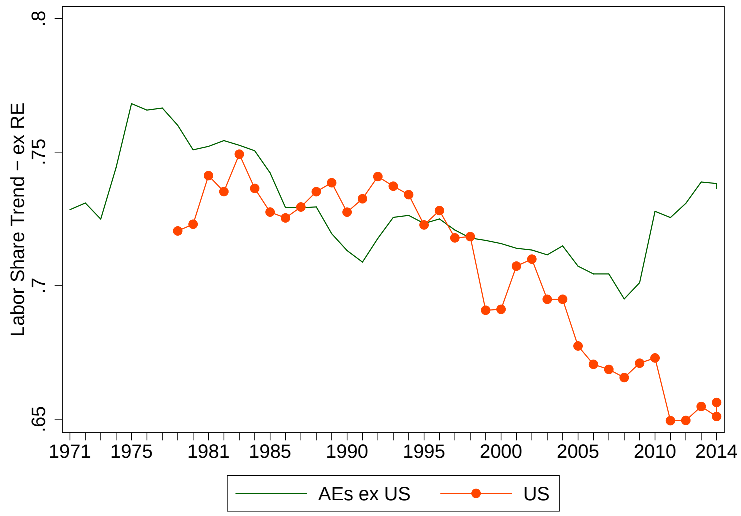
Notes: Figure shows four measures of the Labor Share for Germany. KN - Corp and KN- Agg denote the corporate sector and aggregate labor shares from Karabarbounis and Neiman [2013], respectively. KLEMS - Bus denotes the business sector labor share after excluding Finance and Non-business sectors listed in Figure 1. KN - Ex RE also excludes Real Estate. The vertical line in 2007 highlights the last year included in industry analyses by Karabarbounis and Neiman [2013].

Excluding Real Estate, the Labor Share declined only in the US. Figure 4 plots the evolution of the labor share excluding Real Estate for the US and other Advanced Economies. For the US, the plot shows the labor share directly. For other advanced economies, the plot shows the year fixed effects from a least-squares regression of country labor shares on country and year fixed effects. Country fixed effects eliminate the influence of countries entering and exiting the dataset. Observations are weighted by value added (in US dollars at market exchange rates); and the constant is added to the fixed effect to obtain the average labor share across advanced economies. As shown, the US labor share declined drastically since the late 1990s, while the labor share of other advanced economies has remained largely stable.[19]

to the crisis.

[19] Several measures of the US labor share increase during the Dot-Com bubble. My series begins exhibit a smaller jump both because of the of KLEMS and because I exclude Finance, which as shown in Elsby et al. [2013] was a sizable contributor of the increase.

Figure 4: Labor share ex. RE: US vs. Other Advanced Economies



Notes: The figure shows the evolution of the labor share for the US and other advanced economies, excluding Real Estate, Finance and non-business sectors. The dotted line plots the US labor share directly. The solid line shows the evolution of the labor share for other Advanced Economies by plotting the year fixed effects from a regression of country-level labor shares on year and country fixed effects (after adding the constant). Country fixed effects account for entry and exit during the sample. Observations are weighted by gross value added measured in US dollars at market exchange rates. Annual data primarily based on KLEMS 2012.

Importantly, this decline is unique to the US: no other country experienced as sharp or as consistent a decline. Table 3 shows the country-level labor shares (excluding Real Estate and Finance) since 1985. As shown, while the US experienced a 8% decline in its labor share since 1985, other countries experienced at most a 4% decline. Six out of ten non-US countries experienced an increase in the labor share since 1990; and 9 out of 10 since 2000. Figure 18 in the appendix shows the full time series for each country, which yield similar conclusions. Each country's labor share varies with the economic cycle (e.g., for Canada in 1990 and Germany before the Great Recession) but returns close to its 1980 (or 1990) level by 2014. Except for the US, where there is a sizable and persistent decline.[20]

The US Labor Share Decline is Pervasive across Industries. Figure 5 shows the labor share trend by industry, from 1987 to 2015.[21] For the US, the trend is calculated through an OLS regression of industry labor share on time. For other countries, the trend is estimated via OLS regression of country-industry labor shares on time and country-industry fixed effects. The fixed

[20] Similar, albeit less strong conclusions are reached when considering the labor share evolution of the NFC sector, since 1995 (see Figure 16 in Appendix). The average NFC labor share remained stable outside the US, yet decreased in the US. The stability outside the US, however, masks sizable changes across countries. The labor share increased in half non-US countries, and decreased in the rest. That said, we find similar patterns to those in Figure 3 for most countries with declining NFC labor shares, suggesting that the decrease is largely explained by Residential Real Estate holdings of the NFC sector.

[21] I use 1987 as the starting year because US data under the NAICS segmentation is available from then on. Data is available under the SIC categorization beforehand, which is harder to map to ISIC Rev. 4 segments.

Table 3: Labor Share ex. RE: Evolution by Country

Country	85-89	90-94	95-99	00-09	10-14	Δ85s-10s	Δ95s-10s	Δ00s-10s
USA	73.1	73.4	70.9	68.3	65.2	**-7.9**	**-5.7**	**-3.1**
AUT	73.8	74.6	72.7	69.2	69.5	**-4.3**	**-3.3**	0.3
DEU	74.8	76.4	77.1	74.6	74.3	**-0.5**	**-2.8**	**-0.3**
ESP	64.0	68.4	68.2	65.1	65.5	1.4	**-2.8**	0.3
SWE	.	.	60.3	59.8	61.2		0.9	1.4
NLD	71.9	72.4	73.0	71.8	74.4	2.5	1.4	2.6
FRA	72.5	70.0	68.5	68.9	72.5	0.1	4.0	3.7
GBR	72.3	76.3	74.2	76.6	79.0	6.7	4.8	2.4
ITA	77.3	77.5	72.0	72.1	76.9	**-0.4**	4.9	4.8
FIN	78.9	81.9	73.8	72.2	78.7	**-0.2**	4.9	6.5
CAN	65.6	69.1	65.5	62.7	na	na	na	na
JPN	71.6	68.4	71.0	69.5	na	na	na	na

Notes: Table shows the average labor share, by country, over the periods specified. All measures exclude Real Estate, Finance and non-business sectors. The last columns include the change in labor shares from the corresponding period to the 2010s. Annual data primarily from KLEMS 2012.

effects control for countries entering and exiting the dataset. Observations are weighted by value added; and trends are shown in percentage points for every ten years.

As shown, US labor shares declined in most industries – often by large percentages. The decline is most pronounced in manufacturing, mining and other services; but also present in trade, transportation and leisure.[22] By contrast, labor share trends are lower in magnitude and more varied in other countries. Roughly half of the industries exhibit downward labor share trends, while the other half exhibits upwards trends. Moreover, economic activity reallocated towards higher labor share sectors – resulting in a stable aggregate labor share.

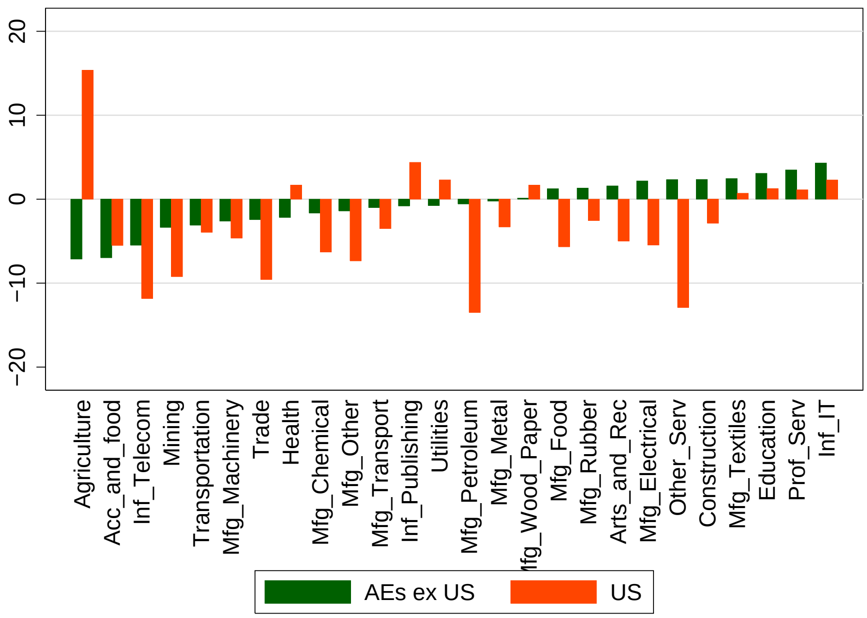
The drastic differences in US labor share patterns compared to other countries poses a challenge for the majority of explanations proposed in the literature. In particular, declining capital prices, automation, technical change, network/winner-take-all effects, rising global returns to housing capital, import competition and the rise of intangibles would all presumably have similar effects across Advanced Economies. A US-specific factor is likely at play.

1.4 Profit Shares

Profit Shares Increased only in the US. Over the same period that US labor shares declined, US profit shares experienced a wide and pervasive increase. Figure 6 shows the evolution of the profit share excluding Real Estate in the US and other Advanced Economies. Country profit-shares are estimated as the weighted average profit share across industries, where weights are based on

[22]The pervasive decline for the US was already emphasized by Elsby et al. [2013]. Our results differ slightly given the longer time period and the use of updated BEA data including intangibles.

Figure 5: Industry Labor Share trend (87-15): US vs. Advanced Economies



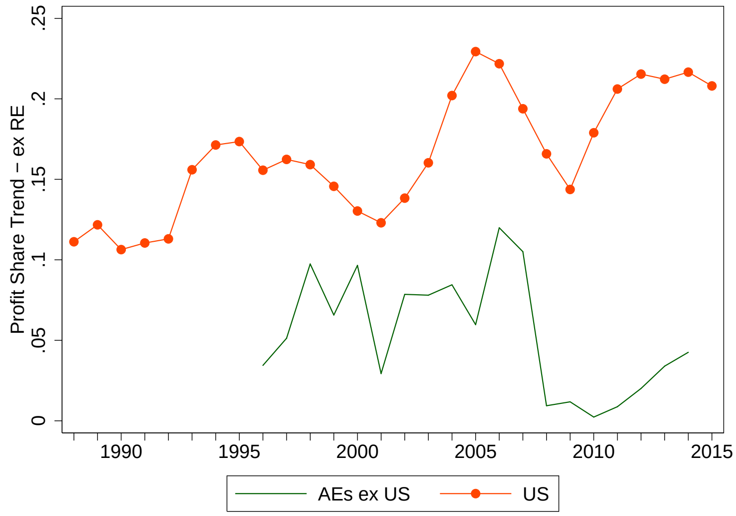
Notes: Figure shows labor share trends for the US and other Advanced Economies over 1987-2014 period, by industry. Trends are shown in percentage points for every ten years. For the US, the trend is estimated via OLS regression of industry labor share on time. For other countries, the trend is estimated via OLS regression of country-industry labor shares on time and country-industry fixed effects. The fixed effects control for countries entering and exiting the dataset. Observations are weighted by value added

value added. Because I use KLEMS 2016, only European countries are included; and the sample period is limited to those years when a broad sample of countries are covered.

As shown, the profit share increased drastically in the US, yet remained largely stable in Europe. Figure 20 in the Appendix shows the same plot but for the profit rate, which covers a a longer period and a slightly larger sample of countries (Japan and Canada).[23] The overall trends are the same, although the increase in the US profit rate is less pronounced than in the profit share. That said, it is unclear whether a decline in competitive dynamics necessarily leads to a higher profit rate. It may instead yield a higher profit share, while the profit rates remain relatively constant.

[23]Note that country-profit rates are based on the weighted average of industry profit rates by value added. Ideally we would weight observations by the current cost of capital, but this information is not available in KLEMS 2012.

Figure 6: Profit share: US vs. Advanced Economies



Notes: The figure shows the evolution of the profit share for the US and other advanced economies, excluding Real Estate, Finance and non-business sectors. Country profit shares are defined as the weighted average profit share across all industries in a given country. Country-industry profit shares are defined as the gross operating surplus less total capital payments ($\Pi_t = Y_t - W_t N_t - R_t^{K,req} K_t$) over value added, Y_t. $R^{K,req}$ measures the required real return on capital and is estimated as $R^{K,req} = \zeta_{t-1}\left(r_t^f + BBB\,spread_t - (1-\delta_t)g_{\zeta,t} + \delta_t\right)$. Capital includes tangible and intangible capital. See Section 1.1 for additional details. The dotted line plots the US profit share directly. The solid line shows the evolution of the profit share for other Advanced Economies by plotting the year fixed effects from a regression of country-level profit shares on year and country fixed effects (normalized to match the average profit share). Country fixed effects account for entry and exit during the sample. Observations are weighted by gross value added measured in US dollars at market exchange rates. Annual data primarily based on KLEMS 2016.

Table 4 shows the average country-level profit share for the major European economies from the early 1990s to the 2010s – where available. As shown, the US profit shares increased by 7.4 percent since the early 1990s and 5 percent since the late 1990s. By contrast, profit shares decreased or remained stable across most other European countries. Profit shares dropped sharply in Spain and Italy (as expected given the large effect of the financial and sovereign crises) and remained stable in France, the UK, Sweden. Profit shares increased in Germany, though the increase appears to be driven by very low profits in the late 1990s and early 2000s rather than truly rising profits. In fact, filling in the German profit share in the early 1990s by holding the difference between profit rate and profit share constant over the years when both are available, suggests that the increase since 1990 is much more limited. The poor performance of the German economy in the late 1990s and early 2000s is well known (see, for example, Dustmann et al. [2014]). For reference, the profit rate in Germany was 3.6% on 90-94, 0.7% in 95-99, 2.1% in 00-09 and 4.5% in 10-14.[24]

[24]Figure 19 in the appendix shows the full time series of profit shares and profit rates by country, which yield similar conclusions. The profit share/profit rate of most countries varies with the economic cycle but returns close to its 1990 level by 2014 – except for the US, Austria and Canada. Profit shares do increase in Austria; but this is a relatively small economy. Profit rates also increase in Canada through 2008; but the series ends at the peak of the bubble so it is unclear what has happened since. Canada's aggregate GOS/K has since decreased (it was 16% in 1990, reached 21% in 2005 and decreased to 16% by 2015), though profits for NFCs remain elevated. It is also

Table 4: Profit Share ex. RE: Evolution by Country

Country	90-94	95-99	00-04	05-09	10-15	Δ90s-10s	Δ95s-10s	Δ00s-10s
USA	13.14	15.93	15.08	19.09	20.58	**7.44**	**4.66**	**5.50**
DEU	1.65*	-1.12*	-2.25	1.62	3.57	1.92*	4.69*	5.82
SWE	na	9.35	11.00	13.20	9.85	na	0.50	-1.15
GBR	na	0.75	4.02	1.16	-1.11	na	-1.86	-5.13
FRA	7.11	11.38	14.46	13.09	8.32	1.20	-3.06	-6.14
ESP	na	6.52	12.99	7.71	-4.58	na	-11.10	-17.57
ITA	na	9.61	12.29	6.55	-2.54	na	-12.14	-14.83
NLD	na	na	3.38	6.99	2.81	na	na	-0.57

* Estimated based on profit rate
Notes: Table shows the average profit share, by country, over the periods specified. All measures exclude Real Estate, Finance and non-business sectors. The last columns include the change in profit shares from the corresponding period to the 2010s. Annual data primarily from KLEMS 2016.

The US Profit Share Increase is Pervasive across Industries. Looking at the industry-level, the pattern is even more striking. Figure 7 compares industry-level profit share trends for the US vs. European Economies(estimated in the same way as Figure 5 above). The top chart includes all European countries while the bottom excludes Spain and Italy. I sort industries by US profit share trend for readability. Profit share trends are large and positive for the majority of US industries, and almost always negative in other Advanced Economies. The increase in the US is particularly pronounced for Mining and Mfg_Petroleum, likely due to Fracking.

1.5 Concentration

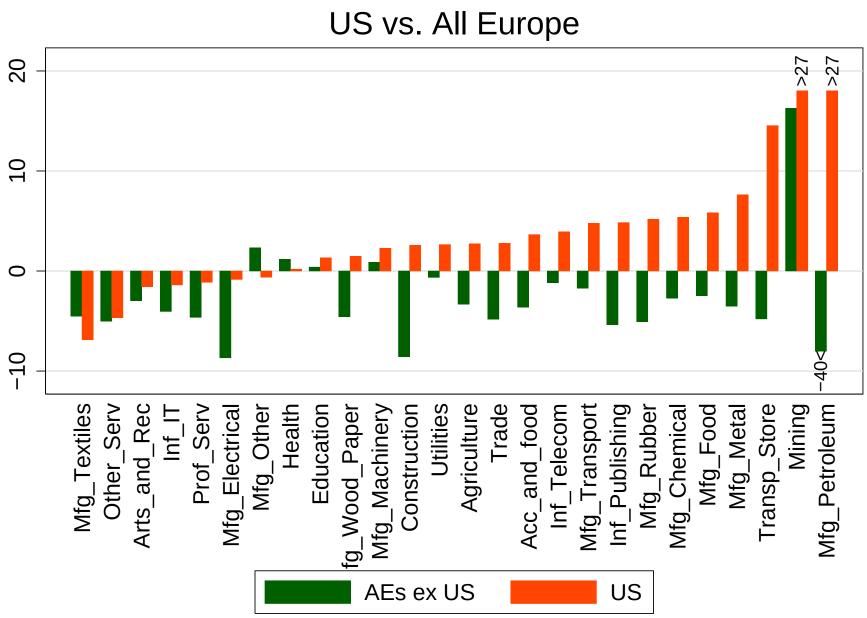
Concentration Measures Increased only in the US. Consistent with the rise in profits, empirical measures of concentration increased in the US. By contrast, similar measures remained stable or decreased in Europe. Figure 8 replicates Figure 10 from Dottling et al. [2017] which compares the weighted average Concentration ratio for the US and Europe. US concentration measures are based on Compustat, while European concentration measures are based on BVD ORBIS (which includes private firms). Similar results are obtained considering Census-based concentration measures in the US and CompNET-based concentration measures in Europe; or considering Herfindahls instead of Concentration Ratios.[25] Unfortunately, I have been unable to find concentration measures for Canada or Japan.

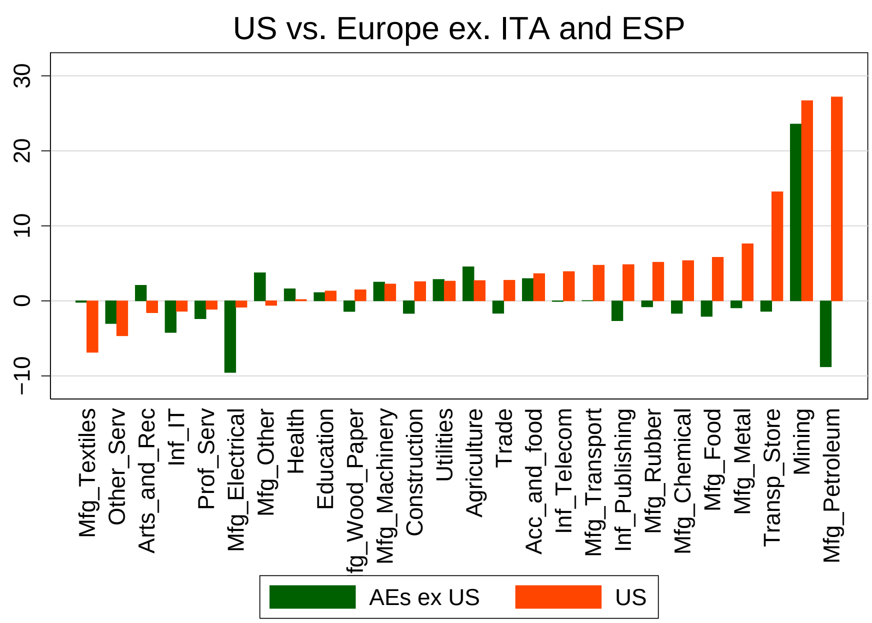
For Europe, concentration ratios are displayed both on an EU-wide level, treating the European

unclear what the pattern looks like excluding Real Estate and Finance. Unfortunately data for the NFC sector is not available in the OECD so I leave gathering additional Canadian data for future work. But I do note that it's evolution of profits may actually resemble that of the US.

[25] See Figures 21 and 22 in the appendix for plots of European concentration measures by country based on the ECB's CompNET; and Autor et al. [2017a] for plots based on the US Economic Census. CompNET was developed by the European Central Bank. It relies on firm-level data from a variety of sources to compute measures of concentration at the industry-year level.

Figure 7: Industry profit share trends (88-15): US vs. Advanced Economies



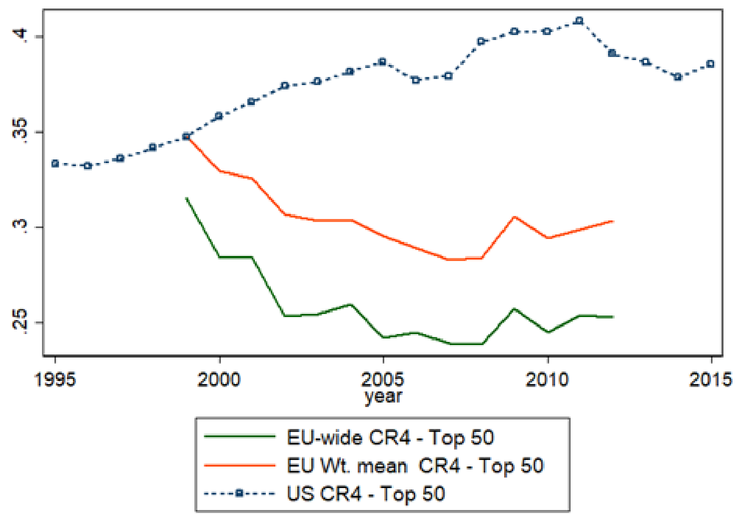


Notes: Figure shows profit share trends for the US and other Advanced Economies over 1988-2014 period, by industry. Trends are shown in percentage points for every ten years. For the US the trend is estimated via OLS regression of industry profit shares on time. For other countries, trend is estimated via OLS regression of country-industry profit shares on time and country-industry fixed effects. The fixed effects control for countries entering and exiting the dataset. Observations are weighted by value added. Top chart includes all European economies; bottom chart excludes Spain and Italy.

Union as a single market, and on a country-level, assuming nationally segmented markets. Beyond the clear differences in trends, one could argue that the increased integration among EU economies essentially shifts the appropriate measure of concentration from the top line towards the bottom one – which further strengthens the trend.

Importantly, such material differences in concentration trends suggest that factors other than economies of scale/network effects are at play, since these would presumably have similar effects in both regions.[26]

Figure 8: Concentration Ratios: US vs. Other Advanced Economies



Notes: Replicated from Dottling et al. [2017]. Figure shows the sales-weighted average 4-firm concentration ratio (CR4) across all industries in the US and Europe. CR4 is defined as the share of sales captured by the top 4 firms in each industry. Ratios are computed based on the top 50 companies in terms of sales in a given industry-year to avoid data issues with smaller firms. European values based on data in Kalemli-Ozcan et al. [2015]. US values based on Compustat. 'EU-wide concentration ratios are computed treating the EU as a single market. 'EU weighted mean' concentration ratios treat each country as a separate market.

2 What might explain the decline in the US Labor Share?

The US appears to be the outlier, so I focus on the corresponding patterns in the remainder of the paper. I begin by discussing six prominent theories put-forth in the literature:

1. **Declining Price of K and Productivity Growth:** Karabarbounis and Neiman [2013] rely on cross-country variation to argue that the decline in the labor share is driven by falling relative prices of capital. They estimate an elasticity parameter of 1.25, which is larger than

[26] Identifying the drivers of these differences is an interesting area of future research. Dottling et al. [2017] point to differences in anti-trust enforcement and product market regulations as potential drivers of these trends. Relatedly, Gutiérrez and Philippon [2017] provide evidence that US concentration increased (and investment decreased) in industries with rising regulation.

most in the literature and implies capital and labor are substitutes. Relatedly, Piketty and Zucman [2014] argue that declining productivity growth has led to capital accumulation and the decline in the labor share.[27]

Several authors have disputed these findings. Elsby et al. [2013] argues that aggregate trends in compensation growth, K/N ratios and skill deepening are inconsistent with the capital deepening story; and that declining capital prices are negatively correlated with falling labor shares in the cross-section. Rognlie [2015] argues that the decline is concentrated in housing capital.

It is also worth noting that declines in the relative price of capital are common across countries, and were most significant from 1980 to 2000. In fact, the relative price of capital has remained relatively stable since 2000. The sharp decline in the US labor share excluding Real Estate – which appears only after 2000 and is unique to one country – appears inconsistent with this story. And the results in the remainder of the paper also challenge this explanation. Like Caballero et al. [2017a], I find that capital accumulation/automation is unable to fully explain labor and profit share trends even with an elasticity parameter of 1.25. Capital accumulation/automation plays a role in selected industries (manufacturing, mining and retail trade) but cannot explain aggregate trends. I also confirm the cross-sectional results of Elsby et al. [2013] in Section 3.2 (although with different data sources), which show that declining capital prices are not correlated with falling labor shares or rising profits.

2. **Increased Import Competition and Offshoring**: Elsby et al. [2013] provides cross-sectional evidence that import competition and offshoring explains the decline in the labor share. However, several patterns appear inconsistent with this hypothesis. First, import competition primarily affects tradeable industries while the decline is pervasive across sectors. Second, import competition affects all countries, not just the US. Last, increased competition leads to lower profits (in most models), which contrasts with the rise in US profits. I test this hypothesis via regression in section 3.2 and find no support. Autor et al. [2017b] reports performing similar tests and finding no support. That said, it is feasible for import competition to have affected the labor share of select sectors – likely manufacturing.

3. **Returns to Housing Capital**: Rognlie [2015] argues that the post-1970 decrease in the net labor share is entirely driven by rising returns to housing capital. This appears to be part of the story: as shown in Figure 2, the labor share excluding Real Estate is stable for most countries. But this is not the case for the US: the post-2000 decline in US labor share is real and significant even after excluding Real Estate. Another explanation is likely at play.[28]

4. **Rise of Intangibles**: Koh et al. [2015] argues that intangible capital accounts entirely for the

[27] It is worth noting that Karabarbounis and Neiman [2013] focus on the gross labor share in the corporate sector; while Piketty studies the net labor share across all sectors. As noted previously, the corporate sector still holds substantial residential assets, hence their results may be affected by the rise of Real Estate. Both papers also rely on evidence before the 2013 BEA revision that incorporated intangibles.

[28] Note also that the post 2000 rise in profits/capital share appears in Rognlie [2015]'s results (see Figure 5). See Section 1.3 for additional discussion on the differences between my results and those of Rognlie [2015].

decline in the US labor share. Part of this is expected, as the higher depreciation of intangibles translates to a higher capital share. I confirm their results internationally by comparing the KLEMS 2012 and KLEMS 2016 releases, where the latter incorporates intangibles other than software. As expected, KLEMS 2016 exhibits lower labor shares that trend down slightly faster.

But this explanation seems unable to explain the post-2000 decline in the US labor share. The top chart of Figure 9 shows the evolution of labor shares including and excluding intangibles, as estimated by Koh et al. [2015]. Including intangibles introduces a slight downward trend from 1980 to 2000 – but the pattern after 2000 is strikingly similar. The bottom chart plots the share of intangible capital and the gap between labor shares with and without intangibles. The share of IPP capital appears closely related to the gap between series. But both the gap and the share of IPP capital stabilize after 2000 – precisely when the labor share declines more rapidly. Thus, intangibles appear to be part of the long-run story, but do not seem to explain the post-2000 decline. In addition, results in section 3 suggest that intangibles alone cannot explain aggregate trends.[29]

5. **Market Power**: Barkai [2017], Caballero et al. [2017a] and De Loecker and Eeckhout [2017] argue that the decline in the labor share is driven by a rise in market power.[30] I interpret my results as supporting this hypothesis – although as discussed below it is hard to differentiate it from a potentially growing efficient scale of operation.

   Appendix A provides additional details for this explanation. In particular, it discusses (i) the long-run evolution of US labor and profit shares; (ii) the large and growing literature on declining competition in the US; and (iii) the evolution of three measures of firm-level mark-ups. It shows that NFC profits today are at levels last observed in the 1960s. And two out of three measures of mark-ups exceed levels observed historically; while the third is at levels last observed in 1960. Together with the unique increase in US concentration measures reported in Section 1, items (i) to (iii) provide strong evidence for a broad decline in US competition.

6. **Technical Change and Composition Effects**: Last, several authors emphasize technical change and composition effects. Acemoglu and Restrepo [2016] argue for capital-biased technical change and automation; while Autor et al. [2017b] and Kehrig and Vincent [2017] provide evidence of a sizable composition effect, under which high-productivity and low labor share firms capture a larger share of the market. Autor et al. [2017b] links the composition effect to concentration measures, showing that US labor shares decreased the most in industries that have become more concentrated.[31]

   The composition effects are well-documented. The implications of such effects for my results,

[29] It is possible, however, for intangibles to help erect barriers to entry. This would increase firm's market power and decrease the labor share per explanation 6.

[30] Karabarbounis and Neiman [2013] and Rognlie [2015] also provide related evidence.

[31] Similar evidence is provided by Barkai [2017], although the interpretation is drastically different. Barkai [2017] argues for a rise in Market Power, while Autor et al. [2017b] argues for a rise in productivity. Autor et al. [2017b] provide similar evidence for Europe which exhibits properly signed although (almost always) insignificant coefficients

however, depend on the nuances of why concentration has risen. In particular, whether and how we can differentiate a rise in concentration due to market power from a growing efficient scale of operation. I therefore consider the "efficient scale hypothesis" under which firms with substantially higher productivity compared to their peers gain market share because of (i) their capabilities or (ii) a change in technology that does not affect consumer's elasticity of substitution but allows more productive firms to capture a larger share of the market.[32] Under this interpretation, a key prediction is that productivity increases with concentration. Autor et al. [2017a] provide long-run evidence of this. However, Gutiérrez and Philippon [2017] show that TFP growth is related to concentration before 2000 but not afterwards – which suggests that rising efficient scale is part of the story before 2000, but not necessarily after. It is also worth noting that concentration increased primarily in the 1990s and early 2000s, while the labor share decreased in the late 2000s. Last, technological changes affecting the efficient scale of operation are likely to have similar effects on industries across advanced economies. The fact that concentration is rising only in the US poses a challenge for the efficient scale hypothesis; although one could argue that the US is a more conducive market for the rise of superstar firms given its size and homogeneity; or that Europe is still 'catching-up' with the US in intangible deepening or other forms of technological change, so that concentration has yet to come. In Section 3.2, I also test whether declines in the labor share and increases in profit shares are related to dispersion in firm-level TFP within industries and find limited support. But, again, this may be because of measurement error in firm-level TFP estimates or other data issues.

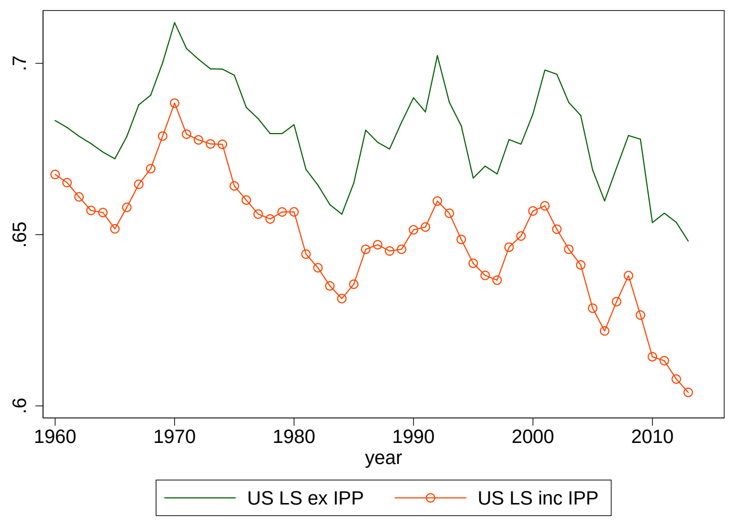
In the end, I am unable to fully differentiate between the market power and efficient scale hypotheses. Indeed these hypotheses may be deeply intertwined. Large firms may attain their leadership position legitimately based on their innovations or efficiency; but may then use their market power to erect barriers to entry and protect their position [Zingales, 2017].

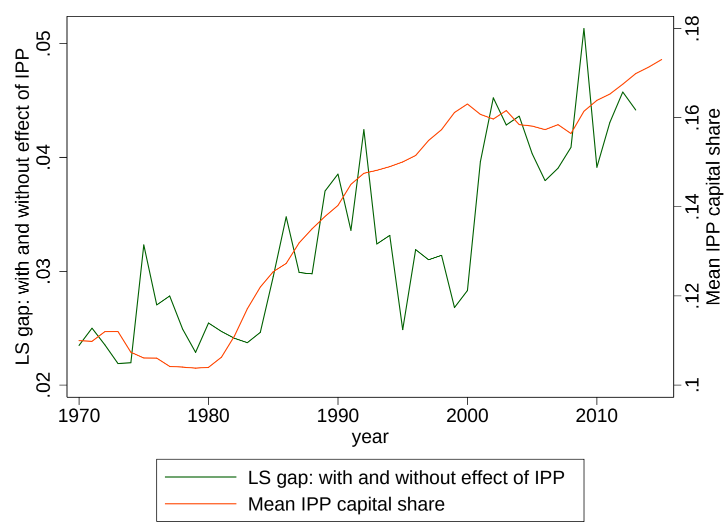
3 Empirical Tests For Falling Labor Shares and Rising Profit Shares

The remainder of this paper tests (most) theories of declining labor shares empirically. Section 3.1 describes the data sources needed to implement these tests. Section 3.2 presents the first set of results, which test each theory non-parametrically via regression. Section 3.3 presents the second set of results, which leverage the accounting framework of Caballero et al. [2017a]. This accounting

[32] This is slightly different from the model presented by Autor et al. [2017b], where superstars arise from an increase in consumer's elasticity of substitution. In said model, a rise in elasticity leads more productive firms to gain market share – but only at the expense of lower price-cost margins (as noted by the authors in Appendix Proposition 4). Profits would increase only if fixed costs are large enough for the rise in sales to offset the decline in price-cost margins. Granted, alternate model specifications yield different implications for price-cost margins and profits so I focus on productivity.

Figure 9: Intangibles and Labor Share





Notes: Top plot shows the labor share including and excluding the effect of intangibles as estimated by Koh et al. [2015]. Bottom plot shows the gap between both labor share series and the share of IPP capital as a percent of total IPP capital for the US.

Table 5: Summary of US data sources

	Data fields	Source	Use
Aggregate data	Macro-data (interest rates, consumption deflator, etc.)	FRED	All
	NFC Capital, depreciation and prices	BEA Section 4	NFC analyses
Industry datasets	Capital, investment and depreciation	BEA Section 3	Industry analyses
	Output, Wages, Taxes and Surplus	BEA Section 3	
	China import exposure	UN Comtrade	Regressions analyses
Firm datasets	Firm-level financials	Compustat	ERP estimation and Regression analyses
	Firm-level analyst forecasts	IBES	ERP estimation

framework incorporates most relevant theories – albeit with clear parametric assumptions. It allows us to disentangle the alternate explanations using aggregate data from FRED and industry data from the BEA. The results are fairly conclusive: increasing mark-ups and rising concentration appear to be the primary explanation for jointly decreasing labor shares and increasing profit shares.

3.1 US data

I use a variety of aggregate-, industry- and firm-level data to study the evolution of US labor and profit shares. The data fields and data sources are summarized in Table 5. The following sub-sections provide an overview and discuss key data issues.

3.1.1 Aggregate data

In addition to 10-year treasury rates and PCE deflators used in the country-level analyses, I use real interest rates based on 10Y TIPS (FRED series FII10). TIPS prices were liquid after 2003, but fairly illiquid before [Campbell et al., 2009]. I therefore use the TIPS prices directly after 2003, but back-fill the series to 1987 using the average spread between 10Y nominal and TIPS bonds from 2003 onward.[33]

3.1.2 NFC data

Data for the NFC sector follows Barkai [2017]. Capital stock and price indices are sourced from BEA Fixed Assets Table 4, which include software, R&D, as well as entertainment, literary, and

[33]The resulting real interest rates are higher than those in Caballero et al. [2017b], which is constructed using median expected price changes from the University of Michigan's Survey of Consumers. Using a lower risk-free rate further strengthens my results.

artistic originals. Output, value added, and compensation are sourced from the NIPA via FRED. Note that compensation of employees includes salaries as well as employer costs in health insurance, pension contributions and the exercising of most options.

3.1.3 Industry data

Industry-level capital, output and value added – including current-cost and chained values for the net stock of capital, depreciation and investment, gross output, gross operating surplus, compensation and taxes – are gathered from the Bureau of Economic Analysis (BEA). Fixed assets data is available in three categories: structures, equipment and intellectual property (which includes intangibles). All data are available at the sector (19 groups) and detailed industry (63 groups) level, in a similar categorization as the 2007 NAICS Level 3. For ease of discussion and to ensure industries have sufficient representation in Compustat, I group detailed industries into 54 industry groupings. I exclude Financial Services from all analyses; and Real Estate from most industry-level analyses. See the data appendix for details on the segmentation.

The following definitions are used:

- Labor share: ratio of 'Compensation of employees' to 'Value added.[34]
- Net labor share: ratio of 'Compensation of employees' to 'Value added' minus 'Current-Cost Depreciation of Private Fixed Assets'.
- Relative price of investment: ratio of the implied deflator for industry-level investment to personal consumption expenditures, all normalized to 1 in 1987
- Net Operating Surplus: 'Gross Operating Surplus' minus 'Current-Cost Depreciation of Private Fixed Assets'.
- Average product of capital: 'Net operating surplus' over lagged 'Current-Cost Net Stock of Private Fixed Assets'.[35]

For regression analyses, I also compute the industry-level share of intangible capital (as % of total capital); and use it to study the effect of rising intangibles on labor and profit shares. And I gather Census-based concentration measures from the Economic Census. These include the share of sales held by the top 4, 8, 20 and 50 firms in each industry. They are available for a subset of industries for 1997, 2002, 2007 and 2012. When necessary, I aggregate concentration ratios to my 54 BEA

[34]Note that compensation for the self-employed is not included in this measure. This has led some authors to refer to this measure as the Payroll share. Elsby et al. [2013] show that trends in the payroll share are similar to aggregate trends so I maintain this estimate throughout. Note also that industry-level labor shares are not robust to changes in composition of capital v. intermediate inputs. For instance, the associated labor shares were affected by the reclassification of software from intermediate to capital. See Koh et al. [2015] and Baqaee [2017 and and] for additional details.

[35]This definition roughly aligns to that in Gomme et al. [2011], with two main differences: Gomme et al. [2011] exclude rental income and other corporate, state and local taxes, while I include intangible capital. Caballero et al. [2017a] use the measures in Gomme et al. [2011] but adjust for intangible capital.

industry groupings by taking the weighted average by sales across NAICS level 3 industries. I use only NAICS Level 3 segments that can be mapped consistently to BEA categories over time.

3.1.4 Firm data

Last, I use firm-level financials (from Compustat) and analyst forecasts (from IBES) to estimate aggregate and industry-level ERP; and to test the alternate explanations via regression.

Firm Financials. For regression analyses, I compute the following measures:

- Mark-ups: I compute three measures of mark-ups as described in Appendix A.
  - Lerner index: First, I follow Grullon et al. [2016] and define the Lerner Index as operating income before depreciation minus depreciation (OIBDP - DP) divided by sales (SALE). The Lerner index is an empirical measure of a firm's ability to extract rents from the market.
  - User-cost implied mark-ups: Second, I estimate firm-level mark-ups by solving Condition (11) below for μ at the firm- and industry-level. APK_i^e denotes the expected average product of capital for firm i. This is measured as the ratio of operating surplus (OIADP - TXT) to lagged capital (PPENT + INTAN). KRP, g_ζ^e and δ are assumed to be constant for all firms within an industry. KRP is estimated at the industry-level following Claus and Thomas [2001]. g_ζ^e and δ are taken from BEA data.
  - DLE mark-ups: Third, I estimate firm-level mark-ups following the methodology of De Loecker and Eeckhout [2017].
- TFP: Last, in order to estimate dispersion in productivity and test the efficient scale hypothesis, I gather firm-level TFP estimates from Imrohoroglu and Tuzel [2014]. Imrohoroglu and Tuzel [2014] implement the methodology of Olley and Pakes [1996] using Compustat data.

Analyst forecasts. Analyst forecasts are sourced from the I/B/E/S database via WRDS. They are mapped to Compustat GVKEYs and used to estimate industry-level ERP as described below (and in the Appendix). Analyst forecasts are available starting on 1980 but are fairly thin until 1985 – so results are provided from 1985 onward.

3.2 Regression results

Armed with the required data, I test whether alternate explanations of declining labor shares can jointly explain the fall in (gross and net) labor shares and the rise in profit shares. In particular, I regress (gross and net) labor shares as well as profit shares against empirical proxies for each theory.

For concentration, census-based concentration ratios CR_{jt} are available every five years. So I regress

Table 6: Summary of Regression Results

Explanation	Proxy	LS	NLS	PS
Market-power and Concentration	% sales of top 4 firms (Census)	✓	✓	✓
	Mark-up estimates (DLE, UC and LI)	✓	✓	✓
Intangibles	Intangible share of K (BEA)	✓	✗	✗
Price of K	Industry-level relative price of K (BEA)	✗	✗	✗
Import Competition	Industry-level import penetration	✗	✗	✗
TFP Dispersion (i.e., 'Efficient Scale')	TFP IQR (IT)	✗	✗	✗

Notes: Table summarizes industry-level regression results across all potential explanations. See test for regression specification. Tick-marks (✓) identify those variables that are significant and exhibit the 'right' coefficient. Crosses (✗) identify variables that are not significant or exhibit the 'wrong' coefficient. See text for caveats and discussions of the limitations of our results (e.g., for dispersion of productivity).

$$S_{jt}^N - S_{jt-5}^N = \beta_0 + \beta_1 \left(CR_{jt} - CR_{jt-5}\right) + \gamma_t + \varepsilon_{jt} \tag{8}$$

where γ_t represents year dummies, and are included in some but nor all regressions. For the remaining hypotheses, I estimate panel regressions of the form

$$S_{jt}^N = \beta_0 + \beta_1 X_{jt} + \eta_j + \varepsilon_{jt} \tag{9}$$

where j denotes industries, $X_{j,t}$ denotes empirical proxies for each explanation, and η_j denotes industry fixed effects. Time fixed effects are included in unreported robustness tests as well. Standard errors are clustered at the industry level. Most proxies are self explanatory. For import competition, I follow Autor et al. [2016] and compute industry-level import penetration.[36]

Table 6 summarizes the empirical proxies and regression results for each explanation. Tick-marks (✓) identify those variables that are significant and exhibit the 'right' coefficient. Crosses (✗) identify variables that are not significant or exhibit the 'wrong' coefficient.

I find strong support for measures of concentration and mark-ups, and limited support for the remaining hypotheses. The rise of intangibles can explain declining gross labor shares, but not declining net labor shares or rising profits. Dispersion in TFP cannot explain declining labor shares, nor rising profits; although as noted previously measuring firm-level TFP with Compustat data is challenging.

Table 7 presents detailed regression results using Census concentration measures (which follow equation (8)). The first three columns regress 5-year changes in labor and profit shares against changes in concentration. The last three columns add year dummies. As shown, a 1 percent increase in the top-4 firm concentration ratio leads to a 0.5 and 0.9 percent decrease in gross and net labor shares, respectively; and a 0.85 percent increase in profit share. Autor et al. [2017b] and Barkai

[36]See Gutiérrez and Philippon [2017] for additional details on the calculations of import penetration.

Table 7: Regression Results: Census Concentration

	(1) LS(t) - LS(t-5)	(2) NLS(t) - NLS(t-5)	(3) PS(t) - PS(t-5)	(4) LS(t) - LS(t-5)	(5) NLS(t) - NLS(t-5)	(6) PS(t) - PS(t-5)
CR4 (t) - CR(t-5)	**-0.49****	**-0.93****	**0.85***	**-0.54****	**-1.01****	**0.96***
	[-2.85]	**[-2.93]**	**[2.21]**	**[-3.12]**	**[-3.25]**	**[2.70]**
Observations	122	122	122	122	122	122
Year Dummies	NO	NO	NO	YES	YES	YES
R^2	0.11	0.12	0.07	0.2	0.18	0.17

Notes: Annual data. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01. Labor and profit shares based on BEA data; concentration ratios from Economic Census for years 1997, 2002, 2007 and 2012. Standard errors clustered at industry-level.

[2017] report similar results linking concentration and gross labor shares; but do not consider net labor shares or profit shares. My estimates are substantially higher – likely because I consider more aggregate data (BEA segments which roughly follow NAICS Level 3 vs. NAICS Level 4 and 6, respectively) so that concentration ratios are less volatile. I use NAICS Level 3 because BEA data is available at that level of granularity.

Table 8 summarizes the estimated coefficients β_1 and associated t-stats for the remaining explanations (which follow equation (9)). The correlation with mark-ups is not surprising, but it is good to confirm it in the data – and with several different measures of mark-ups.

3.3 Framework

This section presents a simple accounting framework used to disentangle the alternate hypotheses for declining labor shares and rising profit shares. The framework builds on the definitions outlined in Section 1 and closely follows Caballero et al. [2017a]. It is grounded on standard macro models used to study labor shares – including the models of Karabarbounis and Neiman [2013] and Barkai [2017]. It shows that, controling for secular macro-trends, the rise in profits and the decline in labor share can only be rationalized with a substantial rise in mark-ups.

3.3.1 Definition.

By the same argument as in Section 1, but accounting for uncertainty and risk, investor indifference between physical capital and risk-free bonds implies

$$E[R_t^{K,req}] = \zeta_{t-1}\left(r_t^f + KRP_t + \delta_t - (1-\delta_t)g_{\zeta,t}^e\right) \tag{10}$$

where ζ and g_ζ^e capture the changes in the price of investment goods emphasized by Karabarbounis and Neiman [2013]. Profit maximization by the firm implies $E[R_t^{K,req}] = MPK_t/\mu_t$. The *realized*

Table 8: Regression Results: Other Measures

		(1) LS	(2) NLS	(3) PS
Intangibles	Share Intan K (t-2)	**-28.24***	2.27	-7.81
		[-2.13]	[0.12]	[-0.32]
Price of K	$LogRelP_K$(t-1)	3.88	-5.7	4.16
		[0.91]	[-0.81]	[0.39]
TFP Dispersion	$IQR(TFP_j)$ (t)	0.55	3.2	-1.3
		[0.43]	[1.02]	[-0.41]
Import Competition	Imp. Pen. (91,t)	-8.84	1.35	-6.98
		[-1.07]	[0.15]	[-0.67]
Mark-ups	μ_j^{DLE}	**-10.10****	**-11.14+**	**15.67+**
		[-2.79]	**[-1.82]**	**[1.70]**
	μ_j^{LI}	**-82.35****	**-158.42****	**204.07****
		[-6.07]	**[-4.27]**	**[4.91]**
	μ_j^{CFG}	**-52.84****	**-87.90****	**203.98****
		[-3.83]	**[-2.98]**	**[5.36]**

Notes: Annual data. T-stats in brackets. + p<0.10, * p<0.05, ** p<.01. Each cell shows the results of a uni-variate panel regression of industry-level gross labor share, net labor share and profit share on the corresponding industry-level dependent variable. All regressions include industry fixed effects. Standard errors clustered at industry-level.

average product of capital APK (net of depreciation and excluding capital gains) is given by[37]

$$APK_t = \frac{1}{\zeta_{t-1}}\left[R_t^{K,req} + \frac{Y_t}{K_t}\left(1 - \frac{1}{\mu_t}\right)\right] - \delta_t.$$

where APK_t adds up rental income and profits, net of depreciation, relative to the capital stock. Taking expectations and substituting $E[R_t^{K,req}]$, we obtain the expected average return to productive capital APK^e

$$APK_t^e = r_t^f + KRP_t + \frac{Y_t}{\zeta_{t-1}K_t}\left(1 - \frac{1}{\mu_t}\right) - (1-\delta_t)g_{\zeta,t}^e. \tag{11}$$

Note that this condition is independent of the production function of the economy – i.e., it is independent of the level of automation, technical change, etc. A rise in the average return of productive capital APK^e or a decrease in the risk-free rate creates a wedge between the left-hand side and the right-hand side of this equation. This wedge must be explained by either (i) an increase in risk premia (KRP), (ii) an increase in rents (μ), or (iii) a more rapid expected decline in the price of investment goods (g_ζ^e). Equation (11) can be used to study the joint evolution of KRP and μ. Given an estimate for KRP (and all other parameters), it implies an average mark-up μ_t – and therefore a profit share $s_t^\Pi = 1 - \frac{1}{\mu_t}$.

As presented, the framework depends on KRP estimates; which in turn depend on the required

[37]To link the discussion in this section to profit rates, note that $\frac{Y_t}{K_t}\left(1 - \frac{1}{\mu_t}\right) = \zeta_{t-1}PR_t$, such that $APK_t = IRR_t - (1-\delta)g_{\zeta,t}^e$.

return on equity capital ERP. Given ERP estimates, I compute the un-levered risk premium KRP using $ERP = (1+\kappa)KRP$, where κ denotes the debt to capital ratio. For NFC analyses, κ is estimated based on the corresponding sectoral balance sheet. For industry-level analyses, κ is estimated based on the aggregate debt-to-capital ratio across all Compustat firms in a given industry-year.

Incorporating substitution between capital and labor requires a production function. I assume a CES production function

$$Y_t = F(K_t, N_t) = \left[\alpha_K (A_K K_t)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_k)(A_N N_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

where σ denotes the (constant) elasticity of substitution between capital and labor; A_K and A_N represent capital-augmenting and labor-augmenting technical change, respectively; and α_K captures automation. The limit of the CES production function as σ approaches 1 is the Cobb-Douglas production function.

The firm's first-order conditions with respect to capital and labor are

$$F_{K,t} = \alpha_k A_{K,t}^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{K_t}\right)^{\frac{1}{\sigma}} = \mu_t E[R_t^{K,req}], \tag{12}$$

$$F_{N,t} = (1-\alpha_k) A_{N,t}^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{N_t}\right)^{\frac{1}{\sigma}} = \mu_t W_t. \tag{13}$$

Substituting the first order condition for capital (equation (12)) into the definitions of income shares in equations (3)-(5), we obtain the labor share

$$s_t^N = \frac{1}{\mu_t}\left[1 - \alpha_K^{\sigma}\left(\frac{\mu E[R_t^{K,req}]}{A_K}\right)^{1-\sigma}\right]. \tag{14}$$

For a given elasticity of substitution σ, equation (14) relates the labor share to mark-ups, automation, capital-augmenting technology, and the rental rate of capital. When $\sigma = 1$, $s^N = (1-\alpha_K)/\mu$ and the decline in the labor share must be accounted for by an increase in rents μ or an increase in automation α_K.

Solving for R^K and substituting with equation (10) above, we obtain

$$\frac{A_K}{\mu_t} E\left[\left(\frac{1-\mu_t s_t^N}{\alpha_K^{\sigma}}\right)^{\frac{1}{1-\sigma}}\right] = E[R_t^{K,req}] = \zeta_{t-1}\left(r_t^f + \delta_t + KRP_t - (1-\delta_t) g_\zeta^e\right). \tag{15}$$

when $\sigma > 1$, a decline in the relative price of investment goods ζ, a decline in the risk-free rate r^s, or an increase in capital-biased technical change A_K contribute to the decline in the labor share. An increase in the capital risk premium KRP pushes in the other direction. These effects are reversed when $\sigma < 1$.

This simple accounting framework incorporates the majority of explanations for declining labor shares. These include automation (α_K), technical change (A_K), rising intangible capital (as K_t includes intangibles), varying relative price of capital (ζ_t); capital accumulation (σ), etc. Thus, it can help us disentangle the relative magnitude of these effects.[38] In particular, equations (11) and (15) form a system of two equations in four (potentially less) unobserved variables: mark-ups μ, capital risk-premia KRP, capital augmenting productivity A_K and automation α_K. This system of equations holds for an aggregate economy as well as sub-sectors such as industries. I propose alternate solution approaches and discuss (aggregate- and industry-level) results in Sections 3.3.3 and 3.3.4, respectively. But first, I discuss the approach for estimating the ERP.

3.3.2 ERP estimation

Estimating the ERP is notoriously challenging. Indeed a large and growing literature in Asset Pricing has tackled this topic.[39] Not surprisingly, the estimates used in the labor share literature differ widely. Caballero et al. [2017a] refers to estimates from Duarte and Rosa [2015] who report ERP above 10% since 2000. These estimates are based on the first principal component of 20 different models. Barkai [2017] reports estimates based on Bond yields and Dividend-price ratios – both of which are well below 5%.

To gain a better understanding of the differences between results, I gather and/or compute 16 different estimates of the ERP that span the five different methods considered by Duarte and Rosa [2015]. The estimates are described in Appendix 15 and include estimates based on historical returns; dividend discount/forecasted earnings models; cross-sectional regressions; time-series regressions; and surveys. I also gather Ian Martin's ERP lower-bound [Martin, 2017].

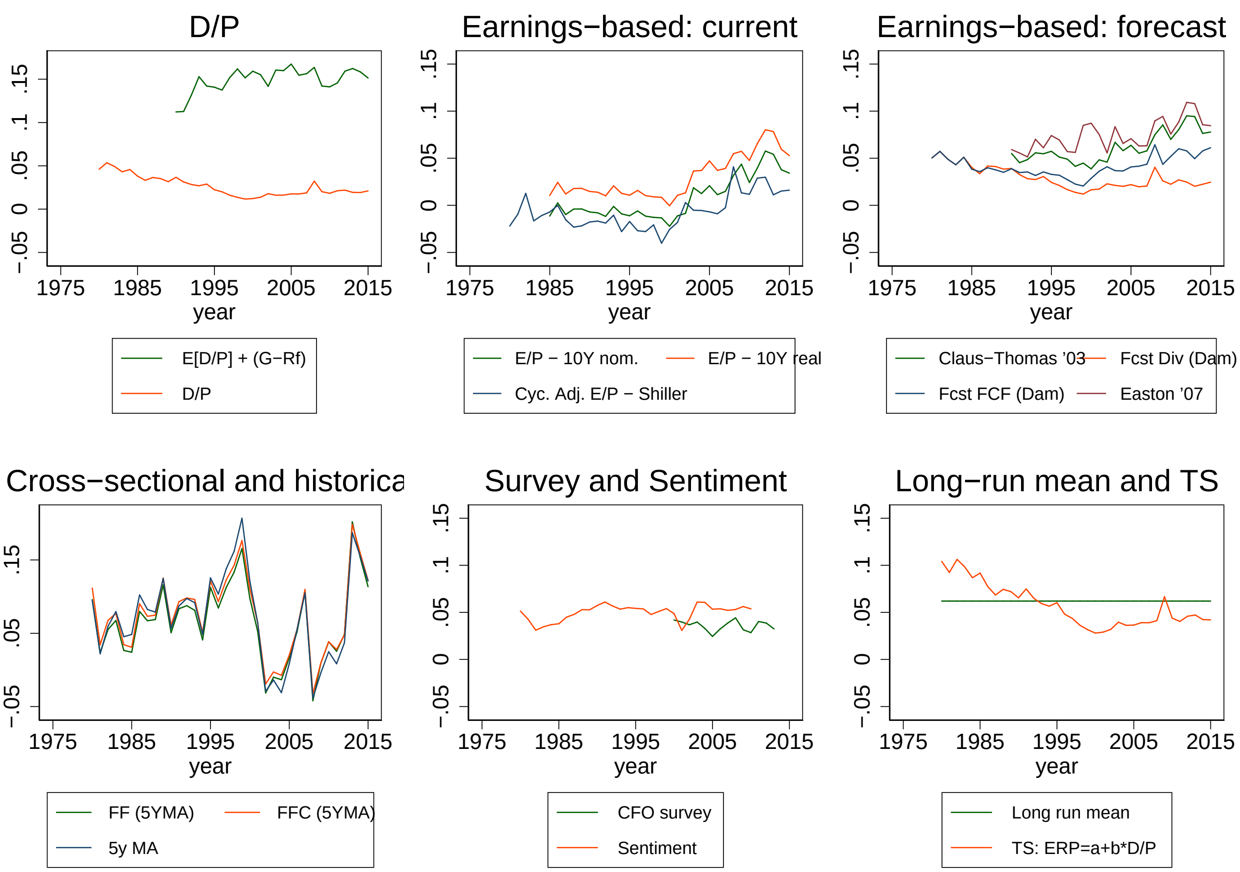
Figure 10 shows the results by broad family of approaches.As shown, some earnings-based estimates were negative before 2000, which appears excessively conservative. Most but not all estimates report a rising ERP. This is particularly true of DDM models. The only estimate that persistently exceeds 10% is the D/P estimate with projected growth based on analyst forecasts. However, this estimate likely over-states the ERP as (typically) 5-year growth forecasts are assumed to apply forever. Adjusting growth estimates beyond the 5-year mark (as in Damodaran and Claus-Thomas) yields substantially lower estimates that range from 6-9%.

Based on a comparison of all estimates to each other, and against Ian Martin's lower bound, I report results based on the methodology of Claus and Thomas [2001] (CT). CT's methodology is preferable for two reasons:

[38] Granted, alternate parametric assumptions could be used, which may affect the conclusions. This is less concerning, however, given the non-parametric regression results discussed above.

[39] See Lettau and Van Nieuwerburgh [2008], Campbell and Thompson [2008] for a recent contributions. I mostly use estimates/approaches proposed in the literature but, in doing so, provide a comparison of the implied estimates across a wide range of approaches. See Section 3.3.2 and the Appendix for additional details.

Figure 10: ERP estimates



Notes: Figure plots 16 different ERP estimates by methodology. See text for details.

- **Conservatism**: Despite including long periods with estimates of only 4%, CT's ERP estimates are generally conservative, and include a sharp rise following the financial crisis. All of these patterns would work against my results, hence using them is conservative.

- **Availability of industry estimates**: CT report only aggregate results; but their methodology can be implemented at the industry-level – which allows us to capture differences in the cost of capital across industries. Industry-level estimates following CT are also stable and intuitive – even when few firms are available.[40]

Figure 11 shows the resulting aggregate (top) and industry-level (bottom) ERP estimates. I floor aggregate ERP estimates with the yearly mean of daily ERP lower-bounds reported by Martin; and scale industry-level estimates whenever the associated aggregate ERP is below the lower-bound estimate. See Appendix for details.

As shown, Martin's lower bound closely follows the aggregate CT estimate. It is binding during the Dot-Com bubble and for a brief period during the Great Recession. The ERP is fairly stable around 4% before the late 1990s, rises slightly at the height of the dot-com bubble and returns to 4%. It then increases sharply during the great recession and remains elevated between 6 and 8% thereafter. The bottom chart shows the industry-level estimates which – although dispersed – follow similar patterns.

I acknowledge that any choice of ERP estimate carries limitations. To mitigate this, I perform thorough sensitivity analysis and report some results where KRP is solved for as part of the system of equations (11) and (15). Ultimately, the rise in profits is so drastic that unintuitive levels of equity premia would be needed to invalidate my conclusions – suggesting that mark-ups must have increased.

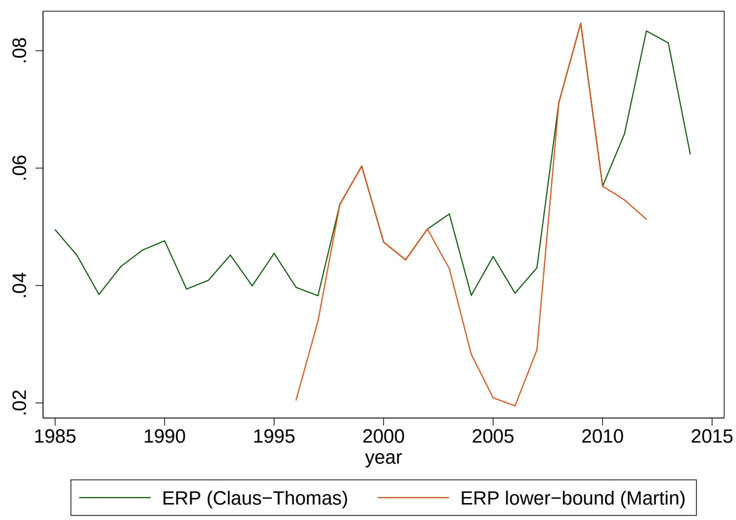
3.3.3 Solution Methods

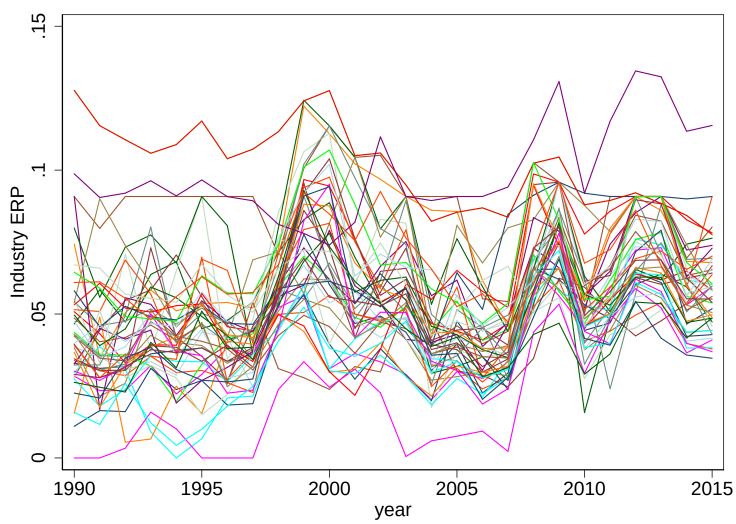
Equations (11) and (15) form a system of two equations in four (potentially less) unobserved variables: mark-ups μ, capital risk-premia KRP, capital augmenting productivity A_K and automation α_K. In order to disentangle the effects of each variable, I solve the system of equations at the aggregate and industry-level under five hypotheses:

- Using Market-implied ERP:
  - ERP_α_k: Use market-implied ERP to find μ_t and α_k, holding A_k constant
  - ERP_A_k: Use market-implied ERP to find μ_t and A_k, holding α_k constant
- Jointly solving for KRP:

[40] I require at least 3 firms with analyst forecasts in a given industry-year to estimate an industry-specific ERP. When fewer than 3 firms are available, I replace the ERP estimate with the aggregate estimate plus the average difference between aggregate ERP and industry ERP over the years where industry ERP is available. If ERP estimates are not available for any years (only Management), the median ERP across all industries is used.

Figure 11: ERP estimates





Notes: top chart shows the estimated US ERP following Claus and Thomas [2001], and after enforcing the ERP lower bound of Martin [2017]. Bottom chart shows the industry-level ERP estimates, also following Claus and Thomas [2001].

- A ("only mark-ups"): jointly solve for μ_t and KRP_t, holding α_K and A_k constant
- B1 ("only automation"): jointly solve for KRP_t and α_K, holding $\mu_t$and A_k constant
- B2 ("only technical change"): jointly solve for KRP_t and A_K, holding $\mu_t$and α_k constant

The first two hypotheses rely on market-implied risk premia estimates, which allows me to jointly solve for mark-ups and one measure of technology. This proves to be the empirically relevant (and more interesting) case, as both mark-ups and technology appear to have changed in some industries. Considering only mark-ups or only technology often fails to solve the system of equations at the industry-level. Given this, most of the reported results consider hypotheses ERP_α_K or ERP_A_K.

Hypotheses A, B1 and B2 are polar opposites. (A) provides no role for capital-biased technical change or automation ($A_K = 1$ and α^K constant), and a maximal role for rents μ. (B1) and (B2) provide no role for rents ($\mu = 1$). When $\sigma = 1$, there is no role for A_K so I only solve for α^K (hypothesis B1). For $\sigma \neq 1$, we can disaggregate (B) into (B1) which loads entirely entirely on automation α_K; and (B2) which loads entirely on capital-biased technical change A_K. Since the production function does not affect KRP, all solutions under (B) yield the same KRP.

Similar to Caballero et al. [2017a], I divide the period into three groups: 1990 to 1999, 2000 to 2007 and 2010 to 2015.[41] I exclude 2008 and 2009 in all analyses given the effect of the financial crisis; and reserve the 1987-1990 period for parameter calibration. Within each period, I compute the average value of r^f, APK, ζ, g_ζ and δ and use it to solve the system. This implicitly assumes that the historical average equals the expectation of APK and g_ζ within each period.

I consider three elasticity parameters $\sigma = 0.8$, 1, 1.25. These parameters cover the range of estimates relevant to the literature. 1.25 is the parameter estimated by Karabarbounis and Neiman [2013], which as noted previously is higher than most in the literature. For manufacturing industries, I also consider the industry-level estimates of Oberfield and Raval [2014] (OR) which range from 0.4 to 08. OR's estimates are based on SIC industries, which I (roughly) map to BEA segments.

The baseline value of A_K is set to 1 and μ is set to solve condition (1) from 1987 to 1990 given the market-implied KRP. α_K is set to match the labor share given the market-implied KRP and the baseline value of A_K and μ (for each value of σ).

3.3.4 Results

Non Financial Corporate Sector. Table 9 shows the results for the Non-Financial Corporate Sector, under hypotheses ERP_α_K, A (only mark-ups) and B1 (only automation). Results for ERP_A_K and B2 yield similar conclusions.

The first set of rows reports historical quantities estimated from the data. As shown, the average return of productive capital APK has increased while the safe interest rate has decreased. This creates a wedge between the left-hand side and the right-hand side of condition (1). This wedge must be explained by either (i) an increase in risk premia KRP, (ii) an increase in rents μ, or

[41] The first period is shorter than in Caballero et al. [2017a] due to industry-level data availability (data before 1987 follows the SIC-87 categorization instead of NAICS)

Table 9: NFC results

			1990-99	**2000-2007**	**2010-2015**
		APK^e	10.4	10.0	11.4
		s_N	63.5	62.3	57.5
		r^s	4.6	2.5	0.4
		ζ	88.3	76.5	72.2
Data		g^e_ζ	-1.8	-0.8	-0.5
		$Y/\zeta K$	25.3	25.5	21.4
		EY	4.9	4.3	5.7
		g^e	2.5	3.2	2.6
		δ	9.1	9.5	9.0
		μ	**106.4**	**120.1**	**137.1**
		KRP	2.6	2.5	**4.7**
ERP_α_K		$\sigma = 0.8$	28.5	22.4	19.6
	α_K	$\sigma = 1$	32.3	25.1	21.0
		$\sigma = 1.25$	38.3	29.2	23.2
	(a)	μ	99.1	98.8	106.5
$\sigma = 1.25$		KRP	4.4	7.1	**9.2**
	(b1)	α_K	**31.4**	**31.4**	**34.3**
	(a)	μ	100.1	101.9	110.2
$\sigma = 1$		KRP	4.1	6.3	8.5
	(b1)	α_K	**36.3**	**37.4**	**42.0**
	(a)	μ	101.7	105.3	114.1
$\sigma = 0.8$		KRP	3.7	5.5	7.9
	(b1)	α_K	**44.1**	**47.6**	**55.4**
	(b1)	KRP	4.1	6.8	**10.5**

Notes: Table reports estimates of μ, α_K and KRP that satisfy equations (11) and (15) for the US Non-financial Corporate sector. Results reported under alternate solution methods and estimates of σ. See text for additional details.

(iii) an increase in the relative price of investment goods g^e_ζ. The price of investment goods is still falling, albeit more slowly – which implies that either KRP, μ or both increased.

Results under hypothesis ERP_α_K suggest that both increased. Mark-ups rise from 106 (where 100 implies price = marginal cost) to 137; and the market-implied capital risk premia nearly doubles. The automation parameter decreases for virtually all values of σ.

Under hypothesis A (only mark-ups), I again find a substantial rise in mark-ups as well as KRP. KRP reaches 9.2% with $\sigma = 1.25$ compared to 7.9% with $\sigma = 0.8$. These translate to roughly 14% and 12% ERP, respectively; which well-exceed all market-implied estimates.

Under hypothesis B1 (only automation), we do observe an increase in automation α_K. But an even higher level of KRP is required to jointly solve the system: 10.6% which translates to an ERP of roughly 15%.

A rise in mark-ups, therefore, appears critical to solving the system with reasonable levels of KRP. And given the market-implied rise in mark-ups, automation appears to play a limited role.

Table 10: Manufacturing results

		1990-99	2000-2007	2010-2015
ERP_α_K	μ	**116.0**	**133.6**	**154.0**
	KRP	3.2	3.6	4.8
	α_k	**30.3**	**35.2**	**43.4**
	% Err	**0.0**	**0.0**	**0.0**
(a)	μ	120.5	128.5	135.4
	KRP	1.3	6.7	**7.1**
	% Err	0.0	18.8	**18.8**
(b1)	α_K	31.4	37.3	50.3
	KRP	4.4	6.6	**10.7**
	% Err	0.0	12.5	**12.5**

Notes: Table reports the weighted average (by capital) of industry-level estimates of μ, α_K and KRP that satisfy equations (11) and (15). Results reported under alternate solution methods. '% Err' denotes the share of industries for which equations (11) and (15) could not be satisfied for a given solution method. Includes only manufacturing industries with elasticity parameters from Oberfield and Raval [2014].

Manufacturing. Let us move on to industry-level results. We start with manufacturing industries, for which industry-specific elasticity estimates are available from Oberfield and Raval [2014].

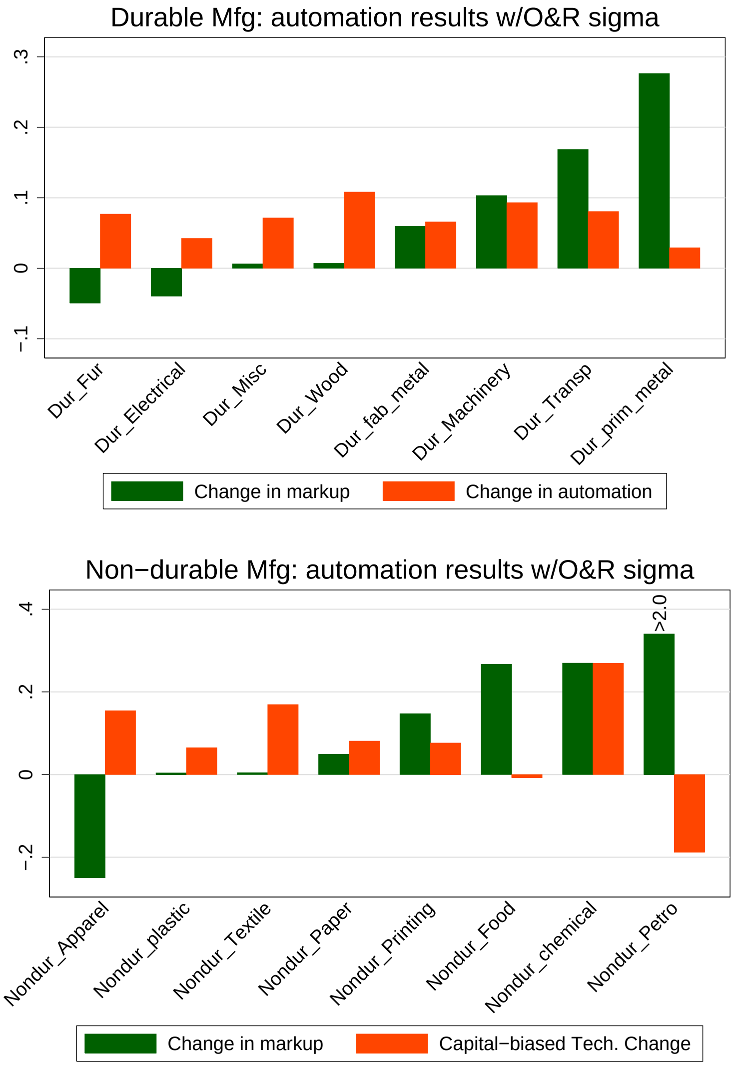
Table 10 shows the results for hypotheses ERP_α_K and (B1). For each parameter, I report the weighted average (by capital) across the manufacturing industries for which Oberfield and Raval [2014] elasticity parameters are available. Rows labeled '% err' show the percentage of industries for which the system could not be solved with reasonable values (e.g., $KRP > 0$, $0 < \alpha < 1$, etc.).

We begin with ERP_α_K. As shown, mark-ups μ increase drastically while KRP increases slightly. Still, this is not enough to match the sharp decline in the labor share. Automation appears to play a significant role, rising from 30 to 43.

This conclusion is further supported by hypotheses (A) and (B1) (as well as ERP_A_K and B2, which are not reported). Both mark-ups and automation appear to increase when considering each of them independently. However, they are not enough to explain the evolution of relevant trends: the resulting KRP estimates are too high, and the system of equations cannot be solved for up to 20% of industries.

Studying the changes in mark-ups and automation at particular industries, we find similar trends. Figure 12 shows the change in estimated mark-ups μ and automation parameter α_K from the first (1990-1999) to the last (2010-2015) period for each industry, under hypothesis ERP_α_K. Durable manufacturing industries are shown in the top chart, and Nondurable manufacturing in the bottom. As shown, both mark-ups and automation increased across the majority of industries. Interestingly, automation increased more than mark-ups in several durable and non-durable industries. Non Durable_Petroleum exhibits a very sharp rise in profits due to Fracking.

Figure 12: ERP estimates



Notes: Figure shows the change in estimated mark-ups μ and automation parameter α_K from the first (1990-1999) to the last (2010-2015) period for each industry, under hypothesis ERP_α_K. Top plot includes durable manufacturing industries while bottom plot includes non-durable manufacturing industries. Results based on Oberfield and Raval [2014]'s industry-level elasticity estimates.

All industries. Considering all industries, we find roughly consistent results as for the NFC sector. Table 11 reports the results under hypothesis ERP_α_K. Mark-ups increase substantially, while automation remains relatively stable across all elasticity parameters α.

Figure 13 shows the implied change in mark-ups, automation and capital-biased technical change by sector (where each bar represents the weighted average change across all industries in a given sector). Results are based on $\sigma = 1.25$ under hypotheses ERP_α_K and ERP_A_K. As shown, a rise in mark-ups appears to be the main driver of results. Automation and/or capital-biased

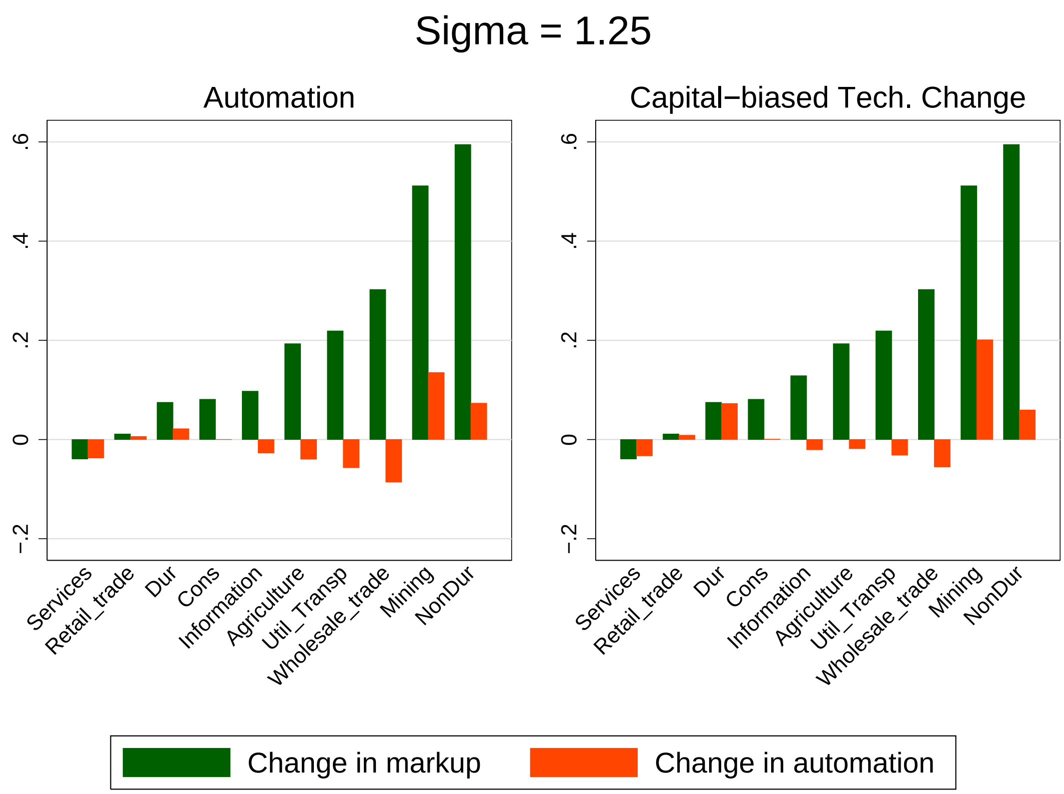
Table 11: All industries - weighted average

			1987-99	**2000-2007**	**2008-2015**
		μ	**116.7**	**124.0**	**128.5**
		KRP	3.0	3.5	4.2
ERP_α_K	$\sigma = 1.25$	α_k	26.8	25.0	25.9
		% Err	0.0	0.0	0.0
	$\sigma = 1$	α_k	29.8	28.5	30.4
		% Err	0.0	0.0	0.0
	$\sigma = 0.8$	α_k	33.9	31.5	33.3
		% Err	4.5	6.8	6.8

Notes: Table reports the weighted average (by capital) of industry-level estimates of μ andα_K that satisfy equations 11 and 15 under hypothesis ERP_α_K for the given values of σ. Results reported under alternate solution methods. '% Err' denotes the share of industries for which equations 11 and 15 could not be satisfied.

technical change are relevant only for select industries: Retail Trade, Durable and Non-Durable Manufacturing and Mining. Conclusions are similar under other hypotheses and/or values of σ.

Figure 13: Automation and Technical Change



Notes: Figure shows the change in mark-ups μ, automation α_K and technical change A_K, from the first (1987-1999) to the last (2010-2015) period, by sector, under hypothesis ERP_α_K. Sector estimates based on capital-weighted average of industry-level estimates.

4 Conclusion

I argue that US labor and profit share trends are unlike those of other Advanced Economies. While the US experienced a sharp decline in its labor share and a corresponding increase in its profit share since 2000, other Advanced Economies exhibit stable trends. The differences appear to be explained by rising concentration in the US, compared to stable or declining concentration in Europe. In fact, a detailed analysis of US industry-level trends suggests that rising mark-ups and increasing concentration are critical to jointly explaining declining (gross and net) labor shares and rising profit shares. Absent increases in mark-ups, the equity premia would need to exceed 15% to explain aggregate trends. Increases in automation/capital-biased technical change are relevant for some industries (mainly Manufacturing, Mining and Retail Trade), but cannot independently explain the patterns. Among empirical proxies for relevant theories, only measures of concentration and mark-ups exhibit statistically significant correlations with industry-level labor and profit shares. Proxies for other theories can explain some or none of these patterns in the cross-section.

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A Declining Competition in the US

In the body of the paper, I argue that declining competition and rising market power are the main culprit for falling labor shares and rising profits. This section provides additional background and evidence for the broad decline in US competition. It discusses (i) the long-run evolution of US labor and profit shares; (ii) the large and growing literature on declining competition in the US; and (iii) the evolution of three measures of firm-level mark-ups. Together, items (i) to (iii) provide strong evidence for a rise in market power in the US.

A.1 A longer historical perspective

Due to data availability, the discussion so far has mostly focused on the gross labor share over the post-1980 period. However, as discussed in Rognlie [2015], the net labor share may be a more appropriate measure of the share of 'available' resources allocated to labor. And a longer historical perspective is useful to understand trends. This section provides exactly that. It discusses (gross and net) labor share and profit share trends for the US since 1960. I focus on the NFC Sector given the widespread data availability; ease to compute labor shares; and consistent segment definition. The US NFC sector is also largely unaffected by changes in the return of housing capital.

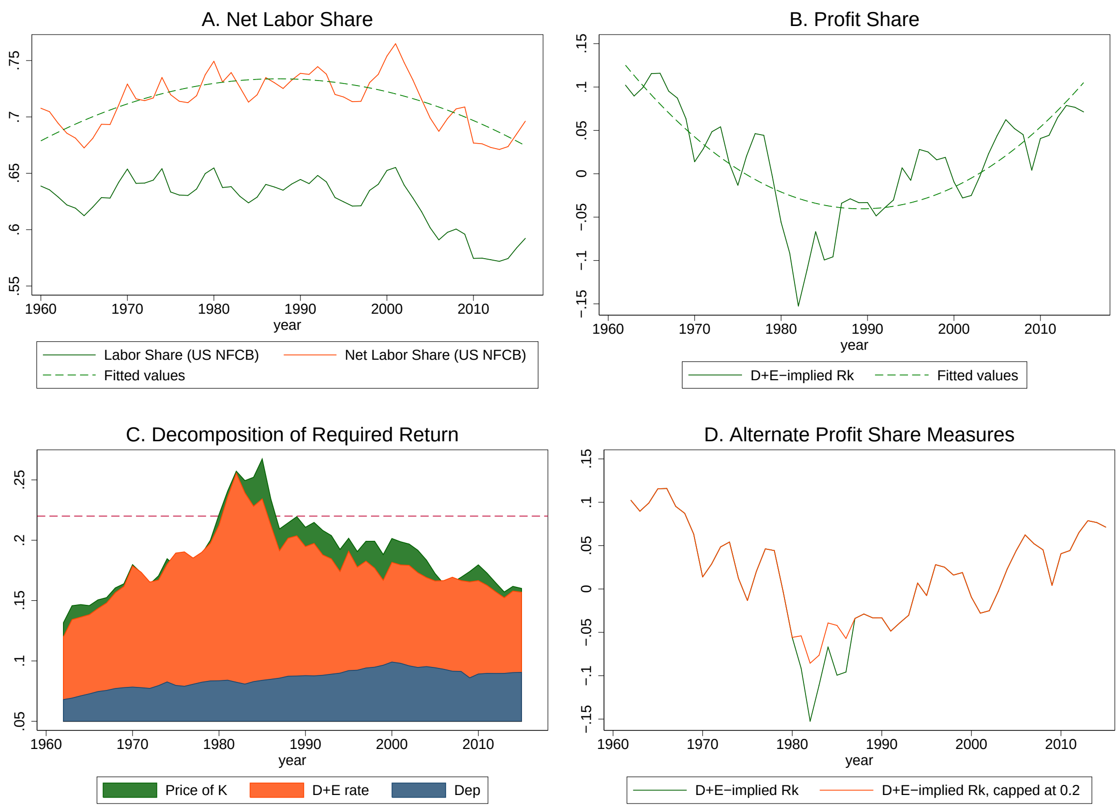
Panel A of Figure 14 starts by plotting the gross and net labor shares since 1960. The gross labor share remained largely stable until its decline in the 2000s. The net labor share increased in the 1960s and 1970s, peaked in the 1980s and started to decrease in the 1990s. The labor share increases in the early 2000s, primarily due to the Dot-Com boom.[42]

Panel B shows the evolution of the profit share, which is close to the reverse.[43] The profit share was highest in the 1960s and reached a trough in the early 1980s. It then started a relentless increase (first discovered by Barkai [2017]). The level of the current profit share was last observed in the late 1960s. The sharp drop in the early 1980s appears to be an outlier – driven by a sharp increase in interest rates and a rapid decline in the relative price of capital (see Panel C). For illustration, Panel D plots the implied profit share after capping the required return at 0.22. The overall trend remains the same, but the sharp drop in the early 1980s disappears. It is worth noting that most of my results are based on the post-1987 period so they are not affected by the sharp drop in the early 1980s.

[42] Elsby et al. [2013] show that the increase is concentrated in IT and Finance.

[43] See Section 3.1 for additional details on the data sources. I mostly follow Barkai [2017], except in two ways: First, I consider changes in relative investment prices, not absolute investment prices when computing required returns. Second, I estimate the required return on capital using the FCF-implied ERP available in Aswath Damodaran's website (see Damodaran [2015] for details). I use Damodaran's estimate instead of AAA bond spreads (used by Barkai) or Claus-Thomas (used above) because it is available through the 1960s and accounts for the equity cost of capital. Claus-Thomas can only be computed after 1985.

Figure 14: Labor and Profit Share: US NFC



Notes: Annual data primarily from FRED. Labor share defined as the ratio of labor compensation to value added. Net labor share excludes depreciation from value added. Profit share defined as the gross operating surplus less total capital payments ($\Pi_t = Y_t - W_t N_t - R_t^{K,req}\zeta_{t-1}K_{t-1}$) over value added Y_t. $R^{K,req}$ measures the required return on nominal capital and is estimated as $R^{K,req} = r_t^f + KRP_t - (1-\delta_t)g_{\zeta,t} + \delta_t$. $KRP_t = \frac{D}{E} BBB\, spread + (1 - \frac{D}{E})ERP_t$, where ERP denotes the FCF ERP estimate available in Aswath Damodaran's website. Capital includes tangible and intangible capital.

A.2 Literature of Declining Competition

Although we must be careful not to draw causal inferences from this analysis, it is worth highlighting that the timing of the profit share evolution closely aligns with declining measures of competition in the US. In fact, a large and growing literature has highlighted a decline in competition starting in the late 1980s/early 1990s.

Davis et al. [2006] was among the first contributions. They highlight a secular decline in job flows beginning in the late-1980s – which was further uncovered using Census data. Haltiwanger et al. [2011] write: "It is, however, noticeable that job creation and destruction both exhibit a downward trend over the past few decades." Decker et al. [2014] provide a fuller picture and conclude that business dynamism (including firm entry and exit) has been declining. Again, the trend started in the late 1980s/early 1990s and has been particularly severe in recent years. In fact, Decker et al. [2015] argue that, whereas in the 1980's and 1990's declining dynamism was observed in selected sectors (notably retail), the decline was observed across all sectors in the 2000's, including the traditionally high-growth information technology sector.

Moving from flows (firm volatility, entry, exit, IPOs, job creation and destruction,..) to stocks (concentration, Herfindahl,..) also happened in stages. The rise in concentration was first noted in studies of specific industries (banking, agriculture, see CEA, 2016 for references). The first broad and systematic study appears to come from the Council of Economic Advisors CEA [2016] who document that the majority of industries have seen increases in the revenue share enjoyed by the 50 largest firms between 1997 and 2012. Similarly, Grullon et al. [2016] study changes in industry concentration. They find that "more than three-fourths of U.S. industries have experienced an increase in concentration levels over the last two decades;" and that firms in industries that have become more concentrated have enjoyed higher profit margins, positive abnormal stock returns, and more profitable M&A deals. Mongey [2016] and Bronnenberg et al. [2012] highlight concentration patterns at the product market level.

More recently, several papers have linked the decline in competition to real outcomes, including rising profits [Barkai, 2017], rising mark-ups [Grullon et al., 2016, De Loecker and Eeckhout, 2017], decreasing investment [Gutiérrez and Philippon, 2017]; and rising prices following mergers [Blonigen and Pierce, 2016]. Of particular relevance to this paper, Dottling et al. [2017] compare concentration, regulation and investment trends between the US and Europe. They find that concentration has increased in the US while it has remained stable (or decreased) in Europe. They compare the evolution of the OECD's Product Market Regulation index for the US and Europe. The US index remained largely stable since 1997; while the index for European economies decreased drastically. All European indices exceeded the US values in 1997, yet all were below the US index by 2014. Dottling et al. [2017] also find that industries that have concentrated in the US decreased investment more than the corresponding industries in Europe.

Several papers link the rise of concentration with an increase in Regulation and a decline in Anti-trust enforcement. During the late 1970s, the US underwent its largest period of de-regulation. But this trend reversed by the 1990s. Gutiérrez and Philippon [2017] show that regulatory restrictions – as measured by the Mercatus Regulation Index of Al-Ubaydli and McLaughlin [2015]– increased sharply starting on the early 1990s; and that increasing regulation predicts increasing concentration across time and industries. CEA [2016] reports rising Occupational Licensing as a concerning regulatory barrier to entry. Woodcock [2017] shows that the aggregate budget of the FTC's Antitrust Enforcement Department and the Department of Justice decreased drastically since the 1980s (after adjusting for inflation, GDP and Federal Government productivity growth). And Grullon et al. [2016] argue that enforcement of antitrust laws declined during the administrations of George W. Bush and Barack Obama. They show that the number of investigations by the Department of Justice filed under Section 2 of the Sherman Act – which allows antitrust agencies to prevent an increase in market power of existing firms – has declined from an average of 12 cases per year during 1980–1999 to fewer than 3 during 2000–2015. Grullon et al. [2016] also show that completion rates for M&A transactions have been increasing over time; and the number of merger enforcement actions filed by the Federal Trade Commission have remained roughly stable since 1996 despite a rise in M&A activity. Combined, these facts support the idea that anti-trust regulators are now less likely to block proposed mergers. Relatedly, Faccio and Zingales [2017] show that competition in the mobile telecommunication industry is heavily influenced by political factors; and that, in recent years, many countries have adopted more competition-friendly policies than the U.S. See also Kwoka [2014] for additional evidence.

A.3 Mark-up estimates

We can further study the competitive trends in the US economy by studying the evolution of firm-level mark-ups. Mark-ups complement concentration measures by providing a direct measure of a firm's ability to extract rents from the market – independent of geographic/product market definitions. Such estimates remain powerful even under complex competitive structures.

I consider three different approaches – from purely empirical measures of profit margins such as the Lerner Index, to more complex estimates such as those of De Loecker and Eeckhout [2017]. Despite relying on fairly different assumptions, all three approaches suggest that mark-ups increased drastically – particularly after 2000. These results provide fairly conclusive evidence that market power (and profits) have increased.[44]

A.3.1 Approaches.

Three different approaches have been used in the recent literature to estimate mark-ups:

1. **Lerner Index** (μ_j^{LI}): A simple, purely empirical measure of mark-ups is the Lerner Index. Grullon et al. [2016] and Gutiérrez and Philippon [2017] both use this measure; Grullon et al. [2016] shows that the Lerner index has increased at industries that have become more concentrated. Gutiérrez and Philippon [2017] shows that the increase has been concentrated

[44] The magnitude and timing of the increases in mark-ups differs substantially across estimates, however. Such differences should be considered when selecting a preferred measure of mark-ups.

at industry leaders, which also exhibit lower investment. The Lerner index is computed in Compustat as the ratio of operating income before depreciation minus depreciation to sales – it essentially measures the profit share.[45] The Lerner index carries several limitations as a measure of market power: see Elzinga and Mills [2011] for a discussion. Most prominently, it does not recognize that some of the deviation between prices and marginal costs may be due to either efficient use of scale or the need to cover fixed costs.[46] It also fails to account for changing cost of capital. Nonetheless, the Lerner index provides a simple, direct empirical measure of average mark-ups.

2. **User Cost-implied mark-ups** (μ_j^{UC})**:** Second – as I do in this paper – mark-ups can be imputed from output and capital series by estimating a user cost of capital from required returns. Barkai [2017] implements a related approach for the U.S. Non Financial Corporate Sector – where the user cost of capital is based on expected returns on bond or equity capital. Caballero et al. [2017b] implement a similar approach but without specifying a cost of capital. The main advantage of this approach is that it estimates profit rates directly – and therefore includes fixed costs. However, it relies heavily on cost-of-capital estimates and potential mismeasurement in capital. I implement this approach by solving equation (11) below at the firm-level, using industry-level estimates of the cost of capital and depreciation.[47] Capital is estimated as PP&E plus intangible capital (PPE + INTAN).

3. **Firm-level estimates from production data** (μ_j^{DLE}): Last, De Loecker and Eeckhout [2017] estimate firm-level mark-ups following the approach of De Loecker and Warzynski [2012], which in turn builds on Hall [1988] and Olley and Pakes [1996] (among others). It relies on cost minimization and there being (at least) one variable input of production free from adjustment cost; for which the wedge between that input's revenue share and its output elasticity is a direct measure of the firm's markup. It assumes that firms optimize against the variable input every period, and therefore requires a sizable expenditure on that item.
   The implementation in De Loecker and Eeckhout [2017] assumes constant coefficients and uses either a Cobb-Douglas or Translog production functions – both of which yield similar conclusions. It treats cost-of-goods sold as the variable input and considers gross PP&E as its measure of capital. Using a Translog production function (partially) controls for technical change that may affect capital and labor shares, but may be unable to capture large shifts with constant coefficients. In principle, the model can be estimated with time-varying coefficients; but this may be computationally challenging. And the implementation may also suffer from measurement error in PP&E (given the rise of intangibles) or cost of goods sold

[45] I convert the Lerrner index to a measure of mark-ups as $\mu^{LI} = \frac{1}{1-LI}$.

[46] Other key issues include the fact that the Lerner index ignores firms' exercise of monopsony power in factor markets and the effect of upstream market imperfections; the departures from cost-minimizing behavior due to, for example, governance problems; the effects of dynamic competition; and the departures from social optimum when a firm uses non-linear pricing tactics (e.g., bundling).

[47] I use the ERP estimates of Damodaran [2015] to obtain a longer time series; but results are similar using Claus and Thomas [2001]. See Section 3.1 for additional details on the data choices.

(as it is increasingly less relevant for high intangible industries such as pharmaceutical and technology). The choice of variable input is particularly critical for the results.[48]

I follow De Loecker and Eeckhout [2017] and implement this approach using an industry-level Cobb-Douglas production function with constant coefficients. I estimate the coefficients separately for each NAICS level 3 industry. Firms with missing NAICS 3 are mapped to the corresponding segments using SIC codes.

A.3.2 Results.

Figure 15 shows the evolution of the weighted average Lerner Index, User-Cost of capital implied mark-ups and DLE mark-ups (by sales). All estimates are based on my Compustat sample (see Section 3.1 for details). Note that I exclude Financials so that my series differs from that reported by De Loecker and Eeckhout [2017]. The top chart shows the full time-series, while the bottom chart normalizes all series to 1 as of 1980 to focus on relative changes. As noted in De Loecker and Eeckhout [2017], the level of the DLE mark-up is not entirely relevant – but the evolution is.

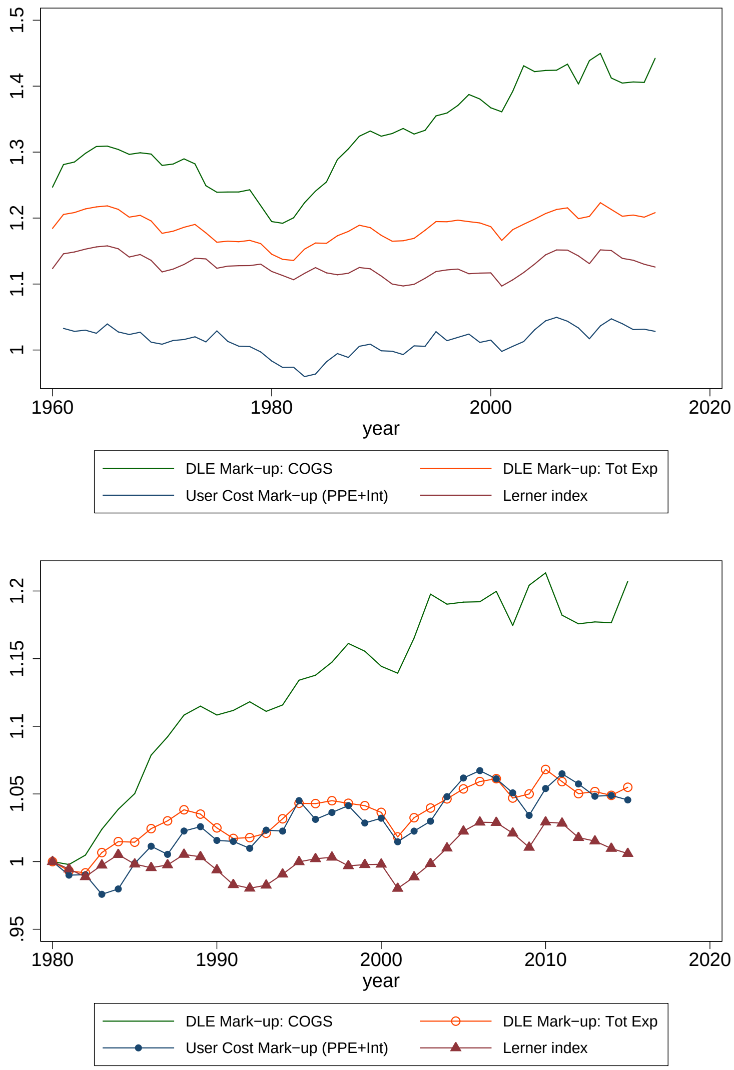
As shown, the DLE mark-up is by far the most volatile. It remains somewhat stable until the 1980s but then increases sharply. The timing of rising DLE mark-ups appears closely related to the rise of intangibles (see Figure 9 above). User cost estimates decrease during the late 1970s and early 1980s given the rise in interest rates. They then increase slowly until 2000 and rapidly thereafter. The Lerner index exhibits a similar trend except for the dip in the late 1970s and 1980s. It drops slightly through 2000 but then increases sharply.

Looking at the long-term evolution, all three mark-up estimates are currently high relative to history. In particular, user cost estimates today exceed any level observed historically; while the Lerner index reached a level last observed in the 1960s. DLE mark-ups are far higher than any level observed previously.

Table 12 shows the pairwise correlation between the three measures of mark-ups, as well as the share of intangible capital (as measured by Peters and Taylor [2016]). Industry-level mark-ups are measured as the sales-weighted average of firm-level mark-ups. As shown, the three measures are highly correlated at the industry-level; but less so at the firm-level. In fact, μ^{DLE} exhibits a negative correlation with both μ^{UC} and μ^{LI}. Note also that μ^{DLE} is strongly correlated with the share of intangibles at the industry and firm -level. . This suggests that μ^{DLE} may be over-stated for high intangible firms.

[48]Note that mark-ups are estimated as in equation (9) of De Loecker and Eeckhout [2017]: $\mu_{it} = \beta_v \frac{Sale_{it}}{COGS_{,it}}$ (with measurement error corrections). Since β_v is constant, the evolution of mark-ups (absent measurement error correction) is essentially the evolution of SALE/COGS. We could alternatively treat total expenses as the variable input, which following Imrohoroglu and Tuzel [2014] can be estimated as sales minus operating income. The result would be a close cousin of the Lerner Index, except that depreciation would be included.

Figure 15: Three measures of mark-ups



Notes: Figure plots the weighted average of three measures of mark-ups. DLE mark-up follows the methodology in De Loecker and Eeckhout [2017].

Table 12: Pair-wise Correlation: Mark-ups

		μ^{DLE}	μ^{UC}	μ^{LI}	IPP share
Industry-level	μ^{DLE}	1			
	μ^{UC}	0.3746*	1		
	μ^{LI}	0.4305*	0.3124*	1	
	IPP share	0.4408*	0.3780*	-0.1723*	1
Firm-level	μ^{DLE}	1			
	μ^{UC}	-0.3692*	1		
	μ^{LI}	-0.2637*	0.8197*	1	
	IPP share	0.1384*	-0.1500*	-0.3444*	1

Notes: Table shows pair-wise correlation matrix of three different measures of mark-ups as well as the share of intangible capital. All series based on Compustat.

B Additional Labor and Profit Share Trends

This Appendix contains additional labor and profit share/profit rate results. Section B defines the Profit Rate and provides details for its empirical estimation. Sections B.2 and B.3 present the following Tables and Figures, respectively:

1. Tables
   (a) Table 13: US Labor Share: Shift-Share Decomposition
   (b) Table 14: US Profit Share: Shift-Share Decomposition
2. Figures
   (a) Figure 16: NFCB Labor Share evolution
   (b) Figure 17: Labor Share by Country: Including and Excluding Real Estate
   (c) Figure18: Labor Share ex RE by Country: KLEMS 2012 vs. KLEMS 2016
   (d) Figure 19: Profit Share and Profit Rate by Country
   (e) Figure 20: Profit rate ex RE: US vs. Advanced Economies
   (f) Figure 21: Mean and Median CompNET CR10 by Country
   (g) Figure 22: Mean and Median CompNET Herfindahl by Country
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B.1 Profit Rate: Definition and Implementation

B.1.1 Definition

The profit rate is computed using the IRR_t reported by KLEMS. In particular, both KLEMS 2012 and KLEMS 2016 follow the standard neo-classical theory of investment introduced by Jorgenson [1963]. Under this theory, investor indifference between buying a unit of capital at relative investment price ζ_{t-1}, collecting a rental fee $R_t^{K,tot}$ and then selling the depreciated asset for $\zeta_t(1-\delta)$ in the next period vs. earning a nominal rate of return i_t on another investment implies:

$$R_t^{K,tot} = \zeta_{t-1}(1+i_t) - \zeta_t(1-\delta_t), \tag{16}$$

$$= \zeta_{t-1}\left(i_t + \delta_t - (1-\delta_t)g_{\zeta,t}\right) \tag{17}$$

where we assume no taxes. $R_t^{K,tot}$ equates the *ex post* return on capital to the capital share of output; and therefore includes profits. Solving for i_t yields the internal rate of return IRR_t (which is reported by KLEMS):[49]

[49] Note that KLEMS considers multiple asset types, which are then aggregated to a total capital input K. For simplicity in the exposition, I assume there is only one type of capital.

$$IRR_t = i_t = \frac{R_t^{K,tot} + (\zeta_t - \zeta_{t-1}) - \zeta_t \delta_t}{\zeta_{t-1}}.$$

Incorporating the profit rate PR_t, we can decompose

$$IRR_t = r_t^f + KRP_t + PR_t$$

where r_t^f and KRP_t denote the risk-free rate and a capital risk premia, respectively. The *realized* profit rate is therefore the excess return over and above the required return on capital:

$$PR_t = IRR_t - \left(r_t^f + KRP_t \right).$$

Note that IRR_t and PR_t are both *ex post* measures – i.e., they account for the realized change in the relative price of investment ζ_t even though this is unknown at the time of investment $t-1$. This is likely to have a limited effect on long-run profit rate trends, however, as agents' likely use prior changes to build expectations.

When using KLEMS 2012, the profit rate is computed as the difference between the KLEMS IRR and the cost of capital; where the cost of capital equals the country-specific 10-year government rate (r^f) plus the US BBB corporate bond spread:

$$PR_t = IRR_t - (r_t^f + BBB\, spread_t)$$

Results are robust to using country-specific ERP estimates based on dividend-price and price-earnings ratios. However, using a common KRP is simpler and conservative as the KRP has likely been higher in Europe than the US since the sovereign crisis.

When using KLEMS 2016 and/or the BEA, the profit rate is then given by

$$PR_t = PS_t \frac{Y_t}{\zeta_{t-1} K_{t-1}}.$$

Table 14: US Profit Share: Shift-Share Decomposition

	V.A. share			Profit rate		Profit share			Profit share total	
Industry	**88**	**15**	**Δ**	**88**	**15**	**88**	**15**	**Δ**	**Shift**	**Share**
Agriculture	1.9	1.2	-0.7	4.6	3.9	14.8	14.1	-0.7	0.0	-0.1
Cons	5.4	5.1	-0.4	69.6	75	22	29	7.6	0.4	-0.1
Dur	13.8	8.2	-5.7	3.3	8.2	1.4	10.6	9.1	1.0	-0.3
Information	5.6	5.8	0.3	4.4	7.6	-2.3	13.2	15.5	0.9	0.0
Mining	1.8	2.3	0.5	-9.0	-4.8	-45	-39	5.1	0.1	-0.2
NonDur	9.1	6.9	-2.2	7.8	20.0	10	33	22.3	1.8	-0.5
RE	14.6	16.4	1.8	0.5	3.4	-42	21	62.8	**9.7**	-0.2
Retail_trade	8.8	7.3	-1.4	6.5	8.8	5.3	10.3	5.0	0.4	-0.1
Services	24.7	33.5	8.8	24.2	17.8	4.7	7.4	2.7	0.8	0.5
Util_Transp	6.9	5.7	-1.1	-5.7	2.1	-33	-7.9	24.8	1.6	0.2
Wholesale T.	7.5	7.6	0.1	11.5	44	6.6	24	17.0	1.3	0.0
Total	**100**	**100**	**0.0**	**12.2**	**16.8**	**-4.6**	**12.6**	**17.9**	**17.9**	**-0.7**

Notes: Table provides a shift-share decomposition of US profit share from 1988 to 2015.

B.2 Tables

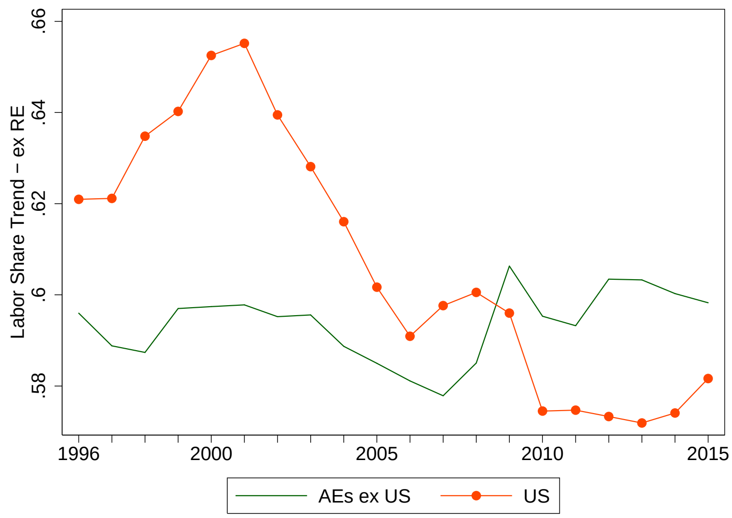
Table 13: US Labor Share: Shift-Share Decomposition

	V.A. share			Labor share			Total	
Industry	**87**	**15**	**Δ**	**87**	**15**	**Δ**	**Shift**	**Share**
Agriculture	1.9	1.2	-0.7	23	30	7.4	0.1	-0.2
Cons	5.4	5.1	-0.4	70	62	-7.7	-0.4	-0.2
Dur	13.8	8.2	-5.7	68	56	-11.6	-1.3	-3.5
Information	5.6	5.8	0.3	40	38	-2.7	-0.2	0.1
Mining	1.8	2.3	0.5	40	28	-12.5	-0.3	0.2
NonDur	9.1	6.9	-2.2	54	34	-19.9	-1.6	-1.0
RE	14.6	16.4	1.8	6.7	5.8	-0.9	-0.1	0.1
Retail_trade	8.8	7.3	-1.4	61	54	-6.3	-0.5	-0.8
Services	24.7	33.5	8.8	70	75	5.0	1.5	6.3
Util_Transp	6.9	5.7	-1.1	49	47	-1.5	-0.1	-0.6
Wholesale T.	7.5	7.6	0.1	54	47	-7.2	-0.5	0.0
Total	**100.0**	**100.0**	**0.0**	**52**	**50**	**-3.4**	**-3.4**	**0.5**

Notes: Table provides a shift-share decomposition of US labor share from 1987 to 2015.

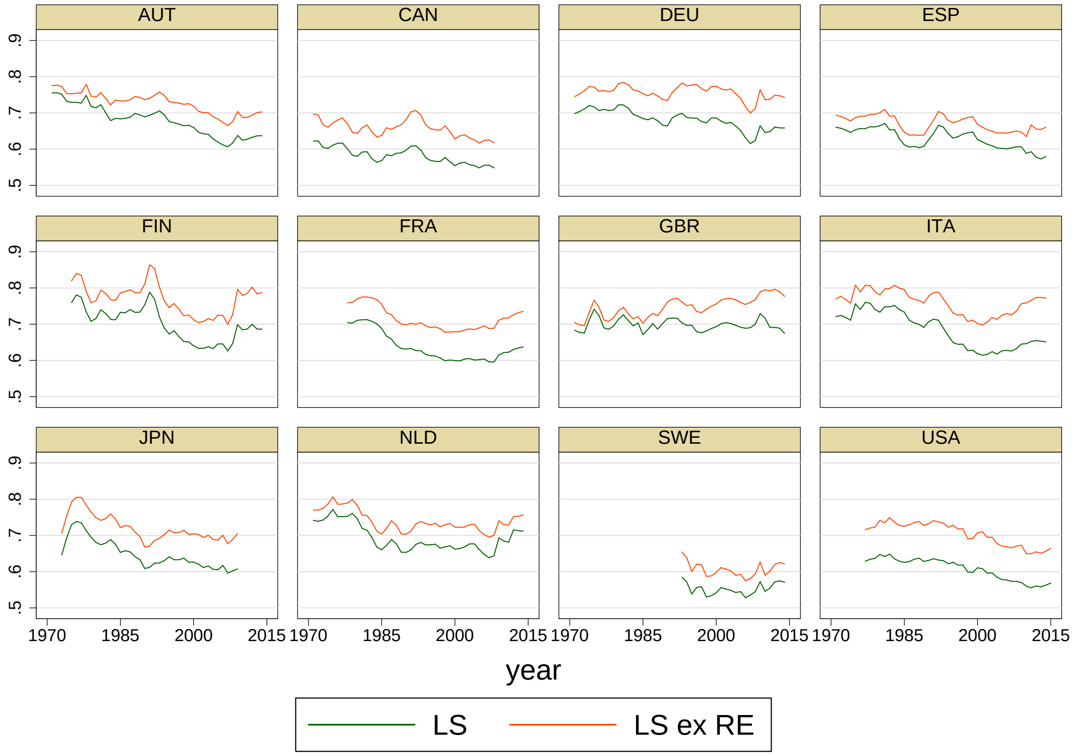
B.3 Figures

Figure 16: NFCB Labor Share evolution



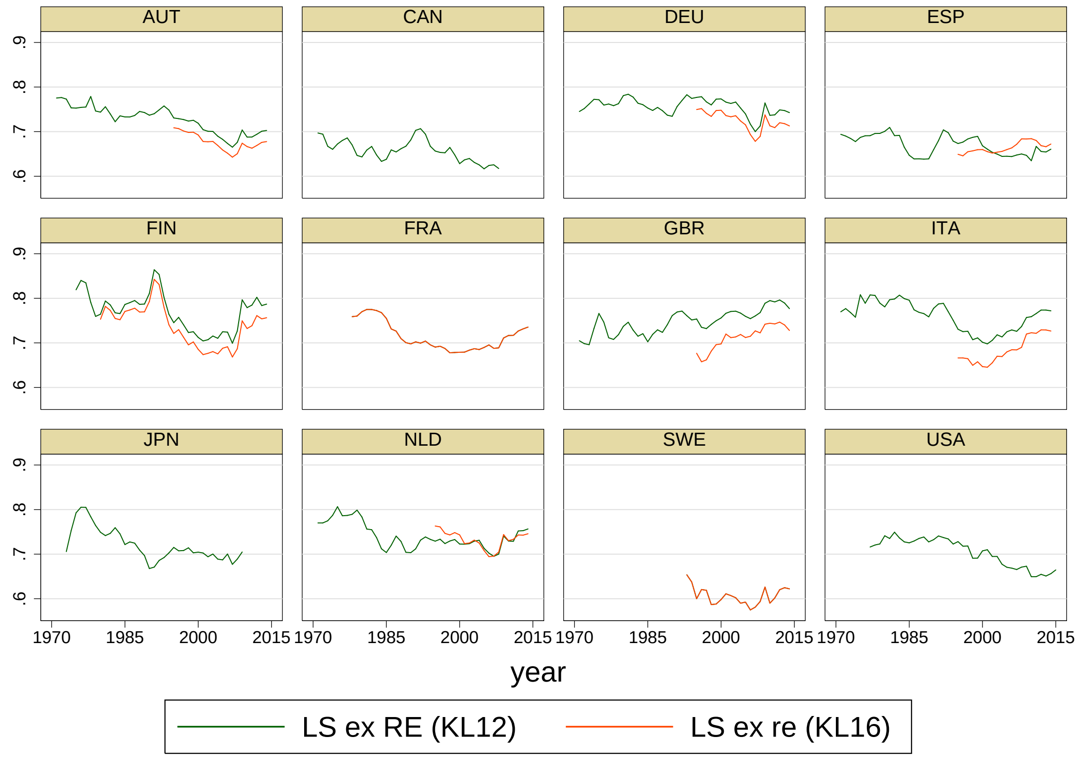
Notes: The figure shows the evolution of the NFCB sector labor share for the US and other advanced economies. The dotted line plots the US labor share directly. The solid line shows the evolution of the NFCB labor share for other Advanced Economies by plotting the year fixed effects from a regression of country-level NFCB labor shares on year and country fixed effects (after adding the constant). Country fixed effects account for entry and exit during the sample. Observations are weighted by gross value added measured in US dollars at market exchange rates. Annual data sourced from the OECD.

Figure 17: Labor Share by Country: Including and Excluding Real Estate



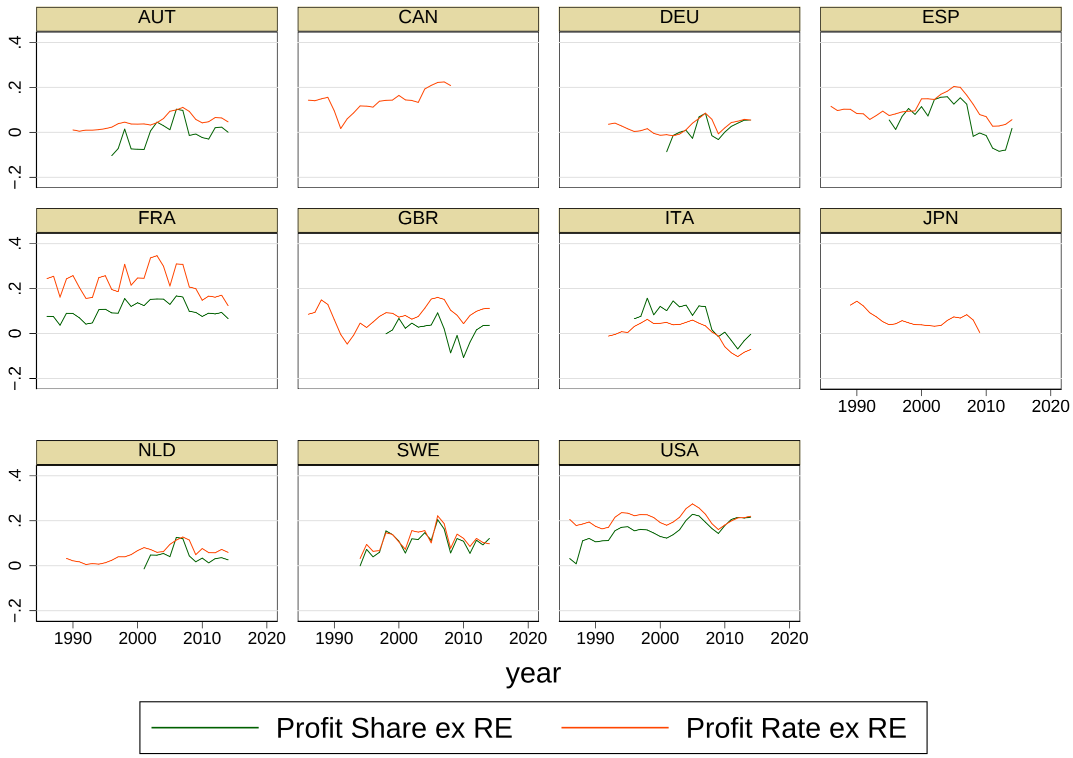
Notes: Figure plots country-level labor shares including and excluding Real Estate. All figures exclude Financial Services and non-business sectors.

Figure 18: Labor Share ex RE by Country: KLEMS 2012 vs. KLEMS 2016



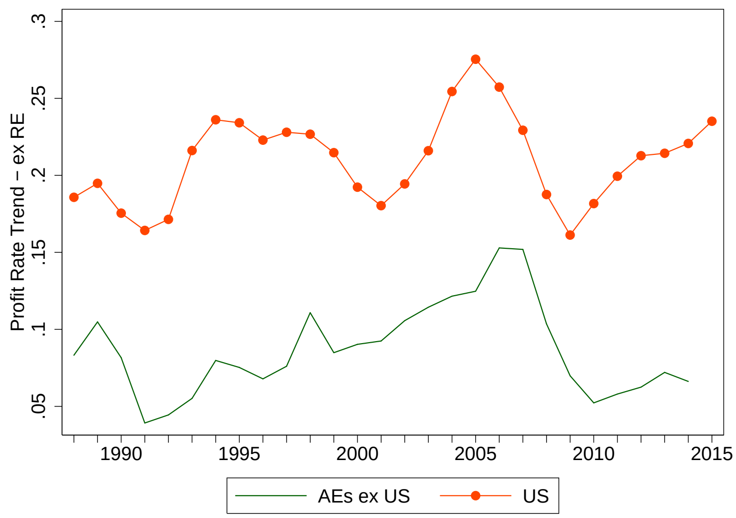
Notes: Figure plots country-level labor shares based on KLEMS 2012 and KLEMS 2016 (when available). KLEMS 2012 series filled in from 2009-2014 based on KLEMS 2016 series. All series exclude Real Estate, Financial Services and non-business sectors.

Figure 19: Profit Share and Profit Rate by Country



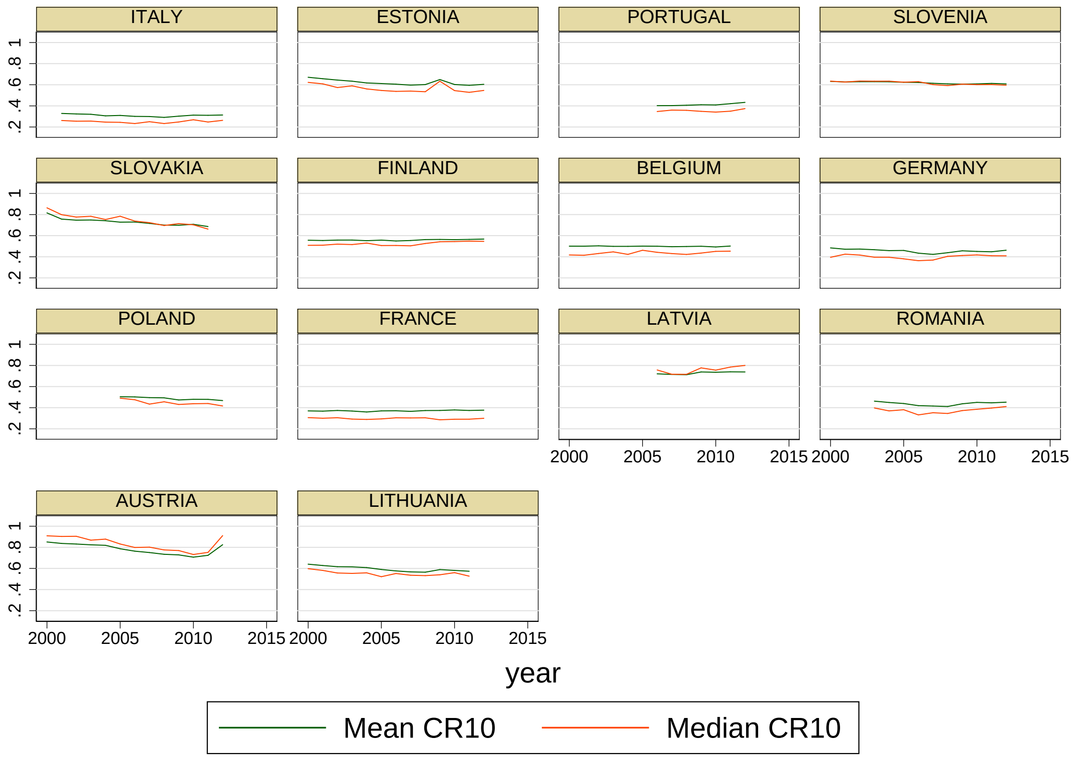
Notes: Figure plots country-level profit shares and rates. Annual data based on KLEMS 2012 and KLEMS 2016. All series exclude Real Estate, Financial Services and non-business sectors. Only Austria and Canada exhibit a persistent increase in profits, in addition to the US. The increase in Canada, however, is primarily because the series ends in 2008 – at the peak of the bubble. As discussed in the text, Canada's economy-wide GOS/K ratio dropped drastically since the Great Recession – though the NFC sector remained somewhat profitable. It is unclear what it's evolution excluding Finance and Real Estate looks like since the Great Recession.

Figure 20: Profit rate ex RE: US vs. Advanced Economies



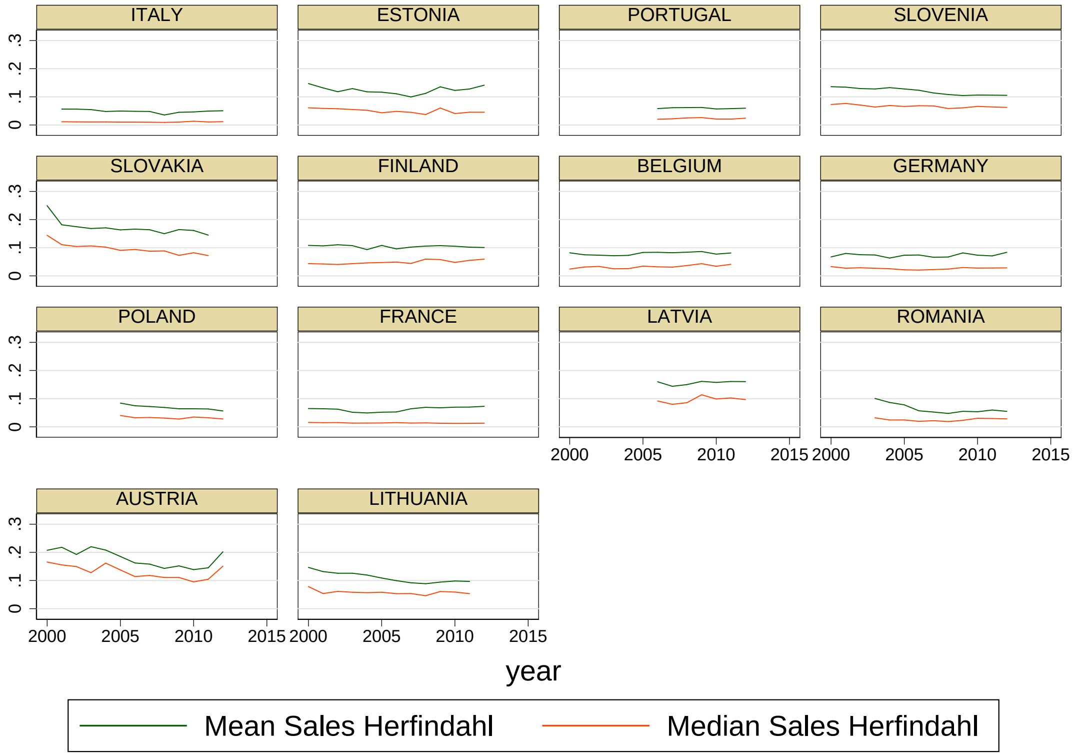
Notes: The figure shows the evolution of the profit rate for the US and other advanced economies, excluding Real Estate as well as the sectors listed in Figure 1. Country profit rates are defined as the value-added weighted average profit rate across all industries in a given country. Country-industry profit rates are estimated as the KLEMS-provided IRR minus the sum of each country's 10-year government bond rate and the BBB bond spread in the US. See Section 1.1 for additional details on the implementation. The dotted line plots the US profit rate directly. The solid line shows the evolution of the profit rate for other Advanced Economies by plotting the year fixed effects from a regression of country-level profit rates on year and country fixed effects (normalized to match the average profit rate). Country fixed effects account for entry and exit during the sample. Observations are weighted by gross value added measured in US dollars at market exchange rates. Annual data primarily based on KLEMS 2012.

Figure 21: Mean and Median CompNET CR10 by Country



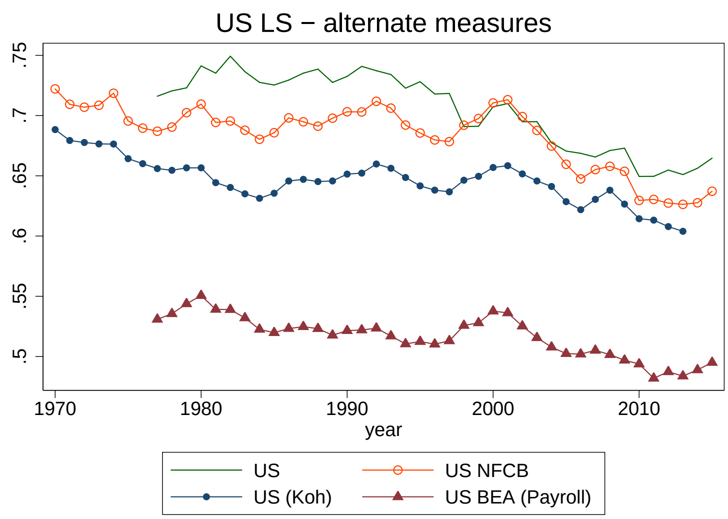
Notes: Figure shows the mean and median 10-firm concentration ratio across industries, as measured in the ECB's CompNET. Includes all countries for which data is available in CompNET. Some of these countries are not in my sample.

Figure 22: Mean and Median CompNET Herfindahl by Country



Notes: Figure shows the mean and median sales Herfindahl across industries, as measured in the ECB's CompNET. Includes all countries for which data is available in CompNET. Some of these countries are not in my sample.

Figure 23: Alternate measures of US labor share



Notes: Figure plots four alternate measures of the US labor share, as noted. All measures exhibit a sharp decline following 2000.

C Estimating the Equity Risk Premia

This Appendix discusses alternate methods to estimate the Equity Risk Premia (ERP). The results are presented and discussed in Figure 11 above.

C.1 Overview of ERP estimation methods

The k-period expected risk premium is defined as

$$ERP_t(k) = E_t[R_{t+k}] - R^f_{t+k}$$

where $E_t[R_{t+k}]$ is the expected k-period return and R^f_{t+k} is the return on a k-period risk-free bond. A variety of ERP estimating approaches are available in the literature – ranging from historical averages to cross-sectional regressions. I consider estimates from the following classes of methods:

- **Historical Models** estimate the ERP based on a (potentially weighted/truncated) average of realized market returns in excess of the contemporaneous risk-free rate.This is the simplest approach to estimating the ERP.

- **Discount Models** solve for the implied discount rate that equates stock prices and projected dividends/earnings. See Easton [2007], Damodaran [2015] for a literature review on the topic; and the next section for a brief overview.

- **Cross-sectional models** rely on the cross-section of stock returns. To generate estimates, we first fit an excess return regression on a variety of predictor variables (economic indicators, measures of risk, etc.)
$$R^i_{t+k} - R^f_{t+k} = \boldsymbol{\beta X_t} + \boldsymbol{\varepsilon}$$
where the excess return on the stock market must be included as a predictor variable X. This regression gives an estimate of the 'quantity' of risk β linked to each predictor X on a given asset i.
The ERP can then be estimated at each point in time, as the value of $\lambda(t)$ that is multiplied by the market coefficient in a regression of
$$R^i_{t+k} - R^f_{t+k} = \boldsymbol{\lambda(t)\hat{\beta}}$$
This second regression finds the value of $\lambda(t)$ that makes exposures $\hat{\beta}$ as consistent as possible with the realized, cross-sectional excess returns $R^i_{t+k} - R^f_{t+k}$. ERP is therefore the 'price' of risk. Resulting estimates closely follow the realized market returns.

- **Time series models** forecast excess returns based on the historical time-series of returns. Namely, we regress the average excess stock return $R_{t+k} - R^f_{t+k}$ on fundamentals X_t, and use the prediction as the ERP

$$R_{t+k} - R^f_{t+k} = \boldsymbol{\beta X_t} + \boldsymbol{\varepsilon}$$

$$ERP_t(k) = \boldsymbol{\beta X_t}$$

- **Surveys,** under which relevant practitioners/academics are surveyed on their expectations of the ERP over a certain horizon.

Table 15 summarizes the 16 methods considered. Most of these approaches are included in Duarte and Rosa [2015] (although the data sources may differ in some cases). I refer the reader to that paper for additional details. Only the methods following Claus and Thomas [2001] and Easton [2004] are new. The next section provides a brief overview of both approaches.

C.2 Drill-Down: DDM methods

All approaches rely on the dividend discount model of Williams (1938)

$$p_0 = \frac{dps_1}{(1+r)} + \frac{dps_2}{(1+r)^2} + \dots$$

Gordon Growth formula. Assuming dividend growth is constant and equal to g, we obtain the Gordon (1962) growth model:

$$p_0 = \frac{dps_1}{r-g}$$

The difficulty in all DDM methods lies in estimating g. Some authors assume g equals the risk free rate, in which case the dividend-price ratio becomes a measure of the ERP. Others forecast dividend growth based on analyst forecasts. I report results under both methods in the top-left chart of Figure 10. For the latter method, dividend growth is set equal to the median long-run EPS growth from analyst forecasts. The long-run growth forecast generally consider a five-year horizon; hence this assumption likely yields too high estimates.

Claus-Thomas, Damodaran and Easton are essentially approaches to refine dividend growth estimates.

Damodaran (2004). Damodaran estimates dividend growth from analyst's earnings forecasts for the first five years, and sets growth equal to the ten-year nominal Treasury yield from then on.

Table 15: List of ERP estimates

Family	Model	Description
Historical returns	Long-run mean	Long-term average of realized S&P 500 return minus risk-free rate
	5Y MA	5Y moving average of realized S&P 500 returns minus risk-free rate
DDM (D/P models)	Gordon (1962) assuming dividend growth = risk free rate	Shiller D/P ratio
	Gordon (1962) with growth forecasts	D/P ratio with growth estimated based on median long-run EPS growth from analyst forecasts
DDM (E/P models)	Gordon (1962) with earnings forecasts (nominal)	Expected next-year E/P ratio (from IBES) minus ten-year nominal Treasury yield
	Gordon (1962) with earnings forecasts (real)	Expected next-year E/P ratio (from IBES) minus ten-year nominal Treasury yield
	Shiller (2005)	Shiller Cyclically adjusted earnings-price ratio minus 10Y nominal Treasury yield
DDM (Fore-casts)	Damodaran (2012)	A six-stage DDM. Dividend growth estimated from analyst's earnings forecasts for the first five years, and set equal to the ten-year nominal Treasury yield thereon
	Damodaran (2012) FCF	Same as Damodaran (2012), but includes buybacks
	Claus-Thomas (2001)	DDM based on analyst-projected abnormal earnings (see section C.2)
	Easton (2007)	Cross-sectional regression of analyst-forecasted earnings (see section C.2)
Cross-sectional	5Y MA Fama and French (1992)	Cross-sectional regression. Use Market HML, SMB as risk factors. For portfolios, use the 25 portfolios sorted on size and book to market and 10 portfolios sorted on momentum
	5Y MA Carhart (1997)	Same Fama and French (1992) but including Carhart's momentum factor
Time-series	Fama and French (1988)	Time-series regression on dividend-price ratio of the S&P 500
	Baker and Wurgler (2007)	Time series regression on Baker and Wurgler's (2007) sentiment measure
Survey	Graham and Harvey (2012)	Mean response from CFOs survey of expected one year-ahead ERP

Easton (2004). Easton relies on estimates of the abnormal growth in earnings. His approach can be derived using the following two equations

$$p_0 = \sum_{t=1}^{\infty} \left(\frac{dps_t}{(1+r_e)^t} \right),$$

$$0 = \frac{eps_1}{r_e} + \frac{\frac{eps_2}{r_e} - (1+r_e)\frac{eps_1}{r_e}}{1+r_e} + \ldots$$

Adding the two equations we obtain

$$p_0 = \frac{eps_1}{r_e} + \sum_{t=1}^{\infty} \left(\frac{\frac{eps_1}{r_e} + dps_t - (1+r_e)\frac{eps_1}{r_e}}{(1+r_e)^t} \right)$$

Re-arranging, we obtain

$$\begin{aligned} p_0 &= \frac{eps_1}{r_e} + \sum_{t=2}^{\infty} \left(\frac{eps_t + r_e dps_{t-1} - (1+r_e)eps_{t-1}}{r_e(1+r_e)^{t-1}} \right), \\ &= \frac{eps_1}{r_e} + \sum_{t=2}^{\infty} \left(\frac{agr_t}{r_e(1+r_e)^{t-1}} \right) \end{aligned}$$

where agr_t denotes the abnormal growth in earnings for year t (i.e., the excess earnings above the required return on equity).

Assuming a constant growth rate of abnormal earnings g_{agr}, the above can be simplified to

$$p_0 = \frac{eps_1}{r_e} + \frac{agr_2}{(r_e - g_{agr})r_e} \tag{18}$$

and further assuming that $agr_2 = 0$, we obtain the standard earnings-yield valuation:

$$p_o = \frac{eps_1}{r_e}.$$

Easton advocates simultaneously estimating the rate of increase in abnormal growth in earnings and the expected rate of return that are implied by market prices and forecasts of earnings. This method relies on equation 1 above. Rearranging, we obtain

$$\frac{ceps_2}{p_0} = \gamma_0 + \gamma_1 \frac{eps_1}{p_0}$$

where $\gamma_0 = r_e(r_e - g_{agr})$ and $\gamma_1 = 1 + g_{agr}$; and $ceps_2$ is a forecast of two-period ahead cum-dividend earnings, $ceps_2 = eps_2 + r_e(dps_1)$. The above equation applies for all firms, so we estimate γ_0 and γ_1 through regression:

$$\frac{ceps_{j2}}{p_{j0}} = \gamma_0 + \gamma_1 \frac{eps_{j1}}{p_{j0}} + \varepsilon_j$$

Note that $ceps_2$ depends on r, which in turn depends on the regression coefficients. The author implements a recursive algorithm until convergence. I implement a simplified approach, first computing r from the earnings-yield approach, using that to compute $ceps_2$ and then performing the regression. This has a limited effect on results.

Claus and Thomas (2001). CT is essentially an implementation of the dividend discount model of Williams (1938). That said, in contrast to traditional DDM implementations such as the Gordon growth formula, CT it relies on expected abnormal earnings rather than dividends. These accounting flows are isomorphic to projected dividends but use more of the available information – which narrows the range of reasonable growth rates and ERP estimates. Still, like virtually all ERP estimates, this method is not without criticism: see Easton [2004] for a survey of methods to estimate ERP from accounting data.

The traditional DDM model of Williams (1938) can be written as follows, assuming dividend growth is constant

$$p_0 = \frac{d_1}{(1+r)} + \frac{d_2}{(1+r)^2} + \dots \tag{19}$$

where d_t denotes the dividend paid at time t and r the required rate of return.

CT let

$$\begin{aligned} d_t &= e_t - (bv_t - bv_{t-1}) \\ ae_t &= e_t - r(bv_{t-1}) \end{aligned}$$

where bv denotes the book value of the firm, e_t denotes that analyst-projected earnings and ae_t denotes the abnormal earnings; adjusted for the cost of capital. Given this, we can re-write the DDM model in 19 as

$$p_0 = bv_0 + \frac{ae_1}{(1+r)} + \frac{ae_2}{(1+r)^2} + \dots$$

Note that this re-interpretation requires a forecast of the book value of a given firm. CT estimate future book values from current book values, assuming 50% of earnings are retained. I maintain this assumption for aggregate estimates (after confirmation that it remains roughly valid), but deviate from it in industry-level calculations. For the latter, I use the average payout ratio observed from 1985- 2015 at the industry level.

I then rely on forecasted earnings for periods 1 through 5 (when available), as well as long term earnings growth forecasts g_5 typically assumed to cover a five-year period.[50] After year five, abnormal earnings are assumed to grow at a rate equal to the real 10-year treasury minus 3%,

[50]Like CT, I require forecasts be available for year 1 and 2 and long-term growth. When forecasts are missing for years 3-5, I project them using g_5

denoted as g_{ae}. Thus, we solve

$$p_0 = bv_0 = \frac{ae_1}{(1+r)} + \frac{ae_2}{(1+r)^2} + \frac{ae_3}{(1+r)^3} + \frac{ae_4}{(1+r)^4} + \frac{ae_5}{(1+r)^5} + \frac{ae_5(1+g_{ae})}{(k-g_{ae})(1+r)^5}. \tag{20}$$

I use Matlab function FMINCON to solve equation (20).

A few additional details on the implementation are worth highlight:

- As developed, CT relies on aggregated earnings and book value projections to derive a market-wide ERP. I implement the method at the aggregate as well as industry-level. Thus, mark-up estimates are based on aggregate/industry level ERP estimates – not firm-level. The latter are not used due to the computational complexity of solving equation (20) for each firm-year observation.

- I require analyst forecasts to be available for at least 3 firms in a given industry-year for the value to be estimated.

- I use shares outstanding and prices from I/B/E/S instead of Compustat for consistency across all measures

- I exclude Financials which yields different results than reported by CT. I confirmed my results are nearly equivalent when mirroring their sample.

- I/B/E/S provides the consensus of all available individual forecasts as of the middle (the Thursday following the second Friday) of each month. Consistent with Claus-Thomas (2001), I collect forecasts as of April of each year for each firm. This is because forecasts and prices should be gathered soon after the prior year-end, as soon as equity book values are available. Alternatively, we could collect forecasts at different points in the year, depending on the fiscal year-end of each firm. However, doing so would imply that equity risk premia are not consistent across firms for a given year. To avoid this inconsistency, I collect data as of the same month each year for all firms. April is chosen because most firms have December year-ends.

- Firm-level forecasts in I\B\E\S are mapped to Compustat GVKEYs using a two-step approach. First, the header map between GVKEY and IBES Ticker provided in Compustat Security table (IBTIC variable) is used. Then, for those GVKEYs that have missing IBTIC in Compustat and a valid PERMNO, the existing link is supplemented with additional historical GVKEY-IBES ticker links. The additional links are obtained by, first, merging the rest of GVKEYS with PERMNOs on a historical basis using CRSP-Compustat Merged Database and, second, bringing in additional IBES Tickers from the IBES-PERMNO link (I use the WRDS ICLINK and CIBESLINK applications).