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Explaining the Labor Share: Automation Vs Labor Market Institutions[☆]

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ABSTRACT

We propose a simple model to assess the evolution of the US labor share and how automation affects employment. In our model, heterogeneous firms may choose a manual technology and hire a worker subject to matching frictions. Alternatively, they may choose an automated technology and produce using only machines (robots). Our model suggests that automation reduces the labor share but increases employment and wages. Furthermore, our model suggests that labor market institutions are unlikely to have played a major role in the fall of the US labor share after 1987. Instead, technological factors are a more promising candidate.

1. Introduction

1.1. Motivation & contribution

The stationarity of the labor share of aggregate income was a celebrated stylized fact of the 20th century: although new technologies were continuously introduced, the labor share apparently fluctuated around the same level (Kaldor, 1961; Jones and Romer, 2010). Yet, starting at the late 20th century, a number of authors questioned this stylized fact

and pointed out the decline of the labor share in developed countries including the US. More recently, new empirical evidence has suggested a sustained downward trend of the labor share in a wider range of countries, including both advanced and developing countries.¹

In light of the overwhelming evidence of a downward trend in the labor share, the literature shifted towards understanding its causes. Two prominent groups emerged within this literature. One group has focused on how technological change and the technological structure of the economy may affect the labor share. Namely, this group has em-

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¹ For earlier contributions questioning the stationarity of the labor share, see, e.g., Blanchard (1997), Caballero and Hammour (1998), Berthold et al. (2002), Jones (2003), and Bentolila and Saint-Paul (2003). For more recent contributions, see, e.g., Bental and Demougin (2010), Elsby et al. (2013), Karabarbounis and Neiman (2014), Oberfield and Raval (2021), Dao et al. (2017), and Autor et al. (2020). There is, however, some controversy about the extent to which the fall in the labor share is driven by measurement issues. For example, Koh et al. (2020) argue that changes in the treatment of intangible capital has driven the reported secular decline in the US labor share. Yet, contrary to Koh et al. who study secular patterns of the labor share for the whole economy, in this paper we aim to explain the fall in the labor share in the US nonfarm business sector (i.e., abstracting from general government, nonprofit institutions, private households, Armed Forces, and farms) as reported by the BLS. Furthermore, as explained in more detail below, we do not aim to explain a secular trend in the labor share but rather explain why it falls more clearly after 1987. Finally, despite some controversy around the importance of mismeasurement issues in the evolution of the labor share, as argued by Autor et al., a general consensus exists that the labor share has indeed fallen in the recent decades.

phasized the roles of automation and robot- or automation-augmenting technological change (e.g., Acemoglu and Restrepo, 2018; Berg et al., 2018), falling price of capital (e.g., Karabarbounis and Neiman, 2014), the emergence of superstar firms together with overhead labor costs (e.g., Autor et al., 2020), and rising markups caused by a combination of changes to market structure and technological innovations (e.g., De Loecker et al., 2021; 2020).² Another group has analyzed the role of labor market institutions and their potential interaction with the technological structure of the economy. In these theories, either the shock emerges in the labor market (e.g., Caballero and Hammour, 1998), or the presence of labor market institutions is crucial for the transmission mechanism of technological shocks (e.g., Hornstein et al., 2007).³ Our paper belongs to the second group, but instead of analyzing how one particular shock shrinks the labor share, we assess which shocks are better candidates to explain the fall in the US labor share. Namely, we build a model with matching frictions to contrast the role of technological factors (automation-related technological change) with the role of changes in labor market institutions (falling workers' bargaining power and decreasing flows in the labor market). We conclude that technological factors are a more promising candidate to explain the fall in the US labor share.

Parallel to this debate, the observed increasing substitutability of machines for workers has raised concerns that machines will make labor redundant and eventually terminate employment (Acemoglu and Restrepo, 2018). Yet, so far, the empirical results indicate that automation, industrial robots, artificial intelligence, and routine-replacing technology shocks have not been employment-displacing at the aggregate level in developed economies (see Bessen et al., 2020 for a review of recent empirical evidence; see also Bessen, 2016, Autor and Salomons, 2018, and Gregory et al., 2021). Different models that allow for a fall in the labor share are unable to simultaneously generate an increase in employment (e.g., Caballero and Hammour, 1998; Zeira, 1998; Acemoglu and Restrepo, 2018). In contrast, our model concurs with the evidence: an automation shock reduces the labor share but increases both employment and wages.

Our paper contributes to the literature in two other ways because of its different approach. First, we propose a rather simple model with matching frictions similar to those in the canonical Diamond-Mortensen-Pissarides (DMP) model (Pissarides, 2000, Ch.1). In our model, heterogeneous firms may choose a manual technology and behave as in the DMP model. Alternatively, they may choose an automated technology and produce using only machines (robots). The canonical DMP model cannot assess the effects of automation. But our simple extension can by only adding one equation to the canonical model. Although the simplicity of our model naturally forced us to abstract from many ingredients, our approach comes with the benefits of analytical tractability and the ensuing clarity of the mechanisms at play in the model. Furthermore, many of the insights of our model find support in empirical evidence. Second, most of the contributions in the literature build and adapt growth models. We, on the other hand, build a model with matching frictions that offers a different perspective on the effects of automation and the evolution of the labor share. In particular, our model with matching frictions is suitable to distinguish how changes in labor market institutions and in technology shaped the dynamics of the US labor share.

1.2. Summary of the model & results

We build a putty-clay model of technology choice with matching frictions and the following main features. When entering the market,

² See, as well, Zeira (1998, 2010), Peretto and Seater (2013), Martinez (2018), Hopenhayn et al. (2018), León-Ledesma et al. (2019), and Prettnner and Strulik (2020).

³ See, as well, Bentolila and Saint-Paul (2003), Blanchard and Giavazzi (2003), Bental and Demougin (2010), Young and Zuleta (2018), Cords and Prettnner (2021), and Stansbury and Summers (2020).

and after paying a sunk cost, each firm faces two alternative technologies to produce output. These technologies are perfect substitutes upon entry: an entrant firm either chooses the automated technology or the manual technology. Each technology entails a specific start-up cost. The automated technology only employs capital, while the manual technology only employs labor and requires each firm to search for a worker in a labor market characterized by an aggregate matching function and where wages are set by Nash bargaining. In the model, at the time of entry, firms draw an endowment (or capability) from a known probability distribution.⁴ Each firm then combines this endowment with either technology (although with possibly different efficiency levels) to determine its productivity. Depending on the draw of the endowment, the firm chooses its technology. Under rational expectations, a no-arbitrage and a free-entry condition must be satisfied. The no-arbitrage condition allows for the derivation of an endogenous threshold, i.e., a cutoff level of the stochastic endowment at which firms are indifferent between one technology or the other. The free-entry condition establishes a link between the two technologies, so that a sort of complementarity between them endogenously arises in equilibrium at the aggregate level.

Our model paves the way to study how automation affects the labor market in models with matching frictions. The canonical DMP model allows us to study how labor market institutions shape wages (*versus* output) and employment. Our model preserves the mechanisms but in a richer context: changes in labor market institutions and productivity shocks propagate in the economy also through the reallocation of resources between firms that choose to operate under alternative technologies. In this context, the labor share reflects the influence of institutions and productivity on both the average wage level (*versus* output) and the distribution of firms between the two technologies (manual *versus* automated).

To inquire into the effects of increasing automation on jobs, we study analytically the effects of an automation-augmenting technological shock, a shock that increases the productivity of all automated firms. We find that both the average wage and employment increase as an aggregate-equilibrium result, which is noteworthy given that manual and automated technologies are *ex ante* perfect substitutes at the micro level. A rise in the productivity of machines incentivizes the reallocation of resources from the manual to the automated technology, displacing labor. Yet, in the aggregate equilibrium of our model, the greater expected value to open a firm induces a significant rise in the number of firms and output that ultimately outweighs the labor-displacing effect, increasing employment and wages. Thus, in our model, the aggregate effect is stronger than the reallocation effect. In a second step, after calibrating the model, we also find that an automation-augmenting shock reduces the labor share. Thus, automation-augmenting shocks have effects that are qualitatively in line with the evidence: they increase employment but reduce the labor share.

We also conduct experiments on our model bearing in mind the historical behavior of the US labor share, which we depict in Fig. 1 for the period 1963–2007. The real wage per worker grew at a rate close to that of real output per worker until the late 1980s. After that (and especially after 2000), their growth rates diverge. In other words, the US labor share clearly drops only after the late 1980s (e.g., Elsby et al., 2013). Given this evidence, we focus on two time periods: 1967–1987, characterized by a relatively stable labor share; and 1987–2007, characterized by a falling labor share.

To analyze each 20-year period, we mainly take two steps. First, we calibrate changes in labor market institutions. Farber et al. (2021) doc-

⁴ The draw of the endowment aims to capture a costly learning state prior to the startup stage as emphasized by the literature on entrepreneurship and venturing (see, e.g., Alvarez and Barney, 2004; Cope, 2005; Gibb and Ritchie, 1982; Kapoor and Furr, 2015; Kerr et al., 2014). This learning mechanism echoes the entry mechanism in Hopenhayn (1992) and Melitz (2003), and agrees with the role of entry costs and technology choice emphasized in, e.g., Caselli and Coleman (2006) and Jones and Romer (2010).

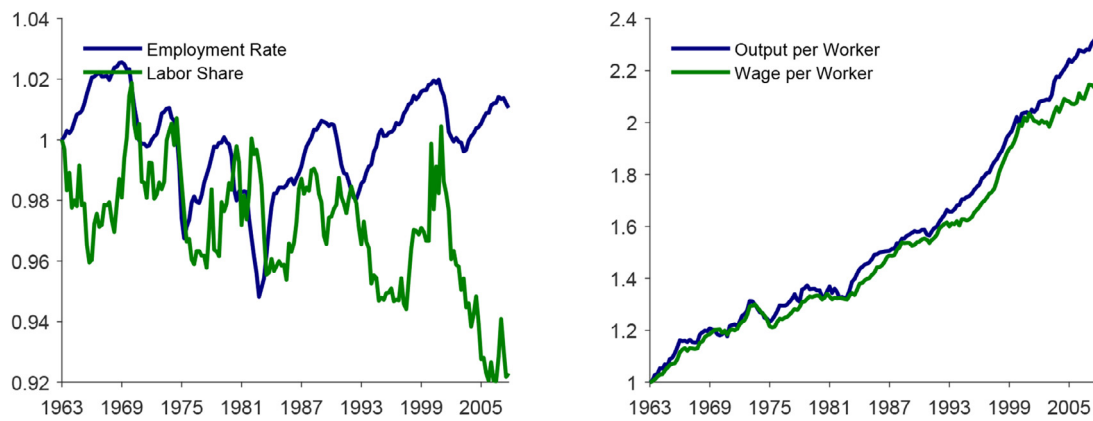


Fig. 1. The US Economy: 1963–2007. *Note:* Both panels plot data for the US economy between 1963 and 2007 downloaded from the FRED and the BLS. The panel on the left-hand side plots the employment rate and the labor share. The panel on the right-hand side dissects the evolution of the labor share by plotting the output and wage per worker. All series are normalized to 1 in 1963. For more details about the data, see Appendix D.

ument that union density fell from about 30% in the 1960s to less than 10% in the 2010s. We rely on this evidence to calibrate a fall in workers' bargaining power. Furthermore, [Shimer \(2012\)](#) and [Davis and Haltiwanger \(2014\)](#) document a substantial reduction in labor market flows (e.g., [Davis and Haltiwanger](#) document that job creation and job destruction fell approximately 33% in 1990–2013 as a percentage of employment). We rely on this evidence to calibrate changes in the exogenous job destruction rate. Second, we use technological variables (including changes in the productivity of the automated and manual technologies) to target the change in output, labor share, and employment observed in the US. Our objective, then, is to assess how the change in each of the parameters has individually contributed to the evolution of the labor share.

Our model suggests that changes in the labor market institutions have actually leaned against the wind since 1987. Even though the fall in workers' bargaining power has reduced the labor share, its effect is negligible and the fall in the job destruction rate has significantly increased the labor share since 1987. In contrast, changes in technology have reduced the labor share. According to our model, the labor share fell after 1987 because of a rapid acceleration in the productivity of the automated technology, which concurs with the estimates in [Martinez \(2018\)](#), [Acemoglu and Restrepo \(2019\)](#), [Bergholt et al. \(2019\)](#), and [Prettner and Strulik \(2020\)](#). To summarize, our model suggests that automation is a more promising candidate to account for the fall in the US labor share than changes in labor market institutions.

1.3. Related literature

As explained earlier, we lay out a model of technology choice exploiting the idea that firms face alternative technologies to produce output, be it a good or a task. This idea enters into numerous models in the literature that are close to ours as, e.g., [Zeira \(1998, 2010\)](#), [Acemoglu and Restrepo \(2018\)](#) and [Alesina et al. \(2018\)](#). In these models, a firm's choice to adopt one technology depends explicitly on a firm-specific exogenous feature, which as in our model, determines the firm's overall productivity or cost level, *ceteris paribus*.⁵ Our paper and these papers also share the simplifying assumption that the manual technol-

⁵ See also [Acemoglu and Zilibotti \(2001\)](#) and [Acemoglu \(2003\)](#). A related literature, with a somewhat different approach, allows optimizing agents to choose the elasticity of output with respect to inputs from a set of known technologies; e.g., [Zuleta \(2008\)](#) and [Peretto and Seater \(2013\)](#). Other papers let firms optimally choose the vector of factor-augmenting coefficients in the production function from a given technology menu; e.g., [Jones \(2005\)](#), [Caselli and Coleman \(2006\)](#), [Growiec \(2008, 2013, 2017\)](#), [Fadinger and Mayr \(2014\)](#), and [León-Ledesma et al. \(2019\)](#).

ogy employs only labor and the automated (or 'industrial') technology only capital.⁶ In this literature, [Acemoglu and Restrepo \(2018\)](#) is closer to our paper as we both study how automation affects the labor share. Yet, [Acemoglu and Restrepo](#) do not calibrate their model and prefer to study the theoretical conditions under which different results occur. In contrast, our calibration of the model allows us to offer insights on the evolution of the US labor share and employment since 1967.

Looking into other strands of the literature, our paper relates to [Caballero and Hammour \(1998\)](#), who also build a "putty-clay" model with labor market frictions to study the evolution of the labor share. In their model, changes in the labor share reflect shifts in technology choice (in their case, a change in the labor-intensity of new production units) as a reaction to given exogenous shocks, which resembles the reallocation between manual and automated technologies in our model. Yet, their model does not generate a simultaneous fall in the labor share and an increase in the average wage and employment, as hinted by empirical studies based on US data.

[Berg et al. \(2018\)](#) also relates closely to our paper as they assess the consequences of robot-augmenting technical progress. Their results are similar to ours: a robot-augmenting shock in their model also implies higher real wages and lower labor share. Their results, however, hinge crucially on the calibrated magnitude of the elasticity of substitution between labor and capital (or robots) imposed by their aggregate CES production function.⁷

Finally, our approach is very much in the spirit of the inter-firm reallocation mechanism analyzed by [Hopenhayn et al. \(2018\)](#) and [Autor et al. \(2020, App. A\)](#). In our model, changes in the labor share also reflect reallocation of economic activity from firms with high labor share to those with low labor share ('superstar firms' in the jargon of [Autor et al.](#)). The difference is that firms in our model differ in their labor shares because of their technology choice (which reflects the endowment draw) while in their models firms differ because of the different weights of labor overheads.

⁶ In all these models, the mechanisms rely on an aggregate production function for the final good, which ultimately implies a certain complementarity effect between the two alternative inputs in task production (labor versus machines). In our model, we get a similar effect without positing an aggregate production function. Instead, as explained earlier, the free-entry condition to open firms establishes a link between the manual and the automated technologies, so that they behave as complements in aggregate equilibrium.

⁷ This caveat about the calibrated elasticity of substitution extends to other papers relying on an aggregate CES production function, e.g., [Acemoglu \(2003\)](#); [Alvarez-Cuadrado et al. \(2018\)](#); [Eggertsson et al. \(2021\)](#); [Growiec et al. \(2018\)](#); [Karabarbounis and Neiman \(2014\)](#).

We developed our model to study long-term trends of the labor share. Yet, a good example of a model suited for the analysis of business cycle dynamics that builds on a setting close to ours is [Choi and Ríos-Rull \(2020\)](#). They propose a model with a ‘putty-clay’ production function and matching frictions in the labor market. They find that a model with these ingredients and where technology advancements favor new units can replicate salient business cycle patterns of the labor share.

The remainder of this paper is organized as follows. [Section 2](#) details our model. [Section 3](#) studies analytically how an automation-augmenting shock affects employment and wages. [Section 4](#) lays out the results of our quantitative exercises. In particular, this section presents the simulated elasticities of our model and the results of our targeted experiments to the periods 1967–1987 and 1987–2007. [Section 5](#) concludes the paper.

2. The model

Our model extends the DMP model set in discrete time as in, e.g., [Ljungqvist and Sargent \(2018\)](#). In our model, entrepreneurs (firm owners) pay a fixed cost Ω to learn both about the menu of technologies that is available to them and about the entrepreneur’s set of capabilities to deal with each technology and with the market. This learning process is modeled as a draw of a ‘productivity’ factor z from a distribution $G(z)$ over the interval $[z_{\min}, \infty)$. This costly learning process is followed by the choice of the production technology and by the payment of a start-up cost to start producing and selling the good in the market. In our model, there are two alternative technologies: an automated and a manual technology. If a firm chooses the automated technology, it is capital-intensive, bears the (start-up) cost of capital, $\kappa_K > 0$, and produces $z_K(z) \equiv z_K z$ units of output using only capital.⁸ If a firm chooses the manual technology, it is labor-intensive and behaves similarly to firms in the DMP model: it employs one worker, bargains the wage $w(z)$ with the worker, bears the (start-up) cost $\kappa_L(\theta) > 0$ to fill its vacancy within a single period, and produces $z_L(z) \equiv z_L z^\alpha$ units of output using only labor.⁹ z_L denotes the productivity of labor, which contrasts with

⁸ Since capital (the automated technology) is regarded, ex ante, as a perfect substitute of the manual technology, capital in our model can be interpreted, more specifically, as robots and the cost κ_K as the cost of a robot. This agrees with the interpretation of capital by, e.g., [Zeira \(1998\)](#), [Acemoglu and Restrepo \(2018\)](#), and [Pretzner and Strulik \(2020\)](#). In most of our analysis below we study the effect of a rise in z_K , an automation shock that we name “automation-augmenting shock”. Because z_K denotes the productivity of the automated technology, an increase in z_K in our model is apparently akin to a capital-augmenting shock as understood in the context of a standard production function with (some degree of) complementarity between capital and labor. Yet, given the perfect substitutability of technologies in our model, such a change in z_K induces the replacement of labor for machines (as we show below). Therefore it gives rise to a ‘share’ effect akin to automation (also as understood in the context of a standard production function). Consequently, an increase in z_K always reduces the labor share in our model (also shown below), again akin to automation, whereas a capital-augmenting shock in the context of a standard production function reduces the labor share only for specific values of the elasticity of substitution between capital and labor.

⁹ Workers are homogeneous in our model. Yet, for completeness, we also consider a version of our model with high- and low-skill workers in [Appendix E](#). We find that, for empirically-reasonable parameter values, our results about the effects of automation on employment and wages stand. We do not, however, use this extended model as our benchmark for three reasons. First, our simple model with homogeneous workers allows us to obtain analytical results (see [Section 3](#)). Second, our aim is to study aggregate variables, which are available since early 1960s. As we are not aware of disaggregated data with this longevity, it would compromise our exercises in [Section 4.3](#). Third, the existing evidence is ambiguous regarding the effects of robots on the employment of workers of different skill level. For example, [Graetz and Michaels \(2018\)](#) find that the employment of low-skill workers falls in relative terms, while that of middle-skill workers increases. And [Domini et al. \(2021\)](#) find no significant change in workforce composition after automation increases.

the productivity of capital, z_K . In the labor market, a standard matching function determines the number of matches. As a result, the job-filling costs, $\kappa_L(\theta) \equiv \frac{\kappa_L}{\chi\theta^{-\eta}}$, and the job-finding probability, $f(\theta) \equiv \chi\theta^{1-\eta}$, are functions of the matching efficiency, $\chi > 0$, the elasticity of the matching function with respect to unemployed workers, $1 > \eta > 0$, and the labor market tightness, θ .

2.1. Firms

A firm that draws the productivity z has the present-discounted values $J_L(z)$ and $J_K(z)$ if it employs the manual and automated technologies, respectively:

$$J_L(z) = z_L(z) - w(z) + \beta(1 - \delta_L)J_L(z), \tag{1}$$

$$J_K(z) = z_K(z) + \beta(1 - \delta_K)J_K(z). \tag{2}$$

We assume a common discount factor of β and an exogenous firm-destruction probability of δ_L for the manual technology and δ_K for the automated technology.

Different draws of productivity may imply different choices of technology. A firm will only be indifferent between the two technologies if its value net of the respective start-up cost is the same for the two technologies:

$$\beta J_L(z^*) - \kappa_L(\theta) = J_K(z^*) - \kappa_K, \tag{3}$$

where we assume that it takes one period for a worker to start production and we use z^* to denote the cutoff productivity draw that makes the firm indifferent between the two technologies.¹⁰ Throughout this paper, we refer to [Eq. \(3\)](#) as a no-arbitrage condition between the two technologies. Also throughout this paper, we assume that higher draws of z are favorable to the automated technology relative to the manual one, implying that $\alpha < 1$. Thus, for draws of z in the interval $[z_{\min}, z^*]$, the firm chooses the manual technology,¹¹ and for draws of z in the interval (z^*, ∞) , the firm chooses the automated technology. This implies that the largest firms (which correspond to the firms with the largest productivity draws and, thus, the largest sales) are capital intensive, as suggested by the empirical evidence (see, e.g., [Autor et al., 2017, 2020](#)). To close the firms’ block of our model, we assume free-entry to open firms:

$$\int_{z_{\min}}^{z^*} (\beta J_L(z) - \kappa_L(\theta))dG(z) + \int_{z^*}^{\infty} (J_K(z) - \kappa_K)dG(z) = \Omega. \tag{4}$$

2.2. Workers

In our model, there is a measure L of risk-neutral workers who are in one of two states: employed or unemployed. If employed, a worker earns the wage $w(z)$, which varies with the productivity draw of the firm, and loses its job with a probability δ_L . We denote the lifetime income of an employed worker by $E(z)$:

$$E(z) = w(z) + \beta[(1 - \delta_L)E(z) + \delta_L U]. \tag{5}$$

¹⁰ We do not assume that there is a time to build in the automated technology merely for simplicity and the results would be almost indistinguishable if we assumed otherwise.

¹¹ In our benchmark, we assume that $\alpha = 0$, which implies that all manual firms obtain the same profits and, thus, if $z^* > z_{\min}$, then all firms that draw a z where $z^* > z > z_{\min}$ produce and choose the manual technology. In our robustness checks, however, we also consider $\alpha > 0$, which might deliver cases in which some firms with very low draws of z prefer to exit without producing; we, however, exclude those cases from our analysis to simplify the model and avoid defining an extra cutoff.

If unemployed, a worker enjoys income $b \geq 0$ and finds a job with a probability $f(\theta)$. We denote the lifetime income of an unemployed worker by U :

$$U = b + \beta \left[f(\theta) \frac{1}{G(z^*)} \int_{z_{\min}}^{z^*} E(z) dG(z) + (1 - f(\theta))U \right], \quad (6)$$

where $\frac{1}{G(z^*)} \int_{z_{\min}}^{z^*} E(z) dG(z)$ is the average expected value of employment.¹²

2.3. The wage

Workers and firms bargain over wages such that the bargained wage maximizes the Nash product:

$$w(z) = \arg \max (E(z) - U)^\phi (J_L(z) - \max [\beta J_L(z) - \kappa_L(\theta), J_K(z) - \kappa_K])^{1-\phi}, \quad (7)$$

where the parameter $1 > \phi > 0$ measures the worker's bargaining power or, in other words, the worker's share of the surplus. In the standard DMP model, workers and firms also bargain over wages. Yet, in the DMP model, the firm's surplus of the match is merely the difference between the value of employment and the value of a vacancy (equal to zero, in equilibrium), which is much simpler than in our model. In our model, a firm has two options. The first is that it may not agree a wage with the worker and search for another worker. The value of this option is $\beta J_L(z) - \kappa_L(\theta)$; that is, the firm may invest $\kappa_L(\theta)$ to find another worker which will generate a value of $\beta J_L(z)$.¹³ The second option is that it may instead threaten the worker it will move to the automated technology; in this case, its outside value is given by $J_K(z) - \kappa_K$. Yet, in an equilibrium of our model, the firm will only bargain with the worker if it has previously chosen the manual technology (that is, $z_{\min} \leq z \leq z^*$). As a result, the value of the relevant outside option of the firm is $\beta J_L(z) - \kappa_L(\theta)$ and $w(z)$ must satisfy

$$E(z) - U = \frac{\phi}{1 - \phi} ((1 - \beta)J_L(z) + \kappa_L(\theta)). \quad (8)$$

Making use of Eqs. (1)–(6), we rewrite the previous equation as

$$\begin{aligned} w(z) = & \frac{1 - \phi}{1 - \phi\beta} b + \frac{\phi}{1 - \phi\beta} [(1 - \beta)z_L(z) + \kappa_L(\theta)(1 - \beta(1 - \delta_L))] \\ & + \beta f(\theta) \frac{\phi}{1 - \phi\beta} \left((1 - \beta) \left[\Omega - \int_{z^*}^{\infty} (J_K(z) - \kappa_K) dG(z) \right] \frac{1}{\beta G(z^*)} \right. \\ & \left. + \frac{(1 - \beta)}{\beta} \kappa_L(\theta) + \kappa_L(\theta) \right). \end{aligned} \quad (9)$$

As in the DMP model, wages increase with the unemployment income, b , the productivity of the match, $z_L(z)$, and with labor market tightness, θ . This equation, however, is more complex than the one in the DMP model due to the mechanism of technology choice in our model and its interaction with labor market frictions.

2.4. Equilibrium

The equilibrium of the model is defined at the aggregate level of the economy and is characterized by the vector $(\theta, z^*, w(z))$, which satisfies the no-arbitrage condition, Eq. (3), the free-entry condition, Eq. (4), and the wage equation, Eq. (9). Furthermore, in equilibrium, the flows

from employment to unemployment must equal the flows from unemployment to employment. This implies that after we derive the vector $(\theta, z^*, w(z))$, the employment rate satisfies $n = \frac{f(\theta)}{f(\theta) + \delta_L}$.

In the equilibrium of our model, we obtain the output, y , by summing up the production of manual and automated firms. To measure the production of each technology, we use the product of the number of firms using that technology and their (conditional) average production. We easily obtain the production of manual firms: because each worker corresponds to a manual firm, there are nL manual firms, each producing an average of $\frac{1}{G(z^*)} \int_{z_{\min}}^{z^*} z_L(z) dG(z)$ units of output. But it is more intricate to obtain the production of automated firms as first we need to pin down their number. Every period there is a measure of firms entering the market that satisfies Eq. (4). A proportion $G(z^*)$ choose the manual technology and a proportion $1 - G(z^*)$ choose the automated technology. In equilibrium, the number of entering firms choosing the manual technology is $f(\theta)(1 - n)L$, which equals the number of manual firms exiting the market, $\delta_L nL$. Because the fraction $G(z^*)$ of total entering firms corresponds to $\delta_L nL$ manual firms, there are $\delta_L nL \frac{1 - G(z^*)}{G(z^*)}$ automated firms entering every period. Furthermore, an automated firm lasts on average $1/\delta_K$ periods. Thus, there are $\frac{\delta_L}{\delta_K} nL \frac{1 - G(z^*)}{G(z^*)}$ automated firms, each producing an average of $\frac{1}{1 - G(z^*)} \int_{z^*}^{\infty} z_K(z) dG(z)$ units of output. Output in our model, then, is

$$y \equiv \frac{nL}{G(z^*)} \left(\int_{z_{\min}}^{z^*} z_L(z) dG(z) + \frac{\delta_L}{\delta_K} \int_{z^*}^{\infty} z_K(z) dG(z) \right). \quad (10)$$

In our paper, it is essential to define the labor share, LS , which corresponds to the fraction of output paid to workers. In our model, there are nL employed workers, each receiving an average wage of $\frac{1}{G(z^*)} \int_{z_{\min}}^{z^*} w(z) dG(z)$. Using the expression for output of Eq. (10), after a few rearrangements, we write the labor share as¹⁴

$$LS \equiv \frac{\int_{z_{\min}}^{z^*} w(z) dG(z)}{\int_{z_{\min}}^{z^*} z_L(z) dG(z) + \frac{\delta_L}{\delta_K} \int_{z^*}^{\infty} z_K(z) dG(z)}. \quad (11)$$

3. Will machines terminate all jobs?

The rising substitutability of machines for workers has driven the conception that machines will significantly reduce (and ultimately terminate) employment. Our model, however, contradicts this conception. We study the effects of an automation-augmenting shock (a rise in z_K) and conclude that a rise in the productivity of machines is capable of increasing both wages and employment.

3.1. Analytical results

In this section, we study analytically how a rise in z_K changes the labor market tightness and, thus, the employment rate. To ease our exposition and derivations, we assume that $\alpha = 0$ (implying $z_L(z) = z_L$), but in the next section we show that our results hold under other calibrations of α . If $\alpha = 0$, our model closely resembles the standard DMP model and we can write the wage equation that satisfies Eq. (9) as

$$\begin{aligned} w = & (1 - \phi)b + \phi(z_L + \theta \bar{\kappa}_L) \\ & - \phi \left[\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K \right) [(\beta - 1)f(\theta) + 1 - \beta(1 - \delta_L)] \right], \end{aligned} \quad (12)$$

which only differs from the wage equation of the standard DMP model because it includes a third term on the right-hand side. An important implication of $\alpha = 0$ is that the wage is independent of the productivity

¹² Although $E(z)$ depends on z , U does not. z is specific to a firm and, thus, only influences the wage of a particular job; it does not influence the value of unemployment. Instead, the value of unemployment depends on the distribution of $G(z)$ in the range that firms decide to open manual firms: $[z_{\min}, z^*]$.

¹³ In the DMP model, the firm may also threaten it will search for another worker. But in that model the value of this option is zero due to the free-entry condition.

¹⁴ As we assume that $\bar{\kappa}_L$, κ_K , and Ω are not expressed in labor units, these costs do not contribute to labor income and, thus, do not directly affect the labor share.

draw z . Thus, the value of the manual technology $J_L(z)$ is the same for all draws of z .

Proposition 1. *Let $\alpha = 0$. Labor market tightness, θ , increases with a rise in the productivity of the automated technology, z_K , iff the elasticity of the cutoff productivity draw, z^* , with respect to z_K is lower than -1 .*

Proof. Log-linearizing the no-arbitrage condition, Eq. (3), and the wage equation, Eq. (12), we obtain:

$$\hat{\theta} = \frac{\psi_1}{\psi_2} (\hat{z}_K + \hat{z}^*), \tag{13}$$

where $\psi_1 > 0$ and $\psi_2 < 0$, and we use hats to denote log-linear variables. (See Appendix A.1 for more details on the derivations.) The signs of ψ_1 and ψ_2 imply that a rise in z_K will only increase θ if the elasticity of z^* with respect to z_K is lower than -1 . \square

Thus, we must understand how a change in z_K changes the distribution of resources between the manual and automated technologies before we know its effects on employment. To this end, we continue to assume that $\alpha = 0$ and combine the free-entry condition, Eq. (4), with the no-arbitrage condition, Eq. (3), to derive:

$$z_K \left(\int_{z^*}^{\infty} z dG(z) + z^* G(z^*) \right) = (\Omega + \kappa_K) [1 - \beta(1 - \delta_K)]. \tag{14}$$

At this stage, Eq. (14) already provides an important result. If $\alpha = 0$, z^* is orthogonal to θ and w and to all of the labor market parameters and institutions (measured by $z_L, b, \phi, \delta_L, \bar{\kappa}_L, \chi$, and η). This implies that the role of labor market parameters and institutions is circumvent to the labor market, without any effect on how resources are split between the manual and automated technologies. In our simulations below, we show that this result does not hold if $\alpha \neq 0$. Yet, even in this case, a change in $b, \phi, \delta_L, \bar{\kappa}_L, \chi$, or η has a minor effect on z^* and the labor share.

Corollary 1. *Under $\alpha = 0$, a rise in the productivity of the automated technology, z_K , increases employment, n .*

Proof. By log-linearizing Eq. (14), we obtain the elasticity of z^* with respect to z_K :

$$\frac{\hat{z}^*}{\hat{z}_K} = - \frac{\int_{z^*}^{\infty} z dG(z) + z^* G(z^*)}{z^* G(z^*)}. \tag{15}$$

(See Appendix A.2 for more details on the derivations.) Independently of the distribution of productivity draws, this elasticity is lower than -1 . Thus, given Proposition 1 and given that employment is only a function of the labor market tightness and increases in tighter markets, if the productivity of the automated technology rises, employment rises. \square

3.2. Interpretation and discussion

To interpret the mechanism underlying an elasticity $\frac{\hat{z}^*}{\hat{z}_K}$ lower than -1 , we first recall that the no-arbitrage condition in Eq. (3) links the manual and the automated technology at the cutoff z^* . This together with the assumption that the automated technology is multiplicatively linear in z imply, per se, a reallocation from the manual to the automated technology with an elasticity of exactly -1 . This is expressed by the denominator and the second term in the numerator on the right-hand side of Eq. (15).¹⁵ On the other hand, the value of the automated technology increases with the productivity draw z multiplied by z_K , being z everywhere larger than z^* for this technology. This implies that, by the free-entry condition, Eq. (4), a firm entering the market must factor in the whole (conditional) expected value of z as regards the automated-technology option (and not only the value at the cutoff z^*). When the

economy is hit by a positive shock to z_K , the average value of the automated technology increases, which reinforces the reallocation of resources towards this technology. This is expressed by the first term in the numerator in Eq. (15). Consequently, for a given shift in z_K , the cutoff z^* shifts more than proportionally in order to satisfy Eq. (4). In other words, the fact that the value of entering depends on a non-null measure of z under the distribution $G(z)$ induces a (negative) multiplier effect in z^* . Then, this effect implies that the value of the automated firm at the cutoff z^* falls. In order for the value of the manual firm at the cutoff also to fall, θ must increase (so that $\kappa_L(\theta)$ increases; see Eq. (3)).

Looking at Eqs. (3), (4) and (9) further suggests that a rise in z_K increases employment even if $\alpha \neq 0$ (as we confirm in Section 4.2) and even if we conjecture different setups of our model. The rise in z_K increases expected profits of the automated technology, $\int_{z^*}^{\infty} (J_K(z) - \kappa_K) dG(z)$ on the left-hand side of Eq. (4). Given that Ω is constant, this increase in expected profits must be compensated by an equal fall in expected profits either through reallocation (change in z^*) or an increase in the costs of the manual technology (greater wages, $w(z)$, or greater labor market tightness, θ). Changes in z^* , however, can only exacerbate the rise in expected profits. Our cutoff equation (Eq. 3) shows that profits using the manual technology (which depend on the draw of z, z_L, w, θ , and all labor market parameters) must equal the profits of the automated technology (which depends on z, z_K, δ_K , and κ_K) when measured at the cutoff productivity, z^* . A rise in z_K must then rise the profit of the automated technology for all z , reducing z^* : firms shift to the automated technology because it increases their profitability upon entry. Therefore, the free-entry condition (Eq. 4) is only satisfied if expected profits using the manual technology fall. Looking at Eq. (9), z_K has a negative direct effect on wages (by increasing $J_K(z)$), which is amplified by the fall in z^* . Thus, after an automation-augmenting shock, the labor market must become tighter, increasing employment.¹⁶

Our result that an increase in z_K raises employment is noteworthy given that the manual and automated technologies are *ex ante* perfect substitutes at the micro level. To shed further light on the mechanism, we log-linearize Eqs. (4) and (12) and obtain:

$$\hat{\theta} = \psi_3 \hat{z}^* + \psi_4 \hat{z}_K, \tag{16}$$

where $\psi_3 > 0$ and $\psi_4 > 0$ are functions of parameters derived in Appendix A.3.¹⁷ If the automated technology becomes more profitable following the rise in z_K , it is only natural that some firms entering the market steer away from the manual technology and invest in the automated technology. In our model, this *reallocation effect* is captured by the fall in z^* , which directly reduces employment (ψ_3 in Eq. 16). Yet, as our model shows, we should distinguish the implications of automation at the micro and aggregate levels. In our model, firms cannot choose technology and start production without first going through a costly learning process (pay Ω to draw z); thus, the choices made by individual firms at the micro level give rise to a sort of complementarity at the aggregate and general-equilibrium level that promotes firm entry and employment (ψ_4 in Eq. 16). It turns out that the rise in z_K creates incentives to open firms (*aggregate effect*; size of the economy) that surpass the reallocation effect, leading to a net increase in employment (as established by Corollary 1). Importantly, this conclusion echoes the results in most of the empirical literature surveyed in Bessen et al. (2020) and also the empirical results by Autor and Salomons (2018) and Gregory et al. (2021). In the spirit of our model, many of these papers find that the direct (negative) effects of automation are outweighed by its indirect positive effects.

¹⁶ This logic also applies to a model in which we distinguish between an economical cutoff (as we have in our model) and a technological cutoff, which would be technologically-determined. See Appendix C for more details.

¹⁷ Eqs. (13) and (16) offer separate partial views of the dynamics of the model. Eq. (13) highlights the dynamics imposed by the cutoff equation, while Eq. (16) highlights the dynamics imposed by the free-entry condition.

¹⁵ We note that if the productivity of the automated technology is concave in z , then the effect of the denominator and the second term in the numerator of Eq. (15) alone implies an elasticity smaller than -1 .

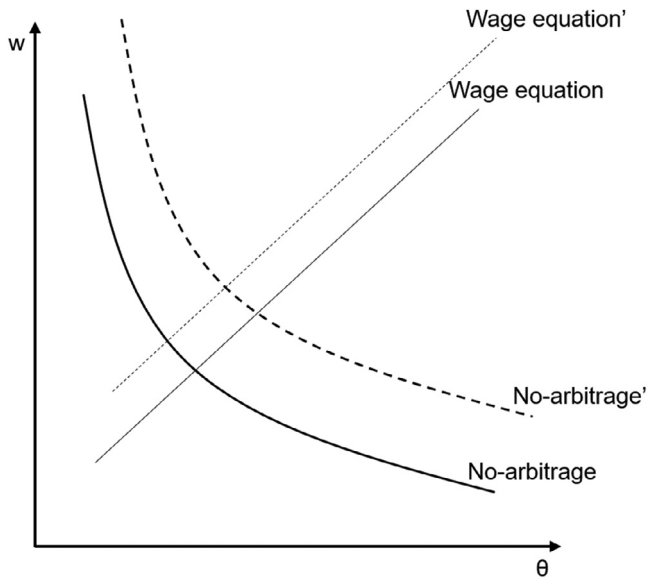


Fig. 2. Equilibrium wage and market tightness - the effect of higher z_K . *Note:* This figure plots the effects of an increase in z_K for the equilibrium of our model in the wage-tightness space assuming that $\alpha = 0$ and the free-entry condition, Eq. (14), is satisfied. The intersection of the solid lines represents the equilibrium before the rise in z_K , whereas the intersection of the dashed lines represents the equilibrium after the rise in z_K .

3.3. Graphical analysis

As mentioned above, our model has a closer resemblance to the DMP model if $\alpha = 0$. Thus, under this condition, we can use the typical graphical analysis of the DMP model to gather further information on the effects of the automation-augmenting shock. Fig. 2 plots the equilibrium of our model in the wage-tightness space assuming $\alpha = 0$. The equilibrium in this space is obtained by the intersection of the wage equation, Eq. (12), and the no-arbitrage condition, Eq. (3) (which replaces the free-entry condition of the DMP model). Both equations maintain their main properties from the DMP model. In tighter labor markets, workers demand higher wages, implying a positively-sloped wage equation. Also in tighter labor markets, the hiring costs are higher because of the greater firm competition for the same pool of unemployed workers. As a result, in tighter labor markets, manual firms only attain the same value if wages are lower, implying the negatively sloped curve named No-arbitrage in Fig. 2. The slope of this curve becomes clearer if we rearrange Eq. (3) as

$$\beta w = \beta z_L + (\kappa_K - \kappa_L(\theta))[1 - \beta(1 - \delta_L)] - z_K z^* \frac{1 - \beta(1 - \delta_L)}{1 - \beta(1 - \delta_K)}$$

This equation also clarifies that the no-arbitrage condition shifts up after a rise in z_K because $z_K z^*$ falls (as we have shown in the case of $\alpha = 0$). The same logic applies to the wage equation, also implying an upward shift. Thus, unambiguously, an automation-augmenting shock increases wages.

4. Simulations: Explaining the labor share

Considering the clear evidence of a downward trend in the labor share, a debate has emerged on whether this trend is mainly driven by technological changes or by changes in labor market institutions. Our model suggests that labor market institutions (relative to automation) play an almost insignificant role in explaining the labor share. The model also indicates that the US labor share only falls after the late 1980/s due to the acceleration of automation's productivity in that period.

Table 1
Benchmark calibration.

Discount factor:	$\beta = 0.996$
Rate of manual-firm destruction:	$\delta_L = 0.036$
Rate of automated-firm destruction:	$\delta_K = 0.036$
Matching function elasticity:	$\eta = 0.5$
Workers' bargaining power:	$\phi = 0.5$
Labor productivity (elasticity):	$\alpha = 0$
Minimum productivity draw:	$z_{\min} = 0.15$
Power term of the Pareto distribution:	$\xi = 3.12$
Unemployment income:	$b = 0.7 z_L z_{\min}^\alpha$
Entry cost:	$\Omega = 1$
Cost of Capital:	$\kappa_K = 1$
Size of the labor force:	$L = 1$

4.1. Calibration

We calibrate the model to monthly US data and summarize our benchmark calibration in Table 1. In particular, we set $\beta = 0.996$, implying an annual discount rate of 4.91%. We set $\delta_L = 0.036$ as our benchmark, which equals the average job destruction rate in the US from 1948 to 2010 (Shimer, 2012). To maintain the parallelism between the two technologies, we set $\delta_K = 0.036$. To calibrate the elasticity of the matching function with respect to unemployment, we draw on the survey of Petrongolo and Pissarides (2001) and set $\eta = 0.5$. We also set $\phi = 0.5$ and normalize $\Omega = 1$, $\kappa_K = 1$, and $L = 1$. In the literature, it is common to fix $b \approx 0.7 z_L$ (e.g., Hall and Milgrom, 2008, Pissarides, 2009, and Coles and Kelishomi, 2018). Based on this, we fix $b = 0.7 z_L z_{\min}^\alpha$. To be consistent with the evidence on firm size distribution (e.g., Ghironi and Melitz, 2005, Luttmer, 2007, Gomes and Kuehn, 2017), in our model, firms draw their productivity from a Pareto distribution, i.e., $G(z) = 1 - \left(\frac{z_{\min}}{z}\right)^\xi$, where ξ determines the shape of the distribution. We set $z_{\min} = 0.15$ because of the normalization of κ_K and Ω . To calibrate ξ , we follow Ghironi and Melitz (2005), who use ξ to target the standard deviation of sales in the US plants. In our case, this target implies $\xi = 3.12$.

Regarding the productivity of the manual technology, we start by assuming that $\alpha = 0$, implying that the productivity of labor-intensive firms is independent of the productivity draw (i.e. $z_L(z) = z_L$). In our sensitivity analysis, however, we consider cases in which z improves the value of the manual technology ($\alpha = 0.2$) and in which z deteriorates the value of the manual technology ($\alpha = -0.2$).¹⁸ Regarding the remaining parameters, z_L , z_K , $\bar{\kappa}_L$, and χ , to increase the comparability of our results under the different experiments carried out in Sections 4.2 and 4.3, we pin down their values to target (i) the employment rate, n , (ii) the labor share, LS , (iii) the labor market tightness value, θ , and (iv) the equilibrium proportion of firms that employ the manual technology, $G(z^*)$. In all our experiments, we target $G(z^*) = 50\%$ and $\theta = 1$.¹⁹ The targets of n and LS change according to the simulation, as further explained below.

¹⁸ Although we have no empirical counterpart of the parameter α , we note that our assumption of a Pareto distribution (for the productivity draws) bounds its calibration. The Pareto distribution implies that there is a large mass of firms with productivity close to the minimum productivity draw, z_{\min} . All of these firms use the manual technology. And, in Section 4.2, we show that the elasticity of z^* with respect to z_K grows at increasing rates as we increase α . Thus, if α is (sufficiently) larger than 0.2, the elasticity $\frac{z^*}{z_K}$ is so high that the cutoff z^* gets very close to z_{\min} and the algorithm that runs the simulations of our model is unable to converge.

¹⁹ As in Shimer (2005), our calibration strategy implies that a different target for θ does not have any effect on our results. Thus, we simply normalize our target for θ to 1.

Table 2
Elasticities.

	Δy	ΔLS	Δn	Δw	Δz^*
Δz_K	5.09	-4.27	0.08	0.52	-2.55
Δz_L	0.75	0.43	0.05	1.13	0.00
$\Delta \kappa_K$	-1.85	1.65	-0.03	-0.20	1.21
$\Delta \kappa_L$	-0.03	-0.01	-0.03	-0.01	0.00
Δb	-0.12	0.02	-0.12	0.02	0.00
$\Delta \phi$	-0.06	0.01	-0.06	0.01	0.00
$\Delta \chi$	0.06	0.01	0.06	0.01	0.00
$\Delta \delta_L$	0.23	-0.43	-0.08	-0.12	0.00

Note: This table shows the effects of the shocks to the parameters using our benchmark calibration. All values refer to percentage changes and all shocks are of 1%. Thus, the values in this table may be interpreted as elasticities. In the first column, we write the respective source of the shock. In the remaining columns, we write the elasticities of output, labor share, employment, average wages, and cutoff.

4.2. Simulated elasticities

In this section, we present the simulated elasticities of key macroeconomic variables with respect to multiple parameters and under various calibrations of our model. We study how the output, y , labor share, LS , employment, n , average wages, $w \equiv \int_{z^*}^{\infty} w(z)dG(z)$, and cutoff, z^* , change in response to two broad types of shocks: technology and labor-market shocks. Regarding technology shocks, we distinguish between automation-augmenting shocks, Δz_K , manual-augmenting shocks, Δz_L , shocks to the cost of capital, $\Delta \kappa_K$, and shocks to the vacancy costs, $\Delta \kappa_L$ (as in, e.g., Hornstein et al., 2007; Karabarbounis and Neiman, 2014; and Acemoglu and Restrepo, 2018). Regarding labor-market shocks, we consider unemployment income, Δb , workers' bargaining power, $\Delta \phi$, matching efficiency, $\Delta \chi$, and job destruction rate, $\Delta \delta_L$ (as in, e.g., Caballero and Hammour, 1998; Bentolila and Saint-Paul, 2003; Blanchard and Giavazzi, 2003; Bental and Demougin, 2010).

Although our numerical exercise is quantitative by nature, for now we focus mainly on the qualitative features of our results. In particular, because we are unable to determine analytically how the various parameters affect the labor share, this section complements our analysis in Section 3. To standardize our experiments, every experiment refers to a 1% increase in the respective parameter. And, in all experiments, we calibrate the model to target an employment rate of $n = 94.3\%$ and a labor share of $LS = 61\%$.²⁰ Table 2 shows the simulated elasticities of our model under the baseline calibration. This table confirms the analytical results of Section 3 and offers a number of other insights.

Result 1. An increase in the productivity of the automated technology, z_K , increases employment, n , and average wages, w , but reduces the labor share, LS .

Table 2 confirms that a rise in the productivity of the automated technology, z_K , increases employment. The significantly negative elasticity of z^* with respect to z_K implies that a rise in z_K reallocates resources from the manual to the automated technology, displacing labor. But, the greater value to open a firm induces a significant rise in the number of firms and output that ultimately outweighs the labor-displacing effect and increases employment. Table 2 also shows that a rise in z_K increases wages but massively reduces the labor share. In our model, the increase in employment allows workers to demand higher wages and capture a greater share of the match surplus. (See the graphical analysis in Section 3.3.) Yet, the greater employment and wage are not able to offset the shift of resources towards the automated technology, which implies the fall in the labor share.

²⁰ Our targets are the labor share in the nonfarm business sector and the average employment rate in the US from 1963 to 2018. Both series are retrieved from the BLS.

Our results agree to a large extent with the results in Berg et al. (2018). Although our models differ in multiple regards, an increase in the productivity of robots in their model also leads to a considerable rise in output, which ultimately increases the real wage but reduces the labor share. Their model, however, is silent on the labor supply response because it is assumed to be inelastic. In this regard, our results are closer to the numerical findings in Cords and Prettnner (2021). These authors analyze the effects of an increase in the ratio of industrial robots per manufacturing workers on low- and high-skill labor. They find that overall employment rises with automation since the increase in high-skill manufacturing jobs compensates for the decrease in low-skill jobs.

Table 2 also confirms that the labor market parameters do not affect the allocation of resources between the two technologies when $\alpha = 0$ because they do not change the cutoff, z^* . Furthermore, technological shocks have a much greater impact on output and the labor share than equally proportional changes in the labor market institutions. In the next section, we will calibrate the shocks in order to interpret the evolution of the US economy in two historical periods and will show that technological shocks are the best candidates to explain the observed fall in the labor share. In Appendix B.1, we also show that our main conclusions from Table 2 hold under different calibrations of α and targeted $G(z^*)$.

4.3. Targeted simulations

In this section, we study how our model interprets the evolution of the US economy in two 20-year periods: 1967-1987 and 1987-2007.²¹ To analyze each 20-year period, we take three steps, summarized in Table 3. First, we calibrate the model to match the state of the economy at the beginning of the period. We start by using our benchmark calibration specified in Table 1. The only exception is for δ_L , which we fix using the employment exit probability series in Shimer (2012) at the beginning of the period instead of the series' average. We also continue to pin down the (starting) values of the parameters z_L , z_K , $\bar{\kappa}_L$, and χ using the same four targets (n , LS , θ , $G(z^*)$; see Section 4.1). But, since we target the employment rate, n , and the labor share, LS , to those observed at the beginning of each 20-year period, this implies that the obtained parameter values are specific to the 20-year period under analysis.²² Second, we impose exogenous changes to two key parameters pertaining to labor market institutions, in order to capture changes in institutions over each period. We use the downward trend of union density reported by Farber et al. (2021) to obtain a proxy for the fall in workers' bargaining power, $\Delta \phi$.²³ And we obtain the change in the job destruction rate, $\Delta \delta_L$, by recalibrating δ_L using the employment exit probability series in Shimer (2012) at the end of the period; this allows us to capture the declining dynamism in the US labor market after 1987 (Davis and Haltiwanger, 2014). Third, given the described exogenous changes in labor market institutions, we recalibrate the model to match the state of the economy at the end of the period. We use L to target the size of the labor force, and we use a scalar (A),²⁴ productivity of the

²¹ We split the data in 1987 because the evidence in Elsby et al. (2013) indicates that the labor share started to fall approximately in that year. Furthermore, Acemoglu and Restrepo (2019) also split their analysis in two periods, before and after 1987. In Appendix B.3, we study 30-year periods (1957-1987 and 1987-2017) and find that our results are robust.

²² The targets for the labor share are 63% and 62%, which correspond to the average labor share in the US nonfarm business sector in 1963-1967 and 1983-1987, respectively. The targets for the employment rate are 95.4% and 92.5%, which correspond to the average US employment rate in 1963-1967 and 1983-1987, respectively. The data is from the BLS.

²³ We choose $\Delta \phi = -9\%$ and $\Delta \phi = -5\%$ in 1967-1987 and 1987-2007, respectively, by interpreting ϕ in our model as a weighted average of the bargaining power of two groups of workers, those who are and those who are not union members. See Appendix D for more details.

²⁴ To avoid clutter, we did not introduce A when presenting the model in Section 2. A is a scalar of z_K , z_L , Ω , κ_K , $\bar{\kappa}_L$, and b . Thus, increases in A in-

Table 3
Targeted simulations – calibration summary.

Beginning of the Period (BOP, either 1967 or 1987)	
Parameter	Source/Target
$\beta, \delta_K, \eta, \phi, \alpha, z_{min}, \xi, b, \Omega, \kappa_K, L$	Table 1
δ_L	Employment Exit Probability at BOP (Shimer, 2012)
$z_L, z_K, \bar{\kappa}_L, \chi$	$\theta = 1, G(z^*) = 0.5, n$ and LS at BOP
$A = 1$	Normalization
End of the Period (EOP, either 1987 or 2007).	
Parameter	Source/Target
$\beta, \delta_K, \eta, \alpha, z_{min}, \xi, b, \Omega, \kappa_K$	Unchanged from BOP
$\bar{\kappa}_L, \chi$	Unchanged from BOP
ϕ	ϕ at BOP adjusted according to the change in union density (Farber et al., 2021)
δ_L	Employment Exit Probability at EOP (Shimer, 2012)
L	L at BOP adjusted by the change in the size of the labor force
A, z_L, z_K	y, n, LS at EOP (given remaining changes)

Table 4
Targeted simulations – 1987 to 2007.

ΔA	Δz_K	Δz_L	$\Delta \phi$	$\Delta \delta_L$	ΔLS	Δn
50.54	2.95	-7.04	-5.00	-33.00	-3.56	2.52
-	2.95	-	-	-	-17.56	0.33
-	-	-7.04	-	-	-2.83	-2.11
-	-	-	-5.00	-	-0.08	0.37
-	-	-	-	-33.00	15.21	3.08

Note: The experiments regard the period 1987-2007 and all values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The last two columns show the implied change in the labor share and employment (respectively) as a result of the shocks to the parameters. In the first line, the shocks are calibrated such that our model targets the changes in output, labor force, employment, and labor share in 1987-2007 given the exogenously-imposed changes in ϕ and δ_L . In the data, the labor share fell 3.6% and employment increased 2.5%.

automated technology (z_K), and the productivity of the manual technology (z_L) to target output, labor share, and employment at the end of the period. The outcome of our exercise is a combination of disturbances ($\Delta A, \Delta z_K, \Delta z_L, \Delta \phi$, and $\Delta \delta_L$) that allows our model to match the evolution of the US economy in each 20-year period.²⁵ Our focus, then, is on the contribution of each separate disturbance.

Between 1987 and 2007, in the data, the labor share decreased 3.6% and the employment rate increased 2.5%. Table 4 shows the results of our experiments for the same period. Changes in the scalar A are neutral for employment and the labor share because they increase productivity, costs, and unemployment income in the same proportion. Thus, we only need to assess the contribution of the other factors to understand the evolution of employment and the labor share.

The model suggests that (given changes in labor market institutions) the productivity of the automated technology has increased more than the increase implied by A , while that of the manual technology has increased less.²⁶ The latter means that the productivity of the manual tech-

crease wages and output in the same proportion, leaving the labor share and employment unchanged. A is akin to Total Factor Productivity in a neoclassical aggregate production function, and we consider changes in A to scale the economy and, thereby, to capture changes in aggregate output in the data due to factors common to both manual and automated technologies.

²⁵ All our analysis refers to changes in 5-year moving averages of the variables and targets. The data is all for the US and was downloaded from the FRED. For more details about the data and our targets, see Appendix D.

²⁶ Table 4 shows a positive deviation of z_K and a negative deviation of z_L with respect to the productivity growth implied by A . There is, however, no technological regress in the manual technology as A grows substantially more than z_L .

nology has been outpaced by growth in the entry and hiring costs as well as in the unemployment income. Looking at the implications of all disturbances, we conclude that employment increased because of the fall in the job-destruction rate, which significantly increases job duration. On the contrary, the labor share decreased because of the technological shocks. Our results in Table 4 suggest that changes in labor market institutions did not contribute to the fall in the US labor share from 1987 to 2007. The fall in workers' bargaining power barely affects the labor share, while the fall in labor market dynamism actually increases it. Indeed, the fall in the job-destruction rate promotes a higher labor share (see Eq. 11) but this increase is not enough to compensate for the highly negative effects of the technological shocks.

Result 2. *Changes in labor market institutions are unlikely to have played a major role in the fall of US labor share after 1987. Instead, changes in technology are a more promising candidate.*

Result 2 leans against a theoretical literature arguing that the labor share has fallen in recent decades due to changes in labor market institutions (e.g., Caballero and Hammour, 1998 and Bental and Demougins, 2010). Yet, the models in this literature predict that the labor share and employment drop simultaneously, while our model predicts that they may go in opposite directions, agreeing with the evidence on the effects of automation (Autor and Salomons, 2018; Bessen et al., 2020; Bessen, 2016; Gregory et al., 2021). Moreover, even though simple, our model is in line with another strand of literature. For example, Autor et al. (2020) argues that countries with very different labor market institutions experienced a fall in the labor share, pointing to the existence of other explanatory factors. The empirical work of Dao et al. (2017) confirms that logic: for developed countries, policy and institutional factors (including labor market institutions) barely play a role in explaining the fall in the labor share; conversely, technological channels explain about half.

Our results broadly agree with the micro-level evidence on the evolution of the US labor share. Despite the fall in the aggregate labor share, wages in our model grow slightly more than manual productivity (z_L) in 1987-2007, implying a marginal increase in the labor share of manual firms. This result agrees with the estimates in Autor et al. (2017, 2020) and Kehrig and Vincent (2021), who find that the labor share at the typical firm has increased in recent decades. Our results also agree with the findings in these papers that the aggregate labor share fell due to reallocation of revenues from high labor share to low labor share firms (manual and automated, respectively, in our model).²⁷ Finally, our

²⁷ Besides the long-term reallocation of value added toward low labor share firms, Kehrig and Vincent (2021) also find that the labor share at the firm level is transient, and emphasize the role of demand factors in explaining it. In our paper, we only study the long-term reallocation pattern, for which it is unclear empirically whether it is driven by demand factors or is instead driven by factors

Table 5
Targeted simulations – 1967 to 1987.

ΔA	Δz_K	Δz_L	$\Delta \phi$	$\Delta \delta_L$	ΔLS	Δn
47.42	-4.36	-4.92	-9.00	27.00	-1.00	-3.05
-	-4.36	-	-	-	10.37	-0.21
-	-	-4.92	-	-	-1.98	-0.78
-	-	-	-9.00	-	-0.10	0.41
-	-	-	-	27.00	-10.01	-1.75

Note: The experiments regard the period 1967-1987 and all values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters and the last two columns show the implied change in the labor share and employment (respectively) as a result of the shocks. In the first line, the shocks are calibrated such that our model targets the changes in output, labor force, employment, and labor share in 1967-1987 given the exogenously-imposed changes in ϕ and δ_L . In the data, the labor share fell 1% and employment fell 3%.

model hints on the causes of the rise in US markups (De Loecker et al., 2020), which we discuss in detail in Appendix F. The main takeaway from our model is that average markups have increased due to a reallocation of sales from low-markup manual firms to high-markup automated firms. Therefore, our model highlights a technological cause of the rise in average markups, which is consistent with the findings in De Loecker et al. (2021).

But why did the labor share only start falling after 1987? Why didn't it fall, for example, between 1967 and 1987? To shed some light on why the labor share barely changed (in the data) until 1987, we rerun the experiments reported in Table 4 but for the 20-year period earlier. The results are reported in Table 5. Interestingly, the model accommodates the fall in employment as a simultaneous negative deviation of the productivity growth of both technologies from the productivity growth implied by A , given the higher job-destruction probability. Regarding the US labor share, we get a clearer picture of its evolution by contrasting the results in Tables 4 and 5.

Result 3. *Our model suggests that the labor share only started to clearly fall after 1987 because the productivity of automated technologies (and ensuing fall in the labor share) accelerated dramatically in this period.*

Different studies and evidence point in the same direction as Result 3. The acceleration in the productivity of automated technologies concurs with the findings in other contributions using substantially different methods, ranging from VAR to structural growth models, to explain the fall in the labor share (Acemoglu and Restrepo, 2019, Bergholt et al., 2019, Martinez, 2018; see also the references in Acemoglu and Restrepo, 2018). The acceleration also agrees with the substantial growth of the stock of industrial robots (Prettner and Strulik, 2020).

Finally, we check whether our results are robust to different calibrations of our model by rerunning the previous experiments in the cases of $\alpha = 0.2$, $\alpha = -0.2$, $G(z^*) = 0.7$, and $G(z^*) = 0.4$. Appendix B.2 shows that the calibrated changes to z_K and z_L depend on the calibration of the model as these changes adapt to the different elasticities.²⁸ Yet, the change in the labor share and employment in each counterfactual exercise is far less sensitive to the calibration. In sum, our main points above are not sensitive to the calibration of our model.

5. Concluding remarks

The labor share has been falling throughout the world. This phenomenon contradicts the much celebrated Kaldor Facts and led many

like technology. Our model suggests that technology has played a very important role in this long-term pattern, which concurs with the conclusions in papers contrasting the roles of market structure and technology (e.g., De Loecker et al., 2021; Hubmer and Restrepo, 2021).

²⁸ Under some calibrations, we find that our model has difficulty converging for all counterfactuals. For example, this is the case for the shock to z_L when $G(z^*) = 0.8$ (shown in Table B.9).

researchers to come forward with theories and evidence to explain it. There are two prominent groups within this literature: those that ascribe the fall in the labor share to technological evolution and those that ascribe it to changes in labor market institutions. In this paper, we build a theoretical model to delve into this issue, which we think is a good starting point to contrast the role of automation with that of labor market institutions in explaining the evolution of the labor share. In our model, firms choose between two technologies: an automated technology and a manual technology. If they choose the automated one, they only employ capital. If they choose the manual one, they only employ labor and behave similarly to firms in the standard DMP model.

Our model suggests that changes in technology are the leading candidate to account for the fall in the US labor share, especially after 1987. In particular, our model suggests that the fall in the labor share coincided with an acceleration of automation-related technological change (which is consistent with the evidence and estimates in Martinez, 2018, Acemoglu and Restrepo, 2019, Bergholt et al., 2019, and Prettner and Strulik, 2020).

In this paper, we also offer insights on how automation shapes employment and wages. In our model, an automation-augmenting shock (which increases the productivity of all automated firms) induces two effects. First, the increased profitability of the automation technology reallocates resources towards this technology, displacing labor. Second, our model suggests that the shock induces greater firm entry as an aggregate-equilibrium result. This aggregate effect benefits labor and outweighs the reallocation effect, implying higher employment as found by empirical studies (see Bessen, 2016, Autor and Salomons, 2018, Gregory et al., 2021, and Bessen et al., 2020).²⁹

Our paper also contributes to the public debate on the introduction of a robot tax. In light of our model, a robot tax can be interpreted as one (or as a combination) of two shocks: (i) as a tax on the returns of the automated technology, which is equivalent to a fall in its productivity, z_K ; or (ii) as a tax on the (startup) cost of capital, which is equivalent to a rise in κ_K . We have shown that both scenarios increase the labor share in the model. But we have also shown that both scenarios reduce wages and employment. Thus, our model suggests that policymakers face a trade-off: if they introduce a robot tax, they may reduce inequality between workers and firms' owners but they also reduce the workers' (absolute) standard of living.

We have chosen to build a simple model, which comes with the benefit of analytical tractability and the ensuing clarity of the mechanisms at play in the model. But, even though our model also provides insightful results that are broadly consistent with the evidence, its abstractions are naturally open to criticism. For example, our model is unsuited to offer insights about business cycle dynamics (see Choi and Ríos-Rull, 2020 for the business cycle dynamics generated by a model similar to ours). Furthermore, there might be extensions of our model that change its predictions. For example, labor supply is inelastic in our model: there is full labor force participation and unemployed workers always supply the same job search effort. In reality, however, workers change their labor force attachment and the amount of time they search for jobs as economic conditions change. As a result, in the presence of high income and wealth effects, workers may prefer to reduce their labor supply because they feel richer when productivity rises. In this case, employment could fall (after automation shocks) not due to lower labor demand but rather due to low labor supply. Another possibility is to build a model in which labor and capital are complementary at the firm level but firms can adjust the elasticity of output with respect to the automated technology. Such a model would likely strengthen the

²⁹ We note, however, that our model is built to study the long run and abstracts from differences among industries. Thus, our model is silent regarding the short-run effects of automation on employment, which may differ from those in the long run. And is silent regarding the heterogeneous effects of automation in different industries.

role of changes in labor market institutions as they induce firms to adjust the elasticity with respect to the automated technology (similar to Caballero and Hammour, 1998). Finally, we can also change the timing of the model. In the model of this paper, firms choose technology at the time of entry (either manual or automated). But we can envision a model in which all firms start as manual and may change to the automated technology later on depending on the incentives (similar to Acemoglu and Restrepo, 2018). In such a model, automation replaces existing labor, which may affect how automation shocks unfold in the economy. We will consider the implications of this extension in a future paper.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.labeco.2022.102146](https://doi.org/10.1016/j.labeco.2022.102146)

References

- Acemoglu, D., 2003. Labor- and capital-augmenting technical change. *Journal of European Economic Association* 1, 1–37.
- Acemoglu, D., Restrepo, P., 2018. The race between man and machine: implications of technology for growth, factor shares, and employment. *American Economic Review* 108 (6), 1488–1542.
- Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives* 33 (2), 3–30.
- Acemoglu, D., Zilibotti, F., 2001. Productivity differences. *Quarterly Journal of Economics* 116 (2), 563–606.
- Alesina, A., Battisti, M., Zeira, J., 2018. Technology and labor regulations: theory and evidence. *Journal of Economic Growth* 23 (1), 41–78.
- Alvarez, S., Barney, J.B., 2004. Organizing rent generation and appropriation: toward a theory of the entrepreneurial firm. *Journal of Business Venturing* 19 (5), 621–635.
- Alvarez-Cuadrado, F., Long, N.V., Poschke, M., 2018. Capital-labor substitution, structural change, and the labor income share. *Journal of Economic Dynamics and Control* 87, 206–231.
- Autor, D., Dorn, D., Katz, L.F., Patterson, C., Reenen, J.V., 2017. Concentrating on the fall of the labor share. *American Economic Review* 107 (5), 180–185.
- Autor, D., Dorn, D., Katz, L.F., Patterson, C., Reenen, J.V., 2020. The fall of the labor share and the rise of superstar firms*. *Q J Econ.* Qja004
- Autor, D., Salomons, A., 2018. Is automation labor share-displacing? productivity growth, employment, and the labor share. *Brookings Pap Econ Act* 1–63.
- Bental, B., Demougis, D., 2010. Declining labor shares and bargaining power: an institutional explanation. *J Macroecon* 32 (1), 443–456.
- Bentolila, S., Saint-Paul, G., 2003. Explaining movements in the labor share. *B.E. Journal of Macroeconomics, Contributions* 3 (1), Article 9
- Berg, A., Buffie, E.F., Zanna, L.-F., 2018. Should we fear the robot revolution? (the correct answer is yes). *Journal of Monetary Economics* 97, 117–148.
- Bergholt, D., Furlanetto, F., Faccioli, N., 2019. The decline of the labor share: new empirical evidence. *American Economic Journal: Macroeconomics*. Forthcoming
- Berthold, N., Fehn, R., Thode, E., 2002. Falling labor share and rising unemployment: long-run consequences of institutional shocks? *German Economic Review* 3 (4), 431–459.
- Bessen, J., Goos, M., Salomons, A., van den Berge, W., 2020. Automation: A guide for policymakers.
- Bessen, J.E., 2016. How computer automation affects occupations: technology, jobs, and skills. *Boston Univ. School of Law, Law and Economics Research Paper*, (15–49).
- Blanchard, O., 1997. The medium run. *Brookings Pap Econ Act* 2, 89–141.
- Blanchard, O., Giavazzi, F., 2003. Macroeconomic effects of regulation and deregulation in goods and labor markets. *Q J Econ* 118 (3), 879–907.
- Caballero, R.J., Hammour, M.L., 1998. Jobless growth: appropriability, factor substitution, and unemployment. *Carnegie-Rochester Conference Series on Public Policy* 48, 51–94.
- Caselli, F., Coleman, W.J., 2006. The world technology frontier. *American Economic Review* 96 (3), 499–522.
- Choi, S., Ríos-Rull, J.-V., 2020. Labour share and productivity dynamics. *The Economic Journal* 131 (639), 2856–2886.
- Coles, M.G., Kelishomi, A.M., 2018. Do job destruction shocks matter in the theory of unemployment? *American Economic Journal: Macroeconomics* 10 (3), 118–136.
- Cope, J., 2005. Toward a dynamic learning perspective of entrepreneurship. *Entrepreneurship Theory and Practice* 29 (4), 373–397.
- Cords, D., Prettnner, K., 2021. Technological unemployment revisited: automation in a search and matching framework. *Oxf Econ Pap*.
- Dao, M.C., Das, M., Koczan, Z., Lian, W., 2017. Why is labor receiving a smaller share of global income? theory and empirical evidence. *IMF Working Paper* 17/169.
- Davis, S.J., Haltiwanger, J., 2014. Labor market fluidity and economic performance. *National Bureau of Economic Research Working Paper* 20479.
- De Loecker, J., Eeckhout, J., Mongey, S., 2021. Quantifying market power and business dynamism in the macroeconomy. In: *National Bureau of Economic Research Working Paper*, p. 28761.
- De Loecker, J., Eeckhout, J., Unger, G., 2020. The rise of market power and the macroeconomic implications*. *Q J Econ* 135 (2), 561–644.
- Domini, G., Grazi, M., Moschella, D., Treibich, T., 2021. Threats and opportunities in the digital era: automation spikes and employment dynamics. *Res Policy* 50 (7), 104137.
- Eggertsson, G.B., Robbins, J.A., Wold, E.G., 2021. Kaldor and piketty's facts: the rise of monopoly power in the united states. *J Monet Econ* 124, S19–S38.
- Elsby, M.W.L., Hobijn, B., Şahin, A., 2013. The decline of the US labor share. *Brookings Pap Econ Act* 2013 (2), 1–63.
- Fadinger, H., Mayr, K., 2014. Skill-biased technological change, unemployment, and brain drain. *J Eur Econ Assoc* 12 (2), 397–431.
- Farber, H.S., Herbst, D., Kuziemko, I., Naidu, S., 2021. Unions and inequality over the twentieth century: new evidence from survey data*. *Q J Econ* 136 (3), 1325–1385.
- Ghironi, F., Melitz, M.J., 2005. International trade and macroeconomic dynamics with heterogeneous firms. *Q J Econ* 120 (3), 865–915.
- Gibb, A., Ritchie, J., 1982. Understanding the process of starting small businesses. *European Small Business Journal* 1 (1), 26–45.
- Gomes, P., Kuehn, Z., 2017. Human capital and the size distribution of firms. *Rev Econ Dyn* 26, 164–179.
- Graetz, G., Michaels, G., 2018. Robots at work. *Rev Econ Stat* 100 (5), 753–768.
- Gregory, T., Salomons, A., Zierahn, U., 2021. Racing with or against the machine? evidence on the role of trade in Europe. *J Eur Econ Assoc*.
- Growiec, J., 2008. A new class of production functions and an argument against purely labour-augmenting technical change. *International Journal of Economic Theory* 4, 483–502.
- Growiec, J., 2013. A microfoundation for normalized CES production functions with factor-augmenting technical change. *Journal of Economic Dynamics and Control* 37, 2336–2350.
- Growiec, J., 2017. Factor-specific technology choice. *Narodowy Bank Polski Working Papers, Economic Research Department* 265.
- Growiec, J., McAdam, P., Muck, J., 2018. Endogenous labor share cycles: theory and evidence. *Journal of Economic Dynamics and Control* 87, 74–93.
- Hall, R.E., Milgrom, P.R., 2008. The limited influence of unemployment on the wage bargain. *American Economic Review* 98 (4), 1653–1674.
- Hopenhayn, H., Neira, J., Singhania, R., 2018. From population growth to firm demographics: implications for concentration, entrepreneurship and the labor share. *National Bureau of Economic Research Working Paper* 25382.
- Hopenhayn, H.A., 1992. Entry, exit, and firm dynamics in long run equilibrium. *Econometrica* 60 (5), 1127–1150.
- Hornstein, A., Krusell, P., Violante, G.L., 2007. Technology-policy interaction in frictional labour-markets. *Rev Econ Stud* 74 (4), 1089–1124.
- Hubmer, J., Restrepo, P., 2021. Not a typical firm: the joint dynamics of firms, labor shares, and capital-labor substitution. *National Bureau of Economic Research Working Paper* 28579.
- Jones, C.I., 2003. Growth, capital shares, and a new perspective on production functions. *UC Berkeley mimeo*.
- Jones, C.I., 2005. The shape of production functions and the direction of technical change. *Quarterly Journal of Economics* 120 (2), 517–549.
- Jones, C.I., Romer, P.M., 2010. The new kaldor facts: ideas, institutions, population, and human capital. *American Economic Journal: Macroeconomics* 2 (1), 224–245.
- Kaldor, N., 1961. The theory of capital. In: *Lutz, F.A., Hague, D.C. (Eds.), Chapter Capital Accumulation and Economic Growth, 177–222*. New York: St. Martin's Press.
- Kapoor, R., Furr, N.R., 2015. Complementarities and competition: unpacking the drivers of entrants' technology choices in the solar photovoltaic industry. *Strategic Management Journal* 36 (3), 416–436.
- Karabarbounis, L., Neiman, B., 2014. The global decline of the labor share. *Q J Econ* 129 (1), 61–103.
- Kehrig, M., Vincent, N., 2021. The micro-level anatomy of the labor share decline*. *Q J Econ* 136 (2), 1031–1087.
- Kerr, W.R., Nanda, R., Rhodes-Kropf, M., 2014. Entrepreneurship as experimentation. *Journal of Economic Perspectives* 28 (3), 25–48.
- Koh, D., Santaella-Llopis, R., Zheng, Y., 2020. Labor share decline and intellectual property products capital. *Econometrica* 88 (6), 2609–2628.
- León-Ledesma, Miguel, A., Satchi, M., 2019. Appropriate technology and balanced growth. *Rev Econ Stud* 86 (2), 807–835.
- Ljungqvist, L., Sargent, T.J., 2018. *Recursive Macroeconomic Theory*. MIT press.
- Luttmer, E.G.J., 2007. Selection, growth, and the size distribution of firms. *Q J Econ* 122 (3), 1103–1144.
- Martinez, J., 2018. Automation, growth and factor shares.
- Melitz, M.J., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71 (6), 1695–1725.
- Oberfield, E., Raval, D., 2021. Micro data and macro technology. *Econometrica* 89 (2), 703–732.
- Peretto, P., Seater, J., 2013. Factor-eliminating technical change. *J Monet Econ* 60, 459–473.
- Petrongolo, B., Pissarides, C.A., 2001. Looking into the black box: a survey of the matching function. *J Econ Lit* 39 (2), 390–431.
- Pissarides, C., 2000. *Equilibrium Unemployment Theory*. Cambridge:MIT Press.
- Pissarides, C.A., 2009. The unemployment volatility puzzle: is wage stickiness the answer? *Econometrica*.
- Prettnner, K., Strulik, H., 2020. Innovation, automation, and inequality: policy challenges in the race against the machine. *J Monet Econ* 116, 249–265.
- Shimer, R., 2005. The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review* 95 (1), 24–49.

- Shimer, R., 2012. Reassessing the ins and outs of unemployment. *Rev Econ Dyn* 15 (2), 127–148.
- Stansbury, A., Summers, L.H., 2020. Declining worker power and american economic performance. *Brookings Pap Econ Act*.
- Young, A.T., Zuleta, H., 2018. Do unions increase labor's shares? evidence from US industry-level data. *East Econ J* 44 (4), 558–575.
- Zeira, J., 1998. Workers, machines and economic growth. *Quarterly Journal of Economics* 113, 1091–1113.
- Zeira, J., 2010. *Machines as Engines of Growth*. mimeo.
- Zuleta, H., 2008. Factor saving innovations and factor income shares. *Rev Econ Dyn* 11, 836–851.