The Mightier, the Stingier: Firms' Market Power, Capital Intensity, and the Labor Share of Income

Pawel Adrjan*

Abstract

What determines the proportion of a firm's income that workers receive as compensation? This paper uses longitudinal firm data from a period of substantial labor share variation to understand the firm-level determinants of the labor share of income—a question that has typically been addressed with country- and sector-level data. Firms with greater market power and a higher ratio of capital to labor allocate a smaller proportion of their value added to workers. These results suggest that firm-level drivers play a key role in the evolution of the aggregate labor share, which has declined significantly since the 1970s.

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* *Indeed.com and Regent's Park College, University of Oxford, padrjan@indeed.com*

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1. Introduction

The classic economic question of how rents are distributed among the factors of production has recently returned to the fore, motivated by a substantial decline in labor's share of national income in many of the world's economies since the 1970s (Rodríguez and Jayadev, 2010; Elsby, Hobijn, and Şahin, 2013; Karabarbounis and Neiman, 2014; IMF, 2017). Figure 1 illustrates this decline for the G7 countries. From a starting point of approximately 70% in 1970, the aggregate labor share of income in this group of advanced economies has declined by an average 2 percentage points per decade. This persistent downward trend contrasts with the historical stylized fact of long-run stability of the labor share, which was prominently noted by Keynes (1939) and Kaldor (1957) and has since become a standard assumption in many micro- and macroeconomic models.

Several potential causes of the decline in the global labor share have been proposed. One leading account is that technological change or declines in the price of capital relative to labor have led firms to substitute capital for labor, thus decreasing the overall share of income that accrues to the latter factor of production (Acemoglu, 2003; Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2014). Another is that deregulation or other drivers has increased the market power of firms, raising the profit share of income at the expense of the labor share (Blanchard and Giavazzi, 2003; Azmat, Manning, and Van Reenen, 2012; Barkai, 2016; Autor, Dorn, Katz, Patterson, and Van Reenen, 2017; De Loecker and Eeckhout, 2017). To date, however, both explanations have only been tested at the country and sector level, even though the aggregate labor share is a result of the production decisions and wage-setting processes occurring at individual, heterogeneous firms. In this paper, I propose a methodology for calculating the labor share of value added at the firm level and use UK data to show that the labor share varies significantly across firms, even within narrowly-defined sectors, as well as within firms over time. I then investigate what determines the labor share at individual firms. I find that firms with greater market power and a higher ratio of capital to labor allocate a smaller proportion of their value added to workers. These results contribute to a better understanding of the drivers of changes in aggregate factor income shares.

To motivate why the labor share might vary across and within firms, I describe a simple model of a firm that employs capital and labor to produce a final good in an imperfectly competitive product market. When the optimal combination of inputs is chosen to maximize profits, the labor share is determined by the firm's market power and the capital intensity of production. Market power matters for the labor share because if a firm can set the price of its product at a higher mark-up over cost, then a greater share of value added will go to profits, at the expense of labor. Capital intensity matters too, because if a production process is highly automated and requires little labor input, then under certain conditions, a higher proportion of the firm's value added will be allocated towards compensating the suppliers of capital. In the model, the exact nature of the relationship between capital intensity and the labor share depends on the elasticity of substitution between labor and capital and the nature of technical progress. Whether the labor share is higher or lower at firms that employ more capital relative to labor is therefore an empirical question.

To test whether a firm's market power and capital intensity impacts the labor share, I use a large longitudinal dataset of firms in the United Kingdom covering the period from 2005 to 2012, during which the aggregate labor share experienced substantial fluctuations. Thanks to mandatory filing requirements that affect nearly all incorporated businesses in the UK, it is possible to calculate the labor share of value added for a wide universe of firms, including small and medium enterprises, operating across a variety of sectors. Using the model to motivate some potential drivers of this heterogeneity, I find an inverse relationship between a firm's labor share and its market power (measured by the market share), and between the labor share and the capital intensity of production (measured by the capital-labor ratio). To account for potential endogeneity that may result, for instance, from a joint response of variables to unobserved shocks, I estimate dynamic specifications of the model using the Generalized Method of Moments (GMM). The finding that the labor share is inversely related to the firm's market power and capital intensity is robust to alternative econometric methods, definitions of key variables, sample selection decisions, and empirical specifications.

The results of this paper have several policy implications. As technological developments and capital accumulation drive many economies to become more capital intensive, my estimates suggest that labor's share of aggregate income may continue to decline. Similarly, the labor share might remain under pressure if economic activity becomes increasingly concentrated in a smaller number of firms that wield greater market power at the expense of the consumer, as some authors have suggested is the case (Barkai, 2016; Autor et al., 2017; De Loecker and Eeckhout, 2017). Moreover, a declining labor share implies a rising disconnect between average productivity and pay within the economy. This is because the labor share of value added can be expressed as the ratio of average compensation to the average product of labor. The link between productivity and pay matters greatly to households, because wages and salaries represent by far the largest source of household income in most developed countries. Understanding the determinants of firm-level labor shares is therefore important for assessing the potential impact of future productivity gains or losses on the earnings of the average household.

Does the finding that higher capital intensity of production lowers the labor share of income mean that in the aggregate, capital and labor are substitutes? This result is consistent with some strands of the factor share literature. For instance, Karabarbounis and Neiman (2014) estimate an elasticity of substitution between capital and labor greater than 1 in their cross-country analysis. In addition, Bentolila and Saint-Paul (2003) find a negative relationship between the labor share and the capital-to-output ratio in sector-level data from selected OECD countries. Piketty's (2014) explanation of the global evolution of aggregate income shares of capital and labor also relies on the high substitutability of these two factors of production. On the other hand, an inverse relationship between capital intensity and the labor share appears to be at odds with a large part of the literature that focuses specifically on estimating the elasticity of substitution between capital and labor. The value of this elasticity continues to be a matter of debate. While available estimates vary widely depending on the methodology and context, often exceeding 1, many authors find lower values that imply a far lesser degree of substitutability (see Chirinko, 2008, for a survey, and Knoblach, Rößler, and Zwerschke, 2016, for a meta-analysis of US studies).

One possible reason for the divergent estimates of the aggregate elasticity of substitution is that different classes of capital and labor are substitutable with one another to a different extent. To understand whether this might drive my overall results, I carry out two tests. First, I divide the sample into high-wage and low-wage firms, based on average compensation per employee. I find that the negative effect of capital intensity on the labor share is driven mainly by low-wage firms. Under the assumption that the average wage level at a firm is a proxy for the average skill level of the workforce, these results imply that it is mainly low-skilled labor that is substitutable for capital, rather than high-skilled labor. Second, I consider the effects of tangible and intangible capital separately, based on the book value of long-term tangible and intangible assets reported in firms' financial statements. Tangible assets are physical, fixed items such as machinery, buildings, and land, while intangible assets represent nonphysical concepts such as patents, trademarks, and goodwill. While it is often difficult to value intangible assets for accounting purposes (particularly those that are internally-generated), I find evidence that an increase in intangible assets per employee has a positive effect on the labor share of high-wage firms, suggesting low substitutability between intangible capital and high-skilled labor. The outcomes of both tests are consistent with intuition provided by the hypothesis of capital-skill complementarity (Griliches, 1969). The paper thus contributes to bridging the gap between the two opposing views on the potential impact of increases in capital intensity on the labor share.

My results complement the macroeconomic literature on factor shares by focusing on the determinants of the labor share at individual firms. Existing theoretical models of aggregate labor share determination ascribe a leading role to factors that, in practice, vary across narrowly-defined sectors and individual firms, such as the characteristics of production technologies, relative quantities of capital and labor inputs, and the extent of monopoly power in the product market (Bentolila and Saint-Paul, 2003; Azmat et al., 2012; Barkai, 2016; Autor et al., 2017; De Loecker and Eeckhout, 2017). The paper's contributions to this literature are to: a) construct firm-level measures of these variables using panel microdata, b) show that the labor share varies substantially across firms, as well as within firms over time, and c) exploit this variation to test hypotheses previously proposed in the context of a representative firm and measured only using aggregate data. A firm-level focus is motivated by the fact that in developed economies, most economic activity outside the public sector is formally organized in firms. In the UK, for instance, the corporate sector represents approximately 65% of aggregate gross value added, while private-sector employees account for 75% of total employment (ONS, 2016). The sharing of income between labor and other factors of production thus occurs primarily at this level. Understanding how the labor share at individual firms is determined is therefore helpful for understanding the distribution of aggregate national income.

This paper also extends a small body of recent research that has begun to use firm-level data to analyze aggregate labor share trends. Growiec (2012) uses data on Polish firms to study the impact of entry/exit behavior, ownership, and market conditions on labor share fluctuations. Böckerman and Maliranta (2012) use plant-level data from Finland to decompose changes in the aggregate labor share into within-plant changes on one hand, and changes in the industry structure due to entry, exit, and reallocation of activity across firms on the other hand. The focus of these two papers is on aggregate labor share dynamics, whereas I assess the role of firm and market characteristics in determining the level of the labor share at individual firms. Siegenthaler and Stucki (2015) exploit a survey of 4,000 Swiss manufacturing, construction and business service firms to estimate correlations between the labor share and a firm's use of computers, number of competitors, modern organizational arrangements, participation in export markets, bargaining coverage, and the share of female employees. In contrast to that paper, I use a large panel of firms operating in all sectors of the business economy to test two leading hypothesized drivers of labor share determination, capital intensity and market power. Moreover, I use methods designed to address the potential endogeneity or simultaneity biases that may arise in estimating the magnitude and direction of these relationships. Finally, two recent papers have focused on the potential relationship between market power and the labor share. De Loecker and Eeckhout (2017) document a rise in average markups of US firms and provide suggestive graphical evidence of a correlation of this trend with the decline in the aggregate US labor share. Autor et al. (2017) use firm data from several countries to construct measures of industry concentration and relate them to sector-level labor share trends. The authors build a model, in which highly productive "superstar" firms capture an increasing market share, leading to a fall in the aggregate labor share through a reallocation of activity to such firms. Imposing a Cobb-Douglas production function, which precludes any role for capital intensity, they document an empirical association between rising industry concentration and declining labor shares within sectors. My paper complements the analysis of these two papers in two main ways. First, it assesses the relative effect of various determinants of the labor share at the level of individual firms, rather than examining sectoral trends. Second, it allows both capital intensity and market power to affect a firm's labor share, allowing the magnitude of these two effects to be compared. The role of capital intensity is particularly relevant, given the threat of labor-to-capital substitution in many industrialized markets and its potential to put further downward pressure on the aggregate labor share in the future. Overall, my results suggest that to understand the underlying causes of the trends in the aggregate labor share, we should look closely to firms, and the environment that they operate in, for answers.

The remainder of the paper is structured as follows. Section 2 discusses how to measure the labor share of income at the firm level and documents the dispersion of labor shares across firms and within firms over time. A simple model of the determinants of the firm-level labor share is discussed in Section 3. Section 4 describes the data, and Section 5 outlines the empirical strategy. Section 6 presents the results and tests their robustness, while Section 7 discusses the role of human capital and the firm's labor market power in determining the labor share. Section 8 concludes.

2. Measuring the labor share of income at the firm level

In this section, I discuss two types of contextual information relevant for the analysis of the determinants of the labor share. First, I discuss how to measure the labor share of income using data from firms' financial reports in a way that mirrors the underlying economic concept. Then, I show that firm-level labor shares are highly dispersed, even within narrowly-defined sectors, which is inconsistent with the predictions of a fully competitive model. This observation motivates the remainder of the paper, which explores the role of market power and capital intensity in labor share setting.

The labor share is defined as the ratio of labor cost to some measure of income. In standard formulations based on national accounts, the numerator typically includes both wage and non-wage compensation of employees. In the denominator, income is usually measured by aggregate gross value added.[1]

$$\text{Labor Share} = \frac{\text{Labor Compensation}}{\text{Income}} = \frac{\text{Wage} \times \text{Labor}}{\text{Price of Value Added} \times \text{Real Value Added}}$$

A well-documented problem with this approach is that it does not account correctly for self-employed individuals. While the output of the self-employed is part of national income, the labor component of their remuneration is not captured in the compensation of employees. This understates the labor share and affects cross-country comparisons (Gollin, 2002).[2]

In this paper, I focus on the firm-level labor share, using data on incorporated businesses. One advantage over macroeconomic data is that focusing on firms and their employees removes the confounding effects of self-employment on labor share estimates. Although some self-employed individuals may in fact operate as incorporated businesses, their impact on the data is mitigated by showing that the conclusions of this paper hold when the smallest firms are excluded.

At the firm level, I define the labor share as the ratio of total employment expense to gross value added. Like in the national accounts, employee compensation reported by individual firms includes non-wage expenses, such as pension and health insurance expenses, as well as social security taxes. I estimate firm-level gross value added as sales minus the cost of intermediate inputs other than employee compensation (calculated from the financial statements as earnings before interest, tax, depreciation, and amortization plus employee compensation expense), adjusted for inventory growth:

[1] In the SNA 2008 national accounting framework, compensation of employees includes wages and salaries, paid in cash or in kind, as well as employer contributions to pensions, healthcare, and social insurance. Gross value added is often used as a measure of income when the labor share is calculated for individual sectors or regions. This is because GDP includes taxes on products, such as VAT, which are only known for the whole economy. In the UK, GVA accounts for approximately 90% of GDP (ONS, 2016).

[2] Guerriero (2012) reviews a range of adjustments to the aggregate labor share proposed in the macroeconomic literature. The income of sole proprietors and unincorporated businesses ("mixed income") represents approximately 7% of total GVA in the UK (France 7%, Germany 10%, United States 10%).

$$\text{Firm-Level Labor Share} = \frac{\text{Employee Compensation}}{\text{Gross Value Added}} = \frac{\text{Employee Compensation}}{\text{Sales - Intermediate Inputs} + \Delta \text{ Inventories}}$$

Adding the change in inventories to the denominator aligns the firm-level measure of value added with the corresponding economic concept of revenue-based output. Consider what would happen if inventory changes were ignored. A firm that has produced goods in a given period but has not yet sold them will have accounted for the full cost of labor, capital, and other inputs used in production. Sales net of the cost of intermediate inputs will thus be low, and the labor share will be overstated. Conversely, reported sales can reflect the running down of inventories of final goods produced in earlier periods.

The adjustment for inventory changes is consistent with the way aggregate gross value added is calculated in the national accounts (ONS, 2016). The existing literature on firm-level labor shares has not incorporated this adjustment into its measures of gross value added. However, year-to-year inventory changes at individual firms can be large. Excluding them from the calculation of gross value added can affect the conclusions about the aggregate evolution of the labor share. I demonstrate this in Section 4, in the context of the data sample.

When the numerator and denominator are divided by the number of employees, the labor share becomes a ratio of the average wage to the average product of labor:[3]

$$\text{Firm-Level Labor Share} = \frac{\dfrac{\text{Employee Compensation}}{\text{Number of Employees}}}{\dfrac{\text{Gross Value Added}}{\text{Number of Employees}}} = \frac{\text{Average Compensation}}{\text{Average Product of Labor}}$$

The lower the labor share, the greater the gap between wages and average productivity. Firms that have low labor shares thus undercompensate workers relative to the amount of output

[3] Average wages and productivity are expressed on a per-employee basis, as I do not have firm-level data on hours worked. Pessoa and Van Reenen (2013) analyze the relationship between aggregate wage and productivity growth in the UK using a variety of measures and macroeconomic data sources.

they create. A declining labor share thus implies a "decoupling" of wages and productivity and a shift in how the benefits of economic activity are shared with workers.

What does basic economic theory predict for the variation of labor shares across firms? In a framework of competitive markets and free mobility of homogeneous input factors, all profit-maximizing firms with identical, well-behaved production functions will choose the same technologically-efficient input allocation. In equilibrium, each factor will be paid its marginal product, and the labor shares will be equal across firms. Nothing will be gained by using firm-, rather than sector-level, data to analyze the determinants of the labor share.

However, the data shows wide dispersion in firm labor shares. Table 1 presents measures of between-firm and within-firm variation in the labor share and its components, both in levels and in logs, derived from the random-effects model, $x_{it} = \alpha + u_i + \varepsilon_{it}$ applied to the pooled sample. Between-firm variation ($\sigma_u/|\bar{x}|$) is measured as the standard deviation of the error term u_i normalized by its mean, while within-firm variation ($\sigma_\varepsilon/|\bar{x}|$) is measured by the standard deviation of ε_{it}, normalized by its mean. When the labor share is measured in levels, between-firm variation is 0.40, and within-firm variation is 0.60, such that 31% of the variance is due to differences across firms. The corresponding measures are 1.14 and 1.08 when the labor share is measured in logs, with 53% of the variance arising between firms. The empirical strategy in this paper exploits both sources of variation.

The simplest framework that predicts no dispersion of the labor share also predicts no dispersion in its individual components. Table 1 shows that both average compensation and the average product of labor vary widely in the sample, and most of this variation is across firms in the same industry. The fact that the ratio of these two variables is also dispersed means that the numerator and denominator do not correlate perfectly. One way to see this is to regress average compensation and the average product of labor and calculate $1 - R^2$ to obtain the proportion of total variation in the former that is not explained by the latter. Controlling for year and 4-digit sector fixed effects, this proportion is 54% when the variables are measured in levels and 42% when the variables are measured in logs. The remainder of this paper investigates the sources of this variation.

3. Why might capital intensity and market power matter for the labor share?

This section outlines a simple model to illustrate why the labor share may differ across firms within a given sector, even under the assumption that the production technologies are identical. The aim is to motivate the empirical analysis that follows in an intuitive manner before proceeding to a discussion of the data and the empirical strategy.[4]

To see why a firm's labor share might be related to its market power and the capital intensity of production, consider a profit-maximizing firm i with the production function $Y_i = Y(A_iL_i, B_iK_i)$, where Y_i is output, L_i is labor, K_i is capital, and A_i and B_i are labor- and capital-augmenting productivity, respectively, which can vary across firms. Labor and capital are supplied elastically at the wage w and rental rate r, but the product market is imperfectly competitive.[5] From the first-order condition for labor, the labor share is

$$s_i^L \equiv \frac{wL_i}{P_iY_i} = \varepsilon_i^{YL}\left(1 + \frac{1}{\eta_i}\right) \qquad (1)$$

where $\varepsilon_i^{YL} = \frac{\partial Y_i}{\partial L_i}\frac{L_i}{Y_i}$ is the partial elasticity of output with respect to labor and $\eta_i = \frac{\partial Y_i}{\partial P_i}\frac{P_i}{Y_i}$ is the price elasticity of demand. The first term, ε_i^{YL}, is a function of the productivity parameters and the labor and capital inputs. The firm's labor share thus depends on the relative productivity-augmented quantities of the factors employed in production. The sign of the

[4] For a discussion of similar predictions generated by general equilibrium models of monopolistic competition, see Karabarbounis and Neiman (2014) and Barkai (2016).

[5] Appendix D contains supporting derivations of key equations in the paper. The assumption of a perfectly competitive labor market is relaxed in Section 7.

relationship between the labor share and the relative quantities of capital and labor inputs is determined by the elasticity of substitution between capital and labor.[6]

If returns to scale in production are constant, then the first term of equation (1) can be expressed more transparently as a function of the labor-to-capital ratio and the firm-specific productivity parameters:

$$\varepsilon_i^{YL} \equiv \frac{Y_L(A_iL_i, B_iK_i)}{Y(A_iL_i, B_iK_i)} L_i = \left(\frac{A_iL_i}{B_iK_i}\right) \frac{Y_L\left(\frac{A_iL_i}{B_iK_i}, 1\right)}{Y\left(\frac{A_iL_i}{B_iK_i}, 1\right)} = g\left(\frac{A_iL_i}{B_iK_i}\right) \tag{2}$$

where Y_L is the partial derivative of output with respect to labor. The empirical analysis that follows will therefore test whether there is a relationship between the relative factor inputs (measured as net tangible assets per employee) and the firm's labor share, with the ratio of productivity parameters absorbed by firm fixed effects.

The second term of equation (1) denotes the firm's product market power and is determined by the characteristics of demand. In the baseline specification of my empirical analysis, I use the firm's share of 4-digit sector sales to proxy for its product market power. This is motivated by the observation that some models of imperfect competition predict a direct relationship between the price elasticity of demand and firms' market shares in equilibrium. For example, consider a Cournot oligopoly with n firms, each producing a homogenous product with marginal cost c_i and facing a linear inverse demand curve, $P = a - bQ$, where $Q = \sum_i q_i$ is total quantity produced. In equilibrium, firm i's market share is $s_i^M \equiv \frac{q_i}{\sum_i q_i} = \frac{n+1}{n}\frac{a-c_i}{a-\bar{c}} - 1$, where $\bar{c}$ is the average marginal cost. The market share can be expressed in terms of the elasticity of demand, η, as

[6] This point was first raised by Hicks (1932) and Robinson (1933). If the elasticity of substitution between capital and labor is exactly 1 (like in the model of Autor et al. (2017), who assume a Cobb-Douglas production function), then the partial elasticity of output with respect to labor, ε_i^{YL}, will be independent of the firm's capital-to-labor ratio. In that scenario, the empirical analysis that follows should find that capital per worker does not matter for a firm's labor share (which is not the case). Arpaia, Pérez, and Pichelmann (2009) develop a model of the aggregate labor share where low- and high-skilled labor differ in their elasticity of substitution with respect to capital.

$$s_i^M = \frac{(n+1)(a-c_i)}{a+n\bar{c}}(-\eta) - 1 \tag{3}$$

This illustrates a possible link between firms' market shares and the price elasticity of demand.[7] The intuition is that when there are fewer firms in a sector, each firm's market share is higher. Lower competition leads to greater monopoly power and a lower total quantity produced, which corresponds to a more elastic part of the demand curve. This simple model motivates the empirical analysis that follows, which uses longitudinal firm data to estimate the firm-level determinants of the labor share.

4. Data

The main source of data for my analysis is the Financial Analysis Made Easy (FAME) database supplied by Bureau van Dijk. It contains the financial filings of UK firms that submit annual reports to Companies House, a government agency responsible for maintaining the official company register. Virtually all companies in the UK, except the smallest ones, are legally required to file an audited annual report. In 2015, the compliance rate with this requirement was 99.1% (Companies House, 2015). Financial information follows standardized accounting conventions. The audit requirement helps ensure that the data is of high quality, partially mitigating potential concerns about reporting error. For these reasons, FAME data is routinely used in research (e.g., Draca, Machin, and Van Reenen, 2011).

Thanks to strict reporting requirements, FAME contains information on a large number of private and unlisted companies. Such companies represent the bulk of the total firm count in the UK (and in most other countries), as well as a high proportion of aggregate

[7] In the empirical model, firm fixed effects absorb any firm-specific cost advantage, which will affect the relationship between market share and equilibrium price elasticity of demand in this model if marginal costs are heterogeneous and the differences are persistent. Note that if demand is iso-elastic, there will be no relationship between the (constant) price elasticity of demand and market shares as industry concentration changes. However, I show in Section 6 that the conclusions about the role of market power in determining the firm-level labor share hold in a number of different specifications.

employment. The inclusion of small, private firms represents both an opportunity and a challenge. On the one hand, it generates a more heterogeneous and representative sample of firms than databases of listed companies, which exclude most small and medium enterprises. On the other hand, many small firms are likely to be family businesses or self-employed individuals operating as incorporated businesses. The labor share of such firms can easily be mismeasured, since the labor and capital components of compensation are difficult to disentangle in the case of business owners. Section 6 considers this issue explicitly and shows that the results of this paper are robust to excluding the smallest firms from the sample.

The sample for analysis is defined by including all market sector firms that report information on labor compensation, sales, tangible assets, employment, and the line items needed to calculate value added. This requirement makes the firms in the sample larger, on average, in terms of sales and employment than the universe of UK firms. The financial sector is excluded due to methodological differences in the calculation of value added. I also exclude sectors with a substantial presence of non-market services (public administration, health, education, arts, etc.), where value added can be difficult to measure. To avoid capturing foreign subsidiaries of UK firms and their employees, I use unconsolidated financial accounts.

The result is a panel of 119,764 observations on 31,402 firms, covering the period from 2005 to 2012. This period was characterized by substantial variation in the aggregate labor share. Figure 2 shows that the aggregate labor share in the sample closely tracks the market sector labor share calculated from the national accounts, and follows a similar downward trend as the labor share in the UK economy and other G7 countries. (Notably, while the Great Recession led the labor share to peak in 2009 as the value of output dropped precipitously, it does not seem to have fundamentally altered the general downward trend over this period.) The firms in the sample represent a substantial proportion of economic activity generated by the UK non-financial market sector. In the last year of the sample period, 2012, they generated total value added of £275bn, employed 5.8 million people, and spent £167bn on employee compensation – 29%, 27%, and 32% of the corresponding aggregate market sector figures reported by ONS (2018).

Table 2 reports basic descriptive statistics for firm sales, employment, and the variables used in the empirical analysis. In the table and in the main specification of the empirical model the labor share is calculated as total compensation expense divided by gross value added, as described in Section 2. Capital intensity is calculated as the book value of tangible fixed assets net of accumulated depreciation ('net tangible assets'), divided by total employment. Tangible fixed assets are long-term assets such as machinery, buildings, and land. The market share is calculated as each firm's share of total sales in the 4-digit sector. Nominal values are converted to constant prices using the GDP deflator and ratios are winsorized at the 1st and 99th percentile. The median firm reports sales of £12 million and employment of 73. It has a labor share of value added of 75%, £11,000 of net tangible assets per employee, and a market share of less than 1%.[8] The sample includes firms of all sizes – from those employing a handful of individuals to the largest businesses in the economy with thousands of employees.

As mentioned in the discussion on measurement above, the year-to-year change in inventories can be very large for an individual firm, substantially affecting firm-level estimates of gross value added (and therefore the labor share). Inventory changes in the sample range from a minimum of -£1.4bn to a maximum of +£1.8bn. To see the importance of including inventory changes for the correct measurement of gross value added, consider the impact of the financial crisis, which represented the largest shock to aggregate output

[8] I show later that the conclusions of this paper hold when using alternative measures of the labor share, capital intensity, and market power. I do not use the perpetual inventory method to calculate a measure of capital due to the short time series of data available for many of the firms in the dataset.

during the sample period. With the correct adjustment for inventory changes, aggregate nominal GVA in the sample fell by 5.4% from 2008 to 2009. This falls squarely between the 4.3% decrease reported in the national accounts for "private non-financial corporations" (ONS, 2016) and the 6.8% decrease reported in the aggregated results of the Annual Business Survey of firms in the "non-financial business sector" (ONS, 2018).[9] On the other hand, excluding the inventory adjustment would have led incorrectly to an estimated nominal GVA *increase* in the sample of 0.3%, contrary to the observed trend. This shows that correct measurement of the labor share is important for drawing macroeconomic conclusions from firm-level data.

Table 2 also shows that, on average, a firm's labor share declines as its capital intensity rises. Firms with tangible assets per employee of less than £10,000 have a median labor share of 81%. As the capital intensity rises across the sample, the average labor share drops precipitously. For instance, firms with £50,000 to £100,000 of tangible assets per worker have a median labor share of 66%, while firms with tangible assets per worker of £100,000 to £500,000 have a median labor share of 52%. In the right tail of firms with tangible assets per worker of £500,000 or more, the median labor share is only 20%. A similar associations holds within broad sectors (manufacturing and services). While the median manufacturer is more capital intensive than the median service firm (£15,068 vs. £9,532 of tangible assets per worker, respectively), the labor share within each sector declines as capital intensity rises.

Similarly, the labor share declines with a firm's market share. Firms with market share within their 4-digit sector of less than 1% have a median labor share of 76%. The average labor share declines gradually for firms observed with higher market shares. Like in

[9] The Annual Business Survey is one of the sources used for calculating aggregate GVA in the national accounts, but the national accounts incorporate a number of other adjustments. See the discussion in Section 2 and ONS (2016) for more details.

the case of capital intensity, the right tail of firms with market share of 20% or greater has the lowest median labor share of 65%. Figure 3 illustrates this relationship visually. Both capital intensity and market power thus appear to be potentially relevant determinants of the firm-level labor share.

5. Empirical strategy

My starting point for assessing whether the negative correlation between a firm's labor share and its capital intensity on one hand, and between the labor share and market share on the other, hold when controlling for other confounding variables and addressing potential sources of endogeneity is the following panel data model, based on log-linearized equation (1):

$$s_{it}^{L} = \beta_1 \left(\frac{K_{it}}{L_{it}}\right) + \beta_2 s_{it}^{M} + \theta_j + \varphi_r + \delta_t + (a_i + v_{it}) \tag{4}$$

where s_{it}^{L} is the labor share at firm i at time t; $\left(\frac{K_{it}}{L_{it}}\right)$ is the capital-to-labor ratio and s_{it}^{M} is the market share. Technology is permitted to vary across sectors j. The firm-specific labor share is also allowed to be affected by factors specific to the region r where the firm is located, and by changes in the average labor share over time, denoted by the year fixed effects δ_t.

Two problems may arise in estimating equation (4) using ordinary least squares. One is the potential correlation between the error term and the covariates. For instance, both the capital-to-labor ratio and the labor share could be jointly determined in response to idiosyncratic shocks, v_{it}. An example of this might be a rise in the bargaining power of workers that leads to a higher labor share while also causing firms to substitute away from labor towards capital, inducing a positive correlation between capital intensity and the labor share. This will lead to biased results.

A second problem is that time-invariant managerial or organizational characteristics, captured by a_i, may be correlated with one or more regressors, such as the firm's choice of factor inputs or market position. For instance, there can be unobserved differences in how value added is shared among labor and other factors of production, which may depend on unobserved preferences of management, working conditions or other social and organizational factors, or the relative size of the firm-specific productivity parameters A_i and B_i. Insofar as those unobserved differences are permanent, they are captured by the time-invariant parameter a_i in equation (4). Reverse causality is also a concern. For instance, firms that have a lower labor share than peers ($a_i < 0$) may find it easier and cheaper to fund increases in their capital stock, thanks to their higher profits and the ability to offer a higher return on capital. A low labor share might thus cause higher capital intensity, not the other way around.

If the shocks v_{it} are serially uncorrelated, then the standard method for dealing with these problems involves estimating equation (4) in differences to eliminate the impact of permanent heterogeneity, a_i, and using instrumental variables to address concerns about the correlation between the regressors and the error term. While external instruments for firms' input choices are typically difficult to find, lagged values of the endogenous regressors themselves, dated $t-2$ or earlier, would be potentially valid instruments, as they would be uncorrelated with the error term.

However, in practice, when the model is estimated using this procedure, the residuals exhibit serial correlation beyond the first-order negative serial correlation that would be induced by first-differencing if the shocks were serially uncorrelated. This casts doubt on the validity of a static model and suggests a need to model serial correlation in the errors explicitly. But if the shocks are serially correlated, then the error term is a function of all past disturbances. In this situation lagged values of the endogenous regressors are no longer valid instruments. A model with firm fixed effects suffers from the same problem. Hence there is no consistent way to estimate the static model.

A standard approach to dealing with this problem in the GMM literature (e.g., Bond and Guceri, 2017) is to estimate a dynamic, autoregressive distributed lag model that contains the lagged labor share and lags of the regressors on the right-hand side and uses first-differencing to remove the time-invariant firm effect:

$$\Delta s_{it}^{L} = \rho \Delta s_{i,t-1}^{L} + \pi_1 \Delta \left(\frac{K_{it}}{L_{it}} \right) + \pi_2 \Delta \left(\frac{K_{i,t-1}}{L_{i,t-1}} \right) + \pi_3 \Delta s_{it}^{M} + \pi_4 \Delta s_{i,t-1}^{M} + \Delta \varepsilon_{it} \qquad (5)$$

In this model, if the unobserved shocks v_{it} are serially correlated and follow an AR(1) process, for instance, then lags of any endogenous regressor x_{it} dated $t-2$ or earlier are now potentially valid instruments for x_{it} and $x_{i,t-1}$, as $E[x_{i,t-s}\varepsilon_{it}] = 0$ for $s \geq 2$. Similarly, the lagged dependent variable $s_{i,t-1}^{L}$ can be instrumented with lags of s_{it}^{L} dated $t-2$ or earlier. The long-run relationship between capital intensity and the labor share is then given by $\frac{\pi_1+\pi_2}{1-\rho}$. Similarly, the long-run effect of market share on the labor share is $\frac{\pi_3+\pi_4}{1-\rho}$. These parameters can be estimated consistently using two-stage least squares or the Generalized Method of Moments (GMM).

An alternative way to motivate a dynamic model with lags of the labor share, capital intensity, and market share is costly or slow adjustment of employment, investment, wages or sales to shocks, especially when adjustments are costly. In the data, firms' labor shares, capital-to-labor ratios, and market shares are highly persistent over time.[10] This observation is consistent with either the presence of adjustment lags or serially correlated productivity shocks.

To estimate the coefficient vector $(\rho, \pi)'$, I use the System GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). In addition to using equation (5) in first differences with lagged levels of the potentially endogenous variables as

[10] Appendix A provides evidence on the persistence of these variables.

instruments, System GMM also exploits the corresponding equation (4) in levels, with lagged first-differences as instruments. This approach has two main advantages compared to applying GMM only to the equation in first differences. First, it uses more information by exploiting between-firm variation, which is a more important source of overall variability in labor shares than within-firm variation. In the pooled sample, 79% of variation in the log labor share is between—rather than within—firms. Second, when the data are persistent, System GMM exhibits a smaller finite-sample bias (Blundell and Bond, 1998).

System GMM is the main approach used in the remainder of this paper. To avoid concerns with overfitting (Roodman 2009), I limit the number of instruments to the lagged levels dated $t-2$ and $t-3$ in the first-difference equation and lagged differences dated $t-1$ and $t-2$ in the levels equation, rather than using all past values.[11] The key additional assumption is that the first-differences of the explanatory variables (as well as the first-differences of the labor share) are uncorrelated with the time-invariant unobserved heterogeneity captured by a_i and not transformed out of the error term for the equations in levels. Appendix B contains a detailed discussion of the assumptions required for the estimates to be consistent and discusses how these assumptions are tested in the data. The conclusion is that the empirical model appears to be well-specified in responding to concerns about serial correlation and potential endogeneity of the variables of interest.

6. Results: Firm-level determinants of the labor share of income

This section presents the findings on the relationship between market power, capital intensity, and the labor share. I begin by showing the results of estimating static models of the labor share to show that the results suffer from a pattern of serial correlation in the residuals that

[11] GMM estimation is carried out using the *xtabond2* command in Stata, implemented by Roodman (2009), with Windmeijer's (2005) finite-sample correction to the standard errors. I also report OLS results with and without firm fixed effects, to provide context for the GMM results.

suggests a need for a dynamic model. I then present the results of estimating a dynamic model and explore the robustness of the results to alternative sample and variable definitions, and empirical specifications.

Table 3 presents the results of estimating versions of the static model given by equation (4). The dependent variable in all columns is the log labor share, defined as total compensation divided by value added. Column 1 regresses the log labor share on capital intensity, measured as the log of net tangible assets per employee, and market share, measured as the log of the firm's share of 4-digit sector sales. The elasticity of the labor share with respect to capital intensity is estimated to be -0.079. In other words, a doubling of capital intensity is associated with a 7.9% reduction in the labor share.[12] The estimated elasticity with respect to market share is much smaller in magnitude, at -0.009. A doubling of the market share is thus associated with a 0.9% fall in the labor share. However, both effects are highly statistically significant, with a p-value below 1%. Column 2 adds sector fixed effects to control for sector-level differences in the labor share. The capital intensity estimate falls slightly to -0.067, while the market share estimate increases substantially in magnitude to -0.020. Both estimates remain highly statistically significant. Column 3 adds region fixed effects to control for any geographic differences in labor share setting that could be driven, for instance, by labor market conditions, but the impact on the results is negligible.

OLS estimates thus highlight strong and significant correlations between firms' labor shares, market shares, and the capital intensity of production. However, as discussed earlier, the coefficients will be biased in the presence of unobserved heterogeneity in how the labor share is determined at the firm level. Column 4 includes firm fixed effects as one way to account for such unobserved heterogeneity. Firm-specific drivers of the labor share may

[12] Note that this is a percentage impact, not a percentage-point impact. The estimated elasticities are interpreted in a more intuitive way further below, after the presentation of the results.

include things like within-sector product differentiation, differences in production costs relative to competitors, or other aspects of the firm's management and organizational structure. The results with fixed effects represent within-firm estimates of the effects of an increase in capital intensity or market share on the labor share. They continue to show a strong negative relationship between the labor share and both market power and capital intensity.

As discussed in Section 5, fixed-effects estimates are biased if productivity shocks are serially correlated. The Arellano and Bond (1991) tests for serial correlation shown in Table 3 cast doubt on the validity of the static model. Table 4, therefore, presents the results of estimating the dynamic model of the labor share given by equation (5). Columns 1 and 2 show the estimates using OLS and fixed-effects (within-firm) estimators. The long-run elasticities are relatively similar to the estimates in the static model. However, the residuals continue to suffer from serial correlation.

Column 3 presents the results of GMM estimation, which uses instrumental variable methods to address potential sources of correlation between the error term and the regressors. The elasticity of the labor share with respect to capital intensity is -0.077, similar to the OLS results, while the elasticity with respect to market share is -0.184, relatively similar to the results with firm fixed effects. Both coefficients are highly statistically significant, suggesting strong links between firms' labor shares, market shares, and capital intensity. The test for serial correlation does not highlight any second-order serial correlation in the residuals (p-value 0.903), implying that there is no need to add more lags of the model variables to ensure consistent estimation in the GMM framework. Moreover, the Hansen test of overidentifying restrictions does not reject the null hypothesis of instrument exogeneity (p-value 0.459). Finally, the validity of the GMM approach is supported by the observation that the coefficient on the lagged dependent variable is between the OLS and fixed-effects estimates (Blundell and Bond, 2000). Together with the results of further tests in Appendix B, these diagnostics suggest that the model is appropriate for the data and is estimated consistently.

How robust are the results to the way the sample has been defined and to the details of the empirical specification? This is tested in Table 5 by modifying the baseline GMM specification described above in several ways. Columns 1 to 3 address potential concerns with sample selection. One such concern is that the universe of incorporated firms that submit financial reports to Companies House may include self-employed individuals. I therefore check whether the estimated coefficients change when firms that are never observed with more than one employees are excluded from the sample. Column 1 reports these results. The estimated elasticities are now -0.070 in the case of capital intensity and -0.192 in the case of the market share, both significant at a 1% level and similar in magnitude to those obtained from the full sample. The main reason is that the smallest firms are typically not required to supply fully detailed financial statements, and therefore few of them make it into the main sample. Next, column 2 focuses on firms observed in each year of the sample period. These tend to be larger and more established firms. This sub-sample is therefore more likely to satisfy the assumptions of System GMM (see Appendix B for a discussion). Again, the results are similar to the baseline model in column 5 of Table 3. The estimated effect of capital intensity on the labor share is larger in magnitude at -0.095, but the difference is not significant, while the estimated effect of the market share is almost identical at -0.182. Finally, column 3 tests the impact of outliers by estimating the model using unwinsorized variables. While this adds some noise to the data and the coefficient estimates shift slightly, the results remain very similar to those in the baseline GMM model.

Columns (4) to (7) explore different functional forms. Column 4 presents estimates in levels, rather than logs. In column 5 only capital intensity is in logs, while the labor share and market share are in levels. In column 6, only the labor share is in levels. Column 7 adds the square of capital intensity to the log-log model, motivated by the non-linear relationship found in plots of the raw data. The market share remains negative and statistically significant across these specifications, with differing magnitudes in columns 4 to 6 reflecting the fact that the interpretation of the coefficient changes depending on whether the variables are expressed in logs or in levels. Similarly, market share enters negatively and significantly when its square is included in the log-log model, with an elasticity at the mean similar to that obtained in the linear model. Capital intensity is somewhat less robust to changes in the model specification.

Table 6 shows that the overall conclusions are also robust to several alternative definitions of the firm-level labor share, capital intensity, and market power. Column 1 replaces the dependent variable with the wage share of value added, excluding non-wage benefits such as pensions and social security taxes from the numerator. The estimated elasticities with respect to capital intensity and market share of -0.070 and -0.201, respectively, differ little from those in the baseline specification. This suggests that the effects on the labor share operate mainly through wages, and not through other forms of compensation.

Next, columns 2 to 5 test alternative measures of market power. A firm's share of 4-digit sector value added, rather than sales, is used in column 2, and the share of sales within the sector and NUTS3 region (approximately equivalent to a county) is used in column 3. Column 4 then repeats the specification from column 3 while restricting the sample to non-tradable sectors, as defined by Mano and Castillo (2015). Finally, column 5 estimates market power by the log of the ratio of value added to sales, as a proxy for the markup. Since this variable is highly correlated with the denominator of the labor share, it is instrumented with lags dated $t-3$ and $t-4$ for the equation in levels and $t-4$ and $t-5$ for the equation in first differences, to avoid an overlap with contemporaneous instruments for the lagged labor share. The results of all the analyses of alternative measures of market power are directionally the same as in the main specification in Table 4. In columns 2 to 4, the coefficients on market share range from -0.108 to -0.158 and the coefficients on capital intensity range from -0.068 to -0.079. In column 5, the estimated coefficient on the markup is -0.660, which suggests that for an average firm, a 1 percentage-point increase in the markup leads to a 1.7 percentage-point decrease in the labor share. All results remain statistically significant, with the exception of the capital intensity variable in the last column. This confirms that the conclusions of the paper are robust to alternative measures of key variables.

Overall, a firm's market power and capital intensity has significant effects on the labor share. How do these results compare to those found in the macroeconomic literature? In terms of the market share, the work of Autor et al. (2017) and De Loecker and Eeckhout (2017), among others, finds a negative relationship between various measures of industry concentration and the industry-level labor share. My firm-level conclusions are consistent with aggregate findings, provided that firms' shares of sales and of value added do not move strongly in opposite directions.

The second finding that higher capital intensity lowers the labor share is consistent with the claims of Bentolila and Saint-Paul (2003), Karabarbounis and Neiman (2014) and Piketty (2014), who explain the trends in aggregate factor income shares through an elasticity of substitution between capital and labor greater than one. However, as mentioned earlier, the degree to which capital and labor are substitutable is a matter of ongoing debate in the literature.

One reason why the conclusions about the substitutability of capital and labor may vary is that different types of capital assets and workers may substitute or complement each other differently. I therefore probe the relationship between capital intensity and the labor share in three ways. First, to determine whether the effect of capital intensity differs according to the skill level of a firm's workforce, I split the sample into low-wage and high-wage firms. I define high-wage firms as those that, on average, are in the top half of the annual distribution of total compensation per employee during their presence in the sample. Given that firms' financial reports contain no information about the characteristics of individual workers, I take the average wage level to be a proxy for the skill level of the employees.[13] This helps judge whether the conclusions about the degree of substitutability between capital and labor vary depending on the type of workforce that firms employ. Second, to determine whether labor is equally substitutable with different classes of capital, I add intangible capital intensity, defined as the log of the book value of intangible assets per employee, as a regressor. Intangible assets reflect items such as patents, copyrights, and software, although accounting rules primarily allow firms to report the fair value of acquired, rather than internally-generated, intangibles on their balance sheet. Third, I combine the two approaches above to determine how the two types of workforces and two types of capital interact.

It turns out that the aggregate results on capital intensity are driven mainly by low-wage firms, suggesting that a low-skilled workforce is more substitutable with capital than a high-skilled workforce. Moreover, higher intangible capital intensity leads to a higher labor share, but only in the case of firms with a high-skilled workforce. These results are presented in Table 7. In column 1, tangible capital intensity is interacted with an indicator for whether the firm is a high-wage firm. The estimated elasticity for low-wage firms is -0.126, larger in magnitude than the aggregate estimate and highly significant. While the estimate for high-wage firms is also negative at -0.034, it is smaller and not statistically significant. Therefore,

[13] Table C2 in the Appendix shows that the sample firms classified as high-wage are more concentrated in sectors such as manufacturing, construction, information and communication, and professional, scientific, and technical activities, where data from the UK Labour Force Survey shows that both a) average wages and b) the average skill level in the employee population (measured through years of education and the proportion of employees with a college degree) are indeed higher.

to the extent that a firm's average wage level can proxy for the average skills of its workforce, these results suggest that high-skilled workers are much less substitutable with (tangible) capital than low-skilled workers. Next, column 2 shows that the estimated elasticity of the labor share with respect to intangible capital intensity is 0.023 and marginally insignificant at a 10% level. Column 3 shows that the estimate on intangible capital intensity is driven entirely by high-wage firms. On the assumption that firms with high average wages have a workforce with high average skills, this suggests that high-skilled workers are less substitutable with intangible capital than low-skilled workers, while low-skilled workers are more substitutable with tangible capital than high-skilled workers. These results are consistent with the hypothesis of capital-skill complementarity (Griliches, 1969) and the findings of the literature on skill-biased technical change (see Hornstein, Krusell, and Violante, 2005, for a review).

How can we interpret the magnitudes of the estimated elasticities? One way to answer this question is to note that the aggregate labor share in the G7 countries has declined by approximately 10 percentage points since 1970, and to ask what size increase in the market share or capital intensity of the average firm would be required to obtain a reduction in the labor share of this magnitude. Using the estimates from column 3 of Table 7, the labor share of the average firm will decline by 10 percentage points if market share rises by 1.2 percentage point, holding capital intensity constant. On the other hand, if market share is held constant, then the same 10 percentage-point decline in the labor share will arise if capital intensity rises by approximately £100,000 for high-wage firms and £42,000 for low-wage firms. Another way to think about these amounts is to compare them with the median real employee compensation cost of £29,500. Thus, net investment equal to 1.4 years of labor costs at low-wage firms and 3.4 years of labor costs at high-wage firms would be needed to reduce the labor share of income by 10 points, all else remaining constant.

An alternative way to assess the magnitude of the estimates in the context of the sample is to consider the actual dispersion of market shares and capital intensities across firms. Most firms observed in the data have low market shares and low capital intensity, but the distributions of both variables are highly skewed to the right, with a large standard deviation relative to the mean. A one standard deviation rise in market share (4.4 percentage points) is estimated to lower the labor share of the average firm by 36.8 percentage points. A move of this size implies almost a tripling of the market share by the average firm. On the other hand, a one standard deviation rise in net tangible assets per employee reduces the labor share of the average firm by 11.7 percentage points in the case of high-wage firms and 19.3 percentage points in the case of low-wage firms. While large, the effect is relatively smaller than that for market share, given the smaller absolute size of the estimated elasticity of the labor share with respect to capital intensity.

7. Human Capital, Labor Market Power, and the Labor Share

While the results for high- and low-wage firms shed light on the possible mechanisms through which capital intensity impacts the labor share, how a firm's income is shared may depend also on the relative bargaining power of the firm and its workers. In this section, I examine the impact of workforce characteristics and the firm's labor market power on the labor share in two ways. First, I explore whether enhancing the empirical model to include human capital variables changes the main findings. Second, I test two ways to account explicitly for the effect of the firm's labor market power (as distinct from product market power) on the labor share. Additionally, I use the information on average workforce characteristics to address potential measurement problems with the capital intensity variable.

One aspect of labor share determination that the results in the previous section do not take into account is the firm's position in the labor market. So far, I have assumed that labor is supplied elastically to the firm at a constant wage w. To the extent that labor markets are not perfectly competitive, variations in the labor share—both within and across firms—may be driven by differences in labor market power. Such differences may arise, for instance, if workers are not perfectly mobile across geographies. Moreover, even firms in the same sector and location may demand workers with different skills and thus participate in separate labor markets (at least in the short term). This can happen, for example, if unobserved product differentiation leads to heterogeneous complementarities between firms' capital assets and different classes of labor. In contrast, unionization, or other forms of collective bargaining, may enhance the bargaining power of workers.

The firm's position in the labor market may be an omitted variable affecting the results for product market power and capital intensity. This is because labor market characteristics might be correlated with firms' current or historical capital investments and market position. For instance, the tightness of the labor market in a specific skill category might affect the type of capital that the firm needs to employ in production and the national market share that it can achieve, or vice versa.

Modifying the simple model outlined in Section 3 to allow for imperfect competition in the labor market predicts that the labor share will be inversely related to the firm's labor market power. The first-order condition for labor becomes:

$$s_i^L = \frac{\varepsilon_i^{YL}\left(1 + \frac{1}{\eta}\right)}{1 + \frac{1}{\lambda}} \tag{6}$$

where $\lambda \geq 0$ is the labor supply elasticity. Inelastic supply of labor to the firm (low λ) reduces the labor share compared to the case of perfectly competitive labor markets (infinitely high λ). This is because highly inelastic labor supply gives the firm greater ability to reduce wages without materially restricting the supply of workers willing to work there. This situation may arise if there are frictions in the labor market, such as mobility costs that limit workers' ability to seek alternative employment.[14] A firm's labor market power may thus be a relevant variable to take into account when estimating the determinants of the labor share.

Unfortunately, FAME does not contain any information about firms' workforce other than total employment. My first step, therefore, is to use the UK Labour Force Survey to construct a range of human capital variables that describe the average workforce characteristics in each 1-digit sector-region-year cell. These human capital variables mirror standard variables found in wage regressions: education, experience, and the percentage of employees that are female, married, non-white, UK-born, and that work part-time. I add them to the estimated model and check whether a) cells with a greater proportion of groups that might be expected to have lower bargaining power in the labor market are associated with a lower labor share, and b) whether controlling for these workforce characteristics changes the earlier results on the role of capital intensity and market share. For instance, immigrants, part-time workers, or other groups with weaker attachment to the labor force or the firm may be less able to influence rent-sharing policies.

Column 1 of Table 8 shows that the estimates for the market share and capital intensity are unaffected when the human capital variables are simply added as controls to the main specification. The labor share appears to be, on average, lower in sector-region cells where a higher proportion of employees work part time or hold "other qualifications," which corresponds to low-level vocational and non-standard qualifications. A higher labor market participation rate is also associated with a lower average labor share. These results give some—albeit imperfect—indication that the labor share is lower at firms operating in sectors and regions where the average worker is more weakly positioned in the labor market.

[14] Manning (2003) sets out a comprehensive case for the empirical relevance of imperfect competition in the labor market, i.e., the supply of labor to an individual firm not being infinitely elastic.

However, these coefficients have many possible interpretations. For instance, the coefficient on the percentage of college-educated employees is negative and significant. Perhaps some of the occupations in this category are susceptible to outsourcing or replacement by machines, giving firms greater power over wage setting, but the mechanism is unclear. The data cannot distinguish to what extent the estimated relationship between workforce characteristics is driven by the tension between the strength of a given group's attachment to the labor market, with the consequential impact on bargaining power, social norms, and various forms of selection.

I therefore attempt to measure firms' labor market power, over and above these average workforce characteristics, in two alternative ways. The first is the proportion of new recruits from non-employment in each sector-region cell. Manning (2003) suggests this as a measure of firms' wage-setting power, on the basis that their ability to reduce wages is kept in check by workers' ability to leave for other employers. The higher the proportion of recruits from non-employment, the lower the competition for workers among firms and more monopsonistic the labor market. Manning (2003) also shows that in a general equilibrium model of the labor market with search frictions, this ratio is monotonically inversely related to the ratio of the job arrival rate to the job destruction rate. As it increases, each worker's wage approaches the marginal product. Thus, a high proportion of recruits from non-employment implies that firms have the power to pay workers significantly less than the marginal product and the labor market is farther away from perfect competition.

Column 2 of Table 8 shows that labor market power measured this way is highly significant, with an estimated elasticity of -0.326. This implies that, at the mean, a one standard deviation increase in the proportion of recruits from non-employment (4 percentage points) is associated with a 1.6 percentage-point reduction in the labor share.[15]

Ideally, the proportion of recruits from non-employment would be calculated at the level of individual firms. I therefore use a second, alternative measure of a firm's labor market position: the log of the number of firms present in the same NUTS3 region (roughly a county) or in the same region-industry cell, as proxies for competition for labor in the local labor market. The results are shown in columns 3 and 4 of Table 8, respectively. To make the sign of the estimate comparable to the other columns, the number of competing firms is multiplied by -1. The estimated elasticity is -0.023. This suggests that a higher number of firms raises the labor share. Perhaps it is easier for workers in such markets to switch jobs without incurring substantial mobility costs, which improves their bargaining position.

There is one other way in which these human variables are helpful, and that is to check whether a potential measurement issue with the capital-labor ratio affects the conclusions of this paper. In the theoretical model outlined in Section 3, capital and labor are homogeneous, while in practice, there is likely to be considerable heterogeneity across firms in the quality of their capital and labor inputs. To the extent that differences in the quality of capital equipment and structures are reflected in the purchase price, they will be reflected in the book value of tangible assets—the numerator of the capital intensity measure. Heterogeneity in worker quality, however, will not be reflected in the number of employees, which forms the denominator of the ratio. This suggests a potential measurement problem related to the differences in the average wage across firms that may also be related to the labor share. One solution would be to measure the labor input using compensation cost, on the assumption that wage differences fully reflect the differences in worker quality. However,

[15] The mean proportion of new recruits from non-employment in the sample is 0.61. While this may seem high, it is in the range reported by Manning (2003) for the UK and the US using different periods and data sources.

the denominator of the capital intensity would then become the same as the numerator of the dependent variable.

My approach is therefore to use the human capital variables to derive a quality adjustment for each firm's labor input and use this estimate of "effective labor" to calculate an alternative capital intensity measure. I begin by regressing the average compensation per employee at each firm on the vector of human capital variables. I use the estimated coefficients from this regression to predict an average wage for each firm. I then adjust each firm's total number of employees by the percentage deviation of its predicted wage from the mean of all of that year's predictions. A firm observed in a sector-region cell where the characteristics of the workforce predict relatively low wages will thus be treated as having a lower effective labor input, and thus higher quality-adjusted capital intensity. The resulting headcount adjustment varies from -43% to +47% and accounting for this increases the standard deviation of measured labor input by 10.2%, compared to using employment as the measure of labor input.

Column 5 of Table 8 shows the results. Since the human capital variables are used as instruments to derive a predicted labor input, they are no longer used as exogenous control variables. Replacing the standard capital intensity variable with the adjusted measure gives similar estimates as the baseline specification in Table 3. If anything, the estimated elasticity with respect to the capital-labor ratio is slightly larger in magnitude (-0.084 vs. -0.077), while the estimate on market share is slightly smaller (-0.179 vs. -0.184), but the differences are not statistically significant. While the employment adjustment is highly imperfect due to the lack of firm-specific labor quality measures in the dataset, it does not highlight any obvious impact of systematic variation in labor quality on the conclusions.

Together, these results suggest that a firm's labor market position may be relevant for labor share determination. However, the dataset does not lend itself particularly well to deriving firm-specific variables that isolate this aspect of labor share setting. Therefore, further exploration of the impact of imperfect competition in the labor market on the labor share, using firm-specific data sources or matched employer-employee datasets, would be a valuable direction for future work—especially since a firm may wield different degrees of power in different labor markets where it recruits employees of different skill levels and occupations.[16] Notably, however, the estimated effects of capital intensity and market share on the labor share do not change with the addition of any of the proposed human capital and labor market variables. They are also unaffected by the attempt to adjust firms' labor input for the average characteristics of the workforce in their sector and region. The main conclusions of this paper are still that firms with greater market power and higher capital intensity share a smaller proportion of their income with workers.

8. Conclusions

This paper considers the relationship between labor share of income at the level of an individual firm and two variables suggested by economic theory: market power and capital intensity of production. It contributes to the literature on factor income shares by documenting the wide dispersion of firm-level labor shares and by estimating a model of labor share determination using longitudinal firm data, with a focus on addressing endogeneity concerns through instrumental variable methods. Its main finding is that the capital intensity of firms' production and their power in the product market are significant determinants of the labor share, consistent with economic intuition and a simple theoretical model. The labor share is lower when firms employ more capital relative to labor. This result

[16] In the UK, available matched employer-employee data suffers from two shortcomings. First, firm information does not include a balance sheet, making it difficult to test the role of capital intensity in labor share determination. Second, employee data comes from a 1% nationwide sample, so it is not possible to characterize the within-firm distribution of employees or new hires. However, data from other countries may be helpful for shedding further light on these questions.

is driven by low-wage firms, suggesting that the elasticity of substitution between capital and labor may be greater than one at firms that employ a low-skilled workforce. In addition, the labor share is lower when firms have greater power in the product market, measured by their share of sales or value added. This is also consistent with intuition: firms that face less elastic demand raise their profit share of output to the detriment of the labor share. GMM estimation suggests further that the effect of the market share is quantitatively larger than that of capital intensity.

The main implication of this paper is that the aggregate labor share of income is impacted to a large extent by the decisions made at the level of individual firms, as well as by the environment that those firms face. To the extent that the relationships estimated here hold in the future, increasing robotization may augur continued declines for the labor share, particularly in the segments of the economy characterized by low-wage employment. Similarly, the labor share may continue to be under pressure in markets where a few large firms command significant or rising pricing power.

Future research could focus on relating these results back to macroeconomic trends by decomposing the historical movements in the aggregate labor share into changes at the firm level and changes in the distribution of firms across capital intensity and market share categories within sectors. The analysis could also be replicated using firm-level data from other countries and expanded to longer time periods that coincide with more dramatic labor share declines. Finally, causal links between capital intensity, market power, and the labor share can also be explored further, perhaps by identifying natural experiments that provide quasi-exogenous variation in access to capital across firms or in market structure across sectors.

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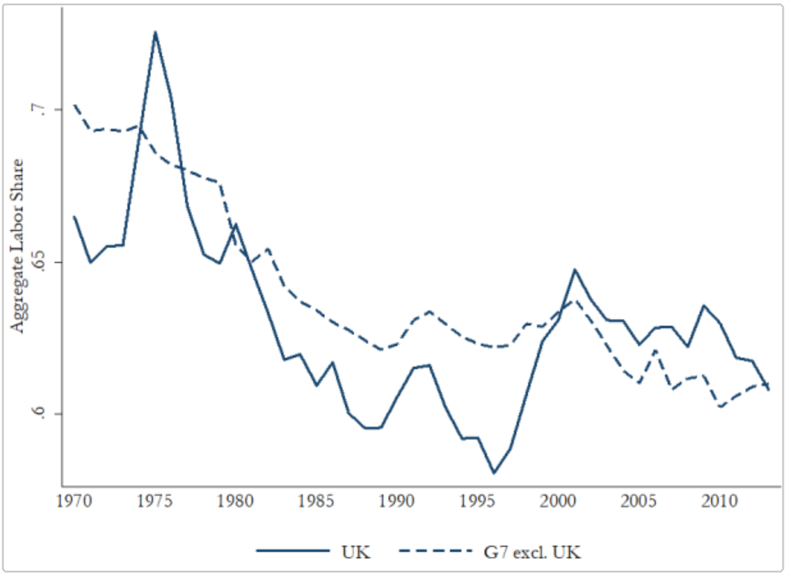
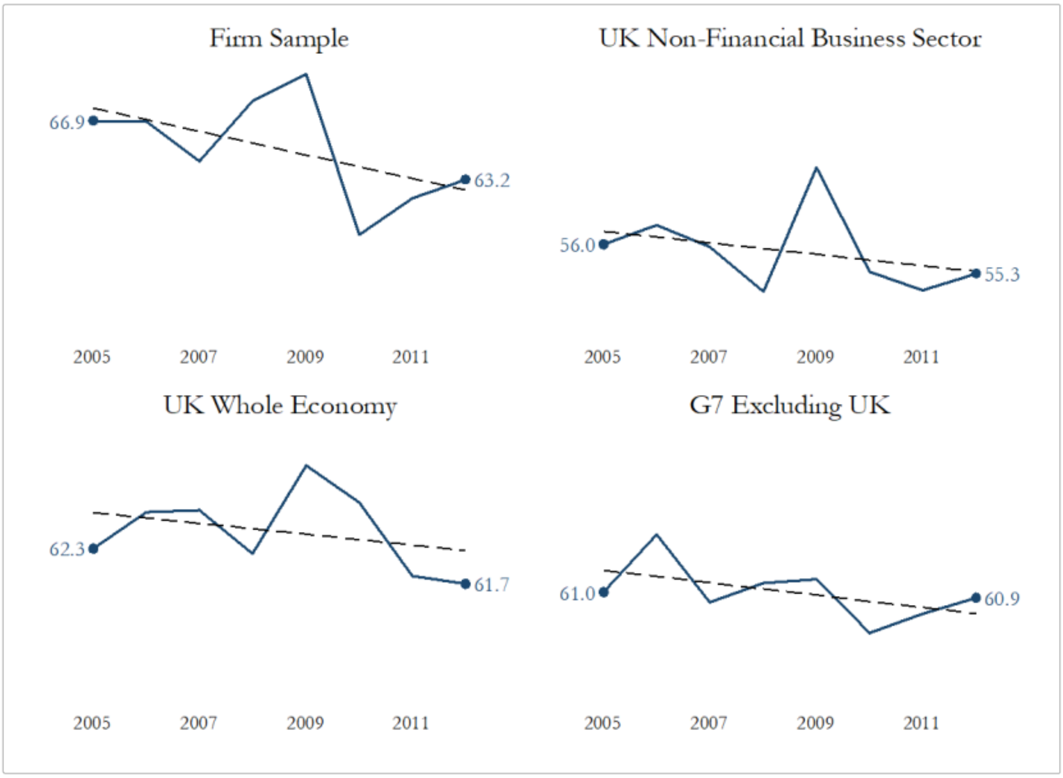
FIGURE 1. LABOR SHARE TRENDS SINCE 1970



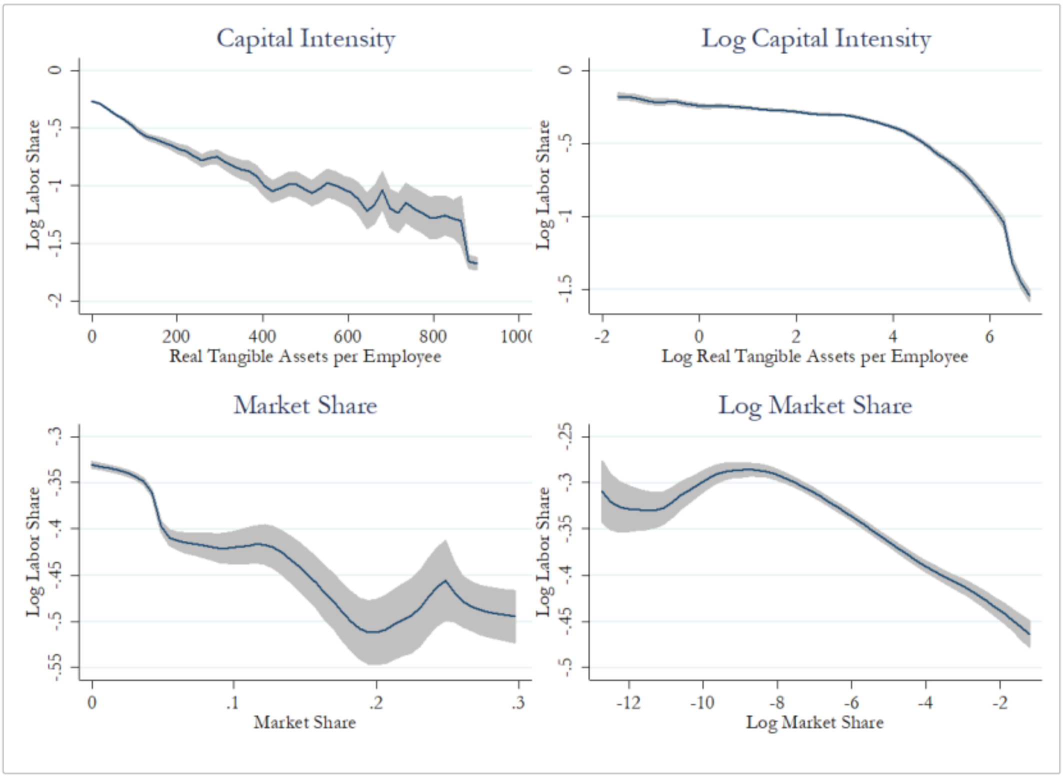
Aggregate labor share is defined as compensation of employees divided by GVA minus mixed income to exclude the output of the self-employed from the denominator (see Gollin, 2002). Data for G7 countries excluding the UK (Canada, France, Germany, Italy, Japan, US) is weighted by GVA. Germany prior to 1990 reflects West Germany only. Source: OECD, own calculations.

FIGURE 2. LABOR SHARE TRENDS OVER THE SAMPLE PERIOD, 2005-2012



The labor share for the whole UK economy and for G7 countries excluding the UK is calculated as aggregate compensation of employees divided by GVA minus mixed income. Data for the UK non-financial business sector is based on published ONS Annual Business Survey results. Dashed lines represent the lines of best fit. The individual plots are on different scales to enable a side-by-side comparison of cyclical fluctuations.

FIGURE 3. LABOR SHARE VS. CAPITAL INTENSITY AND MARKET SHARE



Local polynomial plots of the log labor share against the capital intensity and market share variables for the GMM estimation sample from column 5 of Table 3. The shaded areas correspond to 95% confidence intervals.

TABLE 1. LABOR SHARE DISPERSION

Variable, x	Between firms $\sigma_u/\lvert\bar{x}\rvert$	Within firms $\sigma_\varepsilon/\lvert\bar{x}\rvert$	Within % ρ
Labor Share	0.40	0.60	0.31
Log(Labor Share)	1.14	1.08	0.53
Average Compensation	0.41	0.18	0.84
Log(Average Compensation)	0.13	0.05	0.88
Average Product of Labor	0.88	0.54	0.73
Log(Average Product of Labor)	0.15	0.11	0.67

This table presents dispersion metrics for the labor share and its components, both in levels and in logs. The values σ_u and σ_ε are estimated standard deviations of the error terms from the random-effects model, $x_{it} = \alpha + u_i + \varepsilon_{it}$, normalized by the means to facilitate comparisons across variables. The last column shows the proportion of variance due to differences across firms, $\rho = \sigma_u^2/(\sigma_u^2 + \sigma_\varepsilon^2)$. The model includes year and 5-digit sector fixed effects to account for aggregate trends and cross-sector differences in the labor share. Sample size is 119,764 observations.

TABLE 2. SUMMARY STATISTICS

	Observations	Mean	Median	Std. Dev.	Min	Max
Sales (£ 000)	119,764	67,006	12,105	633,838	2	101,199,900
Employees	119,764	317	73	2,926	1	277,684
Net Tangible Assets (£ 000)	119,764	17,123	974	228,054	1	19,407,766
Labor share (Compensation / Value Added)	119,764	0.83	0.75	0.61	0.00	5.01
Net Tangible Assets / Employee (£ 000)	119,764	40	11	102	0	796
Market Share in 4-Digit Sector	119,764	0.02	0.00	0.04	0.00	0.30

Labor Share by Capital Intensity (Net Tangible Assets/Employee):	Observations	Mean	Median	Median (Manufacturing)	Median (Services)
<£10,000	56,415	0.90	0.81	0.80	0.80
£10,000-50,000	44,186	0.82	0.74	0.74	0.74
£50,000-100,000	10,204	0.77	0.66	0.64	0.68
£100,000-500,000	7,144	0.63	0.52	0.54	0.52
≥£500,000	1,815	0.35	0.20	0.27	0.24

Labor Share by Market Share in 4-Digit Sector:	Observations	Mean	Median	Median (Manufacturing)	Median (Services)
<1%	91,143	0.85	0.76	0.76	0.76
1-5%	19,379	0.78	0.72	0.72	0.71
5-10%	4,397	0.77	0.70	0.71	0.69
10-20%	2,507	0.75	0.69	0.69	0.69
≥20%	2,338	0.72	0.65	0.65	0.67

Data for firm-level observations pooled across all years in the dataset. Sales and net tangible assets are measured in thousands of 2011 pounds. All ratios (compensation cost/employee, labor share, net tangible assets/employee, and market share) are winsorized at the 1st and 99th percentile.

TABLE 3. STATIC MODELS OF THE LABOR SHARE

	OLS			Within-Firm
	(1)	(2)	(3)	(4)
Capital Intensity	-0.079***	-0.067***	-0.068***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.004)
Market Share	-0.009***	-0.020***	-0.019***	-0.219***
	(0.001)	(0.002)	(0.002)	(0.008)
Serial Correlation Test				
1^{st} Order	0.000	0.000	0.000	0.000
2^{nd} Order	0.000	0.000	0.000	0.000
Year FE	x	x	x	x
Sector FE		x	x	
Region FE			x	
Firm FE				x
Sample Size	119,764	119,764	119,764	119,764

This table presents the results of estimating a static model of the log labor share. OLS results from estimating versions of equation (4) with varying fixed effects are presented in columns 1-3. Column 4 additionally includes firm fixed effects. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for first and second-order serial correlation. Robust standard errors clustered by firm are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 4. DYNAMIC MODELS OF THE LABOR SHARE

	OLS	FE	GMM
	(1)	(2)	(3)
Labor Share (t-1)	0.549***	-0.029***	0.159***
	(0.005)	(0.006)	(0.010)
Capital Intensity (t)	-0.050***	-0.035***	-0.476***
	(0.004)	(0.004)	(0.142)
Capital Intensity (t-1)	0.016***	0.011***	0.411***
	(0.004)	(0.004)	(0.127)
Market Share (t)	-0.278***	-0.304***	-0.057
	(0.009)	(0.009)	(0.104)
Market Share (t-1)	0.274***	0.159***	-0.097
	(0.009)	(0.008)	(0.091)
Long-Run Elasticities:			
Capital Intensity	**-0.075*** **	**0.024*** **	**-0.077*** **
	(0.003)	**(0.004)**	**(0.022)**
Market Share	**-0.008*** **	**-0.141*** **	**-0.184*** **
	(0.002)	**(0.009)**	**(0.024)**
Serial Correlation Test			
1st Order	0.000	0.000	0.000
2nd Order	0.000	0.000	0.903
Overidentification Test			0.459
Year FE	x	x	x
Sector FE	x		x
Region FE	x		x
Firm FE		x	
Sample Size	119,764	119,764	119,764

This table presents the main results of dynamic regressions of the log labor share on capital intensity, market share, and controls. Column 1 presents the OLS results from estimating the model

$$s_{it}^{L} = \rho s_{i,t-1}^{L} + \pi_1 \left(\frac{K_{it}}{L_{it}}\right) + \pi_2 \left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \pi_3 s_{it}^{M} + \pi_4 s_{i,t-1}^{M} + (a_i + v_{it}).$$

Column 2 additionally includes firm fixed effects. Column 3 presents GMM results described in the main text, with the lagged levels of the labor share, capital intensity, and market share dated t-2 and t-3 used as instruments for the difference equation, and lagged differences dated t-1 and t-2 used as instruments for the levels equation. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for first and second-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied to GMM. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 5. ROBUSTNESS TO ALTERNATIVE EMPIRICAL SPECIFICATIONS

	Larger Firms	Balanced Sample	Including Outliers	Levels vs. Logs			Squared K/L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Capital Intensity	-0.070***	-0.095**	-0.056***	-0.000	-0.019	-0.005	-0.042*
	(0.022)	(0.040)	(0.020)	(0.000)	(0.029)	(0.038)	(0.022)
Market Share	-0.192***	-0.182***	-0.204***	-3.292**	-3.602**	-0.094***	-0.185***
	(0.025)	(0.050)	(0.025)	(1.370)	(1.544)	(0.035)	(0.024)
Serial Correlation Test							
1st Order	0.000	0.001	0.001	0.000	0.000	0.000	0.000
2nd Order	0.971	0.792	0.919	0.930	0.949	0.950	0.658
Overidentification Test	0.416	0.981	0.619	0.276	0.232	0.115	0.588
Year FE	x	x	x	x	x	x	x
Sector FE	x	x	x	x	x	x	x
Region FE	x	x	x	x	x	x	x
Sample Size	119,121	26,878	119,764	129,878	129,065	129,052	119,764

This table presents alternative empirical specifications of the model relating the labor share to capital intensity and market share. The first three columns consider different definitions of the sample: (1) excluding firms that are only ever observed with one employee (potentially self-employed individuals operating as incorporated companies); (2) balanced sample of firms observed in all periods; (3) without winsorizing any variables. Column 4 presents the results of estimating the model in levels instead of logs. In column 5, the labor share and market share are in levels while capital intensity is in logs, and in column 6, only the labor share is in levels. In column 7, the square of capital intensity is included and the reported coefficient is the elasticity calculated at the sample mean. Coefficients represent long-run elasticities. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for first and second-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied to GMM. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 6. ALTERNATIVE MEASURES OF THE LABOR SHARE, CAPITAL INTENSITY, AND PRODUCT MARKET POWER

	Wage Share	Share of Sector Value Added	Market Share in Sector and Region	Non-Tradable Sectors	Markup
	(1)	(2)	(3)	(4)	(5)
Capital Intensity	-0.070***	-0.068***	-0.079***	-0.076**	-0.045
	(0.023)	(0.021)	(0.022)	(0.037)	(0.030)
Product Market Power	-0.201***	-0.154***	-0.158***	-0.108***	-0.660***
	(0.028)	(0.030)	(0.020)	(0.027)	(0.091)
Serial Correlation Test					
1st Order	0.000	0.000	0.000	0.000	0.000
2nd Order	0.685	0.458	0.616	0.076	0.315
Overidentification Test	0.352	0.253	0.521	0.692	0.626
Year FE	x	x	x	x	x
Sector FE	x	x	x	x	x
Region FE	x	x	x	x	x
Sample Size	115,977	119,764	119,764	52,564	119,764

This table presents variations of the main GMM specification in column 3 of Table 4 using different definitions of the main variables of interest. In column 1, the dependent variable is the log of the wage share, defined as wages excluding non-wage compensation divided by value added. In column 2, market share is calculated as the share of total value added within a 4-digit sector. In columns 3 and 4, market share is calculated as sales share within a 4-digit sector and NUTS3 region (approximately a county), with the sample in column 4 limited to firms in non-tradable sectors. In column 5, the market share is replaced by the markup, calculated as the log of the ratio of value added before employment expense to revenues, as an alternative measure of market power. Coefficients represent long-run elasticities. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for first and second-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied to GMM. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 7. UNDERSTANDING HOW CAPITAL INTENSITY IMPACTS THE LABOR SHARE

	(1)	(2)	(3)
Tangible Capital Intensity (Low-Wage Firms)	-0.126**	-0.078***	-0.096**
	(0.053)	(0.019)	(0.043)
Tangible Capital Intensity (High-Wage Firms)	-0.034		-0.054*
	(0.032)		(0.029)
Intangible Capital Intensity (Low-Wage Firms)		0.023	-0.001
		(0.014)	(0.016)
Intangible Capital Intensity (High-Wage Firms)			0.039*
			(0.023)
Market Share	-0.190***	-0.158***	-0.161***
	(0.027)	(0.024)	(0.023)
Serial Correlation Test			
1st Order	0.000	0.000	0.000
2nd Order	0.576	0.706	0.833
Overidentification Test	0.444	0.400	0.433
Sample Size	119,764	118,500	118,500

This table extends the main GMM results from column 3 of Table 4 to further explore the relationship between capital intensity and the labor share. Tangible capital intensity is the log of the book value of tangible assets per employee (the same variable as capital intensity in Table 4). Intangible capital intensity is the log of the book value of intangible assets per employee. The high-wage firm indicator equals 1 if the firm is, on average, in the top half of the annual wage distribution during its presence in the sample, as a proxy for the average skill level of its workforce. Intangible capital All columns include year, sector, and region fixed effects. Coefficients represent long-run elasticities. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for first and second-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied to GMM. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 8. HUMAN CAPITAL, LABOR MARKET POWER, AND THE LABOR SHARE

	Human Capital	Recruits from Non-Employment	Employer Count		Effective Labor
			Region	Region-Industry	
	(1)	(2)	(3)	(4)	(5)
Capital Intensity	-0.078***	-0.078***	-0.080***	-0.079***	-0.084***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)
Market Share	-0.184***	-0.184***	-0.182***	-0.183***	-0.179***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Labor Market Power		-0.326***	-0.023***	-0.015***	
		(0.102)	(0.006)	(0.005)	
College %	-0.255***	-0.272***	-0.270**	-0.266**	
	(0.111)	(0.111)	(0.112)	(0.112)	
Other Higher Ed. %	-0.149	-0.134	-0.181	-0.183	
	(0.151)	(0.152)	(0.151)	(0.152)	
High School %	0.079	0.071	0.069	0.072	
	(0.124)	(0.125)	(0.125)	(0.125)	
Low Qualifications %	-0.102	-0.090	-0.117	-0.122	
	(0.141)	(0.142)	(0.143)	(0.143)	
Other Qualifications %	-0.328***	-0.347**	-0.354**	-0.343**	
	(0.135)	(0.137)	(0.137)	(0.137)	
No Qualifications %	-0.126	-0.128	-0.130	-0.133	
	(0.151)	(0.151)	(0.152)	(0.153)	
Avg Experience	-0.022	-0.020	-0.021	-0.018	
	(0.014)	(0.014)	(0.014)	(0.014)	
Avg Experience^2	0.001	0.000	0.001	0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	
Female %	0.135	0.130	0.144*	0.158*	
	(0.085)	(0.086)	(0.086)	(0.086)	
Non-White %	-0.092	-0.112	-0.073	-0.075	
	(0.107)	(0.108)	(0.108)	(0.108)	
UK-Born %	0.110	0.130	0.114	0.130	
	(0.103)	(0.103)	(0.103)	(0.104)	
Part-Time %	-0.600***	-0.612***	-0.604***	-0.590***	
	(0.107)	(0.108)	(0.107)	(0.107)	
Participation Rate	-0.455*	-0.552**	-0.433	-0.437	
	(0.274)	(0.279)	(0.274)	(0.274)	
Serial Correlation Test					
1st Order	0.000	0.000	0.000	0.000	0.000
2nd Order	0.912	0.957	0.910	0.907	0.825
Overidentification Test	0.500	0.488	0.506	0.511	0.493
Sample Size	119,764	119,764	119,362	119,362	119,764

This table adds human capital controls and measures of labor market power to the main specification from column 3 of Table 4. Coefficients represent long-run elasticities from GMM estimation. All columns include year, sector, and region fixed effects. Columns 1-4 also include human capital controls, defined as: the proportion of employees that are female, non-white, UK-born, married, part-time, and with different qualification levels; average years of education, experience, experience squared; and the participation rate – each calculated within a 1-digit sector, NUTS1 region, and year using the Labor Force Survey. Labor market power is defined as the proportion of recruits from non-employment in a sector-region cell in column 2; log of the total number of firms in the same NUTS3 region times -1 in column 3; and log of the total number of firms in the same NUTS3 region and 2-digit sector times -1 in column 4. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for 1st and 2nd-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors are clustered by firm, with Windmeijer's (2005) finite-sample correction. *** p<0.01, ** p<0.05, * p<0.10.

Online Appendix A – Time Series Properties of Key Variables

This Appendix provides evidence that the main variables of interest are persistent—a pattern that motivates the use of a dynamic model of the labor share in the empirical analysis. The analysis is similar to that carried out by Blundell and Bond (2000) in the context of estimating firm production functions.

Table A1 reports simple AR(1) specifications of the labor share, capital intensity, and market share variables, estimated using the OLS, within-firm, difference GMM, and system GMM estimators. The reason for showing this range of estimators is that each of them may be biased under different conditions, but they can be used together to draw conclusions about the persistence of each series. For example, in the presence of firm-specific effects, OLS estimates of are expected to be biased upwards, while within-firm estimates are expected to be biased downwards. The OLS results in column 1 and the within-firm results in column 2 thus bracket the autoregressive coefficient. They suggest that capital intensity and market share are indeed highly persistent, while the labor share is somewhat less so.

GMM results help pin down the degree of persistence of each series. Column 3 shows difference GMM estimates, which model the process in differences and use lagged levels dated $t-2$ or earlier are instruments for the lagged first difference of the dependent variable. These estimates suggest that while capital intensity is much more highly persistent than the labor share and the market share. However, difference GMM can be biased towards the within-firm estimator in finite samples when the instruments are weak.[17] Column 4 therefore reports the results of the system GMM estimator, which can help address this bias under certain conditions (see Blundell and Bond, 2000). The system GMM specification reported here uses lagged levels dated $t-2$ or earlier as instrumented in the first-differenced equation

[17] Table A2 estimates reduced-form "first-stage" equations for the last year of the sample, when the greatest number of lagged values is available to serve as instruments. It hows that the instruments for the lagged difference of capital intensity and the market share in the first-differenced AR(1) model do indeed appear to be weaker than in the case of the labor share.

and the lagged difference dated $t-1$ as an instrument in the levels equation. The results suggest that both capital intensity and the market share are highly persistent, with autoregressive coefficients greater than 0.9 and relatively similar to the OLS results in column 1, which served as an upper bound for the estimates. This persistence motivates the use of a dynamic specification in the main body of the paper.

TABLE A1. AUTOREGRESSIVE MODELS OF THE MAIN VARIABLES OF INTEREST

	OLS (1)	Within Firms (2)	Difference GMM (3)	System GMM (4)
(a) Labor share				
Labor share (t-1)	0.598***	-0.017***	0.137***	0.149***
	(0.005)	(0.006)	(0.009)	(0.009)
Overidentification test			0.000	0.000
1st order serial correlation	0.000	0.000	0.000	0.000
2nd order serial correlation	0.000	0.000	0.778	0.381
Observations	119,764	119,764	92,418	119,764
(b) Capital intensity				
Capital intensity (t-1)	0.971***	0.471***	0.757***	0.921***
	(0.001)	(0.008)	(0.035)	(0.011)
Overidentification test			0.000	0.000
1st order serial correlation	0.000	0.000	0.000	0.000
2nd order serial correlation	0.000	0.000	0.476	0.692
Observations	119,764	119,764	93,513	119,764
(c) Market share				
Market share (t-1)	0.996***	0.486***	0.409***	0.935***
	(0.000)	(0.007)	(0.043)	(0.011)
Overidentification test			0.000	0.000
1st order serial correlation	0.000	0.000	0.000	0.000
2nd order serial correlation	0.000	0.000	0.076	0.972
Observations	119,764	119,764	89,523	119,764

This table presents the results of AR(1) regressions. Column 1 presents estimates of ρ from the regression $y_{it} = \alpha + \rho y_{i,t-1} + \delta_t + v_{it}$ estimated using OLS, where y_{it} is the labor share in panel A, capital intensity in panel B, and market share in panel C. Column 2 presents within-group estimates of the model. Column 3 presents GMM estimates of the model in first differences, with lags of y_{it} dated $t-2$ and earlier used as instruments for $\Delta y_{i,t-1}$. Column 4 presents system GMM estimates, where the lagged first difference of y_{it} is additionally used as an instrument for $y_{i,t-1}$ in the equation in levels. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for 1st and 2nd-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied to GMM. * p<0.10, ** p<0.05, *** p<0.01

TABLE A2. REDUCED-FORM EQUATIONS FOR 2012

	First Differences (1)	Levels (2)
(a) Labor share		
F-statistic	161.075	39.502
R^2	0.273	0.041
Observations	10,290	10,290
(b) Capital intensity		
F-statistic	16.244	268.467
R^2	0.021	0.138
Observations	10,942	10,942
(c) Market share		
F-statistic	3.059	41.253
R^2	0.011	0.025
Observations	8,417	8,417

This table presents reduced-form "first-stage" results for the last year of the sample when the greatest number of lagged values is available to serve as instruments. Column 1 (first differences) is an OLS regression of $\Delta x_{i,t-1}$ on $x_{i,t-2}, x_{i,t-3}, \dots, x_{i,t-7}$, where x is the labor share in panel A, capital intensity in panel B, and market share in panel C. Column 2 (levels) is an OLS regression of $x_{i,t-1}$ on $\Delta x_{i,t-2}, \Delta x_{i,t-3}, \dots, \Delta x_{i,t-6}$. The F-statistic reflects a test of the null hypothesis that the slope coefficients are jointly zero. * p<0.10, ** p<0.05, *** p<0.01

Online Appendix B – GMM Assumptions and Instrument Validity

This Appendix discusses the conditions required for the consistency of the econometric estimates given in the paper and provides evidence that these conditions are satisfied. Consistency of the System GMM estimates relies on three assumptions. The first is instrument validity. Instruments are valid if they are strong predictors of the potentially endogenous regressors (relevance), while only affecting the current labor share through the endogenous variables (exclusion restriction). The second assumption is that the disturbances ε_{it} are serially uncorrelated. Third, the use of the levels equation requires an additional assumption of stationarity. I review each of these assumptions below.

I begin by testing whether the lags of the labor share, capital intensity, and market share satisfy the instrument relevance requirement. Consider the market share variable as an example. The market share at time $t-2$ and $t-3$ (instruments in the differenced equation) needs to be highly correlated with the year-over-year change in the market share observed at time t and $t-1$ (the endogenous regressors). Similarly, in the levels equation, the lagged market share changes at time $t-1$ and $t-2$ need to be good predictors of the levels at time t and $t-1$.

Table B1 reports the results of first-stage regressions that correspond to the main GMM specification in column 5 of Table 3. Panel (a) considers the equation in differences, while panel (b) considers the equation in levels. Within each panel, the first row shows the F-statistic from the test of joint significance of the instruments in a regression of the endogenous variable on its lags without any controls. The second row reports the same test statistic after controlling year, sector, and region fixed effects. Finally, the third row controls additionally for all other instruments in the model. The third row represents a standard first stage equation in instrumental variable estimation.

Column (1) of panel (a) shows that the second and third lags of the labor share are strong predictors of the first lag of the change in the labor share. The F-statistic is 4,014.1 when all the controls and instruments are included. Columns (2) and (3) show the strength of the instruments for the current and lagged difference of capital intensity (F-statistics of 219.2 and 265.7, respectively). Finally, columns (4) and (5) show that the instruments for the current and lagged change in market share are also strong (F-statistics of 27.6 and 147.2, respectively). Similarly, in panel (b), which tests the relevance of instruments in the levels equation, all instruments are very strong predictors of the potentially endogenous regressors (F-statistics of 206.9 or greater). Therefore, the first-stage results indicate that inference in the GMM model is unlikely to be affected by problems caused by weak instruments.

The exclusion restriction is more difficult to test directly but can be assessed in two ways. The first is through the Hansen test of overidentifying restrictions. Table B2 reports the results for the baseline specification. Part (a) shows that the null hypothesis of joint instrument validity cannot be rejected for the model as a whole (p-value 0.459). Parts (b) through (d) test several subsets of the instrument set for the levels equation and the first-difference equation separately. The results indicate that the satisfactory overall outcome of the Hansen test is not driven by any single component of the model.[18]

One potential concern with the Hansen test is that it can be weakened by the presence of many instruments. An alternative, intuitive way to evaluate the validity of the exclusion restriction consists of removing each candidate instrument from the GMM instrument matrix, including it directly in the estimated `second-stage' model, and checking that it is insignificant, conditional on the remaining instruments. Table B3 presents the results of this test. None of the coefficients on the tested instruments in columns (1) to (6) are significantly

[18] In the case of capital intensity, the null hypothesis that the second and third lag are exogenous instruments for the difference equation is rejected at a significance level only slightly greater than 10%. Replacing the second lag with the fourth lag improves the Hansen test result for this subset of instruments (p-value 0.510) without materially affecting the estimated coefficients in the model or other diagnostic tests.

different from zero. This result does not suggest any correlation between the instruments and the error term of the estimated model, providing further reassurance about the validity of the instruments in the GMM model used to estimate the relationship between a firm's labor share and its capital intensity and market share.

Besides instrument validity, consistent estimation of the model relies on the assumption that the disturbances ε_{it} are serially uncorrelated, as specified by equation (6). This can be verified by testing for first and second-order serial correlation in the first-differenced residuals (Arellano and Bond, 1991). We would expect negative first-order serial correlation, but no second-order or higher-order serial correlation, in the first-differenced residuals, under the maintained assumptions. The results of these tests are reported in each of the regression tables discussed in Section 6. Together with the conclusions of this Appendix, they suggest that the moment conditions are well-specified.

The use of the levels equation requires two additional assumptions. First, the first differences of the two explanatory variables, capital intensity and market share, should be uncorrelated with the firm fixed effect a_i in equation (4). Second, the model specified by equation (4) needs to be the correct specification for labor shares "sufficiently long" before the first observation in the panel (Blundell and Bond, 2000).

Three tests suggest that this condition applies sufficiently well in the sample. First, limiting the sample to a balanced panel of firms that are present in every year of the sample period, and are more likely to be older and well-established, gives similar results as the main sample (see the discussion of robustness checks and Table 5 in Section 6). Second, the results are similar when limiting the sample directly to firms aged 10 years or more in the first year of the sample period, based on the year of incorporation (see Table C1). Third, the validity of the instruments for the levels equation is tested specifically via a Difference Hansen test in Table B2. None of these diagnostics highlight any concerns.

A final potential problem with GMM estimation relates to overfitting. As the time dimension of the panel increases, the set of possible instruments rises, since more past values of each variable become available. In practice, however, using too many instruments may bias the results (Roodman, 2009). While it is difficult to say exactly how many instruments are "too many," symptoms of overfitting include an implausibly perfect p-value of 1.000 in the Hansen test of overidentifying restrictions. To avoid overfitting, I limit the number of instruments to the lagged levels dated $t-2$ and $t-3$ in the first-difference equation and lagged differences dated $t-1$ and $t-2$ in the levels equation, rather than using all past values. The first-stage results reported in Table B1 and discussed in this Appendix show that these instruments are sufficiently strong to obviate the need for a greater number of them.

The empirical model, which flexibly incorporates the standard assumptions from the literature on estimating production functions, thus appears to be well-specified in responding to concerns about serial correlation and potential endogeneity of the variables of interest.

TABLE B1. FIRST-STAGE REGRESSIONS

(a) Difference equation

	Labor share	Capital intensity		Market share	
	$\Delta s_{i,t-1}^{L}$	$\Delta\left(\frac{K}{L}\right)_{it}$	$\Delta\left(\frac{K}{L}\right)_{i,t-1}$	Δs_{it}^{M}	$\Delta s_{i,t-1}^{M}$
	(1)	(2)	(3)	(4)	(5)
Joint significance of the instruments: lagged levels (t-2 and t-3) (F-statistic):					
(1) No Controls	4,447.1	150.5	181.1	19.9	88.8
(2) Year, Sector, Region FE	4,842.6	235.2	280.5	34.8	130.4
(3) All Instruments	4,014.1	219.2	265.7	27.6	147.2

(b) Levels equation

	Labor share	Capital intensity		Market share	
	$s_{i,t-1}^{L}$	$\left(\frac{K}{L}\right)_{it}$	$\left(\frac{K}{L}\right)_{i,t-1}$	$s_{i,t-1}^{M}$	$s_{i,t-1}^{M}$
	(1)	(2)	(3)	(4)	(5)
Joint significance of the instruments: lagged differences (t-1 and t-2) (F-statistic):					
(1) No Controls	12,025.2	1,354.7	1,942.4	206.9	259.2
(2) Year, Sector, Region FE	12,990.9	1,321.9	2,007.9	362.6	477.6
(3) All Instruments	10,506.6	1,082.0	1,671.4	335.9	468.1

First-stage regressions for the endogenous variables in the main GMM specification in column 3 of Table 4. In panel (a), the dependent variables are in first differences and the instruments are the second and third lagged difference. In panel (b), the dependent variables are in levels and the instruments are the first and second lagged difference. F-statistics test the joint significance of the two instruments for each potentially endogenous regressor. Estimation method: least squares. Robust standard errors (in parentheses) are clustered by firm. The sample size is 119,764.

TABLE B2. TESTS OF OVERIDENTIFYING RESTRICTIONS

	p-value (H$_0$: the instrument set is exogenous
Hansen test	
(a) Overall model	0.459
Difference Hansen test for instrument subsets	
(b) Instruments for the difference equation	
(i) Labor share	0.275
(ii) Capital intensity	0.102
(iii) Market share	0.556
(c) Instruments for the levels equation	
(i) Labor share	0.392
(ii) Capital intensity	0.258
(iii) Market share	0.986
Observations	119,764

Part (a) reports the Hansen test of overidentifying restrictions for the main GMM specification in column 3 of Table 4. Parts (b) and (c) report the Difference Hansen tests of exogeneity for selected instrument subsets. Tests statistics are asymptotically chi-squared distributed with the degrees of freedom equal to the number of instruments in the given subset. The null hypothesis in each test is that the instruments are exogenous. The sample size is 119,764.

TABLE B3. ADDITIONAL TESTS OF OVERIDENTIFICATION

(a) Difference equation

	(1)	(2)	(3)	(4)	(5)	(6)
Instruments tested in the second stage: lagged levels (t-2 and t-3)						
Labor share, $s^L_{i,t-2}$	0.002					
	(0.015)					
Labor share, $s^L_{i,t-3}$		0.025				
		(0.022)				
Capital intensity, $(K/L)_{i,t-2}$			0.005			
			(0.006)			
Capital intensity, $(K/L)_{i,t-3}$				0.003		
				(0.006)		
Market share, $s^M_{i,t-2}$					0.013	
					(0.012)	
Market share, $s^M_{i,t-3}$						-0.004
						(0.020)
Serial correlation test						
1st order	0.000	0.109	0.000	0.000	0.000	0.000
2nd order	0.341	0.730	0.381	0.116	0.387	0.093
Overidentification test	0.818	1.000	0.841	0.915	0.635	0.828

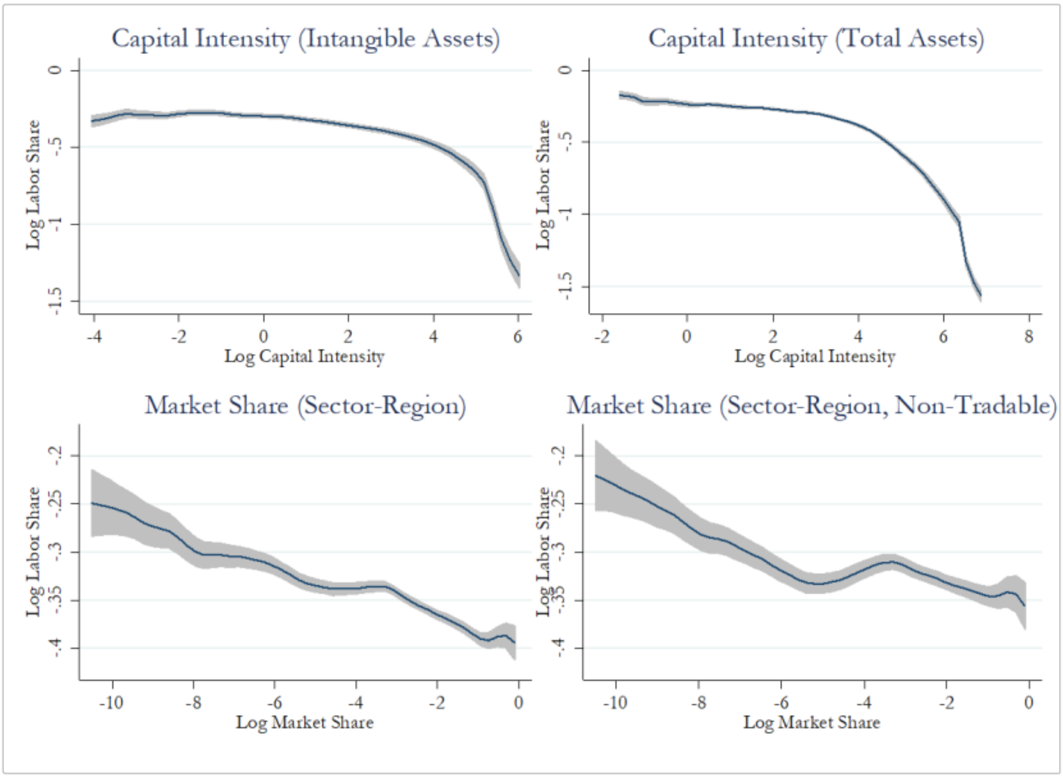
(b) Levels equation

	(1)	(2)	(3)	(4)	(5)	(6)
Instruments tested in the second stage: lagged differences (t-1 and t-2)						
Labor share, $\Delta s^L_{i,t-1}$	-0.002					
	(0.015)					
Labor share, $\Delta s^L_{i,t-2}$		0.003				
		(0.008)				
Capital intensity, $\Delta(K/L)_{i,t-1}$			-0.005			
			(0.006)			
Capital intensity, $\Delta(K/L)_{i,t-2}$				0.001		
				(0.006)		
Market share, $\Delta s^M_{i,t-1}$					-0.013	
					(0.012)	
Market share, $\Delta s^M_{i,t-2}$						0.008
						(0.011)
Serial correlation test						
1st order	0.000	0.000	0.000	0.000	0.000	0.000
2nd order	0.341	0.069	0.381	0.104	0.387	0.109
Overidentification test	0.818	0.844	0.841	0.753	0.635	0.311

This table presents additional, intuitive tests of instrument exogeneity. In each column one of the instruments from the main GMM specification in column 3 of Table 4 is excluded from the instrument matrix and entered directly into the estimated model. The serial correlation test is the Arellano and Bond (1991) test for first and second-order serial correlation (p-values reported). The overidentification test is the Hansen test of overidentifying restrictions (p-value reported). Standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied. The sample size is 119,764. * p < 0.10, ** p < 0.05, *** p < 0.01.

Online Appendix C – Additional Figures and Tables

FIGURE C1. ALTERNATIVE MEASURES OF CAPITAL INTENSITY AND MARKET SHARE



Local polynomial plots of the log labor share against alternative measures of capital intensity and market share for the GMM estimation sample from column 3 of Table 4: (a) real intangible assets per employee, (b) real total fixed assets per employee, (c) market share in a 4-digit sector and NUTS3 region, (d) market share in a 4-digit sector and NUTS3 region for the sub-sample of firms in non-tradable sectors (52,564 obs.). The shaded areas correspond to 95% confidence intervals.

TABLE C1. TESTING THE VALIDITY OF USING THE LEVELS EQUATION IN SYSTEM GMM

	Firms Aged 10+
	(1)
Capital Intensity	-0.067**
	(0.031)
Market Share	-0.213***
	(0.036)
Serial correlation test	
1st order	0.000
2nd order	0.846
Overidentification test	0.339
Year FE	x
Sector FE	x
Region FE	x
Sample Size	83,485

This table tests the validity of using the levels equation in System GMM by checking whether the results are similar to the main specification in column 3 of Table 4 when the sample is limited to firms that have been incorporated for 10 years or more by the first year of the sample period. See the main text for details. Coefficients represent long-run elasticities. Serial correlation test: p-value for the null hypothesis of no serial correlation from the Arellano and Bond (1991) test for first and second-order serial correlation. Overidentification test: p-value for the null hypothesis of instrument exogeneity from the Hansen test of overidentifying restrictions. Robust standard errors clustered by firm are in parentheses, with Windmeijer's (2005) finite-sample correction applied to GMM. *** p<0.01, ** p<0.05, * p<0.10.

TABLE C2. HIGH- AND LOW-WAGE FIRMS

	Distribution of sample firms by sector		Data on the employee population by sector			
			(a) Wages		(b) Skill level	
Sector	Low-wage firms (%)	High-wage firms (%)	Mean gross earnings (£/week)	Median gross earnings (£/week)	Employees with a college degree (%)	Average education (years)
A Agriculture, forestry, and fishing	2.1	1.0	324	288	14.7	12.5
B+D+E Mining, energy, and water supply	1.3	3.1	678	531	24.1	12.8
C Manufacturing	25.6	29.8	603	462	19.7	12.7
F Construction	8.7	13.4	579	500	17.2	12.4
G Wholesale, retail, repair of vehicles	30.8	22.9	298	243	13.7	12.5
H Transport and storage	3.6	3.2	495	423	13.4	12.3
I Accommodation and food services	12.3	0.8	212	157	14.1	12.9
J Information and communication	3.0	8.6	734	635	57.8	15.0
L Real estate activities	2.0	1.6	417	369	27.2	13.1
M Professional, scientific, technical activities	3.6	7.7	669	577	55.9	14.8
N Administrative and support services	7.1	8.0	373	308	18.8	12.8
Total	100.0	100.0				

This table shows the sectoral distributions of high- and low-wage firms in the sample and provides weighted population estimates of wages and qualifications by sector using the Labour Force Survey for the April-June quarter 2012. High-wage firms are defined as those whose total compensation per employee is greater than the year's median, on average during these firms' appearance in the sample. Years of education are calculated as the age when the individual's educational highest qualification was obtained minus five.

Appendix D – Mathematical Derivations
(Not intended for publication)

This appendix contains the following supporting material:
(a) derivations of equations (1), (3), and (5) in the main text;
(b) calculations that support the interpretation of the estimated elasticities in Section 6.

Mathematical derivations of key equations

<u>Equation (1)</u>

This equation relates the labor share of income to the partial elasticity of output with respect to labor and the price elasticity of demand in a simple, partial-equilibrium model of a profit-maximizing firm operating in an imperfectly competitive product market.

Consider firm i with the production function $Y_i = Y(A_i L_i, B_i K_i)$, where Y_i is output, L_i is labor, K_i is capital, and A_i and B_i are labor- and capital-augmenting productivity, respectively. Abstracting from the multiplicative productivity parameters for notational simplicity, the firm's profit maximization problem is

$$\max_{L_i, K_i} \pi_i = P(Y_i)\, Y(L_i, K_i) - wL_i - rK_i.$$

The first-order condition with respect to labor is

$$w = P'(Y_i)\, Y_L(L_i, K_i)\, Y(L_i, K_i) + P(Y_i)\, Y_L(L_i, K_i),$$

where $Y_L(L_i, K_i)$ is the partial derivative of output with respect to labor. Rearranging the right-hand side gives

$$\begin{aligned} w &= Y_L(L_i, K_i)\, [P(Y_i) + P'(Y_i)\, Y(L_i, K_i)] \\ &= Y_L(L_i, K_i)\, P(Y_i) \left(1 + \frac{P'(Y_i)}{P(Y_i)}\, Y(L_i, K_i)\right) \\ &= Y_L(L_i, K_i)\, P(Y_i) \left(1 + \frac{1}{\eta_i}\right) \end{aligned}$$

where $\eta_i = \frac{\partial Y_i}{\partial P_i} \frac{P_i}{Y_i}$ is the price elasticity of demand. In other words, the marginal cost of labor equals the marginal revenue product of labor times the markup. When this first-order condition is satisfied, the labor share is

$$\begin{aligned} s_i^L &\equiv \frac{wL_i}{P_i(Y_i) Y_i(L_i, K_i)} \\ &= \frac{L_i}{P_i(Y_i) Y_i(L_i, K_i)} \left(P_i(Y_i) Y_L(L_i, K_i) \left(1 + \frac{1}{\eta_i}\right)\right) \\ &= \frac{Y_L(L_i, K_i) L_i}{Y(L_i, K_i)} \left(1 + \frac{1}{\eta_i}\right) \end{aligned}$$

Setting $\varepsilon_i^{YL} = Y_L(L_i, K_i)\frac{L_i}{Y_i}$, the partial elasticity of output with respect to labor, the labor share is thus given by

$$s_i^L = \varepsilon_i^{YL}\left(1 + \frac{1}{\eta_i}\right) \tag{1}$$

as shown in the main text.

If the production function is Cobb-Douglas, then ε_i^{YL} is constant, and the labor share will only be a function of the price elasticity of demand. If the production function is not Cobb-Douglas, then ε_i^{YL} will be a function of capital, labor, and the productivity parameters, such that the labor share will depend on both the price elasticity of demand and the factor inputs.

The derivation of equation (8) in the main text follows a similar process, allowing additionally for imperfect competition in the labor market.

Equation (3)

This equation relates a firm's market share to the price elasticity of demand in an illustrative version of a Cournot model with n profit-maximizing firms, each producing a homogeneous product with marginal cost c_i, and linear inverse demand, $P = a - bQ$, where $Q = \sum_i q_i = q_i + q_{-i}$ is total quantity produced.

The market share of firm i is the ratio of the quantity produced by that firm to total quantity produced in the market,

$$s_i^M \equiv \frac{q_i}{Q}$$

The Nash equilibrium solution for each firm's output q_i and total quantity Q arises from the optimal response of each firm to the choices of the remaining firms. In this model, firm i's profit is

$$\pi_i = P(q_i + q_{-i})q_i - c_i q_i.$$

The profit-maximizing first-order condition is thus

$$\frac{\partial P}{\partial q_i} q_i + P - c_i = 0.$$

Given linear demand, this is equivalent to

$$-bq_i + \big(a - b(q_i + q_{-i})\big) - c_i = 0. \tag{C.1}$$

Thus, as a function of total quantity produced, and using $Q = q_i + q_{-i}$, firm i produces

$$q_i = \frac{a - c_i - bQ}{b}. \tag{C.2}$$

To solve for the total quantity produced in the market as a function of the model parameters, note that equation (C.1) yields the system

$$-bq_1 + (a - bQ) - c_1 = 0$$
$$-bq_2 + (a - bQ) - c_2 = 0$$
$$\vdots$$
$$-bq_n + (a - bQ) - c_n = 0$$

Adding these n equations together pins down the relationship between total quantity produced, the number of firms, marginal costs, and the slope and intercept of the demand curve:

$$-bQ + n(a - bQ) - n\bar{c} = 0,$$

where $\bar{c} = \frac{1}{n}\sum_{i=1}^{n} c_i$ is average marginal cost in the market. Rearranging for Q, total quantity produced is thus

$$Q = \frac{n}{n+1}\frac{a - \bar{c}}{b}. \tag{C.3}$$

Combining (C.2) and (C.3) gives an expression for firm i's market share as

$$s_i^M \equiv \frac{q_i}{\sum_i q_i} = \frac{n+1}{n}\frac{a - c_i}{a - \bar{c}} - 1. \tag{C.4}$$

To see how the market share can be expressed in terms of the price elasticity of demand η, note that

$$\begin{aligned}
\eta &\equiv \frac{dQ}{dP}\frac{P}{Q} \\
&= -\frac{1}{b}\left(\frac{a - bQ}{Q}\right) \\
&= 1 - \frac{a}{bQ} \\
&= 1 - \frac{a}{\frac{n}{n+1}(a - \bar{c})} \\
&= -\frac{a + n\bar{c}}{n(a - \bar{c})}
\end{aligned}$$

Rearranging,

$$n(a - \bar{c}) = -\frac{a + n\bar{c}}{\eta}.$$

Substituting into (C.4), the market share can be expressed as

$$s_i^M = \frac{(n+1)(a - c_i)}{a + n\bar{c}}(-\eta) - 1. \tag{3}$$

This illustrates a possible link between firm market shares and the price elasticity of demand in an instance of a model of imperfect competition.

Equation (5)

The autoregressive distributed lag model given by equation (5) can be derived by imposing a specific form of serial correlation on the time-varying component of the error term, v_{it}, in equation (4). Suppose that this variable follows an AR(1) process, such that we have a model given by:

$$s_{it}^{L} = \beta_1 \left(\frac{K_{it}}{L_{it}}\right) + \beta_2 s_{it}^{M} + \theta_j + \varphi_r + \delta_t + (a_i + v_{it}) \quad (4)$$

$$v_{it} = \rho v_{i,t-1} + \varepsilon_{it} \quad (4b)$$

$$\varepsilon_{it} = MA(0) \quad (4c)$$

Solving equation (4) for v_{it} and solving its lagged version for $v_{i,t-1}$ gives

$$v_{it} = s_{it}^{L} - \beta_1 \left(\frac{K_{it}}{L_{it}}\right) - \beta_2 s_{it}^{M} - \theta_j - \varphi_r - \delta_t - a_i$$

and

$$v_{i,t-1} = s_{i,t-1}^{L} - \beta_1 \left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) - \beta_2 s_{i,t-1}^{M} - \theta_j - \varphi_r - \delta_{t-1} - a_i.$$

Substituting these expressions into equation (4b) gives the autoregressive distributed lag specification,

$$s_{it}^{L} = \rho s_{i,t-1}^{L} + \beta_1 \left(\frac{K_{it}}{L_{it}}\right) - \rho\beta_1 \left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \beta_2 s_{it}^{M} - \rho\beta_2 s_{i,t-1}^{M} + (\delta_t - \rho\delta_{t-1})$$
$$+(1-\rho)(\theta_j + \varphi_r + a_i) + \varepsilon_{it}.$$

First-differencing to remove the time-invariant firm effect, we obtain

$$\Delta s_{it}^{L} = \rho\Delta s_{i,t-1}^{L} + \beta_1 \Delta\left(\frac{K_{it}}{L_{it}}\right) - \rho\beta_1 \Delta\left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \beta_2 \Delta s_{it}^{M} - \rho\beta_2 \Delta s_{i,t-1}^{M} + \Delta\varepsilon_{it}.$$

This is equivalent to

$$\Delta s_{it}^{L} = \rho\Delta s_{i,t-1}^{L} + \pi_1 \Delta\left(\frac{K_{it}}{L_{it}}\right) + \pi_2 \Delta\left(\frac{K_{i,t-1}}{L_{i,t-1}}\right) + \pi_3 \Delta s_{it}^{M} + \pi_4 \Delta s_{i,t-1}^{M} + \Delta\varepsilon_{it}, \quad (7)$$

where $\pi_1 = \beta_1$, $\pi_2 = -\rho\beta_1$, $\pi_3 = \beta_2$, and $\pi_4 = -\rho\beta_2$. This equation can be estimated consistently using GMM, as described in the main text.

Interpreting the estimated elasticities in Section 6

Section 6 interprets the estimated long-term elasticities from Column 3 of Table 7 by (a) calculating the estimated labor share reduction that would result from a 1 percentage-point increase in the market share of an average firm in the sample, and (b) calculating the estimated increase in net tangible assets per employee that would be required to reduce the labor share by the same amount as in (a).

The corresponding calculations are as follows. The mean market share in the 4-digit sector is 1.6%. Hence, a 1.2 percentage point rise in the market share corresponds to a 74% increase for the average firm. Multiplying the estimated elasticity of -0.161 by 74% implies a 12% reduction in the labor share. Since the mean labor share in the data is 0.83, this suggests a 10 percentage-point decline in the labor share of the average firm, holding capital intensity constant.

Similarly, a £42,000 increase in net tangible assets per employee is a 123% increase for the average low-wage firm, given that the mean of this variable in the sample of low-wage firms is £34,063. Multiplying the estimated elasticity of -0.096 by 123% gives a 12% reduction in the labor share, which, as above, corresponds to 10 percentage points for the average low-wage firm with the labor share of 0.84. This increase in net tangible assets is approximately 1.4 times the median annual employee compensation cost in the sample of firms (£29,508). The calculations for the average high-wage firm are carried out in a similar way, based on mean net tangible assets per employee of £44,500 and mean labor share of 0.82.

Section 6 also calculates the estimated percentage-point reduction in the labor share for a 1 standard-deviation increase in market share or capital intensity for the average firm. In the sample, the mean market share is 1.6% and the standard deviation is 4.4%. Dividing the standard deviation by the mean and multiplying by the estimated elasticity of -0.161 gives a 44% reduction in the labor share. For the average firm with the labor share of 0.83, this implies a reduction of 36.8 percentage points.

Similarly, the standard deviation of capital intensity (£81,292 and £117,114 for low-wage and high-wage firms, respectively) divided by the mean (£34,063 and £44,500) and multiplied by the estimated elasticities (-0.096 and -0.054) gives a reduction in the labor share of 23% and 14%, respectively. This corresponds to a 19.3 and 11.7 percentage-point fall in the mean labor share for the average low-wage and high-wage firm in the sample, respectively.