Explaining the labor share: automation vs labor market institutions

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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 offers three main insights. First, automation-augmenting shocks reduce the labor share but increase employment and wages. Second, labor market institutions play an almost insignificant role in explaining the labor share. Third, the US labor share only (clearly) fell after 1987 because of a contemporaneous acceleration of automation's productivity.

JEL classification: E24; J64; L11; O33.

Keywords: Automation; Labor Share; Technology Choice; Employment; Matching Frictions.

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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 emphasized the roles of automation (*e.g.*, Acemoglu and Restrepo, 2018), robot- or automation-augmenting technological change (*e.g.*, Berg, Buffie and Zanna, 2018), falling price of capital (*e.g.*, Karabarbounis and Neiman, 2014), and the emergence of superstar firms together with overhead labor costs (*e.g.*, Autor et al., 2017*b*).[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, Krusell and Violante, 2007).[3] Our paper belongs to the sec-

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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, Fehn and Thode (2002), Jones (2003), and Bentolila and Saint-Paul (2003). For more recent contributions, see, *e.g.*, Bental and Demougin (2010), Elsby, Hobijn and Şahin (2013), Karabarbounis and Neiman (2014), Oberfield and Raval (2014), Autor et al. (2017*b*), and Dao et al. (2017).

[2]See, as well, Zeira (1998, 2010), Peretto and Seater (2013), Prettner and Strulik (2017), Martinez (2018), Hopenhayn, Neira and Singhania (2018), and León-Ledesma and Satchi (2019).

[3]See, as well, Bentolila and Saint-Paul (2003), Blanchard and Giavazzi (2003), Bental and Demougin (2010), Young and

ond 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-augmenting technological change and falling price of capital) with the role of changes in labor market institutions (falling workers' bargaining power and decreasing flows in the labor market). We conclude that the fall in the US labor share was most likely caused by technological factors.

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 technological shocks (either TFP or routine-replacing specific) have not been employment-displacing at the aggregate level in developed economies (Autor and Salomons, 2018 and Gregory, Salomons and Zierahn, 2018). Different models that allow for a fall in the labor share are unable to simultaneously generate an increase in employment (*e.g.,* Zeira, 1998; Caballero and Hammour, 1998; Acemoglu and Restrepo, 2018). In contrast, our model concurs with the evidence: an automation-augmenting shock reduces the labor share but increases both employment and wages.

Our paper further contributes to the literature in two other ways because of its different approach. First, we propose a rather simple model that extends the canonical Diamond-Mortensen-Pissarides (DMP) model (similar to 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 mecha-

Zuleta (2018), and Cords and Prettner (2019).

nisms 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 to properly distinguish how changes in labor market institutions and in technology affect the labor share. Thus, our model offers a different perspective on the effects of automation and the evolution of the labor share by bringing the workhorse model of the labor market (DMP model) to the center of the discussion.

1.2   Summary of the Model & Results

We build a model of technology choice with matching frictions and the following main features. When entering the market, 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, which is capital intensive, or the manual technology, which is labor intensive.[4] 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, resembling an undirected technology-search process (as in, *e.g.*, Benhabib, Perla and Tonetti, 2017). 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-

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[4]Jones and Romer (2010) cite evidence that corroborates that many different technologies are used with widely varying intensities throughout the world. For instance, in Germany, Japan, and the United States, in steel manufacturing one can observe the use of minimills versus modern integrated mills, whereas in beer production one can observe small family-run breweries versus mass production equipment breweries. Caselli and Coleman (2006) provide an insightful description of a context where there are two methods to produce output: one consists of an assembly line where a large number of (unskilled) workers produce output with hand tools and the other consists of a computer-controlled and -operated facility that is mainly run by a few (skilled) workers. In our model, we label the former the manual technology and the latter the automated technology.

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.[5]

Our model paves the way to study how automation affects the labor market in models with matching frictions. The canonical Diamond-Mortensen-Pissarides 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).

In order to inquire into the effects of increasing automation on jobs, we study analytically the effects of an automation-augmenting technological change in our model. 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, which agrees with the empirical evidence in Autor and Salomons (2018) and Gregory, Salomons and Zierahn (2018).

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[5]As will be made clear later on, this complementarity arises in the sense that a technological shock that augments one of the technologies/inputs will, to some extent, benefit the other one relatively more.

As a second step, we calibrate our model to the US economy and compute the simulated elasticities of key macroeconomic variables with respect to multiple parameters of our model. The goal is to study quantitatively how the output, employment, average wage, and labor share respond to two broad types of shocks: technological and labor-market shocks. Regarding the former, we distinguish between automation-augmenting shocks, manual-augmenting shocks and shocks to the relative cost of capital (in our model, cost of capital versus vacancy costs) (as in, *e.g.*, Hornstein, Krusell and Violante, 2007; Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2018). Regarding the latter type of shocks, we consider those to the nonemployment income, workers' bargaining power, matching efficiency, and job destruction rate (as in, *e.g.*, Caballero and Hammour, 1998; Bentolila and Saint-Paul, 2003; Blanchard and Giavazzi, 2003; Bental and Demougin, 2010).

Two results stand out. First, an automation-augmenting shock increases the average wage and employment but reduces the labor share. In our model, the labor share falls due to the reallocation of activity towards the automated technology, which offsets the effect of higher wage and employment. Yet, the labor share does not fall at the firm level. This result is particularly relevant as it agrees with the empirical evidence, based on detailed micro data for the US, that points to a (relatively) stable labor share at the firm level over time (Autor et al., 2017*a,b*). Second, technological shocks have a much greater impact on output and the labor share than changes in the labor market institutions (although the latter have non-neglectable effects on employment). Thus, in light of our model, unless labor market institutions change massively, technological shocks are the best candidate to explain a fall in the labor share. All these results agree with recent empirical observations, namely for the US (see, *e.g.*, Karabarbounis and Neiman, 2014; Autor et al., 2017*a,b*; Dao et al., 2017; Autor and Salomons, 2018).

Finally, we conduct experiments on our model bearing in mind the historical behavior of the US labor share, which we depict in Figure 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),

Figure 1: The US Economy: 1963–2007
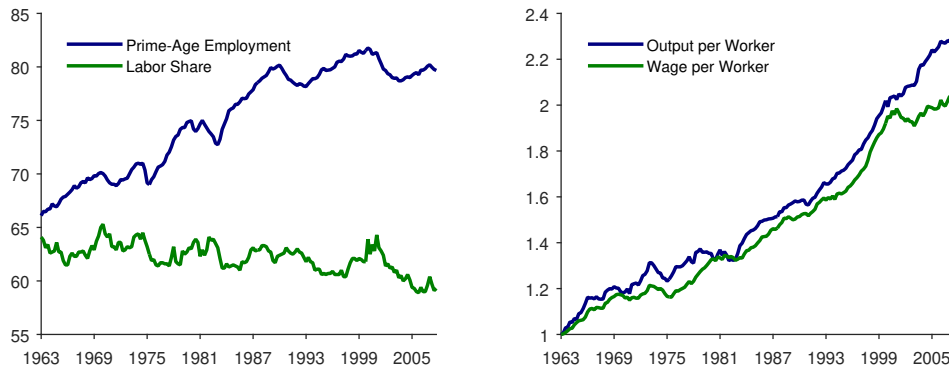
Note: Both panels plot data for the US economy between 1963 and 2007 downloaded from the FRED and the BLS. The panel on the left-hand side plots the employment rate of workers aged 25-54 (prime-age) and the labor share. The vertical axis of this panel measures percentage points. The panel on the right-hand side plots the output and wage per worker in the nonfarm business sector (NBS). Both series are normalized to 1 in 1963, meaning that the vertical axis of this panel measures the ratio of each series relative to its value in 1963. Output per worker is the product of the real output per hour (OPHNFB) and total hours (HOANBS), both in the NBS, divided by the civilian employment level (CE16OV). Wage per worker is the real compensation per hour in the NBS (COMPRNFB) multiplied by total hours in the NBS (HOANBS) and divided by the civilian employment level (CE16OV). This wage is multiplied by the ratio of the Consumer Price Index (CPIAUCSL) over the GDP deflator (GDPDEF).

their growth rates diverge. In other words, the US labor share clearly drops only after the late 1980s (*e.g.*, Elsby, Hobijn and Şahin, 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. Our goal is to answer three questions. (i) Can our model account for the fall in the labor share in the second period? (ii) If yes, what are the forces that our model proposes to explain that fall? (iii) Why are the two periods different as regards the behavior of the labor share? As a calibration strategy, we consider shocks to alternative subsets of (technological and/or labor market) parameters by targeting the growth rate of output and wages in the US data within each 20-year period. Then, we compute the changes in the labor share and employment implied by our model and compare them with the changes observed in the data for the same time period.

Concerning the 1987-2007 period, our model performs remarkably well in two experiments: the combination of automation-augmenting and manual-augmenting shocks and the combination of

cost-of-capital and manual-augmenting shocks. In both cases, the fall in the labor share is extremely close to that in the data, while the employment rate increases only slightly more. In contrast, experiments that include changes in labor market institutions render disappointing results. As suggested by recent empirical studies (*e.g.,* Davis and Haltiwanger, 2014; Farber et al., 2018), we consider combinations of shocks that involve shifts in the workers' bargaining power or in both the job destruction rate and matching efficiency. These combinations of shocks either increase the labor share or decrease it at the expense of counterfactual changes in labor market institutions (*e.g.,* a very high increase in the US labor market flows). We take these results as indicators that the drop in the US labor share after 1987 was most likely caused by technological changes rather than by changes in the labor market institutions.

Concerning the 1967-1987 period, our model suggests that the observed change of output and wages was caused by manual-augmenting shocks, and this is why the labor share did not fall in that period. Contrasting these results for the 1967-1987 period with those for the 1987-2007 period, then it becomes clear that the fall after 1987 occurred because of a significant acceleration of automation-augmenting *vis-à-vis* manual-augmenting technological change. This acceleration concurs with the significant shifts in the task content against labor (and towards automation) after 1987 estimated by Acemoglu and Restrepo (2019). It also concurs with the VAR evidence in Bergholt, Furlanetto and Faccioli (2019), with recent empirical estimates of capital- vs labor-augmenting coefficients based on closed-form aggregate-production functions (see, *e.g.,* Acemoglu and Restrepo, 2018, and references therein) and with direct evidence on the evolution of the stock of industrial robots (Prettner and Strulik, 2017).

1.3   Related Literature

As explained earlier, we lay out a model of technology choice exploiting the idea that, in general, firms face alternative technologies to produce output, be it a good or a task. The concept of alternative technologies enters into numerous models in the literature and agrees with the empirical evidence described by Jones and Romer (2010) and references therein. In several of these models, *e.g.,* Zeira (1998, 2010), Acemoglu and Zilibotti (2001), Acemoglu (2003), Acemoglu and Restrepo (2018) and Alesina, Battisti and Zeira (2018), the incentive for a given firm to adopt one technology *vis-à-vis* the other(s) depends explicitly on a firm-specific exogenous feature. This feature may be interpreted, as in our model, as a firm's endowment or capability and determines, *ceteris paribus*, the firm's overall productivity or cost level. 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 and Satchi (2019).

From the literature above, our paper is closer to Zeira (1998, Sec. 7; 2010), Alesina, Battisti and Zeira (2018), and Acemoglu and Restrepo (2018), with whom it shares the simplifying assumption that the manual technology employs only labor and the automated (or 'industrial') technology only capital. In Zeira (1998, 2010) and Alesina, Battisti and Zeira (2018), there is a final good produced by a continuum of tasks. As new machines are made available for task production, they raise workers' productivity and wages. But firms respond to higher wages by replacing workers (manual technology) with machines ('industrial' technology) in the tasks with the lower cost of machines. Consequently, these models feature an aggregate production function characterized by increasing capital intensity and a decreasing

labor share. Acemoglu and Restrepo (2018) also devise a model of technology choice and technological change where a final good is produced by a continuum of tasks. The authors consider research activities directed either towards automation of existing tasks (*i.e.*, task production switches from the manual to the automated technology) or towards the creation of new tasks in which labor has a comparative advantage (and, thus, the new task uses the manual technology). While automation reduces labor supply, the labor share, and possibly wages, the creation of new tasks has the opposite effects. Depending on the long-run relative cost of the two production technologies (rental rate of capital versus wages), there may be an equilibrium in which all tasks are automated (and, thus, the labor share is driven to zero), or one in which both automation and the creation of new tasks coexist (and, thus, a positive and stable labor share is attained). The latter may occur because automation reduces the cost of producing with the manual technology, thus discouraging further automation while incentivizing the creation of new tasks.

The object of study and approach of our paper differ from that in Zeira (1998, 2010) and Alesina, Battisti and Zeira (2018). Even though their models provide results on the effects of automation on the labor share and employment, the authors explore other insights pertaining to different research questions. In this sense, Acemoglu and Restrepo (2018) is closer to our paper as we share the main object of study. Yet, because Acemoglu and Restrepo do not calibrate their model, they only 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.[6]

Looking into other strands of the literature, our paper relates to the 'putty-clay' model by Caballero and Hammour (1998) and, along different lines, to Hornstein, Krusell and Violante (2007) and Bental

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[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.

and Demougin (2010). Our paper relates to Caballero and Hammour as this paper addresses the issue of the labor share and explicitly considers a form of labor market frictions. In their model, labor can appropriate capital due to the relationship-specificity of capital and limited precontracting possibilities, which are influenced by, *e.g.,* the strength of the workers' bargaining position and by firing costs. In the short run, appropriation shocks (due to, *e.g.,* higher capital-specificity or firing costs) increase wages and the labor share. But these shocks also motivate firms to reduce their exposure to future appropriation by decreasing the labor-intensity of new production units. In the long run, firms reduce hiring, thereby reducing employment, the average wage, and the labor share. These patterns agree very neatly with the evolution of the French economy in 1967-1995, which is the object of study of Caballero and Hammour.

Hornstein, Krusell and Violante (2007) develop a model with (standard) labor market frictions and vintage capital. In their model, production requires matching one machine (capital) of a given vintage with one worker to yield a homogeneous output good. But capital-embodied technological change renders each vintage obsolete and eventually breaks the existing machine-worker match. The authors show that an acceleration of capital-embodied technological change accelerates capital scrapping and reduces firms' incentives to create new jobs. This, in turn, shapes labor-market outcomes, yielding an increase in the level and duration of unemployment, thereby reducing the employment rate and the labor share. More recently, as a variation on the topic, Bental and Demougin (2010) explore the relationship between technology and labor market frictions in a model in which the worker-firm relations are characterized by moral hazard, the allocation of bargaining power between firms and workers is endogenous, and firms' investment is irreversible. They focus, in particular, on ICT shocks that enhance the effectiveness of the monitoring technology, reducing the moral hazard problem. In their model, these shocks lower the workers' bargaining power and, thereby, decrease the wages per effective unit of labor and the labor share.

The mechanism in our model is closer to the one in Caballero and Hammour (1998) than to those in Hornstein, Krusell and Violante (2007) and Bental and Demougin (2010), inasmuch as the former allows for changes in the labor share reflecting shifts in technology choice (in their case, a change in the labor-intensity of new production units) as a reaction to given exogenous shocks. Such a mechanism resembles the reallocation between manual and automated technologies in our model. But differently from the models in these three papers and also the models in Zeira (1998, 2010) and Acemoglu and Restrepo (2018), our model generates simultaneously a fall in the labor share and an increase in the average wage and employment. Therefore, our model offers a better fit to the observed dynamics of the US economy.

Also related to our model, Cords and Prettner (2019) develop a model with automation and matching frictions. In their model, an aggregate production function combines high- and low-skill labor with both traditional physical capital and automation capital (*e.g.*, robots). Physical capital complements both skill types but automation capital is a perfect substitute for low-skill labor and an imperfect substitute for high-skill labor. Cords and Prettner use this model to study how shifts in the stock of automation capital differently affect the unemployment and wages of the two types of labor. Yet, they do not focus on the behavior of the labor share and calibrate their model to the German economy.

Other contributions in the literature focus on alternative mechanisms to explain the shifts in the labor share. In particular, these contributions exploit the interplay between an aggregate CES production function and, namely, factor-augmenting technical progress, the relative price of investment goods, structural change, or increases in market power (*e.g.*, Acemoglu, 2003; Karabarbounis and Neiman, 2014; Alvarez-Cuadrado, Long and Poschke, 2018; Berg, Buffie and Zanna, 2018; Eggertsson, Robbins and Wold, 2018; Growiec, McAdam and Muck, 2018). We emphasize, in particular, the results in Berg, Buffie and Zanna. The authors simulate their model so that the economy moves from one steady state to the other as a consequence of a temporary (exogenous) upward path in the robot-

augmenting factor. Output per capita rises considerably while the strong induced accumulation of the non-robot capital guarantees that overall labor demand and the real wage increase in the long run, while the labor share falls. These results are all consistent with the results in our model following an acceleration of the automation-augmenting factor. The results of this literature (as well as of Cords and Prettner, 2019), however, hinge crucially on the considered magnitude of the elasticity of substitution between labor and capital (or robots).

Finally, our approach is very much in the spirit of the inter-firm reallocation mechanism analyzed by Autor et al. (2017*b*, App. A). Autor et al. develop a partial-equilibrium model of an industry where firms have heterogeneous (constant) total factor productivity and there is imperfect competition in the product market. Each firm produces output using physical capital and (variable) labor under a Cobb-Douglas technology, while putting up a fixed cost measured as overhead labor. There is free entry and, upon entry, firms take an idiosyncratic productivity draw. The authors show that the firms with bigger productivity draws ("the superstar firms") are larger as they produce more efficiently and capture a higher share of industry output. These firms also have a lower share of fixed costs in total revenues and, thus, a lower labor share, in line with the authors' empirical results. When there is an exogenous change (*e.g.*, a globalization or a technological shock) that favors the most productive (larger) firms, the aggregate labor share falls as the economic activity shifts towards these low labor-share firms.[7] Similarly, in our model, the labor share mainly shifts because heterogeneous firms reallocate activity towards those that are capital-intensive. Yet, our mechanism differs from the one in Autor et al. (2017*b*, App. A) in important aspects. Our paper expresses the negative relationship between firm size and the labor share by making explicit the choice between manual and automated technologies by heterogenous firms, where the former entails search and matching costs in the la-

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[7] Hopenhayn, Neira and Singhania (2018) offer a similar mechanism. They develop a dynamic model of heterogeneous firms in which larger and older, more productive, firms have lower labor shares as a result of labor overheads. Thus, in this context, the change in the labor share in the economy also reflects the reallocation of economic activity between firms.

bor market while the latter only entails a fixed start-up cost. Therefore, our model allows us to take a detailed look into the interplay between technology choice, labor market frictions, and labor market outcomes (including the labor share), while emphasizing the reallocation mechanism.

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 discusses how alternative assumptions affect our results. First, this section shows that, although changes in labor market institutions do not seem to explain the evolution of the US labor share, our model requires labor market institutions (in particular, wage bargaining) to fit the US evidence after 1967. Second, it shows that if entry costs are proportional to output, our model continues to point to the acceleration of automation-augmenting technological change to explain the fall in the US labor share only after 1987. Third, it shows that if the cutoff between technologies in our model is technologically constrained, our model continues to suggest that an automation-augmenting shock raises employment. Section 6 concludes the paper.

2   The Model

Our model extends the DMP model set in discrete time as in, *e.g.*, Ljungqvist and Sargent (2018, Ch. 29)]. In our model, firms pay an entry cost Ω to enter the market and draw a productivity z from a distribution $G(z)$ of productivity levels over the interval $[z_{min}, \infty)$.[8] After knowing their productivity, firms choose between 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 $z_K(z) \equiv z_K z$

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[8]We interpret this productivity draw as an endowment or capability accessed through an undirected search process by each firm (*e.g.*, Benhabib, Perla and Tonetti, 2017). We also find a similar assumption in different contexts, including the seminal paper of Melitz (2003).

units of output using only capital.[9] 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 $\kappa_L/\mu(\theta) > 0$ to fill its vacancy, and produces $z_L(z) \equiv z_L z^\alpha$ units of output using only labor. z_L denotes the productivity of labor, which contrasts with 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 probability, $\mu(\theta) \equiv \chi\theta^{-\eta}$, 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 nonemployed 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:

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

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[9]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), Prettner and Strulik (2017), and Acemoglu and Restrepo (2018).

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. 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; 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., 2017a ,2017b). To close the firms' block of our model, we assume free-entry to open firms:

$$\int_{z_{min}}^{z^*} \left(\beta J_L(z) - \frac{\kappa_L}{\mu(\theta)} \right) \mathrm{d}G(z) + \int_{z^*}^{\infty} \left(J_K(z) - \kappa_K \right) \mathrm{d}G(z) = \Omega, \tag{4}$$

where Ω is a sunk entry cost.

2.2 Workers

In our model, there is a measure L of risk-neutral workers who are in one of two states: employed or nonemployed. 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 $E(z)$:

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

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

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

where $\frac{1}{G(z^*)} \int_{z_{min}}^{z^*} E(z) \mathrm{d}G(z)$ is the average expected value of employment.[10]

2.3   The Wage

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

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

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 $\beta J_L(z) - \frac{\kappa_L}{\mu(\theta)}$; that is, the firm may invest $\frac{\kappa_L}{\mu(\theta)}$ to find another worker which will generate a value of $\beta J_L(z)$.[11] 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 $\beta J_L(z) - \frac{\kappa_L}{\mu(\theta)}$ and $w(z)$ must satisfy

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

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[10]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 nonemployment. Instead, the value of nonemployment depends on the distribution of $G(z)$ in the range that firms decide to open manual firms: $[z_{min}, z^*]$.

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

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

$$w(z) = \frac{1-\phi}{1-\phi\beta}b + \frac{\phi}{1-\phi\beta}\left[(1-\beta)z_L(z) + \frac{\kappa_L}{\mu(\theta)}(1-\beta(1-\delta_L))\right] +$$
$$\beta f(\theta)\frac{\phi}{1-\phi\beta}\left((1-\beta)\left[\Omega - \int_{z^*}^{\infty}(J_K(z)-\kappa_K)\,\mathrm{d}G(z)\right]\frac{1}{\beta G(z^*)} + (1-\beta)\frac{\kappa_L}{\beta\mu(\theta)} + \frac{\kappa_L}{\mu(\theta)}\right). \tag{9}$$

As in the DMP model, wages increase with the nonemployment 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 nonemployment must equal the flows from nonemployment 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 $\frac{1}{G(z^*)}\int_{z_{min}}^{z^*} z_L(z)\mathrm{d}G(z)$ 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 $\frac{1}{1-G(z^*)}\int_{z^*}^{\infty} z_K(z)\mathrm{d}G(z)$ units of output. Output in our model, then, is

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

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 $\frac{1}{G(z^*)}\int_{z_{min}}^{z^*} w(z)\mathrm{d}G(z)$. Using the expression for output of Eq. (10), after a few rearrangements, we write the labor share as[12]

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

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 increases both wages and employment.

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[12]As we assume that κ_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.

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

$$w = (1 - \phi)b + \phi(z_L + \theta\kappa_L) - \phi\left[\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K\right)[(\beta - 1)f(\theta) + 1 - \beta(1 - \delta_L)]\right], \qquad (12)$$

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 draw z. Thus, the value of the manual technology $J_L(z)$ is the same for all draws of z. Log-linearizing the no-arbitrage condition, Eq. (3), and the wage equation, Eq. (12), we obtain

$$\hat{\theta} = \frac{A}{B}(\hat{z_K} + \hat{z^*}), \qquad (13)$$

where $A \equiv \frac{z_K z^*}{1 - \beta(1 - \delta_K)}\left(1 - \beta\phi + \beta\phi\frac{(1-\beta)\chi\theta^{1-\eta}}{1-\beta(1-\delta_L)}\right) > 0$, $B \equiv -\left(\phi\beta\frac{(1-\beta)(1-\eta)\left(\frac{z_K z^*}{1-\beta(1-\delta_K)} - \kappa_K\right)\chi\theta^{1-\eta} + \theta\kappa_L}{1-\beta(1-\delta_L)} + \eta\frac{\kappa_L\theta^\eta}{\chi}\right) <$ 0, and we use hats to denote log-linear variables. (See Appendix A.1 for more details on the derivations.) The signs of A and B 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. 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 $z_L, b, \phi, \delta_L, \kappa_L, \chi$, 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 $b, \phi, \delta_L, \kappa_L, \chi$, or η has a minor effect on z^* and the labor share.

Moving to the log-linearization of 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, if the productivity of the automated technology rises, by Eq. (13), employment rises.

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).[13] 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^*.[14]

Our result that an increase in z_K raises employment is noteworthy given that the manual and au-

tomated technologies are *ex ante* perfect substitutes at the micro level. 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. Yet, as our model

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[13]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.

[14]The elasticity of z^* with respect to z_K is also lower than -1 for other calibrations of α. To see this, note that the elasticity in more general terms can be written as

$$\frac{\hat{z}^*}{\hat{z_K}} = -\frac{z_K \left(\int_{z^*}^{\infty} z dG(z) + z^* G(z^*) \right)}{z_K z^* G(z^*) - \beta z^* \int_{z_{min}}^{z^*} j_L'(z) g(z) dz},$$

where we use the definition of $j_L(z) \equiv z_L(z) - w(z)$ and we assume that $\delta_K = \delta_L = \delta$ without much loss of generality. (See Appendix A.2 for more details on the derivations.) $j'(z)$ is the derivative of $j_L(z)$ with respect to z. If $\alpha > 0$, $j_L'(z^*) > 0$ because a higher productivity draw raises the return $z_L(z)$ by more than $w(z)$ (see Eq. (9)). Thus, if $\alpha > 0$, the elasticity of z^* with respect to z_K is even more negative than under the case of $\alpha = 0$. In this case, a firm entering the market must also consider the (conditional) expected value of z as regards the manual-technology option. The decrease in z^* induced by a rise in z_K shifts resources from the most productive and valuable manual-technology firms to the automated technology. Hence, the average value of the manual technology falls, which reinforces the mechanism described in the text. This is expressed by the second term in the denominator in the equation above. To return an elasticity greater than -1, α must be (sufficiently) negative, implying that a higher productivity draw reduces the profitability of the manual technology. In our simulations below, $\alpha = -0.2$ continues to imply an elasticity lower than -1 because, given $G(z^*) < 1$ (*i.e.*, there is a positive mass of firms that choose the automated technology), the first term in the numerator still compensates for the second term in the denominator.

shows, we should distinguish the implications of automation at the micro and at the aggregate level. In our model, 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 promote greater firm entry. 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.

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. As long as Ω is constant, a rise in $\int_{z^*}^{\infty} (J_K(z) - \kappa_K) \, \mathrm{d}G(z)$ leads to an increase of the left-hand side of Eq. (4) that must be compensated by either 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 on the left-hand side of Eq. (4) as firms only shift between technologies if it increases their profitability upon entry. Moreover, 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^* as implied by Eq. (3) (and the fact that the costs of the manual technology must increase to balance Eq. 4). Thus, after an automation-augmenting shock, the labor market must become tighter, increasing employment.[15]

Our result that the aggregate effect is stronger than the reallocation effect echoes the empirical results by Autor and Salomons (2018) and Gregory, Salomons and Zierahn (2018). Autor and Salomons study the effect of total factor productivity (TFP) shocks on employment using data on multiple industries for 18 OECD countries since 1970. Their results indicate that the direct effect of TFP has been to displace employment in the sectors in which it originates. Yet, their results also indicate that the direct effect of TFP is more than outweighed by indirect effects. Namely, Autor and Salomons conclude that an increase in TFP in one sector generates employment gains in the downstream customer industries

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[15]The logic above implies that an automation-augmenting shock leads to greater employment even if we were to conjecture a version of our model in which κ_K would increase as a result of the shock as long as $\int_{z^*}^{\infty} (J_K(z) - \kappa_K) \, \mathrm{d}G(z)$ still increases.

and in other sectors through greater aggregate demand that more than offset its direct employment-displacing effects. Gregory, Salomons and Zierahn, on the other hand, analyze the effects on employment of a more specific type of innovation: routine-replacing technological change (RRTC) in Europe from 1999 to 2010. Still, their findings are very similar to the ones by Autor and Salomons: the direct effect of RRTC has been to significantly reduce employment (about 1.6 million jobs) but these effects have been offset by the indirect effects of RRTC. They conclude that RRTC has increased employment by about 1.5 million jobs.

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. Figure 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 tigher labor markets, the hiring costs are higher because of the greater firm competition for the same pool of nonemployed 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 Figure 2. The slope of this curve becomes clearer if we rearrange Eq. (3) as

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

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.

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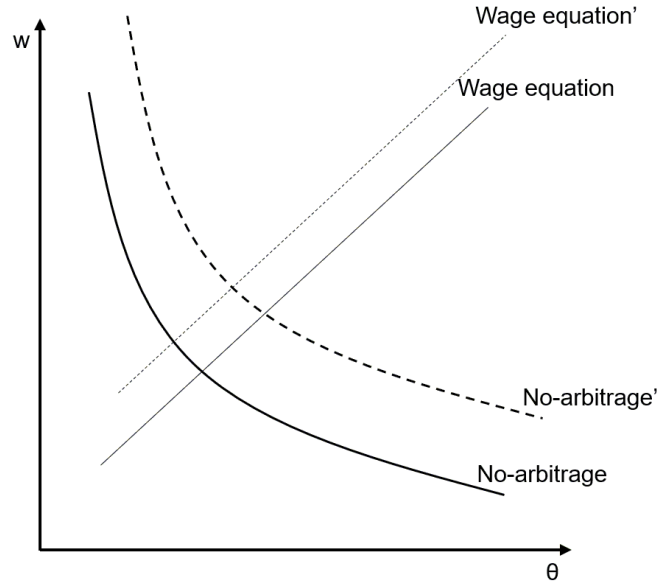
Note: This figure plots the effects of an in increase in z_K for the equilibrium of our model in the wage-tightness space assuming that $\alpha = 0$ and the free-entry condition, Eq. (14), is satisfied. The intersection of the solid lines represents the equilibrium before the rise in z_K, whereas the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

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 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.

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 $\delta_L = 0.036$, which equals the average job destruction rate in the US from 1948 to 2010 (Shimer, 2012). And 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 nonemployment, 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 $b \approx 0.7z_L$ (*e.g.*, Hall and Milgrom, 2008, Pissarides, 2009, and Coles and Kelishomi, 2018). Based on this, we fix $b = 0.7z_L z_{min}^{\alpha}$. 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 $\xi = 3.12$.

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:	$\xi = 3.12$
Nonemployment income:	$b = 0.7z_L z_{min}^{\alpha}$
Entry cost:	$\Omega = 1$
Cost of Capital:	$\kappa_K = 1$
Size of the labor force:	$L = 1$

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 ($\alpha = -0.2$).[16]
Regarding the remaining parameters, z_L, z_K, κ_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 prime-age (aged 25-54) workers' employment rate, n,[17] (ii) the labor share, LS, (iii) the labor
market tightness value, θ, and (iv) the equilibrium proportion of firms that employ the manual tech-
nology, $G(z^*)$. In all our experiments, we target $G(z^*) = 50\%$ and $\theta = 1$.[18] The targets of n and LS
change according to the simulation.

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, $w \equiv \int_{z_{min}}^{z^*} w(z)\mathrm{d}G(z)$, 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, $\Delta \kappa_L$. Regarding labor-market shocks,
we consider nonemployment income, Δb, workers' bargaining power, $\Delta \phi$, matching efficiency, $\Delta \chi$,
and job destruction rate, $\Delta \delta_L$. To make the elasticities comparable, every experiment refers to a 1%
increase in the respective parameter. And, in all experiments, we recalibrate the model to target an

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[16]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.

[17]We target the employment rate of prime-age workers because our model abstracts from demographic changes.

[18]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.

employment rate of $n = 76\%$ and a labor share of $LS = 61\%$.[19] 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 results.

Table 2: Results $\alpha = 0$

	Δy	ΔLS	Δn	Δw	Δz^*
Δz_K	5.08	-4.09	0.34	0.44	-2.55
Δz_L	0.95	0.41	0.23	1.12	0.00
$\Delta \kappa_K$	-1.85	1.58	-0.13	-0.17	1.21
$\Delta \kappa_L$	-0.15	-0.02	-0.15	-0.02	0.00
Δb	-0.56	0.11	-0.56	0.11	0.00
$\Delta \phi$	-0.24	0.05	-0.24	0.05	0.00
$\Delta \chi$	0.30	0.03	0.30	0.03	0.00
$\Delta \delta_L$	-0.08	-0.41	-0.37	-0.13	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.

Table 2 confirms that a rise in the automated technology productivity, z_K, increases employment.

The significantly negative elasticity of z^* with respect to z_K implies that a rise in z_K reallocates re-

sources 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]

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[19]Our targets are the labor share in the nonfarm business sector and the average employment rate of prime-age workers in the US from 1963 to 2018. Both series are retrieved from the BLS.

[20]As noted earlier, our model features gross complementarity between the two technologies as an aggregate equilibrium result of an automation-augmenting shock (a rise in z_K). In the standard framework of a neoclassical production function, gross complementarity also means that an increase in the quantity of one factor implies an increase in the elasticity of output with respect to the other factor; under perfect competition, this implies an increase in the other factor's share of output (see, *e.g.*, Bentolila and Saint-Paul, 2003). Yet, in our model, which departs from the assumption of perfect competition in

Our results agree to a large extent with the results in Berg, Buffie and Zanna (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 Prettner (2019). These authors analyze quantitatively the effects of an increase in the ratio of industrial robots per manufacturing workers on low- and high-skill labor. By calibrating their model with German data, they find that overall employment rises with automation since the increase in high-skill manufacturing jobs compensates for the decrease in low-skill jobs.

The fact that the labor share drops in our model after a rise in z_K further echoes the empirical results by Autor and Salomons (2018). As mentioned earlier, Autor and Salomons conclude that TFP shocks have not been labor-displacing because the indirect effects have outweighed the direct effects. This, however, is not the case for the labor share: the direct negative effect of TFP on the labor share has not been outweighed by the positive indirect effects. Thus, in Autor and Salomons' data, TFP shocks work similarly to a rise in z_K in our model: they both increase employment and reduce the labor share.

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. For example, a rise in the cost of capital, κ_K, implies a change in the labor share about 53 times larger than that implied by a rise in the matching efficiency, χ. Thus, unless labor market institutions change massively, technological shocks are the best candidate

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the labor market, gross complementarity comes hand-in-hand with a decrease in the labor share in the aftermath of an automation-augmenting shock.

to explain a fall in the labor share.[21]

This result 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 Demougin, 2010). We should not, however, take literally our result that changes in labor market institutions play a minor role. Our model is simple and parsimonious, which has its advantages but also implies that it abstracts from other channels. For example, our model assumes the extreme case that the manual technology only employs labor and the automated technology only capital (as in Zeira, 1998, 2010, Alesina, Battisti and Zeira, 2018, and Acemoglu and Restrepo, 2018). Thus, our model abstracts from the interactions between capital and labor at the micro level, which influence how labor market institutions shape the labor share in this theoretical literature. But our model and the models within this theoretical literature also differ in another important result: the latter models usually predict that the labor share and employment drop simultaneously while our model predicts that they may go in opposite direction; this makes our model broadly consistent with the US experience as we show in Section 4.3. Moreover, even though simple, our model is in line with another strand of literature. For example, as argued by Autor et al. (2017*b*), the fact that the labor share has fallen in countries with very different labor market institutions points to the existence of other factors to explain the drop in the labor share. The empirical work of Dao et al. (2017) confirms that logic: for developed countries, Dao et al. conclude that 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. Furthermore, our results concur with the argument by Karabarbounis and Neiman (2014) that the falling price of capital is a good candidate to explain the fall in the labor share.

Tables 3 and 4 show that our main conclusions from Table 2 hold under different calibrations of α

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[21]Table 2 also shows that labor market institutions have non-neglectable effects on employment but have limited power to change wages.

Table 3: Results – α Sensitivity Analysis

	$\alpha = -0.2$					$\alpha = 0.2$				
	Δy	ΔLS	Δn	Δw	Δz^*	Δy	ΔLS	Δn	Δw	Δz^*
Δz_K	3.04	-2.19	0.37	0.42	-1.44	53.07	-33.99	0.43	0.62	-12.59
Δz_L	1.06	0.33	0.26	1.14	-0.05	0.45	0.86	0.21	1.11	0.32
$\Delta \kappa_K$	-1.23	0.91	-0.15	-0.17	0.73	-4.88	4.86	-0.11	-0.15	3.85
$\Delta \kappa_L$	-0.15	-0.01	-0.15	-0.01	0.00	-0.15	-0.02	-0.15	-0.02	0.00
Δb	-0.67	0.11	-0.67	0.11	0.00	-0.48	0.10	-0.48	0.10	0.00
$\Delta \phi$	-0.24	0.04	-0.24	0.04	0.00	-0.24	0.05	-0.24	0.05	0.00
$\Delta \chi$	0.30	0.03	0.30	0.03	0.00	0.30	0.04	0.30	0.04	0.00
$\Delta \delta_L$	-0.19	-0.34	-0.40	-0.14	0.05	0.36	-0.82	-0.35	-0.12	-0.27

Note: This table shows the effects of the shocks to the parameters using our benchmark calibration except for the elasticity of labor productivity, α. 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. The remaining columns are divided in two panels. In the panel to the left, we write the elasticities of output, labor share, employment, average wages, and cutoff assuming $\alpha = -0.2$. In the panel to the right, we write the elasticities of the same variables but assuming $\alpha = 0.2$.

and targeted $G(z^*)$: a rise in z_K raises wages and employment but reduces the labor share; and technological shocks have a much greater impact on output and the labor share than changes in the labor market institutions. There are, however, two new and interesting results. Economies with a relatively high α and a relatively low initial proportion of manual firms, $G(z^*)$, have much higher elasticities with respect to automation-augmenting shocks.

If $\alpha = 0$, all manual firms have the same value. But if $\alpha > 0$, the productivity and (thus) the value of the manual technology increases with the productivity draw z. In this case, the decrease in z^* after a rise in z_K shifts resources from the most productive and valuable manual intensive firms to the automated technology. Therefore, the average value of the manual technology drops, which reinforces the reallocation of resources observed when $\alpha = 0$. (Recall the analytical details in Footnote 14 above.) If $G(z^*)$ is low, then z^* is also low and close to the lower bound z_{min}. This implies a higher preponderance of the mass of firms that operate the automated technology and, hence, of the (conditional) expected value of z for $z > z^*$ in the transmission mechanism (see Eq. (15)). This leverages the effect of a shock in z_K, which translates into a greater elasticity of z^* with respect to z_K.

Table 4: Results – $G(z^*)$ Sensitivity Analysis

| | $G(z^*) = 0.4$ | | | | | $G(z^*) = 0.6$ | | | | |
	Δy	ΔLS	Δn	Δw	Δz^*	Δy	ΔLS	Δn	Δw	Δz^*
Δz_K	10.19	-8.48	0.34	0.50	-3.47	3.02	-2.20	0.36	0.39	-2.00
Δz_L	0.89	0.40	0.20	1.09	0.00	1.03	0.42	0.29	1.17	0.00
$\Delta \kappa_K$	-3.06	2.84	-0.12	-0.18	1.55	-1.17	0.89	-0.14	-0.15	0.98
$\Delta \kappa_L$	-0.15	-0.02	-0.15	-0.02	0.00	-0.15	-0.01	-0.15	-0.01	0.00
Δb	-0.48	0.10	-0.48	0.10	0.00	-0.71	0.11	-0.71	0.11	0.00
$\Delta \phi$	-0.24	0.05	-0.24	0.05	0.00	-0.24	0.04	-0.24	0.04	0.00
$\Delta \chi$	0.30	0.04	0.30	0.04	0.00	0.30	0.03	0.30	0.03	0.00
$\Delta \delta_L$	-0.03	-0.41	-0.34	-0.10	0.00	-0.17	-0.42	-0.43	-0.16	0.00

Note: This table shows the effects of the shocks to the parameters using our benchmark calibration but assuming a different target for the proportion of firms that use the manual technology, $G(z^*)$. 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. The remaining columns are divided in two panels. In the panel to the left, we write the elasticities of output, labor share, employment, average wages, and cutoff assuming $G(z^*) = 0.4$. In the panel to the right, we write the elasticities of the same variables but assuming $G(z^*) = 0.6$.

4.3 Targeted Simulations

The evidence by, *e.g.,* Elsby, Hobijn and Şahin (2013) indicates that the labor share started to fall in the US in the late 1980s and, more specifically, around 1987. Given this evidence, in this section, we conduct experiments to answer three questions: (i) can our model account for the fall in the labor share after 1987? (ii) If yes, what are the forces that our model proposes to explain that fall? Finally, (iii) why are the periods before and after 1987 different?

In our experiments, we use our model to analyze two 20-year periods: 1967-1987 and 1987-2007. To calibrate the model, we always use our benchmark calibration as specified in Table 1 and our targets $\theta = 1$ and $G(z^*) = 0.5$. But, depending on the 20-year period, we target the employment rate, n, and the labor share, LS, to those observed at the beginning of the period.[22] These two targets imply that the values of the parameters z_L, z_K, κ_L, and χ (only) pertain to the 20-year period under analysis. Then, in each experiment, we consider shocks to three parameters to target the growth rate of the size

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[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 67.7% and 76.4%, which correspond to the average US employment rate of prime-age workers in 1963-1967 and 1983-1987, respectively. The data is from the BLS.

of the labor force, output, and wages observed within the 20-year period under study.[23] To target the growth rate of the size of the labor force, we simply impose that L grows at that rate. But to target the observed growth rate of output and wages within each 20-year period, we consider shocks to alternative pairs of parameters. For example, one of the pairs of parameters' shocks we use is $(\Delta z_K, \Delta z_L)$. In this case, Δz_K and Δz_L are the necessary shocks to z_K and z_L that imply growth rates of output and wages in the model equal to those found in the data within each 20-year period (from 1967 to 1987 or from 1987 to 2007). Finally, the key outcomes of each experiment are the pairs of the necessary parameters' shocks that satisfy the targets (for the growth rates of output and wages) and the implied change of the labor share and employment.

Between 1987 and 2007, in the data, the labor share decreased 3.6% and the prime-age workers employment rate increased 3.9%. Table 5 shows the results of our experiments for the same period. Our simple model performs remarkably well in two experiments: the combination of shocks to z_K and z_L and the combination of shocks to κ_K and z_L. In both experiments, the employment rate increases slightly more than in the data while the change of the labor share is extremely close to that of its empirical counterpart. This result adds to the discussion in the previous section: it suggests that a combination of technological shocks is a good candidate to explain the drop in the labor share and the simultaneous increase in employment between 1987 and 2007.

We decompose the effects of the shocks to z_K and z_L in the second and third lines of Table 5. This decomposition confirms the crucial role played by the automation-augmenting shock (or, quantita-

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[23]The target growth rates are the growth rates of 5-year moving averages. The data is all for the US and was downloaded from the FRED. The target for the size of the labor force is the civilian labor force (CLF16OV), which grew approximately 55% in 1967-1987 and 29% in 1987-2007. The target for output, y, is the real output in the nonfarm business sector (henceforth, NBS). We compute this series as the product of the real output per hour (OPHNFB) and total hours (HOANBS), both in the NBS. This product grew approximately 101% in both 20-year periods, 1967-1987 and 1987-2007. The target for the wage, w, is the average wage per worker. To generate this series, we start with the real wage per hour in the NBS. Then, we multiply this series by the total hours in the NBS (HOANBS) and divide it by civilian employment level (CE16OV). Finally, we adjust by the deflators: we multiply this series by the Consumer Price Index (CPIAUCSL) and divide it by the GDP deflator (GDPDEF). Our series for the average wage grew 32% in 1967-1987 and 42% in 1987-2007.

Table 5: Targeted Simulations – 1987 to 2007

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
2.85	35.81	–	–	–	-3.22	6.40
2.85	–	–	–	–	-15.89	1.01
–	35.81	–	–	–	11.45	5.84
–	35.96	-5.72	–	–	-3.26	6.35
–	43.67	–	-68.61	–	7.76	18.47
2.73	36.17	–	-5.00*	–	-2.32	7.39
–	42.59	–	–	67.70	-5.26	4.16
3.68	33.72	–	–	-25.00*	-2.73	6.93

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 shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages in 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007.

tively very similar, the negative shock on the relative price of capital) concerning the decrease in the labor share. The decomposition also highlights the importance of combining Δz_K (or $\Delta \kappa_K$) and Δz_L: the manual-augmenting shock partially counterbalances the strong negative effect of the automation-augmenting shock on the labor share. Furthermore, we also conclude that the combination of the shocks does not have the same effect as the sum of the effects of the shocks. As an outcome of the transmission mechanism of the model, the interaction of the automation- and manual-augmenting shocks attenuates the overall impact on the labor share in 1.22 percentage points (which amounts to about 30% of the total change in the labor share that would result from the two shocks considered separately). Finally, our decomposition of the effects of Δz_K and Δz_L also contributes to the discussion of the relative importance of labor- and capital-augmenting technological progress. Recent empirical estimates (using closed-form aggregate production functions) point to net capital-augmenting technological progress, whereas the usual finding in the literature has been of a net labor-augmenting technological progress (Jiang and Léon-Ledesma, 2018, and references therein). Our quantitative results indicate an alternative scenario: although the size of the labor-augmenting technological shock outweighs that of the capital-augmenting technological shock, the general-equilibrium effects of the latter outweigh those of the former.

Next, we study the role of labor market institutions. We start by considering the downward trend of union density reported by Farber et al. (2018), and take this evidence as an indicator that the workers' bargaining power, ϕ, may have fallen between 1987 and 2007.[24] Yet, our experiments that include the shock to ϕ, $\Delta\phi$, either produce disappointing or quantitatively insignificant results. The worst case is when we experiment with shocks to both ϕ and z_K because no combination of these shocks reaches our targets of output and wage growth (and, for this reason, we decided not to report the results in Table 5). This experiment, therefore, suggests that the combination of $(\Delta z_K, \Delta\phi)$ is not the underlying force behind the evolution of output and wages. The results are not as bad when we experiment with shocks to both ϕ and z_L, but are still inconsistent with the evidence: the combination of $\Delta\phi$ and Δz_L implies an increase in the labor share and a very large increase in the employment rate. Furthermore, in this experiment, the model only matches our targets (of output and wage growth) if the workers lose almost two thirds of their bargaining power, much more than the fall in union density reported by Farber et al. (one third; see also footnote 25 below). Finally, in our last experiment including $\Delta\phi$, we assume that the downward trend of union density led to a fall of 5% of the workers' bargaining power and again use Δz_K and Δz_L to reach the targets of output and wage growth.[25] But this experiment barely changes the shocks to z_K and z_L that match our targets (for output and wage growth) in the first experiment. And it only slightly deteriorates the implied changes in the labor share and employment, suggesting that the combination of productivity shocks continues to be a good candidate to explain

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[24] Blanchard and Giavazzi (2003) make a similar assumption to explain the fall in the European labor share.

[25] We choose $\Delta\phi = -5\%$ 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 members of unions. Farber et al. (2018) report that the union density was on average about 18% in 1983-1987 and 12% in 2003-2007. They also report that the union premium was relatively stable within this period. Absent any other shock that changes the workers' bargaining power, we interpret this stability of the union premium as an indicator that the workers' bargaining power was also stable for the two groups. This implies that the weighted average ϕ only changes due to the distribution of workers between the two groups and not because of a change in the workers' bargaining power. Therefore, because $\phi = 0.5$ in our benchmark calibration for 1987, if union members could capture all the match surplus, ϕ would fall 7.3% from 1987 to 2007. Yet, this is the upper bound for at least two reasons. First, it is rather unlikely that workers capture all the match surplus even if they are union members. Second, Farber et al. report that unions tend to particularly benefit workers who are less educated and non-white, who seem to have less bargaining power. Thus, we deviate slightly from the extreme and choose $\Delta\phi = -5\%$.

the evolution of the US labor share after 1987.

Davis and Haltiwanger (2014) show that the US labor market has become less dynamic: both the job creation and job destruction rates have decreased in the recent decades. Assuming that this trend has been caused by changes in labor market institutions, we interpret the declining dynamism of the US labor market as a simultaneous and proportional drop in the job destruction rate, δ_L, and matching efficiency, χ, in our model. Then we conduct three experiments. First, we combine the shock to z_K with the proportional shock to both χ and δ_L and obtain disappointing results: as in the case of $(\Delta z_K, \Delta \phi)$, the algorithm does not converge and, thus, we do not report the results. Second, we combine the shock to z_L with the proportional shock to both χ and δ_L. In this case, the implied changes in the labor share and employment are very good. Yet, the model only obtains these results if the labor market becomes much more dynamic, against the evidence in Davis and Haltiwanger (2014). Third, we assume that both parameter values decline 25% from 1987 to 2007 and again use the shocks to z_K and z_L to reach our targets for the growth rates of output and wages. The results of this experiment are very similar to those reported in the first line of the same table. This suggests (as in the experiment in which we assume $\Delta \phi = -0.05$) that the combination of productivity shocks $(\Delta z_K, \Delta z_L)$ has almost the same firepower to explain the evolution of the labor share and employment as in the experiment without shocks to χ and δ_L.

We take all these results as indicators that the drop in the labor share in the US after 1987 was most likely caused by a change in technology rather than in labor market institutions, as already hinted by our results in Section 4.2.

But why did the labor share only start falling after 1987? Why didn't it fall, for example, between 1967 and 1987?[26] To shed some light on why the labor share barely changed (in the data) until 1987, we rerun the experiments reported in Table 5 but for the 20-year period earlier. The results are reported

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[26]The employment rate of prime-age workers increased 12.8% within the same period.

in Table 6. Our model suggests that all of the observed change of output and wages was caused by a rise in the productivity of the manual technology. Contrasting this result with the results in Table 5, we get a clearer picture: the labor share did not fall before 1987 because all of the technological change in that period improved labor's productivity; and it started to fall after 1987 because the productivity of automated technologies accelerated. Indeed, our results point out to a significant acceleration of automation-augmenting *vis-à-vis* manual-augmenting technological change between the two time periods.[27] This acceleration concurs with the estimates in Acemoglu and Restrepo (2019). They decompose the evolution of the US wage bill before and after 1987, and document significant shifts in the task content against labor (and towards automation) only after 1987. Bergholt, Furlanetto and Faccioli (2019) also find evidence pointing to greater automation (especially after 1993) by estimating a VAR model. The acceleration of automation-augmenting technological change is also in line with recent empirical estimates based on closed-form aggregate-production functions (see, *e.g.*, Acemoglu and Restrepo, 2018, and references therein). And it is in line with the evidence on the stock of industrial robots reported by Prettner and Strulik (2017): industrial robots barely existed until 1983 but their stock grew substantially thereafter.

Table 6: Targeted Simulations – 1967 to 1987

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
-0.04	28.35	–	–	–	8.97	7.03
-0.04	–	–	–	–	0.14	-0.02
–	28.35	–	–	–	8.84	7.04
–	28.35	0.09	–	–	8.97	7.03
–	28.31	–	0.39	–	8.86	6.92
–	28.30	–	–	-0.56	9.00	7.06

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, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987.

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[27]Alternatively, comparing Tables 5 and 6, the model also suggests that a fall in the price of capital or a combination of this with an acceleration of automation-augmenting technological change would explain the fall in the labor share after 1987.

Finally, we check whether our results are robust to different calibrations of our model by rerunning the previous experiments in the cases of $\alpha = 0.2$, $\alpha = -0.2$, $G(z^*) = 0.6$, and $G(z^*) = 0.4$. In broad terms, our main points stay intact.[28] First, the combination of shocks to z_K and z_L and the combination of shocks to κ_K and z_L imply reasonable responses of both the labor share and employment in the period 1987-2007. Second, in the period 1987-2007, if we use changes in labor market institutions to target output and wage growth, the model continues inconsistent with empirical evidence. Third, also in the period 1987-2007, assuming reasonable changes in labor market institutions, the combination of shocks to z_K and z_L continues to generate reasonable results. And fourth, the model continues to suggest the acceleration of automation-augmenting technological change from 1967-1987 to 1987-2007.

5   Other Results – The Effect of Alternative Assumptions

In this section, we compare the results of three alternative versions of our model with those of our model in Section 2. We reach three conclusions. First, although changes in labor market institutions do not seem to explain the evolution of the US labor share, our model requires labor market institutions (in particular, wage bargaining) to fit the US evidence after 1967. Second, if entry costs are proportional to output, our model continues to point to the acceleration of automation-augmenting technological change after 1987. Third, if the cutoff, z^*, is exogenously set, our model continues to suggest that an automation-augmenting shock raises employment.

5.1   Are Labor Market Institutions Relevant for the Model's Mechanism?

The results in this paper suggest that changes in labor market institutions play a minor role in explaining the drop in the labor share. But, in this section, we show that labor market institutions are crucial

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[28]For the full results, see Appendix B.

for our model's mechanism and results. We make this clear by considering a version of our model in which firms and workers do not bargain wages; instead, workers obtain a constant fraction of firm's output: $w(z) = \phi_{nb} z_L(z)$. Using this version of our model, we rerun the exercises of Sections 4.2 and 4.3.[29] This version of our model cannot account for the drop in the labor share between 1987 and 2007. Moreover, under shocks to productivity and the cost of capital, this model only matches the targets for output and wage growth for the period 1967-1987 if it allows for a strong regression of the automated technology (a drop in z_K) or a strong rise in the cost of capital (an increase in κ_K). Both predictions seem difficult to justify empirically for that period. Thus, we conclude that the consideration of a labor market institution like wage bargaining is crucial for the dynamics of our model to be in line with those suggested by the empirical literature.

5.2 Constant Entry Costs vs. Constant Entry Costs-To-Output Ratio

In Section 4.3, we focus on time spans of 20 years. In such a time span, it may be expected that entry costs, Ω, are not fixed but tend to grow as the overall economy also grows (Bollard, Klenow and Li, 2016). Therefore, in this section, we test whether our results hold in a setting where entry costs are a constant proportion of output: $\Omega \equiv \omega y$. Using this version of our model, we rerun the experiments of Sections 4.2 and 4.3.[30]

We conclude that our main results in Section 4.3 hold. This version of our model continues to suggest that the change in the US labor share was most likely caused by technological changes rather than by changes in labor market institutions. And it continues to hint that the US labor share only falls after 1987 because of an acceleration of automation-augmenting technological change. Yet, this

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[29]We report the full results in Tables C1-C3 in the Appendix C. In all these experiments, we use our benchmark calibration (as detailed in Table 1) except for ϕ, which is replaced by ϕ_{nb}. We calibrate κ_L as implied by the respective exercises using the version of our model in Section 2. For example, we use the same value of κ_L to generate the results reported in Tables 2 and C1. Finally, we calibrate ϕ_{nb} together with z_L, z_K, and χ to satisfy our targets for employment, the labor share, labor market tightness, and the proportion of firms that use the manual technology.

[30]We report the full results in Tables D1-D3 in the Appendix D. In all these experiments, we use our benchmark calibration and calibrate ω such that $\Omega = \omega y = 1$.

version of our model implies different results from those we obtain in Section 4.2. If $\Omega = \omega y$, a change

in a parameter that affects output, y, also affects the entry cost, ωy. Thus, the elasticities we report in

Table D1 combine two effects: the effect of the ('pure') elasticity reported in Table 2 and the effect of

the implied change in the entry cost. In this context, and contrary to our previous results, we find that

automation-augmenting technological change slightly reduces employment and the average wage.

The (implied) increase in the entry cost discourages entry. As result, the reallocation effect (towards

the automated technology) dominates the aggregate effect (of greater firm entry), implying the fall in

employment.

This result, however, builds on the extreme assumption that entry costs grow proportionally to

output, which may be unreasonable as suggested by the evidence in Bento (2014) and Bollard, Klenow

and Li (2016). The empirical estimates in Bento rely on large cross-country data sets and point to a

negative (partial) correlation between entry costs as a percentage of output per worker and both TFP

and output per worker. In time-horizons of 15 years, Bollard, Klenow and Li find similar results using

time-series data of the present discounted value of profits as a proxy for entry costs. Thus, both studies

indicate that entry costs grow less than proportionally with output per worker, which is consistent

with our model in Section 2.[31] Contrasting the elasticities of our model assuming constant Ω (in Table

2) with those of the model assuming $\Omega \equiv \omega y$ (in Table D1), we can see that the elasticity of n with

respect to z_K is much higher (in absolute terms) in the former than in the latter. Therefore, if we

consider that these versions of our model are the extremes and reality is somewhere in the middle,

then our experiments continue to suggest that automation-augmenting technological change very

likely increases employment.

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[31]Our starting assumption of a constant entry cost, Ω, ensures that countries more technologically advanced enjoy greater (aggregate) output per worker, y/n, and lower ratio of entry costs to output per worker, $\Omega/(y/n)$.

5.3   Technological vs. Economical Cutoff

In our model, the cutoff, z^*, is economical in the sense that it is the level of the productivity draw, z, for which firms are indifferent between the two technologies, manual and automated. In the literature, however, some models embed a technological cutoff: in this case, technological constraints stop some firms from adopting (or some tasks from being executed using) the automated technology. This is the case of the model in Martinez (2018), in which firms would like to use machines for all tasks but, due to technological constraints, are forced to also use labor. On the other hand, Acemoglu and Restrepo (2018) build a model with both an economical and a technological cutoff but in which only one binds.

In this section, we follow Acemoglu and Restrepo (2018), and assume that technological constraints make it unfeasible for some firms to adopt the automated technology. We denote this cutoff as z^{**}, meaning that only firms with a productivity draw above z^{**} may choose the automated technology. To make this case relevant for our analysis, we focus on the scenario of $z^{**} > z^*$. These assumptions simplify our model. Because we set the cutoff exogenously, we drop Eq. (3) from our list of equations. Then we find θ and $w(z)$ using the following free-entry condition, instead of Eq. (4),

$$\int_{z_{min}}^{z^{**}} \left(\beta J_L(z) - \frac{\kappa_L}{\mu(\theta)} \right) \mathrm{d}G(z) + \int_{z^{**}}^{\infty} \left(J_K(z) - \kappa_K \right) \mathrm{d}G(z) = \Omega, \tag{16}$$

and the wage equation, Eq. (8).

Using this version of our model, we still conclude that an automation-augmenting shock increases employment. Because the cutoff does not move, this version of our model mutes the reallocation effect but keeps the aggregate effect. Mechanically, a rise in z_K increases the left-hand side of Eq. (16), which must be compensated by an equal fall also on the left-hand side because Ω is constant. Because $w(z)$ is directly reduced by z_K, a rise in z_K must increase θ and, thus, employment.

We can also use this version of our model to obtain insights about an automation shock repre-

sented by a fall in z^{**}. In Acemoglu and Restrepo (2018), a shock that makes it feasible for a greater proportion of firms to use the automated technology reduces employment. In our model, we find the opposite result. If z^{**} drops when $z^{**} > z^*$, then the left-hand side of Eq. (16) must increase. And by the same logic as for the shock in z_K, θ and employment must rise for the economy to reach the new equilibrium.

6   Concluding Remarks

The labor share has been falling throughout the world. This phenomenon contradicts the much celebrated Kaldor Facts and led many 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 labor market institutions play an almost insignificant role in explaining the fall in the labor share. On the contrary, technological shocks have a huge power to induce fluctuations in the labor share. Furthermore, we have inquired into the causes of the relatively stagnant US labor share in 1967-1987 and the falling US labor share in 1987-2007. Our model suggests that the fall in the labor share coincided with an acceleration of automation-augmenting technological change (which is consistent with the evidence and estimates in Acemoglu and Restrepo (2018, 2019), Bergholt, Furlanetto and Faccioli (2019), and Prettner and Strulik (2017)).

In this paper, we also offer insights on how automation shapes employment and wages. In our model, an automation-augmenting technological change 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, again, that our model concurs with the empirical evidence (see Autor and Salomons, 2018 and Gregory, Salomons and Zierahn, 2018).

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: or (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 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. We have pointed out a few of those simplifying abstractions over the previous sections. Here, we discuss how some abstractions of the model may shape the way productivity-augmenting shocks affect employment. Our model suggests that if productivity continuously rises, employment should continuously increase and, therefore, asymptotically there should be full employment. This seems unrealistic and clashes with the evidence that the US prime-age workers' employment rate is currently below that observed in the late 1990s. There are, however, a few abstractions in our model that if

alleviated could improve the flexibility of its results. One is that entry costs may increase with output (even if less than proportionally), undermining the effect of productivity on employment as we discuss in Section 5.2. Another is that labor supply decisions – decisions on labor force participation and job search effort – may matter.[32] In our model, there is full labor force participation and nonemployed 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 would fall not due to lower labor demand but rather due to low labor supply.

We end this paper with some considerations for future research. We have just discussed endogeneizing labor supply in the model but there are a number of other extensions that could be considered. One is to build a model that distinguishes between workers of different skill levels. In this context, machines could be complementary to high-skill labor and substitute low-skill labor as in Cords and Prettner (2019). This model would offer insights on, for example, wage premium and how automation affects the employment of workers of different skill levels. Another extension 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. As we have discussed in Section 4.2, such a model would likely strengthen the 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

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[32] Indeed, labor force participation among US prime-age workers has fallen since the late 1990s; see Daly et al. (2018) for a recent discussion of this evidence.

labor, which may affect how the automation-augmenting technological shock unfolds in the economy. We will consider the implications of this extension in a future paper.

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A   Analytical Derivations

For Online Publication

A.1   Derivation of $\hat{\theta}$

In this appendix, we show how we obtain Eq. (13). Using the definition of $f(\theta)$ and $\mu(\theta)$ in Eqs. (3,

assuming $\alpha = 0$) and (12) imply

$$w = (1 - \phi)b + \phi(z_L + \theta\kappa_L) - \phi\left[\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K\right)\left[(\beta - 1)\chi\theta^{1-\eta} + 1 - \beta(1 - \delta_L)\right]\right],$$

$$\beta\frac{z_L - w}{1 - \beta(1 - \delta_L)} - \frac{\kappa_L}{\chi\theta^{-\eta}} = \frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K.$$

Using hats to denote log-linear variables, we log-linearize the two equations above assuming that only

z_K and the endogenous variables vary after the shock to z_K:

$$w\hat{w} = \phi\theta\kappa_L\hat{\theta} - \phi\left[\frac{z_K z^*}{1 - \beta(1 - \delta_K)}\left[(\beta - 1)\chi\theta^{1-\eta} + 1 - \beta(1 - \delta_L)\right]\right](\hat{z_K} + \hat{z^*}) +$$

$$-(1 - \eta)\phi\left[\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K\right)(\beta - 1)\chi\theta^{1-\eta}\right]\hat{\theta},$$

$$-\beta\frac{1}{1 - \beta(1 - \delta_L)}w\hat{w} - \eta\frac{\kappa_L\theta^\eta}{\chi}\hat{\theta} = \frac{z_K z^*}{1 - \beta(1 - \delta_K)}(\hat{z_K} + \hat{z^*}).$$

Defining $C \equiv \left[\frac{z_K z^*}{1 - \beta(1 - \delta_K)}\left[(\beta - 1)\chi\theta^{1-\eta} + 1 - \beta(1 - \delta_L)\right]\right]$ and

$D \equiv (1 - \eta)\left[\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K\right)(\beta - 1)\chi\theta^{1-\eta}\right]$, we replace the first equation in the second one:

$$-\beta\frac{1}{1 - \beta(1 - \delta_L)}\left[\phi(\theta\kappa_L - D)\hat{\theta} - \phi C(\hat{z_K} + \hat{z^*})\right] - \eta\frac{\kappa_L\theta^\eta}{\chi}\hat{\theta} = \frac{z_K z^*}{1 - \beta(1 - \delta_K)}(\hat{z_K} + \hat{z^*}) \Leftrightarrow$$

$$\hat{\theta}\left(\beta\frac{\phi(D - \theta\kappa_L)}{1 - \beta(1 - \delta_L)} - \eta\frac{\kappa_L\theta^\eta}{\chi}\right) = \left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \beta\frac{\phi C}{1 - \beta(1 - \delta_L)}\right)(\hat{z_K} + \hat{z^*}). \tag{A.1}$$

Using the definition of C, we rearrange the term on the right-hand side of Eq. (A.1) to

$$\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \beta \frac{\phi}{1 - \beta(1 - \delta_L)} \left[\frac{z_K z^*}{1 - \beta(1 - \delta_K)} \left[(\beta - 1)\chi\theta^{1-\eta} + 1 - \beta(1 - \delta_L) \right] \right] =$$

$$\frac{z_K z^*}{1 - \beta(1 - \delta_K)} \left(1 - \beta\phi + \beta\phi \frac{(1 - \beta)\chi\theta^{1-\eta}}{1 - \beta(1 - \delta_L)} \right) \equiv A > 0.$$

Using the definition of D, we rearrange the term on the left-hand side of Eq. (A.1) to

$$\phi\beta \frac{(1 - \eta)\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K \right)(\beta - 1)\chi\theta^{1-\eta} - \theta\kappa_L}{1 - \beta(1 - \delta_L)} - \eta \frac{\kappa_L \theta^\eta}{\chi} =$$

$$-\left(\phi\beta \frac{(1 - \beta)(1 - \eta)\left(\frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K \right)\chi\theta^{1-\eta} + \theta\kappa_L}{1 - \beta(1 - \delta_L)} + \eta \frac{\kappa_L \theta^\eta}{\chi} \right) \equiv B < 0.$$

Using the definitions of A and B in Eq. (A.1), we obtain Eq. (13).

A.2   Derivation of the Elasticity of z^* with Respect to z_K

In this appendix, we show how to obtain the elasticity of z^* with respect to z_K without assuming any distribution of productivity draws and any value of α. As in Footnote 14, we denote $j_L(z) \equiv z_L(z) - w(z)$. This notation allows us to rewrite the free-entry condition, Eq. (4), as

$$(1 - G(z^*)) \left(\frac{z_K \frac{1}{1 - G(z^*)} \int_{z^*}^\infty z\, dG(z)}{1 - \beta(1 - \delta_K)} - \kappa_K \right) + G(z^*) \left(\beta \frac{\frac{1}{G(z^*)} \int_{z_{min}}^{z^*} j_L(z)\, dG(z)}{1 - \beta(1 - \delta_L)} - \frac{\kappa_L}{\mu(\theta)} \right) = \Omega.$$

Next we replace $\frac{\kappa_L}{\mu(\theta)}$ using the no-arbitrage condition, Eq. (3):

$$(1 - G(z^*)) \left(\frac{z_K \frac{1}{1 - G(z^*)} \int_{z^*}^\infty z\, dG(z)}{1 - \beta(1 - \delta_K)} - \kappa_K \right) +$$

$$+ G(z^*) \left(\beta \frac{\frac{1}{G(z^*)} \int_{z_{min}}^{z^*} j_L(z)\, dG(z)}{1 - \beta(1 - \delta_L)} + \frac{z_K z^*}{1 - \beta(1 - \delta_K)} - \kappa_K - \beta \frac{j_L(z^*)}{1 - \beta(1 - \delta_L)} \right) = \Omega.$$

Assuming that $\delta_K = \delta_L = \delta$, without much loss of generality, and after some rearrangements, we obtain

$$z_K \left(\int_{z^*}^{\infty} z dG(z) + z^* G(z^*) \right) + \beta \left(\int_{z_{min}}^{z^*} j_L(z) dG(z) - j_L(z^*) G(z^*) \right) = (\Omega + \kappa_K)[1 - \beta(1 - \delta)]. \quad \text{(A.2)}$$

Eq. (A.2) nests Eq. (14). To see this, note that, if $z_L(z) = z_L$ ($\alpha = 0$), then $j_L(z)$ is the same for all z. Thus the second term on the left-hand side of Eq. (A.2) is zero and we obtain Eq. (14).

Using the Leibniz rule, the log-linearization of Eq. (A.2) implies:

$$z_K \left(\int_{z^*}^{\infty} z dG(z) + z^* G(z^*) \right) \hat{z_K} + z_K z^* G(z^*) \hat{z^*} - \beta \int_{z_{min}}^{z^*} j'_L(z^*) g(z) dz z^* \hat{z^*} = 0 \Leftrightarrow$$

$$\frac{\hat{z^*}}{\hat{z_K}} = -\frac{z_K \left(\int_{z^*}^{\infty} z dG(z) + z^* G(z^*) \right)}{z_K z^* G(z^*) - \beta z^* \int_{z_{min}}^{z^*} j'_L(z^*) g(z) dz}, \quad \text{(A.3)}$$

where $j'_L(z)$ denotes the derivative of $j_L(z)$ with respect to z. If $\alpha = 0$, note that $j'_L(z^*) = 0$. Thus, in this case, the second term in the denominator of Eq. (A.3) is 0, and we obtain Eq. (15).

B   Targeted Simulations – Sensitivity Analysis

For Online Publication

Table B1: Scenario $\alpha = 0.2$ – 1987 to 2007

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
1.24	37.13	–	–	–	-3.77	5.79
1.24	–	–	–	–	-65.84	0.46
–	37.13	–	–	–	28.45	5.70
–	37.23	-2.49	–	–	-3.80	5.77
–	39.19	–	-27.07	–	0.59	10.67
1.25	37.45	–	-5.00*	–	-2.83	6.82
–	41.25	–	–	54.07	-4.82	4.64
1.50	35.70	–	–	-25.00*	-3.48	6.11

Note: The results pertain to experiments for the period 1987-2007 using our baseline model calibrated with $\alpha = 0.2$. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages within 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007.

Table B2: Scenario $\alpha = 0.2$ – 1967 to 1987

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
1.13	28.30	–	–	–	8.74	6.81
1.13	–	–	–	–	-27.14	0.27
–	28.30	–	–	–	24.78	6.68
–	28.36	-2.36	–	–	8.71	6.78
–	33.38	–	-47.63	–	22.22	20.05
–	30.01	–	–	23.40	7.98	6.06

Note: The results pertain to experiments for the period 1967-1987 using our baseline model calibrated with $\alpha = 0.2$. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987.

Table B3: Scenario $\alpha = -0.2$ – 1987 to 2007

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
4.35	34.64	–	–	–	-2.57	7.11
4.35	–	–	–	–	-12.14	1.61
–	34.64	–	–	–	8.95	6.18
–	34.76	-8.72	–	–	-2.61	7.07
–	40.97	–	-59.18	–	6.45	17.03
4.10	35.03	–	-5.00*	–	-1.72	8.05
–	43.79	–	–	76.47	-5.85	3.50
5.77	31.90	–	–	-25.00*	-1.86	7.89

Note: The results pertain to experiments for the period 1987-2007 using our baseline model calibrated with $\alpha = -0.2$. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages within 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007.

Table B4: Scenario $\alpha = -0.2$ – 1967 to 1987

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
-1.41	28.44	–	–	–	9.24	7.30
-1.41	–	–	–	–	2.35	-0.58
–	28.44	–	–	–	7.05	7.67
–	28.43	3.13	–	–	9.25	7.31
–	27.58	–	7.06	–	7.27	5.36
–	26.86	–	–	-13.80	10.16	8.20

Note: The results pertain to experiments for the period 1967-1987 using our baseline model calibrated with $\alpha = -0.2$. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987.

Table B5: Scenario $G(z^*) = 0.6$ – 1987 to 2007

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
4.69	33.87	–	–	–	-2.24	7.47
4.69	–	–	–	–	-14.61	1.75
–	33.87	–	–	–	11.30	6.58
–	34.11	-9.43	–	–	-2.31	7.39
–	41.30	–	-68.88	–	8.25	19.01
4.49	34.22	–	-5.00*	–	-1.39	8.42
–	43.82	–	–	70.94	-5.93	3.42
6.14	30.82	–	–	-25.00*	-1.45	8.35

Note: The results pertain to experiments for the period 1987-2007 using our baseline model calibrated by imposing $G(z^*) = 0.6$ in steady-state. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages within 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007.

Table B6: Scenario $G(z^*) = 0.6$ – 1967 to 1987

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
-0.58	27.57	–	–	–	9.86	7.91
-0.58	–	–	–	–	1.07	-0.23
–	27.57	–	–	–	8.90	8.04
–	27.56	1.32	–	–	9.87	7.92
–	27.23	–	3.13	–	8.98	7.04
–	26.93	–	–	-4.86	10.24	8.28

Note: The results pertain to experiments for the period 1967-1987 using our baseline model calibrated by imposing $G(z^*) = 0.6$ in steady-state. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987.

Table B7: Scenario $G(z^*) = 0.4$ – 1987 to 2007

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
1.62	37.39	–	–	–	-3.83	5.72
1.62	–	–	–	–	-16.74	0.56
–	37.39	–	–	–	11.57	5.41
–	37.46	-3.24	–	–	-3.85	5.70
–	45.51	–	-68.25	–	7.42	18.10
1.55	37.75	–	-5.00*	–	-2.90	6.74
–	41.82	–	–	66.31	-4.97	4.47
2.07	36.03	–	–	-25.00*	-3.56	6.02

Note: The results pertain to experiments for the period 1987-2007 using our baseline model calibrated by imposing $G(z^*) = 0.4$ in steady-state. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages within 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007.

Table B8: Scenario $G(z^*) = 0.4$ – 1967 to 1987

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
0.08	29.04	–	–	–	8.40	6.47
0.08	–	–	–	–	-0.47	0.03
–	29.04	–	–	–	8.83	6.46
–	29.04	-0.16	–	–	8.40	6.47
–	29.16	–	-1.20	–	8.77	6.83
–	29.14	–	–	1.68	8.36	6.43

Note: The results pertain to experiments for the period 1967-1987 using our baseline model calibrated by imposing $G(z^*) = 0.4$ in steady-state. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987.

C The Results of the Model without Wage Bargaining

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Table C1: Model without bargain – Elasticities

	Δy	ΔLS	Δn	Δw	Δz^*
Δz_K	7.24	-4.51	2.40	0.00	-2.55
Δz_L	1.57	0.28	0.85	1.00	0.00
$\Delta \kappa_K$	-2.72	1.75	-1.01	0.00	1.21
$\Delta \kappa_L$	-0.24	0.00	-0.24	0.00	0.00
Δb	0.00	0.00	0.00	0.00	0.00
$\Delta \phi_{nb}$	-6.14	1.00	-6.14	1.00	0.00
$\Delta \chi$	0.48	0.00	0.48	0.00	0.00
$\Delta \delta_L$	-0.75	-0.29	-1.04	0.00	0.00

Note: This table shows the effects of the shocks to the parameters using our model without bargaining, as explained in Section 5.1. 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.

Table C2: Model without bargain – 1987 to 2007

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi_{nb}$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
0.69	41.71	–	–	–	6.50	17.09
0.69	–	–	–	–	-2.94	1.69
–	41.71	–	–	–	8.98	16.72
–	41.71	-1.48	–	–	6.47	17.05
–	43.43	–	-1.20	–	7.95	18.68
-2.80	49.17	–	-5.00*	–	11.05	22.09
–	41.70	–	–	33.38	1.43	11.44
1.82	41.71	–	–	-25.00*	8.62	19.41

Note: The results pertain to experiments for the period 1987-2007 using our model without bargaining, as explained in Section 5.1. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages within 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007. See Section 4.3 for more details on the experiments.

Table C3: Model without bargain – 1967 to 1987

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi_{nb}$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
-4.42	31.59	–	–	–	15.96	13.90
-4.42	–	–	–	–	10.98	-8.33
–	31.59	–	–	–	6.66	17.12
–	31.59	10.92	–	–	16.15	14.08
–	28.31	–	2.56	–	8.80	6.87
–	31.59	–	–	76.33	-8.13	-9.76

Note: The results pertain to experiments for the period 1967-1987 using our model without bargaining, as explained in Section 5.1. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987. See Section 4.3 for more details on the experiments.

D   The Results of the Model with $\Omega = \omega y$

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Table D1: Elasticities of the Model with $\Omega = \omega y$

	Δy	ΔLS	Δn	Δw	Δz^*
Δz_K	1.40	-1.50	-0.05	-0.07	-0.74
Δz_L	0.31	0.86	0.15	1.02	0.38
$\Delta \kappa_K$	-0.63	0.72	0.04	0.05	0.45
$\Delta \kappa_L$	-0.05	-0.09	-0.14	0.00	-0.06
Δb	-0.18	-0.17	-0.51	0.17	-0.22
$\Delta \phi$	-0.08	-0.07	-0.22	0.07	-0.10
$\Delta \chi$	0.10	0.18	0.27	0.00	0.12
$\Delta \delta_L$	-0.03	-0.45	-0.36	-0.12	-0.03

Note: This table shows the effects of the shocks to the parameters using our model with proportional entry costs, as explained in Section 5.2. 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.

Table D2: Model with $\Omega = \omega y - 1987\text{-}2007$

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
30.03	43.01	–	–	–	-5.50	3.89
30.03	–	–	–	–	-38.68	-3.63
–	43.01	–	–	–	22.90	4.35
–	44.38	-61.27	–	–	-6.02	3.32
–	64.99	–	-96.27	–	12.29	23.45
29.77	43.38	–	-5.00*	–	-4.55	4.94
–	33.55**	–	–	-96.61**	24.56**	31.81**
31.65	39.08	–	–	-25.00*	-4.24	5.27

Note: The results pertain to experiments for the period 1987-2007 using our model with proportional entry costs, as explained in Section 5.2. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters. The shocks marked with an asterisk are exogenously imposed in the respective experiment. The other shocks are calibrated such that our model targets the growth rates of output and wages in 1987-2007. 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 data, the labor share fell 3.6% and employment increased 3.9% in 1987-2007. See Section 4.3 for more details on the experiments. Note that the algorithm that runs our simulations is unable to converge in the experiment considered in the seventh line (the values are marked with double asterisk), meaning that the pair $(\Delta z_L, \Delta \chi = \Delta \delta_L)$ does not attain our targets for output and wage growth.

Table D3: Model with $\Omega = \omega y - 1967\text{-}1987$

Δz_K	Δz_L	$\Delta \kappa_K$	$\Delta \phi$	$\Delta \chi = \Delta \delta_L$	ΔLS	Δn
13.29	31.88	–	–	–	6.83	4.93
13.29	–	–	–	–	-19.06	-1.29
–	31.88	–	–	–	18.55	4.89
–	32.26	-29.05	–	–	6.59	4.69
–	37.54	–	-41.83	–	17.85	15.75
–	198.96**	–	–	-95.76**	37.90**	36.25**

Note: The results pertain to experiments for the period 1967-1987 using our model with proportional entry costs, as explained in Section 5.2. All values refer to percentage changes. The first five columns show the magnitudes of the shocks to the parameters, which are calibrated such that our model targets the growth rates of output and wages in 1967-1987. 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 data, the labor share fell 0.7% and employment increased 12.8% in 1967-1987. See Section 4.3 for more details on the experiments. Note that the algorithm that runs our simulations is unable to converge in the experiment considered in the last line (the values are marked with double asterisk), meaning that the pair $(\Delta z_L, \Delta \chi = \Delta \delta_L)$ does not attain our targets for output and wage growth.