Parameters for Solving the AI Productivity Puzzle

A Theoretical Critique of Daron Acemoglu's Macroeconomic Approach to AI

Hansjörg Herr, Christian Kellermann[1] & Zeynep Nettekoven

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Abstract

This paper develops an alternative theoretical framework for analyzing AI's macroeconomic effects, building upon and critically extending Daron Acemoglu's influential 2024 model. While Acemoglu's task-based approach represents a significant advancement in estimating modest productivity gains from AI, we identify three fundamental limitations: the assumption of constant returns to scale despite AI's tendency toward market concentration, unresolved problems in measuring capital stock, and a static task framework that neglects work process integration and expertise requirements.

Drawing on post-Keynesian and institutional economics, we propose a complementary framework emphasizing four dimensions: (1) functional income distribution driven by profit rates determined by financial conventions and corporate market power rather than marginal productivity; (2) wage structures shaped by institutional factors such as collective bargaining, minimum wages, and social norms, rather than task-level automation potential alone; (3) demand-side dynamics where employment outcomes depend critically on aggregate demand growth alongside productivity changes; and (4) institutional mediation of technology's distributional effects, with particular attention to Germany's co-determination system.

Keywords: Artificial Intelligence, Productivity, Income Distribution, Institutional Economics, Post-Keynesian Theory, Labor Markets, Co-determination

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[1] Corresponding author: Christian Kellermann (University of Labour, Frankfurt/Germany, Christian.kellermann@university-of-labour.de), Hansjörg Herr (Berlin School of Economics, Germany), Zeynep Nettekoven (European Academy of Labour, Frankfurt/Germany). This working paper has not yet undergone professional language editing.

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1. Introduction

GenAI amplified the voice of publications on AI's potential to push productivity growth to new limits and confirmed political reliance on that phenomenon as automatism. Widespread implementation of AI would help mitigate demographic pressures on labor supply just as it would reconnect the economy to periods of high productivity growth. The main reason for these high hopes is the general applicability of GenAI in fields of work, which have long been characterized by lower or no productivity growth. Routine cognitive tasks are described to be especially prone to that new stage of automation.

"White collar massacre", "Blue collar bonanza" as headline making scenarios selectively refer to studies finding a strong complementary nature of AI for jobs with lower qualifications, while groups with higher qualifications are negatively affected by GenAI's capabilities. Estimations of the effects of AI on productivity tend to be derived from the calculations of the level of complementarity and the degree of substitution of professional tasks. Saving working time and upgrading performance and the respective output of work fuel the accounting of input-output-relations and hence the potential of productivity. Especially, firm-level surveys (often conducted by consulting firms) end up with AI's potential to enhance labor productivity and create corresponding expectations among managers and policy makers alike. Up to 3% AI-induced annual labor productivity growth can be the result according to such surveys. Even though there are obvious methodological limitations to such surveys, they dominate the public picture of AI's potential for the economy.

Not only do the multi-purpose functions of GenAI increase the level of complexity to measure AI as an input factor. There is also a lack of qualitative (and quantitative) data regarding core work systems and processes, in which an AI application is integrated or to be implemented. The study landscape on AI and productivity is characterized by aligning complexity-levels of tasks a profession comprises based on the existing occupation data bases with AI's potential to take-over these tasks based on technical estimations or on tests that simulate human competences. Despite this common ground of many studies to measure AI's productivity potential, there is a wide range of such estimations' results (for a study overview cf. Kellermann/Markert 2023).

This low level of resilience in empirical findings or model-based scenarios is problematic at least in two ways. (1) The gap between AI's hype cycle and reliable effects on productivity promotes reluctance to implement AI on company level. This is particularly true for SME, where relative procurement costs are higher compared to large companies. (2) The lack of a comprehensive set of AI's "success factors" for enhancing labor productivity narrows the policy focus on promoting AI on the company-level, rather than merging micro-insights into a bigger, macro-economic picture, which would render necessary a policy debate about distributing asymmetric productivity effects across sectors and skill groups for noticeable welfare effects against the background of the questions of the future of work —particularly concerning working time, task composition, skill requirements, a wage distribution and income distribution in general.

The recent study by Daron Acemoglu (2024) provides a substantial leap forward in the challenge to specify AI's productivity effects on the macroeconomic level. His

“Macroeconomics of AI” provides the departure point for our paper. His analysis shows that the high expectations of GenAI’s productivity promise are hasty and full of prerequisites to materialize. On that account he provides an important basis for further model development as well as for policies necessary for better outcome of GenAI on the future of work.

We pose the question: What are the critical limitations of Acemoglu's approach from a post-Keynesian theoretical perspective, and how can these insights inform the development of an alternative theoretical framework for analyzing GenAI's micro- and macroeconomic effects on labor markets and income distribution?

In the following we will briefly illuminate the core aspects of Acemoglu’s approach, before we delve into a critique of this approach from a theoretical stance focusing on circular flows and dynamic effects on demand. We will then demonstrate a further developed approach to analyze productivity effects of AI, by considering the following dimensions: the functional income distribution, inter-and intra-sectoral interactions, demand side effects on employment and wages, and the institutional context of wage setting.

2. Acemoglu's Approach in a Nutshell

Acemoglu (2024) developed a macroeconomic model, which follows the task-based approach. Opposite to such models’ usual results – such as high levels of automation for tasks with high proportions of routine and low levels of complexity[2] – Acemoglu’s model draws a different picture of AI’s potential for productivity growth. The “calculation implies that total factor productivity (TFP) effects within the next 10 years should be no more than 0.66% in total—or approximately a 0.064% increase in TFP growth annually (ibid.: 4).”

The basic approach of the model is comparable with other task-based models. Estimating the nature (complementary or substitutive) and degree of AI’s effect on a professional task is core to the method. Finetuning this method can be done either by refining the data base and / or by modifying GenAI’s capabilities compared to complexity levels of human tasks.

Acemoglu (2024: 24-28) elaborates on Eloundou et al. (2023), which use the O*NET task as well as the Detailed Work Activity (DWA) descriptions.[3] He also evaluates qualitative studies to refine estimations of actual levels of substitution. The calculation of AI’s overall cost saving potential (labor costs on the sector level and the average overall cost saving potential) vary slightly according to adjusted labor shares exposed to AI. Productivity increases reduce different types of costs. The span ranges between 14% and 19% on firm level, while at sector-

[2] One example is the Job Futuromat of the German Federal Government (https://job-futuromat.iab.de). Users receive an estimation of the level of automation of core tasks of a profession, which tends to be very high without delivering background information on the empirical and methodological limitations of such estimations in a way that users can classify the results.

[3] The Occupational Information Network (O*NET) is a comprehensive database maintained by the U.S. Department of Labour that provides standardized occupational information across the American economy. The O*NET task descriptions offer detailed inventories of specific activities workers perform in each occupation, capturing the concrete actions and responsibilities that constitute work at a granular level. The Detailed Work Activities (DWAs) provide an intermediate layer of abstraction between tasks and broader work functions, categorizing related tasks into standardized work activities that cut across occupational boundaries.

level, labor cost savings could be up to 36% (e.g. in the IT-sector and the task spectrum of programming).

These findings are in line with other similar studies and support the optimistic outlook on GenAI's productivity potential, even though he stresses that several factors could counter this potential: (1) an asymmetric diffusion of AI due to monopolizing GenAI leaving SME behind, (2) the expected J-shaped-pattern of AI's effects taking about 20 years to materialize and (3) the reality check of AI's capabilities opposite to experimental settings of many qualitative studies (Acemoglu 2024: 30).

Excluding (1) and (2), incorporating "hard tasks"[4] in (3) in the aggregation for estimating overall productivity effects is a crucial step in his model building. He adds the level of Intermediate Work Activities (IWAs), which are often associated with evaluations (of the quality of the accuracy of data for example) and improve the quantitative approach by obtaining a "probabilistic assignment of … tasks into easy or hard task category" (ibid., 33). As a result, roughly one third of all exposed tasks remain hard, i.e. not to be automated by AI. Transferring this into Total Factor Productivity (TFP) gains over the next 10 years reduces the estimation outcome. "Since automating hard-to-learn tasks—and even more so, introducing task complementarities for them—will be more challenging, I view this estimate to be more reasonable. Either way, the TFP gains within the next 10 years appear quite modest." (ibid.: 33).

Several macroeconomically relevant findings can be taken from Acemoglu's model.

(1) Even though AI exposure is more equally distributed across demographic groups (compared to previous technologies of digitalization), the effect of AI will not reverse polarization of previous inequalities due to automation. "Rather, my analysis suggests that it may have a small positive effect on overall (between-group) inequality and reduce the real earnings of low-education women. It will also further widen the gap between capital and labor income." (ibid.: 42).

(2) Acemoglu assumes that relative wages are determined by the marginal productivity of labor of specific tasks. When AI boosts productivity in tasks requiring lower qualifications, prices for these tasks might fall more than productivity gains rise. This is because that a lower demand for labor for these tasks reduces relative wages. This may push higher skilled workers (who could also fulfil these tasks) away from these tasks, leaving only low-skilled workers to perform them. Higher-level tasks, where relative wages are determined by the higher marginal productivity ratio, meet a limited supply of higher qualified workers, leading to higher relative wages of high-skilled workers and increasing inequality despite the AI induced narrowed skill gap (ibid.: 22f.).

Acemoglu's model indicates that AI's polarizing effects might be less severe compared to previous automation advancements, as AI exposure is more evenly distributed across demographic categories, such as across age cohorts, educational attainment, and income quintiles. But contrary to some predictions, AI is unlikely to reduce inequality within employees

[4] Following Acemoglu/Restrepo (2018a), we distinguish between «easy-to-automate» tasks (routine cognitive and manual tasks with clearly defined procedures) and «hard-to-automate» tasks (non-routine tasks requiring creativity, complex problem-solving, or interpersonal interaction).

to a significant extent, which is also the main reason for him to argue, why projections of high productivity gains for the macroeconomic level are unsubstantial (ibid.: 45).

Asymmetric effects on functional income distribution and changes of wage structures are the basis for Acemoglu's (22f.) scenarios regarding polarization. Here he also assumes that functional income distribution, at least in a competitive environment, is determined by the marginal productivity of labor and capital, following the traditional neoclassical approach.

In one scenario, AI systems are deployed to augment the productivity of human labor in existing tasks. Workers become more productive at their current jobs through AI assistance, increasing both automation productivity and task-specific labor productivity. However, due to the elasticity of substitution between capital and labor being less than one ($\sigma < 1$), meaning that despite higher productivity of labor less workers are demanded, the enhanced productivity paradoxically reduces labor's share of total income, concentrating gains toward capital owners and reduces real wages.

In another scenario, following the usual neoclassical argument, AI generates massive efficiency gains, creating economic growth. While absolute wages may rise, labor's relative share continues to shrink. Workers benefit from higher real incomes, but capital owners capture a disproportionately larger share of the productivity gains, widening capital-labor inequality despite higher growth.

In a third scenario AI tools particularly benefit lower-skilled workers, increasing their relative productivity compared to high-skilled workers. This creates a scenario where traditional skill premiums compress and labor income inequality between worker types decreases. However, the fundamental capital-labor divide still widens as overall labor share declines.

Only in a fourth scenario would there be no polarization effect. New AI-enabled tasks emerge, creating novel roles that complement rather than substitute for human labor. If these new tasks particularly emerge in complementary to lower-skilled tasks, favoring lower-skilled workers, the substantial increase in marginal productivity of labor among these groups of workers leads to the result that both capital-labor inequality and within-labor inequality could potentially decrease.

3. Critique: Where Acemoglu Remains in Murky Waters

The analysis by Acemoglu on the effects of AI on the productivity of different groups of workers and on labor and capital is innovative and has advanced research. In Acemoglu's approach productivity effects of AI play a key role for a changing wage structure as well as for changing functional income distribution. However, we assess the effects of productivity changes differently in terms of both functional income distribution and wage structure. In our view, there is no simple and clear link between the relative productivity of different groups of workers and the wage structure, nor is there a clear link between the productivity of capital and labor and the functional income distribution. Our critique in this section regarding the outcomes of his model concentrates on two fundamental conceptual aspects of this model, namely the "constant

returns to scale" assumption and the concept of "capital stock", but also his model's comprehension of "tasks".

The first critique of his analysis is on the assumption of constant returns to scale. "The nexus of the many effects of AI on the economy is its impact on productivity. To gauge the extent of this impact, we can appeal to Hulten's theorem, which provides a simple formula for competitive economies with constant returns to scale, specifying how micro level productivity improvements translate into macro changes." (Acemoglu 2024: 13)[5]. Charles Hulton (1978) demonstrated that under specific economic conditions—perfect competition, constant returns to scale, and frictionless reallocation of production factors—a firm's productivity increase translates into a proportional macroeconomic effect based on that firm's share of total output. For example: if a firm accounts for 0.1% of GDP and increases its productivity by 20%, the resulting increase in overall GDP would be 0.02% (calculated as 0.1% × 20%).

The formula $Y = \frac{\partial \mathrm{Y}}{\partial \mathrm{L}} L + \frac{\partial \mathrm{Y}}{\partial \mathrm{K}} \mathrm{K}$

shows the neoclassical macroeconomic model of functional income distribution with Y as aggregated income or net domestic product, L as labor input, K as capital input, $\frac{\partial \mathrm{Y}}{\partial \mathrm{L}}$

as marginal product of labor and $\frac{\partial \mathrm{Y}}{\partial \mathrm{K}}$ as marginal product of capital. The marginal product of labor corresponds to the real wage per labor input, while the marginal product of capital corresponds to real profit per unit of capital. Functional income distribution according to this rule is fair, each factor gets what it contributes to the output. Under constant returns to scale, the equation above holds. However, with economies of scale (increasing returns), the neoclassical distribution rule would distribute more income than is produced. Conversely, with diseconomies of scale (decreasing returns), not all produced income would be distributed according to this rule.

While Acemoglu does not strictly adhere to simple neoclassical marginal productivity theory for income distribution, his theoretical conclusions nevertheless depend critically on the assumption of constant returns to scale. This creates important limitations: if certain economic sectors exhibit increasing returns to scale—and if AI further accelerates oligopolistic tendencies in these sectors—then Acemoglu's predictions about AI's effects on wage shares and profit shares would no longer hold at the macroeconomic level. Similar validity problems arise under conditions of decreasing returns to scale.

Increasing returns to scale are typical for many types of production. Already Adam Smith (1776) explained the logic of mass production based on increasing division of labor and specialization using his example of pin production. In many production processes, it only makes sense to choose a certain technology for large production volumes. There are indivisibilities – it takes a great deal of effort to write a computer program, once it is there, it can be copied almost free of charge – or network effects – only big networks can collect comprehensive data.

[5] "We assume throughout that F is continuously differentiable, concave, and exhibits constant returns to scale." (Acemoglu/Restrepo 2018a: 3)

Research departments need to be of a certain size to produce synergies and become innovative, to name just a few factors for increasing economies of scale.

A new empirical study of companies in Europe has found that in significant parts of the economy, increasing returns to scale do exist, for example in manufacturing, transport and IT sectors. In many service industries decreasing returns to scale are comparatively common (McAdam et al. 2025). In addition, growing firms may first have economies of scale and at a certain point constant or decreasing returns to scale.

Where there are economies of scale, there are large companies, because economies of scale simply mean that companies become more productive and save costs as they grow. As soon as there are increasing returns to scale, market-endogenous oligopolies or even monopolies form. If further proof of increasing returns to scale is needed, one can look at the increasing market concentration in many markets. For example, Dlugosch et al. (2025) took the sales of the biggest four firms relative to the market's total sales as indicator and found in Europe and the USA a substantial increase in market concentration. Increasing market concentration means that companies' monopoly or oligopoly power is growing, enabling them to enforce higher profit markups. On the purchasing side, powerful companies are gaining market power over suppliers within the framework of monopsony structures as well. Higher markups can be expected. "Data from listed firms show a notable increase in markups – measured as the ratio of total revenue to the cost of goods sold – across most advanced economies." (Dlugosch et al. 2025: 25f.) Overall, models which assume constant returns to scale therefore do not draw a sufficient realistic picture for macroeconomic developments including functional income distribution.

A second critical point is that Acemoglu uses the concept of "capital stock" without addressing the underlying theoretical debates surrounding this term. For example: "Suppose aggregate output is given by $Y = F(A_K K, A_L L)$, where K denotes capital, L is labor, and A_K and A_L denote capital-augmenting and labor-augmenting technology, respectively. We assume throughout that F is continuously differentiable, concave, and exhibits constant returns to scale. Let F_K and F_L denote the derivatives of F with respect to capital and labor."[6] (Acemoglu/Restrepo 2018a: 3) In many publications it is spoken about the "stock of capital" (Acemoglu/Restrepo 2018c: 17) or "if the capital-output ratio rises" Acemoglu (2024: 19) or "US capital-output ratio which is approximately 3" (Acemoglu/Restrepo 2018a: 8).

The question immediately arises how a capital stock is measured. This brings us way back to the Cambridge capital controversy of the 1950s and 1960s. Capital in production functions obviously must be measured in prices, because it makes no sense to aggregate it in tons or liters. The value of a given stock of capital and output depends on the structure of relative prices of goods. The problem is that the structure of relative prices depends on the functional distribution of income. Any change in the wage structure will also have an impact on the structure of relative prices. If the minimum wage rises, the salaries of experts increase or the salaries of specific professions decrease – for whatever reason – this will change the structure of relative prices. Here, any macroeconomic model which must use the stock of capital for explaining the profit rate is tangled up in a vicious circle. Given a certain technology and structure of production

[6] "F" denotes the production function.

and consumption each income distribution is correlated with a specific structure of relative prices and a specific stock of capital. The value of stock of capital changes with every change in income distribution – even if the stock of capital physically did not change (for an overview about the debate, see Herr 2019; 2020; Sraffa 1960; Robinson 1953; Pasinetti 1966; Harcourt 1972; Samuelson 1966).

AI undoubtedly increases productivity, changes income distribution, the structure of relative prices and the measured value of the capital stock. Any theoretical contribution and longer-term empirical investigation must take this into account. This is a general problem and does affect not only Acemoglu's model. However, the problem of measuring the capital stock should at least be acknowledged, even if it is difficult to solve the problem.[7]

Another critical point of Acemoglu's model concerns his focus on tasks, which remains static and isolated from wider work context such as work processes as well as relevance of experience and expertise. Autor/Thompson (2025) developed a "conceptual model of occupational task unbundling" based on expertise requirements that change due to collaboration with AI. Their approach offers a more realistic picture of tasks as the basic unit of professions and jobs with differentiated model of labor division.[8] Core to this approach is a more holistic understanding of task bundles as being indivisible. The isolation of individual tasks leads to a loss of relevant information about job profiles and the role within a work process just as it does not do justice to the structure and complexity of even the simplest of activities. "A key innovation of the present paper is to distinguish between task expertise exposure versus task quantity exposure." (ibid.: 6)[9] The potential change of expertise (requirements) by using AI is altering the picture of automation estimations at hand and provides important information for AI's effects on productivity, even though the study itself develops no macroeconomic implications. According to Autor/Thompson (2025) the relationship between automation, skill requirements and wage dynamics exhibits a pattern that challenges conventional assumptions about technological progress and labor compensation. When automation reduces the expertise required for certain occupations, it effectively expands the pool of workers capable of performing these task bundles required for an occupation, leading to an increased labor supply that subsequently depresses wages. This phenomenon occurs, because the deskilling effect of AI makes previously specialized roles accessible to a broader workforce, intensifying competition among workers

[7] The problem "disappears" when the assumption of only one capital good is made which can be aggregated in physical units. It is worth noting that Karl Marx (1894) failed to aggregate the capital stock correctly when transforming values into prices. His transformation problem also disappears with the assumption of only one capital good.

[8] Their concept of expertise shows similarities with a labour sociological understanding of work and competences and challenges the quantitative capture of isolating routine tasks for estimating a degree of automation. Unbundling tasks connects to incorporating experience and uncodified knowledge or competencies for unexpected situations in work processes, which (as of today) cannot be represented or even imitated by AI due to its "tacit" nature (Polanyi 1966). Polanyi fills an important research gap to measure labour-related effects in a differentiated way and make them quantifiable for macroeconomic approaches to model these effects for productivity estimations.

[9] Methods used: "We introduce a novel content-agnostic tool for measuring occupational expertise from job task descriptions. This tool is grounded in the Efficient Coding Hypothesis and requires only information on the statistical frequency and entropy of words occurring in commonplace usage. We introduce a second tool for measuring longitudinal changes in occupational expertise. This tool uses word embeddings—geometric representations of the semantic content of words—to determine which tasks have been removed, retained, and added to occupations across epochs without requiring that the tasks are described consistently across time." (Autor/Thompson 2025: 52).

and driving down compensation. Conversely, occupations that experience rising expertise requirements face a constrained labor supply, as fewer individuals possess the advanced skills necessary to perform these roles effectively. This scarcity of qualified workers creates upward pressure on wages.

This relationship demonstrates that the impact of technological advancement on wages is not simply determined by the degree of automation implemented, but rather by how AI affects the skill barriers to entry and the resulting equilibrium between labor supply and demand in on the labor market. These AI-related "shifts in the labor supply curve" (ibid.: 3) provide a qualitative basis for modelling quantitative effects. „Employment initially rises in occupations as they become inexpert, owing to the elimination of expertise requirements. Entry causes wages in newly inexpert occupations to fall to the level of all other inexpert occupations. (…) Automation is always output-increasing in the model but never Pareto-improving." (ibid.: 7f.) By not Pareto-improving it is meant that the introduction of AI is also producing losers, even if the general wage level should increase.

Even though the expertise framework does not focus on macroeconomic consequences, it supports the somewhat counterintuitive findings on productivity by Acemoglu (2024). Following Autor/Thompson (2025) occupational expertise correlates with wage levels, so the effect of AI on adding or removing expertise requirements go into the price of labor.

Two aspects need to be considered: (1) automation of expertise competences reduces wages and increases labor supply, while automation which increases expertise requirements drives up wages, while the labor supply is limited or reduced. (2) Employment falls in fields with increasing expertise requirements and it rises in fields with declining expertise requirements (ibid.: 52). Rising expertise means rising wages, falling expertise pushes wages down. Extrapolating these connections to macroeconomic estimations of AI's productivity potential suggests a counteracting effect. More jobs with relatively higher degrees of automation experience lower wages, while less (expert) jobs with relatively lower degrees of automation will experience rising wages. There is a lot of potential in combining a better understanding of microeconomic dynamics of how automation reshapes occupational expertise requirements and wage structures with a macroeconomic modelling.

4. An Alternative Approach to Analyze Productivity Effects of AI

In this subsection, we outline an alternative approach to explain functional income distribution and an at least complementary approach to explaining the effects of AI on the wage structure. Then we move on to the role of aggregate demand. As theoretical background we use a monetary Keynesian approach based on the original works of Keynes (1936 and 1930).

4.1. Functional Income Distribution and the Necessary Focus on the Profit Rate

AI has the potential to change the functional income distribution in a substantial way. National income (Y) is given by the sum of wages and profits $Y = w \cdot L + q \cdot P \cdot K_r$ with w as wage per hour, L as labor input, q as profit rate, P as the price level and K_r as the real value (adjusted to price level changes) of capital. The wage share or labor share with $W = w \cdot L$ as national wage sum per definition is

$$\frac{W}{Y} = 1 - \frac{q \cdot P \cdot K_r}{Y}$$

and with $k = \frac{P \cdot K_r}{Y}$

as capital coefficient, we get

$$\frac{W}{Y} = 1 - q \cdot k$$

In a Keynesian approach the key factor to explain functional income distribution is the profit rate. This determines – together with the capital coefficient – the wage share.[10] For the profit rate two factors are important. Firstly, a rate of return demanded by the financial sector; secondly the market power of companies in the economy (Herr 2019 and 2020).

Let us start with the arguments of Keynes (1936: 214) who rejected the idea that capital gets a fair share of income because of its productivity: "I sympathise, therefore, with the pre-classical doctrine that everything is produced by labour. ...It is preferable to regard labour, including, of course, the personal service of the entrepreneur and his assistants, as the sole factor of production, operating in a given environment of technique, natural resources, capital equipment and effective demand." This argument holds true even if almost full automation were to occur in individual industries. This is because the machines in these industries would be produced in other industries, and the disappearance of humans from production is not to be expected. The minimum rate of profit is determined by the *medium-term* interest rate. Interest payments are for firms a kind of cost which must be covered by prices, otherwise firms go bankrupt. "If, however, the rate of interest exceeds zero, a new element of cost is introduced which increases with the length of the process." (Keynes 1936: 216) These costs must be covered by prices. If companies use equity capital, they will demand at least a return equal to the interest rate – so called opportunity costs exist -, because otherwise it is more advantageous to hold monetary assets. Sraffa (1960: 33), following Keynes, suggests that "the rate of profits ... is ... susceptible of being determined from outside the system of production, in particular by the level of the money rate of interest". Interest rates and thus minimum profit rates do not reflect capital's productivity. Instead, they are set through monetary policy decisions and shaped by the expectations and risk assessments of financial institutions and asset owners. Depending on convention and market constellation the minimum rate of profit also can be higher than the interest rate. This is because there is a general idea or expectation of how high the rate of profit should be to cover risks and other factors.[11]

Let us come to the second factor. Kalecki (1971, 1965/2009) stressed, following mainstream economic thinking, that the profit markup depends on the market power of companies, that means the existence of monopolies, oligopolies, monopsonies etc. which earn extra profits. The

[10] In the classical paradigm and in Marxian thinking, at least in (Marx 1867) which remained unfinished, wages are given, and the profit and profit rates result from this (Sraffa 1960). The Classical paradigm assumes that real wages are negotiated. However, this assumption does not hold. Nominal wages are negotiated. And empirically and theoretically the development of nominal wages primarily influences the price level and not the real wage level (Heine/Herr 2024).

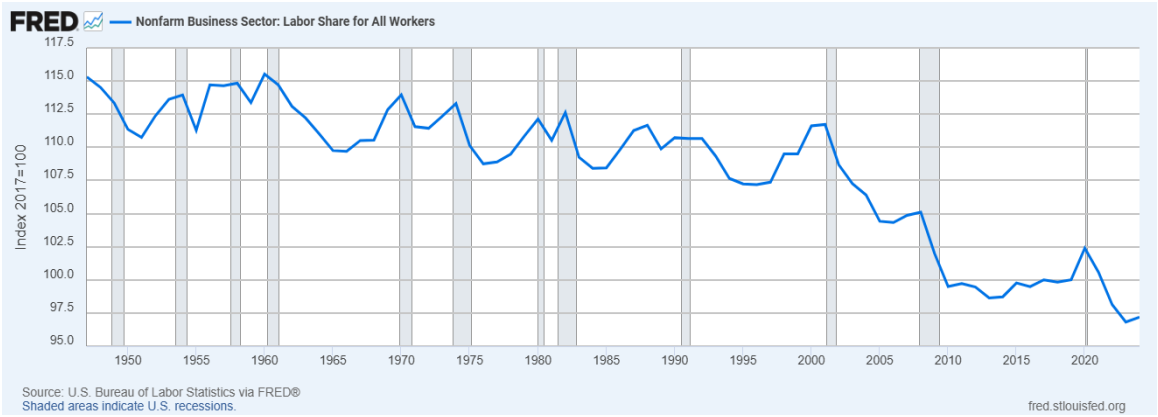
[11] The profit rate is therefore q = i + l, where i is the interest rate and l is the profit margin above the interest rate. Keynes introduced the subjective liquidity premium on money holdings to explain why wealthy individuals hold financial assets without interest (Keynes 1936: Chapter 17). Similarly, we can introduce a profit premium.

higher the market power of firms, the higher the profit markup and the profit rate. Kalecki emphasized that strong trade unions can succeed in converting parts of extra profits of a company into wages. “High markups in existence will encourage strong trade unions to bargain for higher wages since they know that firms can ‘afford’ to pay them. If their demands are granted but ... [the markup is] not changed, prices also increase. ... But surely an industry will not like such a process making its products increasingly expensive and thus less competitive with the products of other industries. To sum up, trade-union power restrains the markups.” (Kalecki 1971: 161) Here the corporate governance system as well as the power of agents in the financial system becomes important (see below).

Given the rate of profit, the total profit and, consequently, the functional income distribution can be calculated for a given capital coefficient. Any change in distribution will influence the capital coefficient, as a new structure of relative prices is created. However, there is a major difference between traditional approaches to explaining functional income distribution. No knowledge of the size of the capital stock is required to determine the rate of profit. Theoretically, therefore, there are no problems at this point even if the capital stock changes permanently with changes of income distribution.

On this theoretical basis, we can discuss the empirical development of functional income distribution and the role of AI. Figure 1 shows the development of the wage share in the USA. It clearly shows that the wage share fell significantly, especially from the beginning of the 2000s onwards. This development is not only typical for the USA and mainly based on higher profit markups. In an OECD paper it is written: “Data from listed firms show a notable increase in markups – measured as the ratio of total revenue to the cost of goods sold – across most advanced economies.“ (Dlugosch et al. 2025: 25f.). The markup is calculated as revenues over cost of goods sold. The OECD average markup rose from 1.5 at the beginning of the 2000s to over 1.6 after 2020 which to a large part explains falling wage shares.

Figure 1: Index of labor share in the nonfarm business in the United States



Labor share is measured as employee compensation as share of gross value-added output, which is defined as gross output minus intermediate inputs, Source: FRED (2025)

This leads us to the question of what role AI plays in changing the functional income distribution and what role it may play in the future. The AI industry is highly concentrated, and we can expect that the concentration process will continue. "The potential for an increasing concentration of AI resources (data, hardware and talent …) could exacerbate these effects on wealth inequality as AI capital becomes increasingly held by a few firms and shareholders." (Dlugosch et al 2025: 39) In addition it must be seen that tech-companies are concentrated in a small number of countries, especially the USA and China (Muro/Liu 2021). Thus, AI companies have high oligopolistic power on the selling side and high monopsony power on the buying side.

Autor et al. (2020) correctly argued that there is a tendency of the development of so-called "superstar firms" with very high financial resources, managerial capability and know-how. Rent-seeking of these firms is especially high as entry in the market for newcomers is difficult. Especially in the sector of AI superstar firms can be expected. The AI industry, particularly among companies developing foundational AI technologies, is highly dynamic. New competitors can emerge and displace established players. However, this potential for disruption does not negate the enormous economies of scale inherent in the industry, nor the resulting tendency toward market concentration and corporate power.

The characteristics of AI companies discussed are embedded in a general development. Firstly, corporate governance changed in the 1990s, shifting from stakeholder corporate governance to shareholder value corporate governance. At the same time the power of trade unions became weaker and profit sharing as under the stakeholder corporate governance system became the exception. This is part of the financialization of the economy, which has made the institutions in the financial system more powerful which are pushing for high short-term dividend payouts and unconditional profit maximization of firms (Detzer et al. 2017; Gutiérrez/Philippon 2017). This has driven up the profit rate substantially above the interest rate. Secondly, within the framework of shareholder corporate governance and financialization in general the power of trade unions has declined. Thirdly, concentration in markets has increased significantly. Calligaris et al. (2025) took the sales of the biggest four firms relative to the market's total sales as indicator and found in Europe and the USA a substantial increase in market concentration.

The market concentration in the AI industry—dominated by a handful of tech giants with substantial computational resources and proprietary data—has direct implications for profit distribution in the broader economy. As these companies license AI technologies across sectors, they capture a significant share of AI-generated productivity gains through licensing fees and platform rents. This creates a two-tier effect: rising profit rates for AI-developing firms and potentially compressed margins for AI-adopting firms that must share productivity gains with technology providers.

To sum up this point: In the determination of the wage share and the role of AI two factors play a role (see equation above). Firstly, the profit rate which depends on a minimum profit rate and, more important for AI, on market power of firms and financialization. We can expect that AI increases the profit rate. Secondly, the capital coefficient. It depends on technological factors, but also on functional income distribution and structure of wages which influence relative prices and the value of the capital stock. The long-term trend of the capital coefficient ($K_r \cdot P/Y$) shows

in Europe and the USA in the early 20th century a falling trend, then from the 1950s an increasing trend from around 3 to 4 in 2010. Piketty expects until the end of the century a further increasing capital coefficient (Piketty 2014: 165, 196). AI is certainly part of the explanation for this expected trend. Further research is needed to analyze these factors empirically in detail. Overall, we come to the same conclusion as Acemoglu, namely that AI reduces the wage share. However, our reasoning for this is different.

4.2. Baumol Revisited: Structural Change Within and Between Sectors

The above section explained how technological changes brought about by AI are changing the tasks performed by employees, which groups of employees are experiencing de-skilling and being partially replaced, and which groups are benefiting from AI. The task approach can be supplemented by considering hidden qualification requirements such as experience, etc. These analyses are valuable, but it would be wrong to draw the conclusion that these changes automatically alter the wage structure, which, according to the neoclassical view, reflects the marginal productivity of employees in each segment of the labor market. Acemoglu (2024) and Acemoglu/Restrepo (2018a-c, 2019) also examine the productivity effects of AI for individual tasks and then conclude that there will be a corresponding change in the structure of wages.

One problem with measuring wage structure based on productivity at work is that it is often difficult or impossible to measure productivities. This is the case, for example, with complementary tasks or team tasks. Examples include surgeons and surgical nurses, designers and developers, and assembly line workers. Although it can be argued that a surgeon has more qualifications and should therefore earn more than a surgical nurse, it is difficult to determine the wage difference based on productivity. Productivity development in certain segments in the labor market, de-skilling, shortages of experts etc. play a role for wage development, but *as important* other factors must be added. The wage structure and as a result relative prices are influenced or even controlled by social and political processes.

The phenomenon that wages in an industry do not correspond to the productivity of workers in that industry has already been highlighted by Baumol and Bowen (1965). This is because there are industries in which productivity can only increase slowly compared to other industries – such as nursing compared to car manufacturing. If nursing were remunerated according to its productivity, the wage differences between employees working in the care sector and in the automotive sector would steadily increase. In a common labor market, hospitals etc. are forced to pay higher wages than the productivity development of the sector to find workers. Trade unions will at least partly try to get the same wage level in different sectors of the economy. An electrician in a hospital cannot be completely disconnected from the wages of his colleague in the automotive industry. These processes increase the wage costs in sectors with relatively low productivity increases more than in sectors with relatively high productivity increases as unit labor costs, assuming the same nominal wage increases, increase in low-productivity sectors faster than in high productivity sectors. Cars in relation to nursing or personal services in general become cheaper. This is a necessary and beneficial process to prevent wage disparities in a country from exploding (see also Baumol 2004). If, for example, statutory minimum wages applicable to all sectors in a country are significantly increased, wage costs will rise much more sharply in low-wage sectors than in sectors with relatively high wages. This leads to higher

price increases in the sectors that are particularly affected by minimum wages. The entire price structure changes with higher price increases in sectors with relatively low wages (Herr 2025).[12]

If we assume that all firms in the sector produce under the same conditions and other costs in form of depreciation, profit mark-up and costs for intermediate goods are added, together with wage costs we get the price of the good. Thus, the price of a good to a substantial extent depends on the wage costs, which depend to a large part on the nominal wage level in the sector. And the nominal wage level in a sector depends on many factors, on productivity, but also on the power of trade unions in the sector, existing minimum wages, traditions and conventions and so on.

Even within a sector, the wage structure does not reflect the productivity of different employees. Education, experience, etc. certainly play a role in remuneration, but the wage structure within a sector or company also depends on institutions, trade union power, minimum wages, notions of fairness, the position of women, etc.

The wage spread in different countries shows that the wage structure is not determined by purely economic factors. In 2021, the ratio of D9 to D1 for wages[13] was for example in the USA 4.6, in Poland 4.0, in Germany 3.3, in France 2.7, in Finland 2.4 or in Sweden 2.1. In low- and middle-income countries the ratio is even much higher than in the US. These figures certainly do not in any way reflect marginal productivity (ILO 2024: 41).

The structure of relative prices is also influenced by the profit mark-up which depends among other things on the market power of companies. A monopoly in a market, for example, will set another price compared to a price under perfect competition. Market power depends on whether companies in the market in question have an oligopoly or even a monopoly. Monopsony structures also influence profits and the structure of prices. Market power of firms is not an exception; it is the norm and perfect competition is the exception.

The wage structures observed in global value chains (GVCs) provide compelling empirical evidence for the weak relationship between productivity and wage levels. Workers performing comparable tasks within the same industry—but situated at different nodes of a GVC—exhibit substantial wage differentials that cannot be attributed to productivity differences. Indeed, the persistent wage gap between workers in the Global South and the Global North constitutes a

[12] To illustrate this point, consider the following example. Under perfect competition and standard microeconomic assumptions, a profit-maximizing firm follows the condition $p_1 \cdot \frac{dX_1}{dL_1} = w_1$ with p_1 for the price of the produced good X_1, L_1 for the labour input, and w_1 for wages. As long $p_1 \cdot \frac{dX_1}{dL_1}$, the price of the good multiplied with the number of the goods produced by the last employed worker (the marginal product of labour), is higher than the wage cost (w_1) it is advantageous to employ more workers. The wage and the price of the product are given by the market, the marginal product of labour by the technology. The market price has to cover all costs, $p_1 = \frac{w_1}{\frac{dX_1}{dL_1}}$. Thus, the wage costs of the good depend on the (marginal) productivity of labour and the nominal wage.

[13] D9 indicates the lowest earnings of the top 10% of earners and D1 indicates the highest earnings of the bottom 10% of earners. Above D9 wages become very unequal – think about managers or sports stars. Also, below D1 wages can become very unequal with sectors with very low wages.

structural feature of contemporary global capitalism rather than an anomaly (see Hickel et al. 2024).

The analysis on wage effects of AI adoption therefore cannot be abstracted from this power asymmetry inherent to global capitalism. If the argument goes that wage levels across different occupations in an industry and across different sectors do not necessarily reflect the productivity differentials in a certain domestic economy, but rather reflect the necessity of a certain sense of egalitarianism in the society, this analysis cannot be blind to the constructs behind the extremely unequal wage structure in the global value chains. The conclusion is that the introduction of AI can have completely different effects in different countries. Firstly, this concerns the manner of introduction; for example, is it for the purpose of controlling employees or for the purpose of facilitating and enriching work? Secondly, the effects of technological changes brought about by AI, for example the effects on the wage structure, depend on the country's institutions, the power of workers and political regulations.

4.3. Role of Demand for Employment and Wage Structure

The volume of employment depends on three factors: the existing technology, changes in technology (or productivity developments), and the level and growth of aggregate output. If L is labor input and GDP gross domestic product we get π = GDP/L as (labor) productivity. By definition is GDP = (GDP/L)·L or GDP = π·L or L = GDP/π. If we transform the last equation in growth rates, we get $\dot{L} = G\dot{D}P - \dot{\pi}$.

The change in employment is therefore, by definition, identical to the change in GDP minus the change in productivity. If productivity increases by 2%, for example, GDP growth must be at least 2% to prevent employment from falling. If AI increases labor productivity, this can lead to unemployment when the economy stagnates. If GDP growth is sufficiently high, even very high productivity increase will not lead to unemployment. The problem with capitalism is that an increase in productivity does not automatically lead to growth. GDP growth depends on many factors that have nothing to do with productivity development.

Given a certain level of productivity, under the condition of available labor and production capacities aggregate demand determines GDP. Typically, and in most historical phases, there is a surplus of labor in capitalism, so that labor shortages or a lack of skilled workers can be an obstacle to growth, but this is rather rare. Usually there are also capacities available so that output changes with demand. Aggregate demand depends on investment demand, consumption demand, government demand and (net) export demand. As only investment demand creates capacities there must be a certain proportional development between investment demand and the other demand elements. In capitalism, this proportion is established through a chaotic process. Waves of investment increase capacity and often lead to overcapacity, but capacity bottlenecks are also conceivable.

Demand dynamic can lead to a GDP growth above productivity growth, but also below productivity growth and unemployment. Whether productivity effects of AI lead to unemployment, therefore, depends largely on whether its introduction takes place within the context of an expansive growth process or not. This is the basic idea of the Keynesian paradigm

which rejects the argument that supply side effects determine economic dynamic and development alone (Keynes 1936).

Within this framework the overall effects of AI can be explained (see Figure 2). AI increases productivity differently in different economic sectors and tasks within sectors. This influences the wage structure between sectors and within sectors. However, beyond the productivity effects of AI many other factors play a role, from strength of trade unions over minimum wages to tradition and ideas of justice. The distributional effect of AI depends on two factors. The first one is related to the question: how does AI affect the oligopolistic and monopsonistic power of companies—and thus their rent-seeking capacity—and how can governments control such concentrations of economic and political power? The second one: how do institutions such as minimum wages, collective bargaining systems, and government interventions influence both the adoption of AI and the resulting wage structure?

Typically, in low productivity sectors minimum wages tend to rise faster than sectoral productivity. In high productivity sectors, this is the opposite. Strong trade unions and wage bargaining system can protect the high wages of workers even if there are tendencies of de-skilling. Or strong trade unions can keep wage dispersion low in a sector. The macroeconomic effect of productivity increases through AI also depends on whether sectors with low productivity growth, such as care services or leisure activities, grow faster than the economy as a whole.

However, countries can differ greatly in how they accept sectoral wage differences and wage differences within a sector. Productivity effects plus institutional factors both influence the wage structure and thus cost development of sectors and relative prices. Unit labor costs typically increase in low-productivity sectors more rapidly than in high-productivity sectors. This influences relative prices. The changes of the structure of prices become even more complex because many industries use the outputs of other industries as inputs in their own production processes. This creates interconnected price effects throughout the economy.

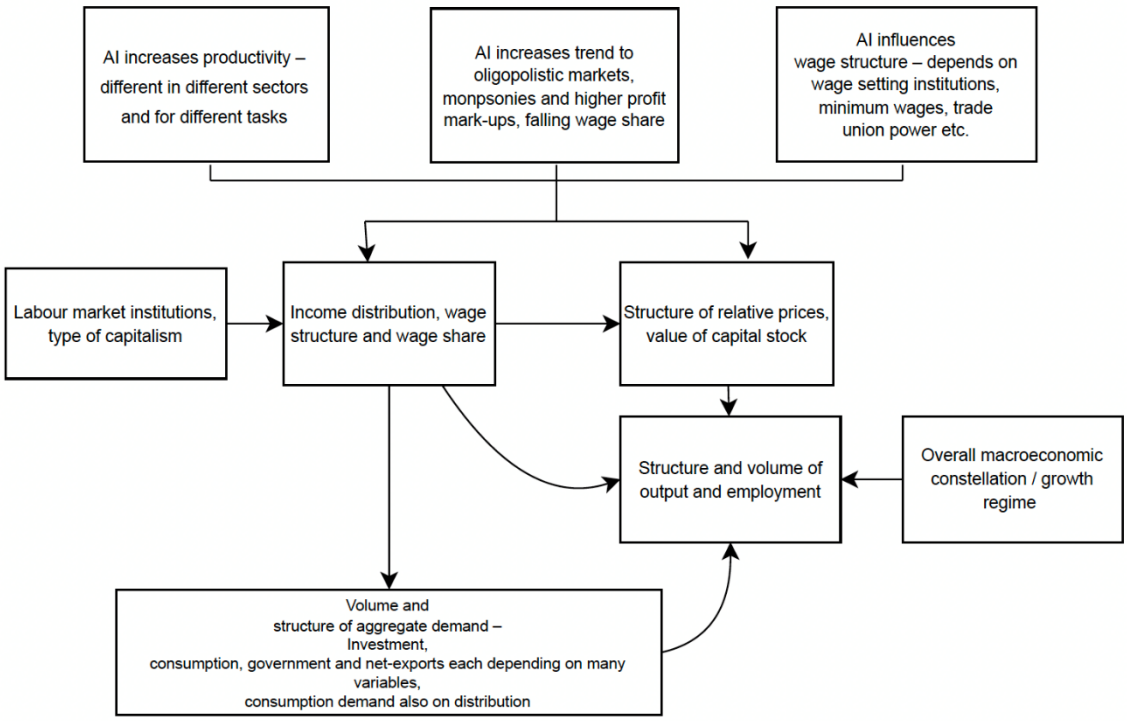
A comprehensive OECD study (2019) confirmed what labor economists have long observed: strong trade unions with coordinated wage bargaining reduce wage dispersion both overall and between sectors. Moreover, countries with such institutional arrangements exhibit greater labor market inclusion of disadvantaged groups and higher employment rates.[14]

AI has the tendency to increase the market power of a small number of firms. The logic of "superstar firms" and "the winner takes it all" leads to higher extra profits and to falling wage shares. Oligopolistic pricing strategies also influence relative prices. A falling wage share and potentially changing wage structures due to AI are leading to a further increase in income and wealth inequality. This, in turn, has clearly negative effects on aggregate demand, as it weakens aggregate consumption demand. The changing income distribution also influences the structure

[14] "Comparing collective bargaining systems across countries, co-ordinated systems … are linked with higher employment and lower unemployment (also for young people, women and low-skilled workers) than fully decentralised systems." And: "Collective bargaining also tends to affect wage dispersion, with greater dispersion in systems with no collective bargaining or where firms set wages independently." (OECD 2019: 106)

of demand - concentration at the top of the income pyramid increases demand for luxury villas and sailing boats, for example, and reduces demand for mid-range cars.

Figure 2: Effects of AI on productivity, wages, prices and employment



Source: own illustration

If the productivity effect of AI is not offset by GDP growth, assuming that working hours, labor force participation, migration, etc. remain unchanged, employment will decline and unemployment will rise. GDP growth, as mentioned, is first determined by aggregate demand. The latter depends on many factors beyond AI, including monetary policy and the expectations of banks and businesses, fiscal and tax policy, and surpluses or deficits in the trade with goods and services with rest of the world. To understand the effects of AI on employment, a country's growth regime must therefore be considered.

AI in a dynamic growth regime with high investment, high consumer demand based on relatively equal income distribution and stabilizing fiscal policy has completely different effects than the introduction of AI in a regime of crisis-ridden economic stagnation. AI will naturally play a role in the context of ecological transformation. Here, it is conceivable that an innovative regime with deliberately low growth could positively integrate the effects of AI through reduced working hours, further training and regulations on how AI is implemented.

4.4. Institutional Mediation of Productivity-Wage Linkages

We understand wage formation processes as fundamentally embedded in power relations, institutional structures, and strategic stakeholder interactions. This perspective does not deny

the relevance of productivity for wage determination but insists that the relationship between the two is institutionally mediated rather than technically determined. Productivity gains generating economic surpluses are subject to distributional contestation; as soon as rents or extra profits exist, a widespread and growing phenomenon in capitalism, the share accruing to labor versus capital depends upon the relative bargaining power of each party—power that is itself institutionally constituted (Baccaro/Pontusson 2016). The same argument holds for the structure of wages.

This theoretical restatement has direct implications for the productivity-wage nexus. In the absence of countervailing institutions, employers with market power capture productivity gains through oligopolistic or even monopolistic prices, wage restraint, work intensification, or the substitution of labor with capital. Under this conditions productivity improvements translate into wage increases only when workers possess sufficient institutional resources—collective organization, bargaining rights, codetermination mechanisms, or minimum wage floors—to claim a share of the resulting surplus. The strength of the productivity-wage linkage is therefore not a technical parameter but an institutional variable that differs systematically across political economies and historical periods (Heine/Herr 2024).

The German Case: Codetermination and the Social Mediation of Technological Change

Germany presents a paradigmatic case for examining the institutional mediation of technology's distributional effects in respect to functional income distribution as well inequality within employees. The German political economy is characterized by a long-standing corporatist tradition in which wage formation, working conditions, and technology investment decisions cannot be adequately analyzed without accounting for the countervailing power of trade unions, employers' associations, and codetermination institutions. These institutional arrangements do not merely constrain market outcomes but actively shape the trajectory of technological change and its distributional consequences.

Empirical research substantiates the wage-enhancing effects of German social dialogue institutions. Establishments covered by sectoral collective bargaining agreements and possessing works councils exhibit significantly higher wage levels, on average, than comparable establishments lacking these institutions, controlling for productivity and other firm characteristics (Ellguth/Kohaut 2020). This wage premium reflects the capacity of institutionalized worker voice to capture a share of firm-specific rents and to resist downward wage pressure that might otherwise result from employer monopsony power or competitive price and wage cutting.

More directly relevant to the present analysis, the distributional consequences of automation technology differ markedly between Germany and the United States—differences attributable to divergent institutional configurations. Whereas Acemoglu/Restrepo (2018a) document significant displacement effects from industrial robot adoption in American labor markets, Dauth et al. (2021) find no comparable increase in aggregate unemployment from robot adoption in Germany, as the slower new job creation (rather than job displacement) in manufacturing sector due to industrial robots was shown to be compensated by emerging jobs in the service sector. Instead, the German evidence indicates that automation was associated with increased worker reskilling and reallocation to non-routine tasks within firms, rather than

labor displacement. The interpretation advanced by Dauth et al. (2021) and elaborated by Krämer/Cazes (2022) attributes this differential outcome to the role of strong social dialogue institutions in mediating the employment effects of technological change—although the precise causal mechanisms remain to be fully identified empirically.

The institutional mechanisms through which German social dialogue institutions shape technology's distributional effects operate at multiple levels. At the sectoral level, trade unions engaged in collective bargaining can negotiate framework agreements that establish principles for technology adoption, including provisions for retraining, redeployment, and employment security. At the enterprise level, works councils possess statutory information and consultation rights regarding the introduction of new technologies under the Works Constitution Act (*Betriebsverfassungsgesetz*), enabling negotiated approaches to automation that balance efficiency gains with worker protection (Haipeter et al. 2024). At the supervisory board level, codetermination rights in larger companies embed labor interests in strategic decisions regarding technological investment and organizational restructuring. These institutional complementarities collectively constitute what Streeck (1991) termed beneficial constraints—arrangements that channel technological change toward productivity-enhancing and skill-upgrading trajectories while ensuring that resulting gains are shared with labor.

Emerging Research on Social Dialogue and AI Adoption

The literature examining the intersection of social dialogue institutions and AI adoption effects remains nascent but is developing along several complementary trajectories. One strand investigates the perceptions, strategies, and responses of social dialogue actors to AI integration, with particular attention to the mechanisms through which worker representation can promote human-centric AI deployment. Research in the German context has examined the areas of action available to worker representatives for shaping AI implementation (Köhne et al. 2023), the salience that social dialogue actors attribute to AI's effects on work processes (Pfeiffer 2025), the strategies pursued by trade unions in response to AI-driven transformation (Krzywdzinski et al. 2023), and the role of employee participation in AI integration at the enterprise level (Haipeter et al. 2024). Krämer and Cazes (2022) find that establishments with institutionalized worker voice exhibit attenuated negative effects of AI adoption on working conditions and job security relative to establishments lacking such representation. However, as the authors acknowledge, the direction of causality in this finding remains ambiguous: it is unclear whether worker voice causally mitigates AI's adverse effects or whether establishments with stronger worker representation differ systematically in ways that independently produce superior outcomes. Resolving this identification challenge represents a priority for future research.

This body of work proceeds from the premise that AI will generate significant effects on employment outcomes and that social dialogue institutions constitute crucial stakeholders capable of shaping the trajectory and distributional consequences of AI adoption.

Implications for Cross-National Analysis of AI and Wage Dynamics

The foregoing analysis suggests that the distributional consequences of AI adoption will be institutionally contingent, varying systematically across capitalist configurations. In coordinated market economies with robust collective bargaining institutions, strong worker representation, and stakeholder-oriented corporate governance, productivity gains from AI are

more likely to translate into broad-based wage growth. The institutional resources available to German workers—sectoral bargaining, works councils, and codetermination—provide mechanisms through which labor can negotiate for a share of AI-generated productivity improvements, contest unilateral managerial prerogatives in technology deployment, and influence the pace and direction of automation toward human-centric outcomes.

In liberal market economies characterized by decentralized wage determination, weakened collective organization, and shareholder-oriented corporate governance, AI-induced productivity gains are more likely to be captured by capital owners and high-skilled workers capable of leveraging individual bargaining power. The productivity-wage decoupling may intensify as AI amplifies the returns to scarce complementary skills while displacing routine cognitive tasks previously performed by middle-wage workers.

However, institutional configurations are neither static nor deterministic. The weakening of German labor market institutions and reforms since the 1990s—declining collective bargaining coverage, the expansion of the low-wage sector through the Hartz reforms, and the proliferation of opening clauses permitting firm-level derogations from sectoral agreements—has attenuated the productivity-wage linkage even within this archetypal coordinated market economy. Conversely, recent policy developments in the United States, including state-level minimum wage increases, renewed organizing efforts in previously non-unionized sectors, and legislative proposals to strengthen collective bargaining rights, suggest potential trajectories of institutional reconstruction. The distributional consequences of AI will ultimately depend not only on inherited institutional configurations but also on the political contestation that shapes institutional evolution in response to technological change.

Germany, as the paradigmatic case of institutionalized codetermination and sectoral collective bargaining, offers a crucial comparative reference point for analyzing AI's distributional effects. Yet significant research gaps remain. The interdependence between social dialogue institutions and AI adoption effects at enterprise and sectoral levels requires further empirical investigation. The causal mechanisms through which worker representation shapes technology's productivity and wage effects—whether through direct bargaining over the distribution of gains, influence over the trajectory of technological development, or the promotion of complementary investments in skills and organizational capabilities—remain to be fully specified and tested. Addressing these questions is essential for developing a comprehensive understanding of how institutional configurations mediate the relationship between AI-induced productivity growth and wage dynamics.

5. Conclusion

The analyses presented in this paper reveal that the macroeconomic effects of AI are far more nuanced and potentially problematic than the prevailing optimistic narratives suggest. Drawing on Acemoglu's macroeconomic model, enriched by insights from the labor capacity/expertise framework and augmented with our Keynesian perspective on functional income distribution and wage dispersion, we can draw several conclusions about AI's likely trajectory and its implications for economic inequality.

AI's effects cannot be understood through a purely technological lens. The structural characteristics of AI development (characterized by economies of scale, network effects, and data monopolies) shape its economic impact. These specifics drive market concentration, enabling superstar firms to capture disproportionate value while limiting the diffusion of productivity benefits across the broader economy.

The implications for wage structure are highly problematic, pointing toward increased dispersion and the creation of numerous economic loser groups despite (modest) overall productivity gains. AI's impact on wages operates through multiple, often contradictory channels that defy simplistic predictions about skill-biased technological change.

As shown by Autor/Thompson (2025) there is a peculiar dynamic: occupations experiencing the highest levels of automation may see wage declines as deskilling expands the labor supply pool. When AI reduces expertise requirements, previously specialized roles become accessible to broader segments of the workforce, intensifying competition and depressing wages even as productivity rises. Conversely, occupations where AI increases expertise requirements face constrained labor supply, driving up wages despite potentially lower automation levels. This creates a complex mosaic of winners and losers that cuts across traditional skill categories.

We showed that wage determination does not show a convincing link to marginal productivity considerations which in many cases are anyway difficult to measure. The Baumol effect ensures that wages in low-productivity sectors must partially track those in high-productivity sectors to maintain labor market equilibrium, while institutional factors – minimum wages, collective bargaining strength, social norms around fair compensation – shape wage structures. Countries with strong labor institutions and compressed wage distributions may experience fundamentally different AI impacts than those with weak unions and high inequality.

The analysis of functional income distribution – the division between labor and capital income – shows that the trend for the labor share is negative for most scenarios. This is mainly driven by the tendency to concentrate market power and enable high levels of rent extraction. The AI industry exemplifies winner-take-all dynamics, where network effects, data advantages, and massive fixed costs create insurmountable barriers to entry. As Acemoglu (2024) notes, this concentration of capital in the hands of few firms and shareholders exacerbates wealth inequality. Our Keynesian analysis extends this insight by demonstrating how market power translates directly into higher profit markups. We argue that this increasing market power of firms – oligopoly, monopoly and monopsony and oligopsony – explains falling wage shares and not the higher marginal productivity of capital. Further oligopolistic tendencies in markets must be countered with competition policy. From an industrial policy perspective, attempts should be made at European level to promote European companies, particularly in the internet sector.

In situations where trade unions are weak and co-determination rights are limited companies tend to pursue technology-centric AI strategies so that AI becomes a tool for labor displacement rather than augmentation, for cost minimization rather than capability enhancement. Often this strategy turns out to be short-sighted, as it neglects socio-technical insights for AI’s functionalities.

Given these dynamics, the paper's analysis points to a need for comprehensive policy intervention to steer AI development toward human-centered, labor-augmenting trajectories. The current laissez-faire approach, which treats AI as a neutral technology whose benefits will automatically diffuse through market mechanisms, ignores both the structural tendencies toward concentration and inequality inherent in AI systems and the institutional factors that shape technological deployment.

A human-centered AI policy framework must begin by rejecting the false dichotomy between technological progress and worker welfare. The choice is not whether to develop AI, but how to develop it – whose needs it serves, what problems it solves, and how its benefits are distributed. This requires active state involvement in shaping innovation trajectories, moving beyond market failure corrections toward mission-oriented innovation policy that prioritizes augmentation over automation.

Key policy priorities emerge from our analysis but need to be more worked out based on further research as well as enhanced macroeconomic model building. One key aspect seems to be a comprehensive institutional approach to managing AI's transformative effects on labor markets and income distribution. Rather than accepting market-driven outcomes that risk creating extreme inequality and widespread displacement, an active state and social partner intervention are necessary to ensure that AI becomes a tool for shared prosperity rather than concentrated wealth accumulation. Such a comprehensive approach could consist of elements of solidarity wage policies based on the principle that equal work should command equal pay as well as a strategic approach to wage floors or a general minimum wage as a tool to drive innovations and stabilize demand by preventing high income inequality. Technology dividend schemes could be part of such an approach, making sure that measurable productivity increases through AI would contribute to funds for distributing benefits to all workers. Furthermore, targeted task development by public investment and regulatory incentives could prioritize AI applications that create new roles for middle- and lower-skill workers. Human-centric design requirements could be a tool to focus on cognitive strengths and limitations, prioritizing interpretability and meaningful human control.

Germany's corporatist governance structure, with its intricate interplay between federal and Länder authorities, social partners, and works councils, creates both opportunities and constraints for AI policy that differ markedly from other countries. Research must examine how existing institutions like co-determination could be leveraged or must be reformed to govern AI implementation effectively. The role of works councils in negotiating AI adoption at firm level requires particular attention, as these bodies possess unique powers and responsibilities absent in Anglo-Saxon or even other continental European contexts.

The principle of technology impact assessment embedded in German policy culture provides foundations for systematic AI evaluation. However, research must determine how existing assessment frameworks apply to AI's unique characteristics, what new methodologies are needed for evaluating distributional impacts, and how to institutionalize ongoing monitoring as AI capabilities evolve (Albrecht/Kellermann 2022).

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