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GenAI, Growth, and the Multi-Sector Multipliers

Tero Kuusi
ETLA Economic Research, Finland
tero.kuusi@etla.fi

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Abstract

This paper analyzes the macroeconomic impact of Generative Artificial Intelligence (GenAI) on the Finnish economy, integrating recent literature and empirical evidence into a quantitative multi-sector general equilibrium model. The results indicate that, over a ten-year horizon, GenAI adoption increases annual economic growth by less than 0.5 percentage points in the baseline scenarios, with the potential for larger impacts—exceeding 1 percentage point—under scenarios involving greater automation and shifts in labor and ICT factor shares. The model's input-output structure reveals significant multiplier effects, as productivity gains in one sector propagate to others. The service sector emerges as a pivotal driver of adjustment, with its adaptability helping to offset slower growth in sectors less amenable to automation. The study acknowledges uncertainties regarding the broader impacts of artificial general intelligence, emphasizing the limitations of current forecasts, adaptation frictions, and the importance of anticipatory behavior in financial markets. Overall, the findings underscore the transformative potential of GenAI, contingent upon proactive policy measures to foster economic growth.

Tiivistelmä

GenAI, talouskasvu ja sektorien väliset kerroinvaikutukset

Tämä tutkimus arvioi generatiivisen tekoälyn (GenAI) makrotaloudellisia vaikutuksia Suomen kansantaloudessa syöttämällä viimeaikaisen tutkimuksen empiirisiä vaikutushavaintoja monen sektorin kasvumalliin. Perusskenaarioissa GenAI:n käyttöönotto lisää talouden vuosittaista kasvua alle 0,5 prosenttiyksikköä kymmenen vuoden aikajänteellä. Suuremmat, joskin epätodennäköisemmät, muutokset työtehtävien automatisaatiossa voivat johtaa yli yhden prosenttiyksikön vaikutuksiin. Mallin panos–tuotos-rakenne synnyttää huomattavia kerrannaisvaikutuksia, kun tuottavuuden kasvu yhdellä sektorilla välittyy muihin sektoreihin. Odotukset GenAI:n vaikutuksista ovat merkittäviä perinteisesti matalan tuottavuuden palvelusektorilla. Tutkimus korostaa mallintamisen epävarmuuksia ja ennusteiden rajoittuneisuutta muun muassa koskien yleistä tekoälyä ja sopeutumisen kitkoja. Se kiinnittää huomioita myös ennakointivaikutukseen rahoitusmarkkinoilla.

Ph.D. (Econ.) **Tero Kuusi** is a Research Director at ETLA Economic Research.

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Keywords: Artificial Intelligence, Productivity, Technology adoption

Asiasanat: Tekoäly, Tuottavuus, Teknologian käyttöönotto

JEL: C6, E1, O3, O4, O5

1. Introduction

Among economists, there is a significant debate regarding the extent to which Generative Artificial Intelligence (GenAI) can drive economic growth. Proponents argue that this technology has the potential to fundamentally transform economic activity by extensively substituting human labor, thereby accelerating growth. Conversely, more cautious perspectives highlight the limitations of technology in assuming essential human tasks, due to technological, organizational, or ethical constraints. Even within a relatively short 10-year forecast horizon, estimates vary substantially: some studies—such as Baily, Brynjolfsson, and Korinek (2023), McKinsey (2023), Goldman Sachs (2023), and Aghion and Bunel (2024)—project annual growth increases well above one percentage point; others, including Bergeaud (2024), Misch et al. (2025), and Filippucci et al. (2024A, 2025), forecast gains below one percentage point; while Acemoglu (2025) suggests an increase of less than 0.1 percentage points.

In this study, I employ a quantitative multi-sector macroeconomic model[1] to synthesize prior research on the productivity prospects of artificial intelligence (AI) and associated sectoral economic dynamics, producing forecasts for economic growth and structural transformation in Finland. The versatility of GenAI enables its application across a broad spectrum of economic sectors, thereby introducing the potential for profound structural changes. Consequently, analyzing the propagation of productivity shocks across sectors is critical. Productivity improvements in one sector can enhance the productive capacity of other sectors by reducing the cost of intermediate inputs. Furthermore, patterns of structural change are driven by significant imbalances in productivity growth across sectors, which may shift as a result of the broader adoption of GenAI technologies.

I compile sector-level GenAI productivity growth assessment by integrating data on improvements in worker performance, the proportion of tasks enhanced by AI, and the extent of GenAI adoption across firms. Impacts of GenAI are considered within a tractable reduced-form framework, that aim to encapsulate the essential (task-based) macroeconomic dynamics of AI. First, the transformation influences the nominal factor shares of labor within production functions. According to the Acemoglu and Restrepo (2018) task-based theoretical model, this share corresponds to the proportion of tasks automated relative to the total number of remaining and new tasks (Trammell and Korinek, 2023).[2] Second, both automation and the introduction of new tasks drive productivity gains by altering total

[1] Kuusi (2013) developed the model, and it has also been used by Ali-Yrkkö et al. (2017) and Jysmä et al. (2019).

[2] The displacement effect arises when GenAI technologies substitute for other production inputs in specific tasks, thereby reducing the value-added share of those displaced factors. The reinstatement effect counteracts displacement by generating new tasks in which alternative inputs—most notably labor—possess a comparative advantage. (Acemoglu and Restrepo, 2018)

factor productivity.[3] Finally, macroeconomic composition effects emerge from the reallocation of activity across sectors, which differ in their susceptibility to GenAI and in their fundamental roles within the macroeconomy.

A dynamic general equilibrium model with forward-looking investment decisions and the reallocation of labor and capital across sectors provides valuable insights into the propagation effects and allocative impacts of artificial AI. In this paper, I analyze the effects of GenAI under several scenarios. Sectoral total factor productivity (TFP) shocks are calibrated using recent literature on the productivity growth potential of different sectors. Following Filippucci et al. (2024B, 2025), I consider both the lower and upper bounds of the productivity impact distribution of the GenAI.[4] Additionally, I vary the extent to which these impacts affect labor alone or both labor and capital. In the benchmark scenario, the sectoral share of automated tasks—represented by the labor share in the production function—is held constant; however, I also examine the growth implications of changes in this share.[5]

This paper makes several contributions. The results indicate that, under scenarios emphasizing the use of existing TFP impact calculations, the effects on real GDP growth are at the lower end of the estimated range. Utilizing benchmark calibration of GenAI adaptation similar to those in Acemoglu (2025), I find an annual growth impact of approximately +0.14 percentage points for the period 2023–2033, compared to +0.07 percentage points in Acemoglu (2025). More extensive adaptation scenarios yield an effect of +0.44 percentage points per year, which remains moderately below the estimates reported by Filippucci et al. (2024B, 2025).

When baseline adaptation is accompanied by a 1 percentage point increase in the share of automated tasks—corresponding to a 1 percentage point rise in the ICT factor share and a decrease in the labor share—the resulting impact on GDP growth becomes substantially more pronounced. Under this scenario, annual GDP growth reaches 3.1%, compared to 1.8% in the benchmark case. Although there is currently limited empirical evidence supporting permanent changes in factor shares, these results clearly indicate that considerable variation in estimates of the growth impact of ICT may arise from differing assumptions regarding the extent of automation affecting the factor shares.

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[3] The productivity effect is observed when GenAI increases overall productivity by enabling a more flexible allocation of tasks among production factors. This efficiency gain contributes positively to labor demand in non-automated tasks.

[4] I use US productivity impact data at the ISIC 2-digit industry level for Finland in my calculations.

[5] The scenarios discussed mostly assume that GenAI introduces permanent level changes in the relevant economic indicators over the 10-year horizon. Following this transition, exogenous variables—primarily productivities—resume growth at their benchmark rates, but from levels reflecting the influence of AI where applicable. To analyze the impact of the longer term expectations, I also consider an alternative scenario in which the baseline shock persist for 20 years. I find that the impact of expectations is relatively small.

The general equilibrium analysis yields several interesting insights into the mechanisms of AI-induced structural transformation. First, the model facilitates the estimation of the capital multiplier—defined as the ratio of labor productivity growth to TFP growth—which appears to be moderately higher than the 1.5 multiplier utilized by Acemoglu (2025) and Filippucci et al. (2024B, 2025). Across scenarios, the capital multiplier ranges from 1.75 to 1.94. This elevated multiplier contributes to a relatively greater estimated effect of GenAI on productivity and economic growth compared to the findings of Acemoglu (2025).

Furthermore, the model's input-output structure amplifies the impact of GenAI on productivity and economic growth by generating indirect growth effects.[6] Building upon the growth decomposition framework proposed by Baqaee and Farhi (2020), I identify an input–output multiplier that emerges as productivity gains in one sector enhance the productive capacity of other sectors by reducing the input prices they encounter. This effect is particularly significant in the context of GenAI, as the technology's influence extends beyond direct productivity enhancements to encompass complex shocks transmitted through the input–output framework as production processes are reorganized across all sectors. I illustrate these dynamics using a model with sectoral Cobb–Douglas production functions for intermediate production, which demonstrate the constancy of factor shares even amid substantial changes in the relative prices of intermediates, a phenomenon previously observed during the ICT revolution.

Finally, the findings indicate that the service sector has significant potential for AI-driven productivity growth, with the capacity to generate substantial indirect effects across the broader economy. Notably, these advances may help counteract the persistent unbalanced productivity trends observed in recent decades. Simulation results of structural transformation patterns suggest that GenAI could mitigate the so-called "Baumol's cost disease" in services—that is, the phenomenon in which resources are increasingly allocated to a stagnating service sector, thereby restraining aggregate economic growth. By enabling greater productivity enhancements in services, GenAI may support a more balanced sectoral development and contribute to higher overall economic growth.

This paper relates to a large previous literature on the macroeconomics of the task-structure of work and structural change. Earlier research has demonstrated that the automation of existing tasks is systematically accompanied by the emergence of new, higher-productivity activities, which are initially performed by human workers (Goldin and Katz, 2009; Acemoglu and Autor, 2012). In considering GenAI

[6] Acemoglu (2025) builds on Hulten's theorem suggesting that aggregate productivity gains are approximated by the value-added share weighted average of sector-level gains. However, this approximation is only first-order exact and can be significantly biased if large shocks or nonlinearities—such as non-unitary elasticities, network effects, or reallocation barriers—are present (OECD, 2024B).

within a reduced-form, task-based theoretical framework, this paper is closest to Filippucci et al. (2024B), while alternative approaches have been provided by Acemoglu and Restrepo (2018), Acemoglu and Autor (2019), Acemoglu (2025), and Trammell and Korinek (2023) among others.

Following methods from Acemoglu (2025), my analysis is grounded in recent micro-level findings that assess how AI boosts task performance efficiency. However, I do not take a firm stance on whether AI mainly boosts labor or capital productivity, as both are plausible. Instead, I focus on overall impacts on total-factor productivity and run alternative scenarios with changing labor shares and employment. This analysis does not address labor market imperfections, as it only considers reduced-form shocks. Broader employment and distributional outcomes in a unified context would require separate modeling approaches, such as those in Acemoglu and Restrepo (2018).

Instead, this paper connects more closely to the macroeconomic literature that models structural transformation across sectors experiencing unbalanced productivity growth. Productivity differentials serve as a potential source of structural change (see, e.g., Baumol and Bowen, 1966; Baumol, 1967; Kaldor, 1966; Fuchs, 1968). Sectors with lower productivity growth must compete for the same inputs, particularly labor, with faster-growing sectors, resulting in an increase in the relative prices of their outputs. As final consumption—especially of services—is typically price inelastic, the nominal share of these low-productivity products tends to rise over time in consumption.

More recently, Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008) examine how differences in technological progress, factor shares, and capital deepening contribute to structural change. Further, studies such as Oulton (2001), Martinez et al. (2010), Foerster et al. (2022), Ngai and Samaniego (2009), and vom Lehn and Winberry (2022) highlight the role of investment and production network interactions in amplifying sector-specific trend shocks. Additionally, the analyses by Baqaee and Farhi (2020) and Liu (2019) focus on sectoral distortions, emphasizing the complex interplay of factors in shaping macroeconomic outcomes.

Recent literature provides quantitative estimates of AI-driven performance improvements at the micro-level, often employing both human and GenAI evaluators to measure task efficiency. These works introduce key concepts like increase in performance in affected tasks and GenAI exposure (Briggs and Kodnani 2023; Felten et al., 2021; Eloundou et al., 2024; Kauhanen and Rouvinen, 2025; Teutloff et al., 2025) and develop measures for different GenAI capabilities. Other literature such as Filippucci et al. (2024A), Kinder et al. (2024), Boston Consulting Group (2024), and Ernst & Young (2024) have focus on sectoral analysis, underscoring both the promise of substantial productivity and efficiency gains and the caveats of current limitations, risks, and the incomplete readiness for widespread adoption.

While this paper focuses on the potential impacts of GenAI shocks within the context of the aforementioned quantitative literature, utilizing a multi-sector model, it is important to recognize that this approach adopts a relatively narrow perspective on the influence of artificial intelligence. The ongoing debate regarding the potential of artificial general intelligence (AGI) to drive endogenous economic growth—contrasted with more cautious growth projections such as those of Acemoglu (2025)—highlights the inherent challenges in forecasting the true macroeconomic implications of AGI. These uncertainties stem from varying assumptions about the capabilities, adoption rates, and integration of GenAI technologies (see Economist, 2025; Trammell and Korinek, 2023).[7]

2. Collecting stylized facts

2.1. Productivity effects

To assess the aggregate gains from GenAI, recent studies frequently begin with micro-level performance data from workers and firms utilizing GenAI technologies. This line of research typically employs both human evaluators and AI-based tools, such as OpenAI's GPT models, to assess the extent to which task completion times can be reduced through GenAI augmentation. The principal metric in these assessments is the share of tasks for which the completion time decreases significantly when leveraging GenAI large language models (LLMs) under baseline exposure conditions. Following Briggs and Kodnani (2023), Acemoglu (2025), and Filippucci et al. (2024A, 2024B), a baseline effect corresponding to a 30% increase in performance over ten years for tasks amenable to GenAI intervention appears to be a reasonable estimate. In line with Acemoglu (2025), I interpret these gains as primarily accruing to labor, while also incorporating the perspective of Filippucci et al. (2024B), who consider the improvements as reflecting efficiencies for both labor and capital. In practice, this implies that performance gains are weighted according to the nominal share of each factor in the production process.

A potential limitation of these studies is their reliance on experimental settings and early adopter firms, which may not accurately represent broader, real-world applications. The observed effects of GenAI could be attenuated in more heterogeneous environments, and it is essential to account for the costs associated with GenAI implementation to ascertain net productivity gains. Conversely, longer-term advantages may emerge from the creation of new economic activities that more fully integrate GenAI, as well as from innovative firms adopting data-centric business models. It is plausible that future GenAI architectures will address current limitations, thereby enhancing capabilities and potentially

[7] While, this analysis concentrates on the effects of generative AI, whereas Filippucci et al. (2024B) further explores the integration of GenAI and robotics in future automation scenarios.

generating more substantial and widespread productivity improvements. Nevertheless, it remains premature to predict the full extent of these evolving real-world applications.

AI exposure refers to the degree to which artificial intelligence can affect a particular job or sector (Felten et al., 2021; Eloundou et al., 2024). This exposure is contingent on the composition of human-performed tasks and the extent to which GenAI can perform or assist with these activities. High levels of exposure indicate that a significant portion of sectoral tasks are amenable to GenAI augmentation. This concept facilitates the extrapolation of task-level performance gains to broader sectoral or macroeconomic productivity enhancements. Building on the analyses of Acemoglu (2025), Eloundou et al. (2024), and Filippucci et al. (2024B, 2025), the present study evaluates tasks that can be executed more efficiently with GenAI assistance, using assessments conducted by both human evaluators and AI-based tools.

Two measures from Filippucci et al. (2024B) are employed in this analysis: (1) the proportion of tasks for which completion time is substantially reduced through the application of GenAI large language models (baseline exposure); and (2) alternative metric encompassing tasks where further improvements could be realized if supplementary software were developed to enhance current models (expanded capabilities). Incorporation of this more optimistic, forward-looking scenario is justified by the significant advances already documented in certain capabilities of large language models, as noted by Eloundou et al. (2024). Furthermore, the baseline exposure scenario assumes 23%, while the extended capabilities scenario assumes 40% of firms actually adopt the exposed AI over the time period.

Figure 1 presents calculations of the potential productivity growth attributable to GenAI adaptation across the three major sectors under consideration. These calculations are based on Filippucci et al. (2024B) and are weighted at the sub-industry level by the average Finnish output value shares at the 2-digit industry level post-1995, consistent with the calibration period for the sectors.[8] The estimated productivity effects are further adjusted according to the proportion of input factors (labor and capital) of all nominal input costs identified as being affected by GenAI integration.

Utilizing the United States as a reference for these calculations is well justified. Kauhanen et al. (2023) replicated the analysis performed by Eloundou et al. (2023) in the Finnish context and found that exposure to GenAI in Finland closely mirrors that of the US. Specifically, Figures 4 and 5 of Kauhanen et al. (2023) demonstrate that both countries display remarkably similar patterns of exposure across

[8] For each of the three sectors, the TFP gain is $productivity\ gain\ x\ affected\ factor\ share$ at the sector level, where $productivity\ gain$ consists of aggregation of subsectors i: $productivity\ gain = \sum_i Microlevel\ gains_i\ x\ Exposure_i\ x\ Adaptation\ rate_i x\ output\ weight_i$

sectors. This empirical alignment supports the validity of applying US-based estimates to Finland in this analysis.

These findings underscore the sectoral dimension, and especially the considerable potential of GenAI in the service sector. Anecdotal evidence and sectoral analyses are provided by Filippucci et al. (2024A), Kinder et al. (2024), Boston Consulting Group (2024), and Ernst & Young (2024), among others. Filippucci et al. (2024A) identify the most exposed sectors as knowledge-intensive services reliant on cognitive tasks, including Finance, ICT services (notably telecommunications), Publishing and Media, and Professional services.

However, the potential impact of GenAI does not stop there. As noted by Kinder et al. (2024), office and administrative support occupations present substantial potential due to their high exposure, automation feasibility, and large workforce. Technological advancements have already led to workforce reductions in roles such as bookkeepers, legal secretaries, HR assistants, bank tellers, and payroll clerks, and GenAI is likely to accelerate this transition.

Boston Consulting Group (2024) projects notable transformations within the governmental sector. GenAI can enhance the quality and efficiency of decision-making and improve public policies and program implementation. Specifically, GenAI optimizes policy design, service delivery, management, support functions, and regulatory compliance. Additionally, GenAI can streamline support functions and shared services, reducing monitoring costs, mitigating risks, and simplifying administrative processes to benefit citizens, businesses, and other stakeholders. Central agencies can leverage GenAI to develop, implement, and standardize government-wide strategies.

Ernst & Young (2024) anticipate substantial productivity gains in the healthcare sector over the coming decade. For example, GenAI can improve diagnostic accuracy and the quality of specialist-patient interactions, enhance clinical workflows via improved patient risk stratification, and support more effective hospital management. In the education sector, as reported by Kinder et al. (2024), teachers may benefit from GenAI through accelerated grading, streamlined planning, test administration, record maintenance, and report preparation.

Having said that, current conditions are not yet sufficient for the widespread adoption of GenAI and the full realization of its benefits. Multiple risks must be addressed, including concerns related to accuracy, security, privacy, bias, and intellectual property rights (Boston Consulting Group, 2024). Consequently, the focus remains on the growth potential of technology while acknowledging the prerequisites for its responsible and effective deployment.

Finally, it is important to note that this analysis does not encompass the broader trajectory of automation, since the tasks influenced by GenAI are distinct from those automated through earlier digital technologies such as robotics, advanced manufacturing equipment, or traditional software systems. Eloundou et al. (2024) provide evidence of a negative statistical association between GenAI exposure and exposure to robots and manual routine tasks, as previously discussed by Acemoglu (2025). This suggests that, at present, it is feasible to delineate GenAI from prior waves of automation. Filippucci et al. (2024) highlight the potential for combined applications of GenAI and robotics, which may yield further advancements in task automation.

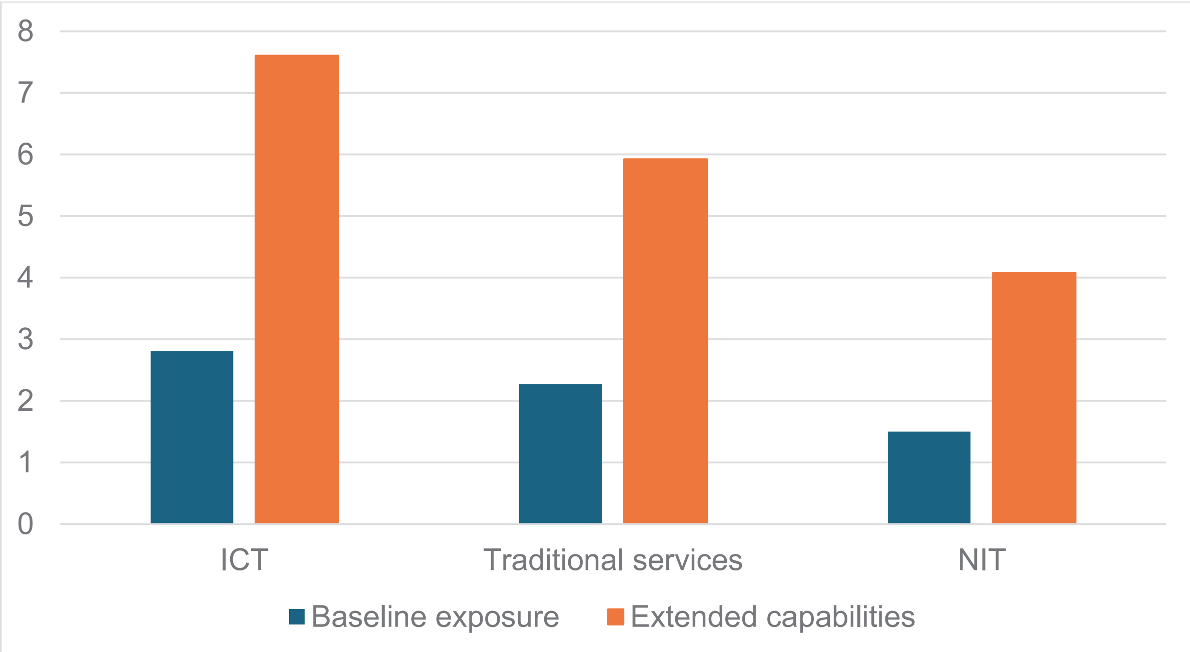

Figure 1. Productivity gains (%) are based on Filippucci et al. (2024B), calculated as Microlevel gains x Exposure x Adaptation rate over 10 years for 2-digit industries. These gains are aggregated into Finland's three main sectors using post-1995 output weights and further multiplied by the sector factor share of the affected input to construct the scenario-specific shocks. Following Elondou et al. (2024), the baseline reflects tasks where GenAI (LLMs) significantly reduces completion time; expanded capabilities also include tasks with potential gains if additional software is built on LLMs. The baseline assumes 23% of firms adopt AI, while extended capabilities assume 40%. ICT = ICT manufacturing and services; traditional services = other private/public services; NIT = remaining industries, excluding primary production. Source: Filippucci et al. (2024B), Statistics Finland and own calculations.

2.2. Within-sector factor shares and the sectoral composition of labor

The impact of GenAI on productivity and employment remains uncertain, as the pace and nature of these changes are not yet determined. GenAI has the potential to enhance employee productivity through improved work processes, debugging, error-checking, and facilitating skill acquisition. Conversely, GenAI may automate routine tasks and at least some code generation, which could result in job displacement. It is important to distinguish situations where GenAI complements human labor from those where it substitutes for it, and to identify individuals who may be more susceptible to displacement compared to those likely to adapt.

Figure 2 examines the dynamics of labor shares, defined as the proportion of total labor compensation relative to gross value added. As previously outlined, the displacement effect arises when GenAI technologies substitute for other inputs—particularly labor—in certain tasks, resulting in a reduced share of labor in value added. Conversely, the reinstatement effect offsets displacement by generating new tasks in which non-AI inputs maintain a comparative advantage.

The Figure shows that over time the shares have remained remarkably constant in Finland. At face value, the evidence of relative constancy of sectoral factor shares indicates that the displacement and reinstatement effects cancel out in the production functions, and therefore a reasonable calibration is to keep the factor shares constant.

It is important to note, however, that factors driving task composition may obscure the effects of AI. For instance, price substitution between factors can reduce the nominal share of inputs with declining prices, primarily ICT, while automation may simultaneously increase their shares. In this analysis, I nevertheless approximate the production functions using Cobb-Douglas specifications, wherein changes in the relative prices of inputs do not alter their nominal factor shares. Correspondingly, prior findings regarding the introduction period of the Internet indicate a broader stability of factor shares beyond only the ICT sector during 1995–2005, supporting the appropriateness of Cobb-Douglas as a production function specification, as shown in Figure 8.

Compared to the US, the share of manufacturing value added in Finland has remained relatively stable. Since 1995, the labor share within U.S. manufacturing has declined to levels comparable to those observed in Finland. This pattern may be attributed to significant restructuring within Finland's manufacturing sector following the economic downturn of the 1990s. Notable fluctuations in the ICT sector are likely linked to the evolving role of Nokia; during the early 2000s, Nokia's strong profitability translated into substantial capital gains and a high capital share in production. Following the collapse of its mobile phone business, the sector's labor share reverted to levels similar to those found in the broader manufacturing industry.

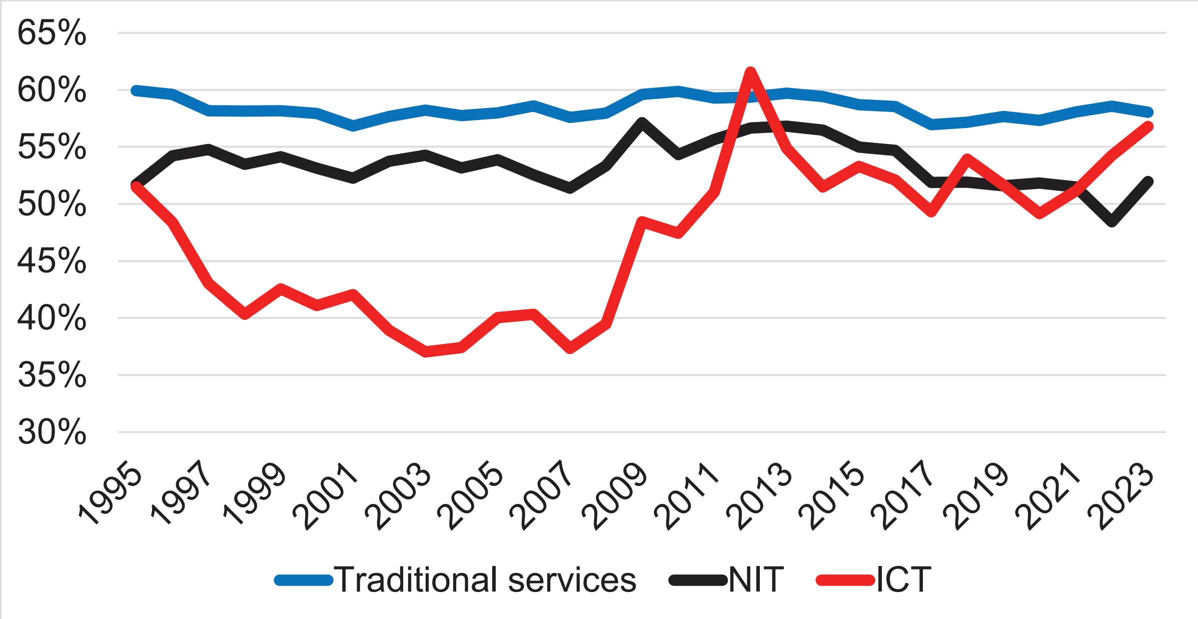

Figure 2. The dynamics of sectoral labor factor shares 1995–2023, as defined by the total labor compensation as relative to gross value added. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Statistics Finland and own calculations.

Moreover, a critical aspect of assessing the impact of GenAI lies in the evolving composition of tasks. At the sectoral level, this phenomenon is most evident in the allocation of resources across different sectors. As illustrated in Figure 3 , from 1995 to 2023, sectoral changes in the composition of aggregate labor input have been substantial, surpassing the variations observed within individual sector labor shares. Notably, the most significant development is the increased share of services within the overall employment.

It is important to recognize that the composition effect reflects the reallocation of value added across sectors, influenced by a complex interplay of factors beyond technological advancement alone. These include structural transformations, shifts in consumer preferences, differences in resource intensity, varying rates of sectoral productivity growth, and the effects of international trade on final goods. In analyzing the role of GenAI, it is essential to account for these additional dynamics and model the interactions among them.

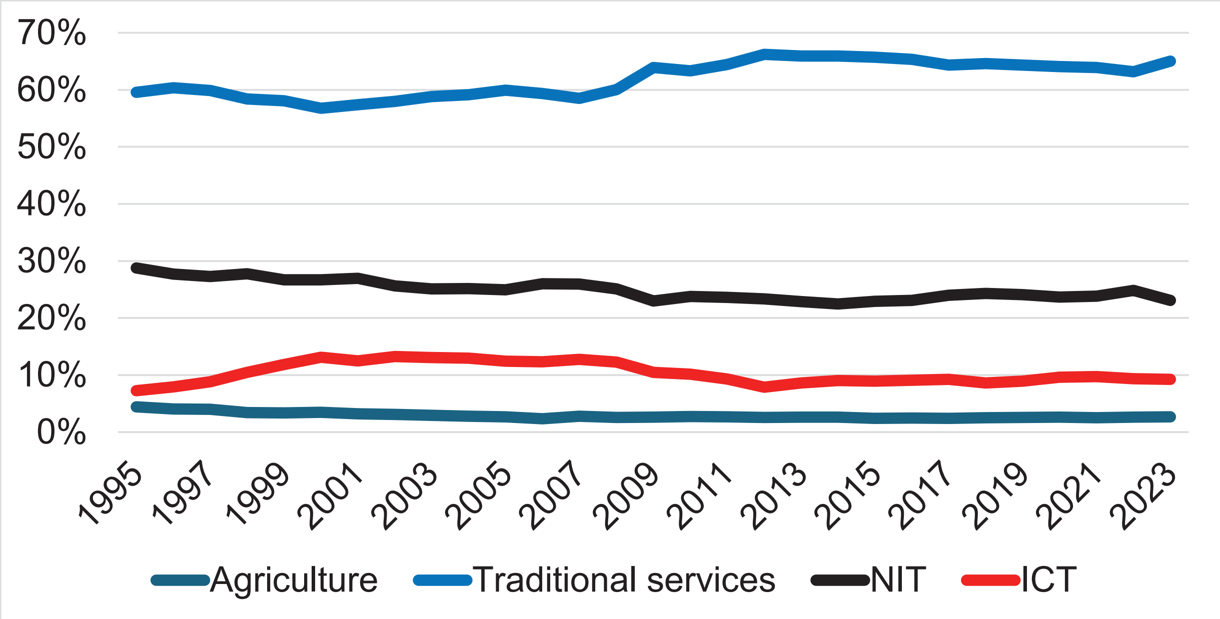

Figure 3. Composition of total hours worked for different sectors 1995-2023. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Statistics Finland and own calculations.

3. Macroeconomic model

3.1. Outline of the model

The outline of the model is presented Figure 4. The production side of the economy closely resembles Ngai and Samaniego's (2009) version of the investment-specific technological change model. However, the representative household is assumed to consume sector-specific goods according to a CES aggregator with intratemporal elasticity strictly lower than 1. This relates the model to Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008). Furthermore, the economy considered is open for international trade (Uy et al., 2013).

The model economy consists of sectors producing ICT (ICT), non-ICT traditional products (NIT), and traditional services (S).[9] Each sector has a unique Cobb-Douglas production function with industry-specific factor intensity shares and total-factor productivity terms, which are calibrated using the National Accounts. The sectors produce sector-specific intermediate and capital goods, the difference being that intermediate goods have to be used during the period of its production. There are two capital stocks based on ICT and traditional goods.

[9] ICT = ICT-related manufacturing and services; S = other private and public services; NIT = other industries, excluding primary production.

The representative household is assumed to consume sector-specific goods according to a CES aggregator. The model provides an estimate of the welfare impact of GenAI in a frictionless economy, while I also test the sensitivity of results to simultaneous declines in employment. The domestically manufactured or imported products are always allocated to their optimal use as production factors, consumption goods, or exports. A representative household owns the firms and decides whether to consume or save firm income. The labor input and population are assumed to grow exogenously.

The economy engages in international trade. The patterns of trade reflect the comparative advantage of countries in different sectors. Especially the changes in the competitiveness of trade in high-tech goods and services in exports is modelled closely to analyze the role of the Finnish ICT sector. Tradable sectors consist of heterogeneous firms and sector-specific goods are composites of firm-level goods produced either in a domestic country or abroad. Distribution of firm-level productivities is modelled in a manner that makes it easy to estimate unit costs of foreign countries and trade barriers. The considered economy is a small open economy: The size of the foreign market and unit costs abroad are taken to be exogenous, but not constant. Modeling international trade is based on Uy et al. (2013), who considers a version of Ngai and Pissarides (2007) in an open economy.

The baseline growth path is calibrated to match the key structural changes in the Finnish economy. The total-factor productivity growth rates are close to their historical averages, the population and employment growth is matched with the medium-term available forecasts, and the external market is calibrated to match the structure of the exports and the share of imported products in the domestic market. The model is matched with the sectoral shifts of the consumption and value added, as well as movement of labor across sectors.

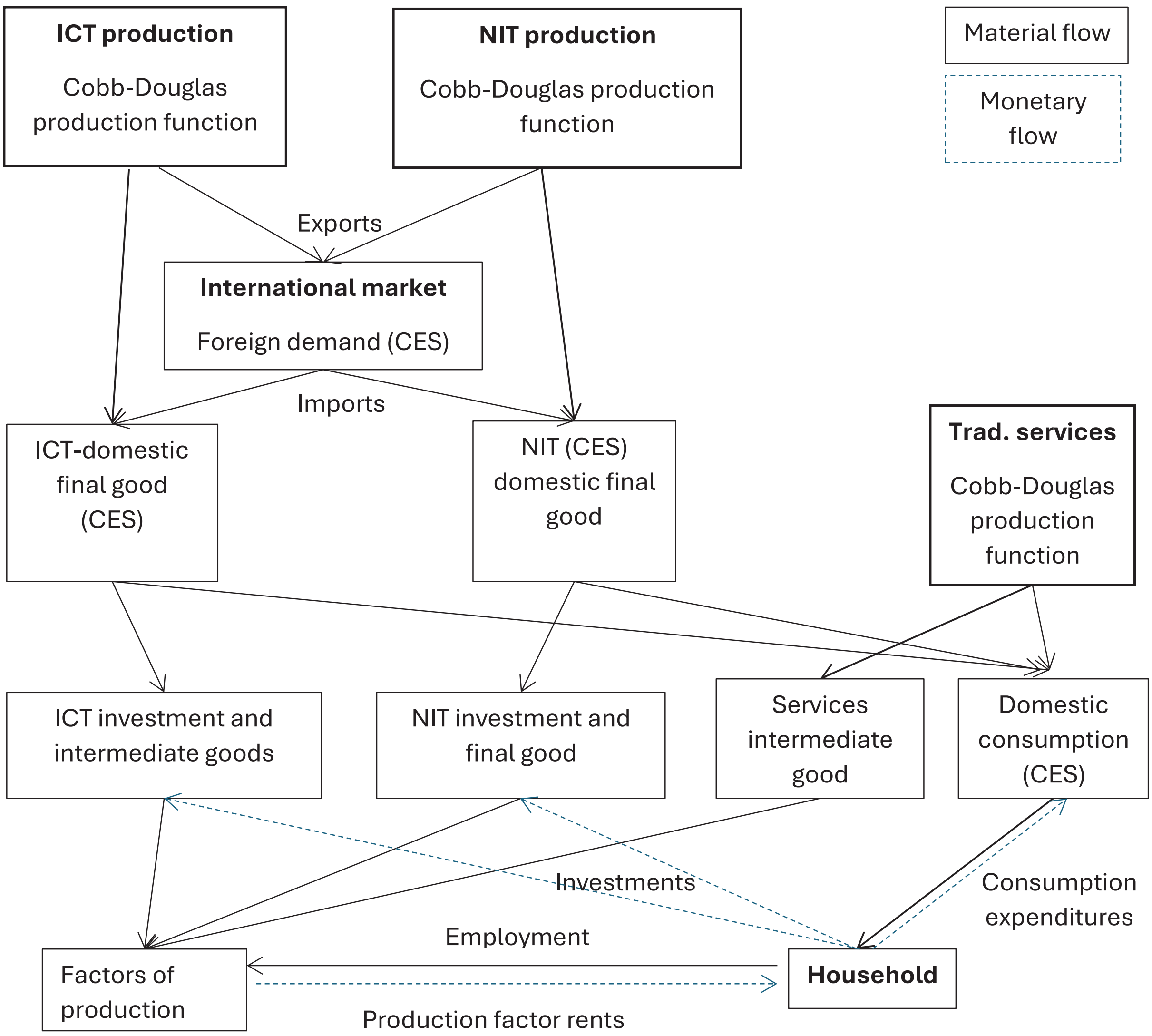

Figure 4. Outline of the multi-sector model.

3.2. Firms

In the open sectors (ICT and NIT), the final domestic good consists of both domestic and imported goods and services. The closed service sector (S) supplies domestic final goods directly. The open sectors are responsible for producing investment, intermediate, and consumption goods. Investment goods contribute to the total productive capital stocks in the economy, which consist of NIT and ICT capital stocks. The service sector (S) provides intermediate and consumption goods for domestic use.

Each sector uses six inputs (m_k)—ICT capital, NIT capital, labor, and S-, ICT-, and NIT-intermediate goods—to produce output via a Cobb-Douglas production function. In intermediate production, this function ensures factor shares stay constant even when relative prices of intermediates change significantly. Figure 8 demonstrate the constancy of factor shares even amid substantial changes in the relative prices of intermediates during the emergence of Internet 1995–2005.[10]

The total-factor productivity of a firm i is denoted as MFP_i. The three sectors are competitive and the firms maximize their profits. In particular, the firms maximize the value of their production by adjusting the amounts of inputs given the prices of their final good p_i and the sector-specific (denote sector by q) rental prices of inputs w_{kq}:

$$\max\left[p_i * F_i - \sum_{k=1}^{6} w_{kq} * m_{ki}\right] = \max\left[p_i * MFP_i * \prod_{k=1}^{6} m_{ki}^{\alpha_{kq}} - \sum_{k=1}^{6} w_{kq} * m_{ki}\right], \tag{1}$$

where α_{kq} is the nominal factor share k in sector q. The total-factor productivities do not differ across firms in the closed sector, but in the open sectors they vary.

It is useful to describe the result of the optimization problem in terms of the unit cost function that defines the optimal unit cost of the firm i in sector q $\mathrm{UC_{iq}}$:

$$\mathrm{UC_{iq}} = \frac{1}{A_i}\prod_{k=1}^{6} w_{kq}^{\alpha_{kq}}, \tag{2}$$

where $A_i = MFP_i \prod_{k=1}^{6} \alpha_{kq}^{\alpha_{kq}}$ is the total-factor productivity with additional factor-weight terms that arises from the optimization. In the model, the firms do not make excess profits, and thus the unit costs equal the unit price of the goods and services, $\mathrm{UC_i} = p_i$. The price of the intermediate goods is the same as the domestic final goods (combination of the domestic good and the intermediate good).

The closed, service sector produces homogenenous goods with identical production functions at the firm level. The competitiveness assumption implies that $\mathrm{UC_S} = p_S$, and the optimality of the production:

$$\mathrm{UC_S} = \frac{1}{A_S}\prod_{k=1}^{6} w_{kS}^{\alpha_S}. \tag{3}$$

[10] The assumption is not a priori inconsistent with the CES aggregate production function (see, e.g. Jalava et al. 2006) because the demand functions in the model have the CES form, and the demand effect is similar to the effect that the use of the aggregate CES production function would generate.

In order to model international trade, I use assumptions concerning the sectoral productivity that are similar to Uy et al. (2013). The tradable sectors sell differentiated goods. Let us denote the sectors by q = [NIT,ICT], and the individual firms receive an index value $i_q \in [0,1]$. Within sectors, the firms are otherwise identical, but the total-factor productivities may differ. The firms may operate domestically or in other countries, and their products are combined symmetrically to domestic final goods:

$$F_q = \left(\int_0^1 F_{i_q}^{\eta_q}\, dz\right)^{\frac{1}{\eta_q}} \tag{4}$$

where $\eta_q < 1$ is the elasticity of substitution between the goods. Each individual good i_q is purchased from a country that provides it with the cheapest price, and it is imported to the purchasing country and used as a part of the domestic final good. The transportation involves a cost.

When the distribution of the total-factor productivities is assumed to exhibit the Frechet-distribution—a flexible functional form—, and furthermore, it is assumed that the purchases are always made from the location that has the lowest price when the price of the shipping is included, the model yields simple functional expressions for the key trade equations. Eaton and Kortum (2002) show that the price of product q in country c is a function on the transportation costs and unit prices:

$$p_{qi} = \gamma \Phi_{qc}^{-\frac{1}{\theta_q}}, \tag{5}$$

where $\Phi_{\mathrm{qc}} = \sum_{j=1}^{N} TC_{qcj}^{-\theta_q}\, UC_{qk}^{-\theta_q}$, TC_{qcj} is product q transportation cost from country j to country c, and θ_q is a parameter that quantifies the importance of the relative advantage.

Similarly, the structure of the trade can be expressed as a function of the unit costs. Under the Frechet distribution, the shares of the different countries c in the total demand in sector q in country j are

$$\pi_{qcj} = \frac{TC_{qcj}^{-\theta_q} UC_{qj}^{-\theta_q}}{\Phi_{\mathrm{qi}}} \tag{6}$$

3.3. Household

A representative household earns labor income and receives rental income from capital. The household can save or consume its income. The household saves by investing in the sectoral investment goods (ICT or NIT) that accumulate into the productive capital stocks of the economy.[11] The household maximizes the value of its consumption basket over time. The aggregate utility function exhibits a standard CRRA form, and the household weighs each of its member (N_t) with an equal weight

$$V_s = \sum_{t=s}^{\infty} \beta^{t-s} N_t \frac{U(C_t)^{1-\rho} - 1}{1-\rho} - \xi_{St} L_{St} - \xi_{ITt} L_{ITt} - \xi_{NITt} L_{NITt} \tag{7}$$

so that the wage and the capital income, as well as the lump-sum capital tax returns equals the cost of investment, consumption, and the capital tax.

$$\begin{aligned} &\sum_{i}^{S,ICT,NIT} w_t^{L_i} L_i + \sum_{q}^{S,ICT,NIT} \sum_{k}^{ICT,NIT} w_{K_k qt} K_{qkt} + T_t \\ &= \sum_{q}^{S,ICT,NIT} p_{q,t} C_{q,t} + \sum_{q}^{ICT,NIT} p_{q,t} I_{i,t} + \sum_{q}^{S,ICT,NIT} \sum_{k}^{ICT,NIT} \tau_{K_k qt} w_{K_k qt} K_{qkt}, \end{aligned} \tag{8}$$

where $w_{K_k qt}$ denotes the capital k rental cost in sector q. Because the tax returns match with the collected taxes that for the sake of simplicity also involves the depreciation of the capital, the tax return, T_t, is

$$T_t = \sum_{q}^{S,ICT,NIT} \sum_{k}^{ICT,NIT} \tau_{K_k qt} w_{K_q kt} K_{qkt} \, , \tag{9}$$

where $\tau_{K_k qt}$ is the tax rate of capital k in sector q. The individual decision makers take the tax rate as given, and since the there is a lump-sum tax return, the tax has a distortive effect in the economy.

The labor input $L_t = L_S + L_{IT} + L_{NIT}$ is assumed to be exogenous and dictated by a population projection. The labor input is calibrated to match the potential hours of the economy. There are permanent wage differentials across the sectors. In the model, they are caused by differentiated disutility of work across sectors.

[11] While the current version of the model omits investments in technology, in the previous work, Ali-Yrkkö et al. (2016), I have extended the model to include investments in R&D by using a variant of Acemoglu and Guerrieri (2006) endogenous growth model. While it is shown that the model can replicate the R&D behavior, it is notable that the model outcomes are similar.

For a single member of the household, the utility function is of the CES form:

$$U(C_t) = \left(\omega_S \left(\frac{C_{St}}{N_t}\right)^{\frac{\epsilon-1}{\epsilon}} + \omega_{IT} \left(\frac{C_{ITt}}{N_t}\right)^{\frac{\epsilon-1}{\epsilon}} + \omega_{NIT} \left(\frac{C_{NITt}}{N_t}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \tag{10}$$

The utility maximizing consumption basket fulfills the following optimality conditions (subindices i and j refer to all sectors, k refers to the capital producing sectors, and $w_{K_k it}$ refers to the rental cost of capital produced in sector k in sector i):

$$\frac{\frac{\partial}{\partial C_{it}} V(C_{it})}{\frac{\partial}{\partial C_{jt}} V(C_{it})} = \frac{p_{jt}}{p_{it}} \tag{11}$$

$$\frac{\frac{\partial}{\partial L_{it}} V(C_{it})}{\frac{\partial}{\partial L_{jt}} V(C_{it})} = \frac{\xi_i}{\xi_j} = \frac{w_{it}}{w_{jt}} \tag{12}$$

$$\frac{\frac{\partial}{\partial C_{kt}} V(C_t)}{\frac{\partial}{\partial C_{kt+1}} V(C_{t+1})} = \beta \left(\frac{(1-\tau_{K_k qt}) w_{K_k it}}{p_{kt+1}} + (1-\delta_k)\right). \tag{13}$$

The last equation states that the differences in the equilibrium rental costs across sectors are defined by capital taxation:

$$\frac{w_{K_k jt}}{w_{K_k it}} = \frac{(1-\tau_{K_k it})}{(1-\tau_{K_k jt})}. \tag{14}$$

3.4. Product markets and the general equilibrium

In the general equilibrium, the price levels match demand and supply in each sector and market. A useful way to formalize the equilibrium is to use Shephard's lemma. It states that the marginal unit cost with respect to price changes of a production factor multiplied by the total demand of the product yields the total demand of the production factor (Roe et al. 2010). Thus, it holds for each factor of production (labor, capitals, and intermediate goods of each sector) that:

$$\sum_{q}^{S,IT,NIT} \frac{\partial}{\partial w_{kqt}} [UC_{qt}] F_{qt} = m_{kt} \tag{15}$$

Furthermore, the volume of production in the closed service sector must match the amount of consumption and intermediate goods of the sector. Finally, the foreign trade is balanced, and the net foreign asset position is at zero. Therefore, interest rates are determined within the country. Although Finland maintains open financial markets, this approach is not considered restrictive because comparable shocks occur simultaneously in Finland and globally.

4. Calibration

4.1. The benchmark growth path

The model is represented as a non-linear system of discrete time-series equations. It is solved by using a non-linear solution algorithm available in Matlab/Dynare. The solution consists of a transition between an initial steady state in 1980, and a final steady state that is gradually reached after the year 2060. With a reasonable initiation period and discounting of future consumption, the solution provides a good approximation of the infinite horizon problem's solution at the considered time interval.

The baseline growth path is calibrated to match the key structural changes in the Finnish economy. A key aspect of recent Finnish history is the rise and decline of its domestic ICT cluster. The economy faced a major structural shock when Nokia's influence waned after 2007. In our model, Nokia's impact is seen through significant R&D investment, higher incomes, and rapid ICT productivity growth, followed by a reversion to long-term productivity trends. The model calibrates this shock to reflect reduced export shares in ICT goods and services.

The sectoral total-factor productivity growth rates are based on the average total-factor productivity growth rates of the sectors in 1980–2005, with later adjustments. In the data, the TFPs grow at the annual rates ICT: 3.3%, NIT: 0.7%, S: 0.1%. However, in order to better match the model with the data, I have recalibrated the TFP growth rate of the service sector to -0.5% per annum in order to better match sectoral dynamics and the relative prices.

To account for the Nokia shock, I shock the model with an additional 5% increase in the TFP at the mid-2000s that is followed by 1.5 pps slower TFP growth in 2008–2012, as compared to the long-term trend (Figure 7). Finally, in order to match the role of the NIT sector, I use 0.1 pps slower TFP growth than in the data. All in all, the measurement of the TFP, especially in the public sector, is extremely difficult, and therefore I am inclined to believe that our model calibration that is based on the market responses rather than the productivity statistics can provide a reasonable approximation of the TFP growth.

The basic Input-output structure is based on the mid-2000s OECD input-output tables, again with later adjustments. The sectors' nominal shares of the inputs used in the production are shown in Table 5. To capture trends in the shares, NIT -sector's own intermediate goods are gradually replaced by the service sector intermediate goods at the rate of 0.35 pps per annum in 1995–2015 due to outsourcing of manufacturing sector tasks to the service sector.

Moreover, changes in labour supply and demographics are important structural growth factors in Finland. An ageing population and low fertility rates are expected to reduce the labour force and working hours, lowering production capacity and demand for investment. These trends will also influence aggregate consumption and saving behaviour. In the model, the forecasts for future population and labor supply is based on the forecasts of Statistics Finland (total population and the working aged population) until 2059, and the European Commission's potential total hours forecast until 2022. The potential total hours are expected to follow the amount of working aged population after 2022. In this respect, I study how the recent downward revision of the employment growth in the 2018 Finnish population forecasts will affect economic growth.

The labor force and the population are expected to grow at the rates forecasted by the European Commission's estimate of the potential hours and the latest long-term population projection by the Statistics Finland from the year 2024. In particular, the potential hours grow according to the EC potential until 2029, and thereafter the hours are growing at the same rate as the working aged population in the Statistics Finland's forecast. Finally, it is assumed that prior to the year 2008, the potential hours remain constant. Thus, I omit the role of the prior swings in the labor force that were mainly caused by the Finnish Great Depression of the 1990s.

Otherwise, the model follows standard calibration of the Finnish economy. The depreciation rates of capital stocks are ICT: 24% per year., NIT:6% per year are based on the EU KLEMS database. In the NIT and ICT sectors the capital tax rate is set at 30 percent, while in the service sector the tax rate is 30 % for private services and 0 % for public services. Because I do not distinguish between private and public services in the model, I set the tax rate as the weighted average of these tax rates according to the average value-added weights of the private and public parts of the service sector in the data. In our previous analysis (Ali-Yrkkö et al. 2016), I show that under these tax rates the model matches relatively well with the actual investment rates of the Finnish economy.

Consumption discount factor β = 0.96 and the intertemporal elasticity of substitution $\rho = 2$ are calibrated following Buera ja Kaboski (2009). The intratemporal elasticity of substitution $\epsilon = 0.5$ (see,

Figure 9 in the Appendix) and the cost shares of the sectors are based on the domestic consumption data (ω_{IT} = 0.001, ω_{NIT} = 0.163, $\omega_S =$ 0.836).

The parameterization of trade is based on an estimated bilateral trade model for the year 1995, and the trends in the competitiveness and the size of the external sector are extrapolated thereafter to match the share of domestic products in the domestic final good and the sectoral shares of the exports. The elasticity of trade parameter, $\theta = 8.3$, is based on Eaton & Kortum (2002). The external market volume grows at the rate of 5 percent per annum. The foreign ICT sector's unit costs are assumed to decrease steadily by 6% per annum. The foreign NIT sector's unit cost decrease by 2.4% per annum. It is notable that the changes in the relative price of ICT goods follows quite closely the estimates by Jorgenson and Timmer (2011).

A notable feature of the model is that the trade is assumed to be balanced. While the Finnish economy has experienced several periods of trade inbalances and there are extensive investments abroad, it can be argued that over the long-term this assumption is a reasonable one. In particular, the ratio of the Finnish gross national income and gross national product has been markedly stable over the long-run. This implies that while the option to invest in the foreign markets is used, there are no clear changes in the external investment behavior and thus its impact on should be more on the level of economic activity rather its growth.

4.2. AI shocks

I have constructed four alternative scenarios. In each scenario, I shock the economy in the time-period 2023–2033. In the first scenario I assume baseline GenAI adaptation of Filippucci et al. (2024B), depicted in Figure, and focus its impact on labor. In this scenario, the TFP shocks are 0.05%, 0.04%, and 0.09% annually, for ICT, NIT, and traditional services, respectively, taken that the impact of GenAI only affects the labor input. We maintain the production function factor shares constant.

In the second scenario I assume baseline GenAI adaptation, but allow the impact on both labor and capital. In this scenario, the corresponding TFP shocks for ICT, NIT, and traditional services are, 0.09%, 0.05%, and 0.13% annually, respectively. In the third scenario, I consider the extended GenAI capacities and focus the impact again on labor. In this case the TFP shocks are 0.10%, 0.10%, and 0.29% per year.

In each case, I assume a corresponding productivity impact on the foreign ICT and NIT sectors. From the Finnish perspective, sufficient variables to characterize model dynamics are the average unit price changes in the foreign sector. In each simulation, I assume the same TFP productivity shock that affects the domestic sector. I use Filippucci et al. (2024B) capital multiplier 1,5 to receive an approximation of the labor productivity impact. Finally, I employ a price elasticity of productivity shocks from Filippucci et al. (2024B) model with flexible movement of resources across the economy (Appendix Figure A.7). Following this procedure, I approximate a 1.15% price reduction for each 1 percentage point TFP gain in the Foreign sector.

Finally, my fourth scenario considers the impact of factor share changes. While I consider the constancy of the factor shares as a reasonable baseline assumption in the three first scenarios, in this scenario I let the factor share of labor to gradually decline by 1 percentage point while increasing the factor share of ICT intermediates by corresponding 1 percentage points to maintain constant returns to scale production function. The change occurs in the period 2023 to 2033 at a constant pace 1/11 percentage points per year for both inputs.

In the absence of clear guidance on how to adjust foreign sectors for a similar change, I do not make changes to its production function. Therefore, the scenario includes a competitiveness effect arising from the difference in the domestic and foreign effects of AI.

It is worth noting that in all scenarios employment remains at full level. However, I acknowledge that GenAI may have a lowering impact on aggregate employment and also consider the possibility of an additional decline in employment (-1%) as an alternative version of the fourth scenario.

5. Results

5.1. Benchmark economic dynamics

I first report the behavior of the model in 2000–2022 and use it to assess the model performance prior to the GenAI shocks. Figure 5 shows the benchmark real GDP growth path of the model and compares it to the actual GDP volume growth in the years 2000 to 2022. The figure suggests that it matches rather well with the aggregate volume growth of the Finnish economy, while not taking into consideration short-term shocks: The upturn before the 2008 financial crisis and the Covid-19 years 2020–2022.

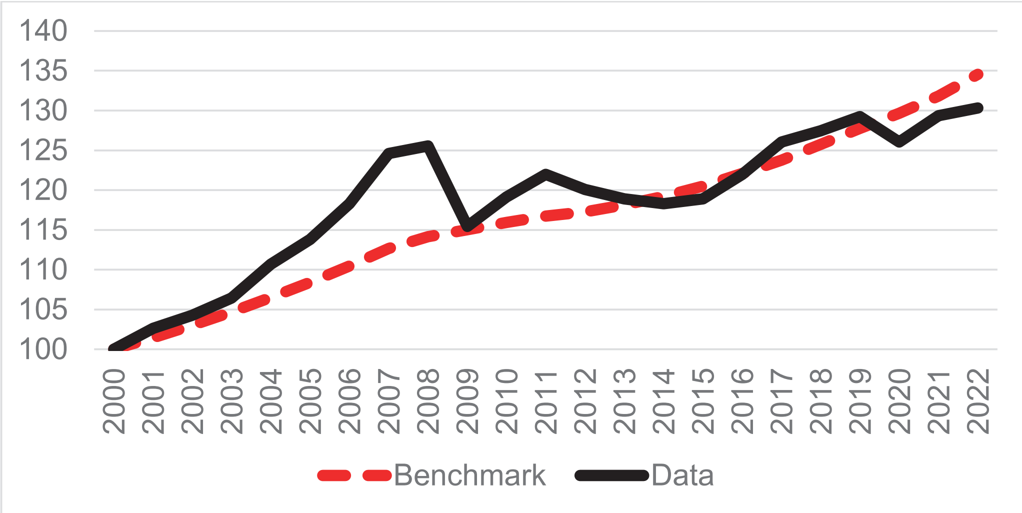

Figure 5. The baseline growth path of the multi-sector model and the actual real GDP growth for Finland. Source: Statistics Finland and own calculations.

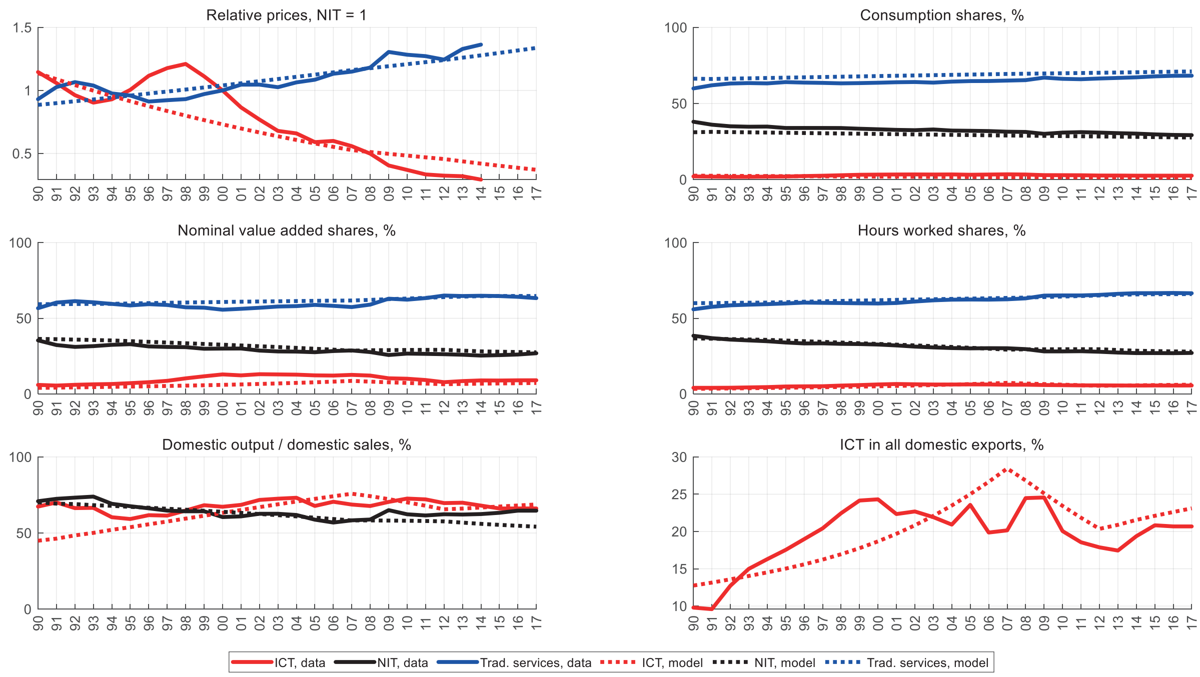

Figure 6. The key structural changes of macroeconomic variables in the model vs. the data. The relative prices are the prices of a sector's consumption aggregate as relative to the price of the consumption aggregate of the traditional manufacturing sector. The consumption shares are the sectoral nominal share of the total consumption. The employment shares are the sectoral share of the total working hours. The domestic shares are defined as the value of domestic production as relative to the total value of domestic demand. The share of ICT in total exports is the share of ICT goods and services in the total exports. Source: OECD, Statistics Finland and own calculations. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production.

Furthermore, Figure 6 reports the key structural changes of the macroeconomic variables for 1990 to 2017, where I have collected the structural change data. It shows that the model replicates dynamics concerning (1) the relative prices of the sectors; (2) the consumption shares of the sectors, the production shares of the three sectors; (3) the value added shares of the sectors; (4) the employment shares of the sectors; (5) the domestic content of the domestic final good; and (6) the share of ICT goods and services of the total exports. All in all, given that the model fits relatively well to the structural changes, I am confident in using its projections to forecast GenAI related growth and structural changes 2023–2033.

5.2. Growth impacts of AI

Table 1 presents a comparative analysis of economic growth and the contributions of domestic sectors under different scenarios. In the benchmark scenario, real GDP growth is 1.86%, and labor productivity growth is 1.41%. When the economy adjusts for labor exposure alone, real GDP growth rises to 2.00%, representing a 0.14 percentage point increase in annual growth.[12]

When both labor and capital adjustments are factored in, real GDP growth increases further to 2.08%, with labor productivity growth reaching 1.63%. This marks a difference of +0.22 percentage points for real GDP growth compared to the benchmark.

With extended capacities enabled by GenAI, which enhance labor productivity, real GDP growth climbs to 2.30%, accompanied by labor productivity growth of 1.81%. This reflects a notable improvement of +0.44 percentage points in GDP growth and +0.43 percentage points in labor productivity growth relative to the benchmark.

These results are somewhat larger than those reported in Acemoglu (2025), where the benchmark impact is estimated at 0.07 percentage points per year, compared to 0.14 percentage points in my modeling. This discrepancy likely reflects, in part, a greater capital multiplier in my framework—that is, a larger effect of TFP shocks on labor productivity through capital accumulation—as well as differences in the composition of intermediate goods, which provide a general equilibrium channel that amplifies the aggregate effect of GenAI. Conversely, when considering the combined impact on both capital and labor, the most comparable reference is Filippucci et al. (2024B). Here, my estimate is moderately lower (+0.22 percentage points) relative to their reported value of +0.36 percentage points.[13]

[12] The EC potential total hours time series projects an increase in potential hours over the 10-year period, which results in a positive employment impact in the scenarios.

[13] While the underlying GenAI shock are similar, there may be several contributing factors to dissimilarities in their propagation to the economy. On one hand, their consumption function creates possibility for a larger

I return to these differences in the following subsection.

	Real GDP growth	Labor productivity growth	Contributions of domestic sectors ICT	NIT	Services
Benchmark					
	1.86	1.41	1.2	0.5	0.2
1.Baseline exposure, only labor					
	2.00	1.55	1.2	0.5	0.3
Difference	0.14	0.14	0.0	0.0	0.1
2.Baseline exposure, labor and capital					
	2.08	1.63	1.2	0.5	0.3
Difference	0.22	0.22	0.0	0.1	0.1
3.AI, extended capacities, only labor					
	2.30	1.84	1.2	0.6	0.5
Difference	0.44	0.43	0.0	0.1	0.3
4.Baseline exposure, only labor, 1pps increase in ICT factor share / decline in labor share					
	3.14	2.64	1.6	0.9	0.7
Difference	1.28	1.23	0.4	0.4	0.5

Table 1. A comparative analysis of 2023–2033 real GDP growth, labor productivity growth, and the contributions of domestic sectors under different scenarios. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Own calculations.

The results indicate that alterations in factor shares can produce substantial impacts on economic growth. Specifically, when the labor factor share declines by 1 percentage point in favor of increased ICT utilization—effectively representing the automation of 1% of all tasks within the economy—real GDP increases by more than 1 percentage point annually relative to the benchmark, ultimately reaching a growth rate of 3.14%.[14]

In this final scenario, it is important to note that a simultaneous decline in employment is not considered, which would otherwise attenuate the growth effect. Instead, the model assumes that the economy adjusts to maintain full employment. Nevertheless, given the magnitude of the projected growth increase, the effect would remain substantial even if accompanied by a significant negative employment impact. To further explore this, an alternative scenario combines the 1 percentage point shift in factor share toward ICT with a constant annual decrease in total labor input of 0.1% during 2023–

multiplier effect through more price-elastic demand, while their production input-output structure is likely to be less prone to multiplier effects through less elasticity.

[14] The effect may be partially explained by an increase in the competitiveness of the domestic sector as relative to the foreign sector. The corresponding structural changes are described more closely in the subsection “Structural changes in key variables”.

2033, resulting in a cumulative reduction of 1% in working hours. This adjustment yields a corresponding decrease in economic activity of approximately 0.1 percentage points over the same period. While this growth impact is modest, a decline in employment would undoubtedly raise critical questions about the redistribution of the benefits associated with AI-driven technological advancements.

From an anticipatory standpoint, the behavior of financial markets offers valuable insights, as the framework also provides estimates of the real interest rate impact of GenAI (Figure 10 in the Appendix). If a significant impact of GenAI on productivity were widely expected, one would anticipate a pronounced rise in real interest rates, driven by an immediate increase in willingness to consume and simultaneous increase in the need to finance investments. In the model, the anticipatory real interest rate hikes range between ca. 0.1 percentage points in the baseline adaptation scenario (1) to ca. 0.5 in scenario with the labor shares changing (4).

The scenarios so far have assumed that the AI shock provides a level shift in the affected variables, after which the changes remain in effect, while growing exogenous variables continue to grow afterwards according to their benchmark growth rates, but with level shifts occurring from the AI shock. I also consider an alternative scenario, where the baseline scenario (1) dynamics continue for 20 years, that is, there is an anticipation of further productivity growth.

The scenarios discussed thus far assume that the AI introduces permanent changes in the relevant economic indicators over the 10-year horizon. Following this transition, exogenous variables—primarily productivities—resume growth at their benchmark rates, but from revised initial values reflecting the influence of AI where applicable.

To analyze the effects of expectations beyond the 10-year horizon, I also consider an alternative scenario in which the baseline productivity growth from scenario 1 continues for 20 years. This means that ongoing productivity gains driven by GenAI are anticipated over a longer period. The analysis reveals that such long-term expectations have a secondary—but noticeable—impact on economic growth: projected growth decreases by 0.02 percentage points per year over the initial 10-year horizon, alongside a slight increase in real interest rates.

5.3. Growth decompositions

Sectoral growth contributions

I first continue to inspect results in Table 1. A simple growth decomposition follows from the standard Törnqvist indexation of value added to different sectors:

$$\Delta RGDP_t = \sum_{i \in I} \frac{1}{2} \left(\frac{siVA_t}{sVA_t} + \frac{siVA_{t-1}}{sVA_{t-1}}\right) \Delta RVA_t, \tag{16}$$

where $\Delta RGDP_t$ is the relative change in real GDP and ΔRVA_t the corresponding changes in the real value added, and $siVA/\ sVA$ is the nominal value-added share of the sector in total value added.

In the scenario characterized by baseline exposure affecting only labor, ICT contributes substantially to growth, accounting for 1.2 pp, while NIT and service sectors add 0.5 pp and 0.2 pp, respectively. Relative to the benchmark scenario without a GenAI shock, the positive growth impact is primarily attributed to the NIT and services sectors. Across alternative scenarios, the relative sectoral contributions to growth remain largely consistent. However, in the extended capacities scenario, the growth contributions from the NIT and service sectors increase to 0.6 pp and 0.5 pp, respectively, further underscoring their significance in overall economic growth. Notably, the services sector exhibits the most pronounced increase in its contribution.

Finally, when there is a 1 pp shift in the factor share towards ICT in the fourth scenario, the surge originates from all sectors of the economy.

Growth accounting and the capital multiplier

To deepen the analysis, a standard Solow growth decomposition is employed, where labor and capital input growth are weighted by their respective Törnqvist weights, and TFP is calculated as the residual. Notably, in contrast to the Filippucci et al. (2024B) multi-sector framework, the TFP component in this approach can be measured directly, removing the need for additional assumptions regarding the capital multiplier—that is, the effect of a TFP shock on capital accumulation.

Table 2 provides results under varying scenarios of exposure to GenAI in columns 1–4. The growth accounting decomposition suggests that TFP shows consistent growth across the scenarios, starting from 0.68 in the benchmark scenario and reaching a peak of 1.0 under AI's extended capacities to labor.

	VA growth accounting				TFP decomposition			Real output growth		
	TFP	ICT capital	NIT capital	Labor	Direct	Input-output	Comp-osition	ICT	NIT	Services
Benchmark										
	0.7	0.3	0.6	0.3	0.0	0.5	0.1	8.8	1.4	1.0
1.Baseline exposure, only labor										
	0.8	0.3	0.6	0.3	0.1	0.6	0.1	8.6	1.7	1.1
Difference	0.1	0.0	0.0	0.0	0.1	0.1	0.0	-0.3	0.3	0.1
2.Baseline exposure, labor and capital										
	0.9	0.3	0.6	0.3	0.1	0.6	0.1	8.9	1.7	1.2
Difference	0.2	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.4	0.2
3.AI, extended capacities, only labor										
	1.0	0.3	0.6	0.3	0.3	0.7	0.1	8.7	2.1	1.4
Difference	0.4	0.0	0.0	0.0	0.2	0.2	-0.1	-0.2	0.7	0.4
4.Baseline exposure, only labor, 1pps increase in ICT factor share / decline in labor share										
	1.7	0.3	0.8	0.3	0.1	0.6	1.0	12.2	3.2	2.1
Difference	1.0	0.1	0.2	0.0	0.1	0.0	0.9	3.4	1.8	1.1

Table 2. Solow growth decomposition, TFP growth decomposition by Baqaee and Farhi (2020), and sectoral real output growth in different scenarios for 2023-2033. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Own calculations.

The capital multiplier, measured as the ratio of labor productivity growth to TFP growth within the model, indicates moderately higher values than the 1.5 multiplier employed by Acemoglu (2025) and the Filippucci et al. (2024B). Across various scenarios, the capital multiplier ranges from 1.75 to 1.94, which partially accounts for the larger impacts observed compared to Acemoglu (2025).

Input contributions remain relatively stable across scenarios. Changes in ICT capital are modest, increasing by only 0.01 in each case, suggesting that GenAI exposure has a limited effect on ICT capital investment. Instead, gains are primarily realized through total factor productivity. NIT capital maintains a significant role in all scenarios, exhibiting slight increases—up to 0.04—under the extended GenAI capacities to labor scenario. Meanwhile, labor input demonstrates minor fluctuations, with the largest decrease (-0.02) occurring under extended GenAI capacities to labor.

A factor shift leads to higher TFP and capital deepening, with economic growth driven by both types of capital. Table 6 shows that while NIT capital investment rates moderately decline in the service and ICT sectors, the NIT sector increases its own NIT capital investments.

Direct and indirect sources of growth

According to the approach used by Filippucci et al. (2024B) and Baqaee and Farhi (2020), the growth rate in aggregate TFP can be decomposed into direct and indirect components as follows:

$$\Delta TFP = \sum_{i \in I} \frac{si0VA}{s0VA} \Delta TFP_i + \sum_{i \in I} \left(\frac{si0Y}{s0Y} - \frac{si0VA}{s0VA} \right) \Delta TFP_i + Composition \tag{17}$$

where $\frac{si0VA}{s0VA}$ are the initial nominal value-added share of sector I and $\frac{si0Y}{s0Y}$ is the initial Domar weight - defined as sector i's nominal gross output over GDP.

The direct effect is the sum of the sectoral productivity gains with each sector weighted by its value-added share. The input-output multiplier, on the other hand, is constructed by first computing the sum of the sectoral productivity gains with each sector weighted by its gross sales over GDP (i.e., its Domar weight) and then subtracting the direct effect.

The input-output multiplier arises as one sector's productivity gains also helps to expand the productive capacity of other sectors by lowering the input prices that they face. Finally, the composition effect is derived by subtracting the sum of the direct and indirect effects from the overall macroeconomic effect. In this I follow Baqaee and Farhi (2020) who interpret Baumol's growth disease as the discrepancy between within-sector productivity growth, aggregated at fixed nominal output shares and actual aggregate productivity growth.

The direct effects of TFP rose from 0.03 in the benchmark scenario to 0.25 in the scenario where GenAI extended capacities impact labor, indicating the direct association between GenAI and changes in productivity. The input-output effect plays a significant role, peaking at 0.72 with expanded GenAI capabilities. This aligns with Ngai and Samaniego (2009), who highlight the importance of input-output structures in assessing productivity shocks. Sectors with higher TFP growth, especially when used as intermediates, drive economic growth. Table 2 shows that ICT output growth, driven by lower prices, substantially impacts overall real output across sectors.

Special attention should be placed on the propagation in case of GenAI. Its impact does not only involve technological change, but results in complex shocks through input-output framework as production is reorganized in all sectors.

Conversely, the residual composition effects remain minimal across scenarios, except in the case where factor shares are permitted to adjust. In this context, the findings diverge from those of Filippucci et al. (2024B), which identified substantial contributions from the composition effect.

In their model, the elasticity of substitution among intermediate products is very low; in situations where intermediate goods behave almost as perfect complements, the Baumol effect component becomes both negative and pronounced. However, empirical data on the Finnish sectoral structure at the three-sector aggregation level indicate that substitutability is considerably higher—approaching that of a Cobb-Douglas production function.

Factor shares in Finnish sectoral production have remained relatively stable, even amid significant changes in relative factor prices, particularly the declining price of ICT during the first phases of the Internet (Figure 8). My approach aligns more closely with the methodology of Ngai and Samaniego (2009), whose objective is to explain the growth effects of intermediate products within a framework that accommodates rapid changes in the relative prices of those intermediates. Having said that, it is probable that incorporating a more detailed sectoral structure, as in Filippucci et al. (2024B) and Baqaee and Farhi (2020), would further enable the analysis of sectoral distortions in propagation, which may attenuate the impact of GenAI through the input-output framework.

Finally, when factor shares are allowed to adjust in the fourth scenario, the composition effect becomes strongly positive. The modifications in the production function induced by the GenAI shock generate a significant growth effect that is not captured by the initial direct or input-output components of the decomposition.

5.4. Structural changes in key variables

To further contextualize the analysis, it is essential to examine the primary determinants of structural transformation within the economy. A review of previous research on economic growth during the information age reveals that sectoral performance has been heterogeneous, with certain sectors exhibiting limited productivity improvements while others have experienced substantial gains due to digitalization and automation.

This uneven growth trajectories have significant implications for aggregate macroeconomic performance, as sectors compete for common inputs—most notably labor—and productivity advancements in select sectors may contribute to cost increases in others. In particular, the slower productivity growth observed in traditional services sectors has driven increases in their relative prices. As demand for these services tends to be price, their share in total production and resource utilization has increased over time, exerting downward pressure on aggregate productivity growth rates.

	Price of final product relative to NIT, 1995 = 100		Domestic product nominal share in final product		Share of ICT in exports
	ICT	Services	ICT	NIT	
Benchmark					
	23.7	157.9	76.7	48.2	27.6
1.Baseline exposure, only labor					
	23.6	157.4	76.0	48.5	26.6
Difference	-0.1	-0.5	-0.7	0.4	-1.0
2.Baseline exposure, labor and capital					
	23.6	157.5	76.8	48.3	27.6
Difference	-0.1	-0.5	0.1	0.1	0.0
3.AI, extended capacities, only labor					
	23.6	157.6	76.7	48.2	27.6
Difference	0.0	-0.3	0.1	0.1	0.0
4.Baseline exposure to labor, 1pps increase in ICT factor share / decline in labor share					
	23.5	159.3	78.0	48.9	28.4
Difference	-0.2	1.4	1.3	0.7	0.8

Table 3. Relative prices, average domestic value share in the sales of final product, and the average share of ICT in the value of all exports 2023-2033 in different scenarios. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Own calculations.

Based on the modeling results, GenAI produces a distinct pattern in relative prices. As presented in Table 3, both the services and ICT sectors exhibit a decline in price growth relative to the NIT sector. This outcome represents a reversal from the traditionally increasing price trends in the service sector and mitigates some of the Baumol-disease effects observed in conventional growth models.

It is noteworthy that the shocks introduced in these scenarios lead to observable shifts in Finland's external competitiveness, as evidenced by changes in the domestic product share of final goods and the relative contributions of NIT and ICT products to exports. The resulting changes remain modest. This outcome is consistent with the calibration strategy of the first three scenarios, which aim to provide comparable shocks to both domestic and foreign sectors.

In the first scenario, there is a slight decline in the ICT sector and a corresponding increase in the NIT sector, indicating a moderate shift in Finland's comparative advantage toward NIT activities. In the fourth scenario, which involves changes in factor shares, there is an improvement in the international competitiveness of both NIT and ICT products. This enhancement may further amplify the productivity effects associated with the factor share change, although the magnitude remains moderate.

Finally, I investigate changes in the sectoral shares of nominal consumption and total hours in different scenarios. I find that the overall shifts in consumption are small, indicating an increase in the nominal consumption in the NIT consumption and decline in the service consumption. This results directly from the changes in relative prices of the products.

Interestingly, the share of total working hours allocated to services increases. However, given the findings concerning consumption shares, this change does not stem from the traditional inelastic consumption (Baumol effect) but rather results from alterations in the input-output structure.

In the final scenario, a change in factor shares is considered. When labor intensity decreases across all sectors, a compositional effect emerges: the relative price of traditional services rises, and labor shifts toward these activities. This scenario effectively illustrates the dynamics of GenAI-driven substitution and reinstatement effects. While the substitution effect reduces demand for labor as automation advances, the reinstatement effect counteracts this displacement by generating new tasks within the service sector, ultimately increasing overall labor demand.

	Share of total nominal consumption			Share of total working hours		
	ICT	NIT	Services	ICT	NIT	Services
Benchmark						
	1.0	26.1	72.9	7.5	26.0	66.5
1.Baseline exposure, only labor						
	1.0	26.2	72.8	7.4	26.0	66.6
Difference	0.00	0.07	-0.08	-0.03	-0.05	0.07
2.Baseline exposure, labor and capital						
	1.0	26.1	72.9	7.5	26.0	66.5
Difference	0.00	0.02	-0.02	0.00	-0.04	0.04
3.AI, extended capacities, only labor						
	1.0	26.2	72.8	7.4	26.0	66.6
Difference	0.00	0.07	-0.08	-0.03	-0.05	0.07
4.Baseline exposure, only labor, 1pps increase in ICT factor share / decline in labor share						
	1.0	26.0	73.0	7.8	25.5	66.7
Difference	-0.01	-0.09	0.09	0.35	-0.52	0.17

Table 4. Sectoral shares of nominal consumption and total hours in different scenarios. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Own calculations.

6. Conclusions

This study employed a quantitative multi-sector macroeconomic model to analyze the economic impact of Generative Artificial Intelligence (GenAI) on the Finnish economy. The methodology integrates sector-level GenAI productivity growth estimates within a dynamic general equilibrium framework, considering displacement, productivity, and reinstatement effects in a reduced-form framework.

The results indicate that, over a 10-year horizon, GenAI can contribute less than 0.5 percentage points to annual economic growth, based on recent empirical evidence concerning the extent of GenAI adoption. Within this framework, I demonstrated how larger effects could arise from more pervasive automation, particularly if the nominal labor share of production were to decline. In the baseline scenario, an increase in total factor productivity (TFP) driven by GenAI adaptation, combined with a one percentage point reduction in labor share or a corresponding rise in the ICT share, would yield an annual growth impact of a bit over 1 percentage points.

While the present analysis centers on the potential impacts of GenAI shocks in the context of the existing literature, it is important to note that this perspective remains relatively narrow regarding the broader influence of AI. The ongoing discourse on the prospects of AGI and robotics—when contrasted with the more conservative growth assumptions applied here—underscores the challenges inherent in accurately forecasting the full macroeconomic implications of AI.

From an anticipatory standpoint, the model-based behavior of financial markets offers valuable insights. If a significant impact of GenAI on productivity were widely expected, one would anticipate a pronounced rise in real interest rates, driven by an immediate increase in both propensity to consume and the need to finance investments. In the model, the anticipatory real interest rate hikes range between 0.1–0.5 percentage points. Given that large market responses have not materialized to date, expectations for macroeconomic growth effects from GenAI seem to remain moderate in the financial markets.

Another interesting insight is that the input-output structure of the model generated significant multiplier effects, amplifying the impact of GenAI on productivity and economic growth. Productivity gains in one sector enhance the productive capacity of other sectors by reducing the input prices they encounter, thereby creating indirect growth effects. Moreover, the modeling outcomes highlighted considerable compositional shifts within the economy toward sectors characterized by lower productivity, in which the adoption of advanced technologies is constrained. The deployment of GenAI holds promises to mitigate these trends.

Notably, the service sector emerges as a pivotal driver in the economic adjustments associated with GenAI adoption. The findings indicate that AI-induced productivity improvements within services can help counterbalance the effects of conventional unbalanced growth patterns, thereby enhancing overall economic performance.

From a policy perspective, the potential for AI to stimulate economic growth and mitigate stagnation seems considerable. Even under the baseline scenario, the additional annual growth contribution of 0.1 to 0.2 percentage points for 2023–2033 represents a meaningful increase for economic and fiscal policy planning. However, realizing these benefits necessitates the implementation of well-designed policies that facilitate the effective integration of GenAI across a range of sectors. Although this study did not specify an optimal policy mix, it highlights the critical need for a comprehensive policy framework to maximize the potential of GenAI and promote sustained economic resilience.

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Appendix

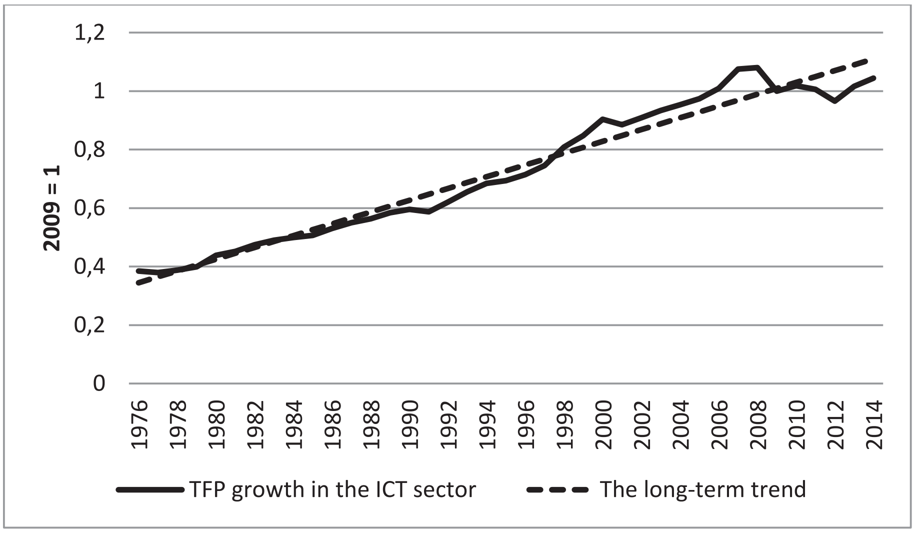

Figure 7. The TFP growth in the Finnish ICT sector and the long-term trend. Source: Statistics Finland and own calculations.

	ICT	NIT	S
ICT-capital	0.03	0.01	0.02
NIT-capital	0.12	0.12	0.17
Service intermediate goods	0.20	0.17	0.27
Labor	0.18	0.24	0.39
ICT intermediate goods	0.35	0.02	0.05
NIT intermediate goods	0.12	0.44	0.10

Table 5. Factor shares in sectoral Cobb-Douglas production functions. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Own calculations.

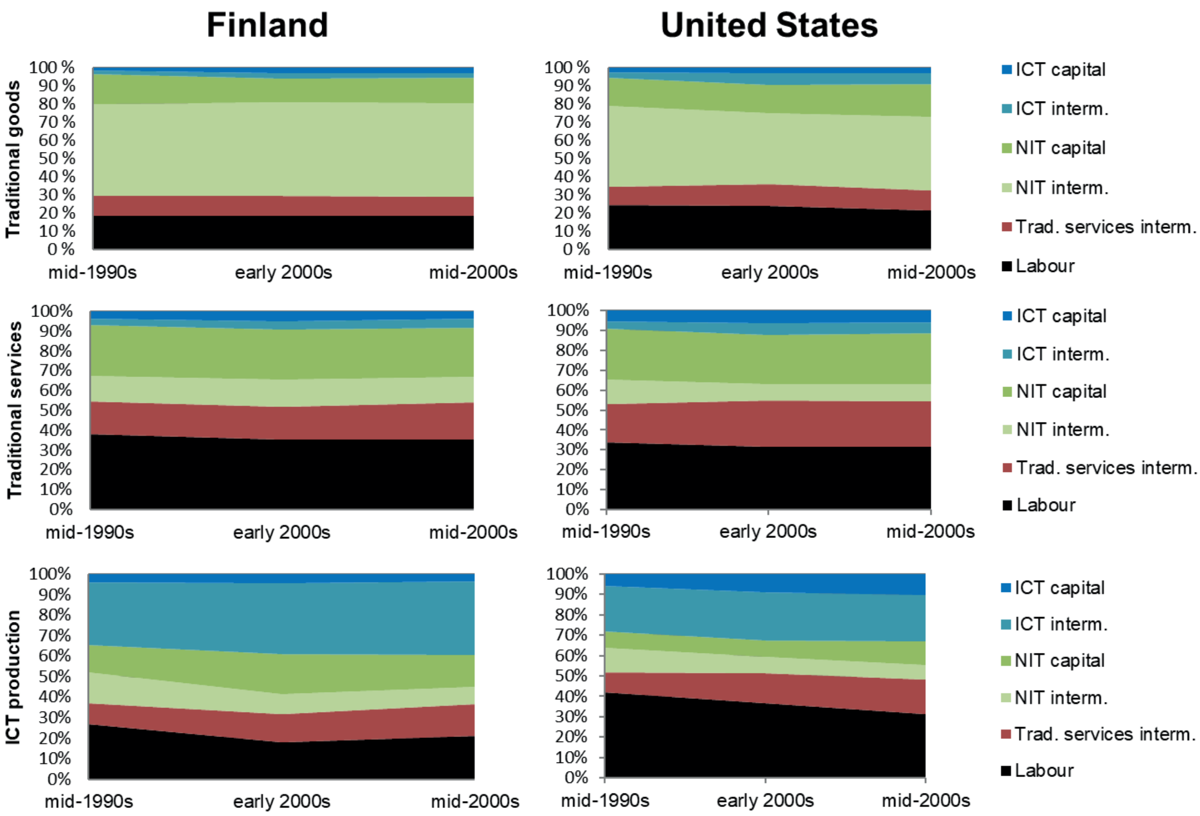

Figure 8. Nominal factor-share changes during the mid-1990s to mid-2000s period of the ICT revolution. Source: OECD, Statistics Finland and own calculations.

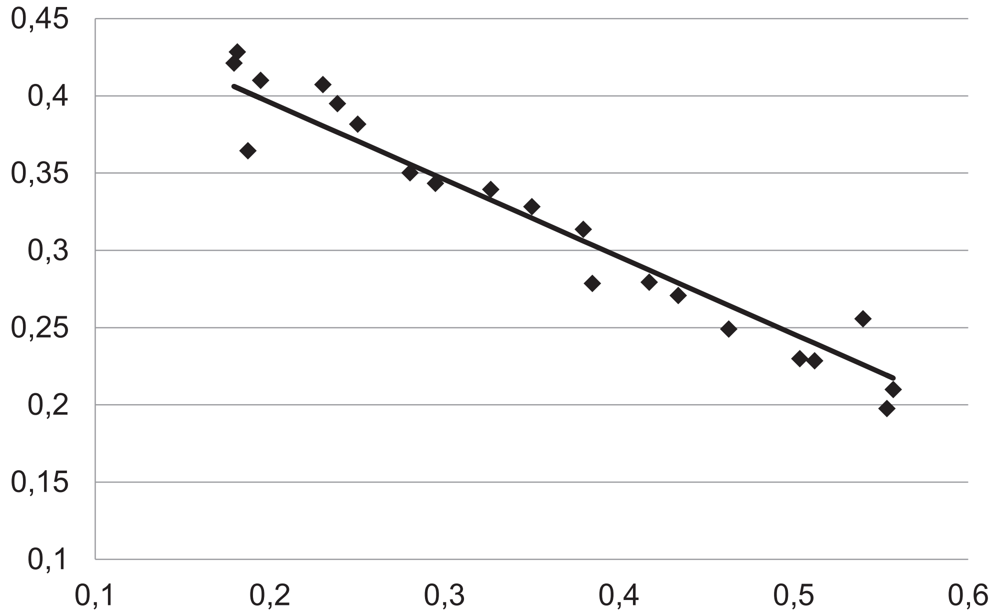

Figure 9. A fitted line to the consumption data with the intratemporal elasticity of substitution receiving the value 0.5. Y-axis: the logratio of real consumption between traditional services and manufacturing. X-axis: the log-ratio of prices between traditional services and manufacturing. Source: Statistics Finland and own calculations.

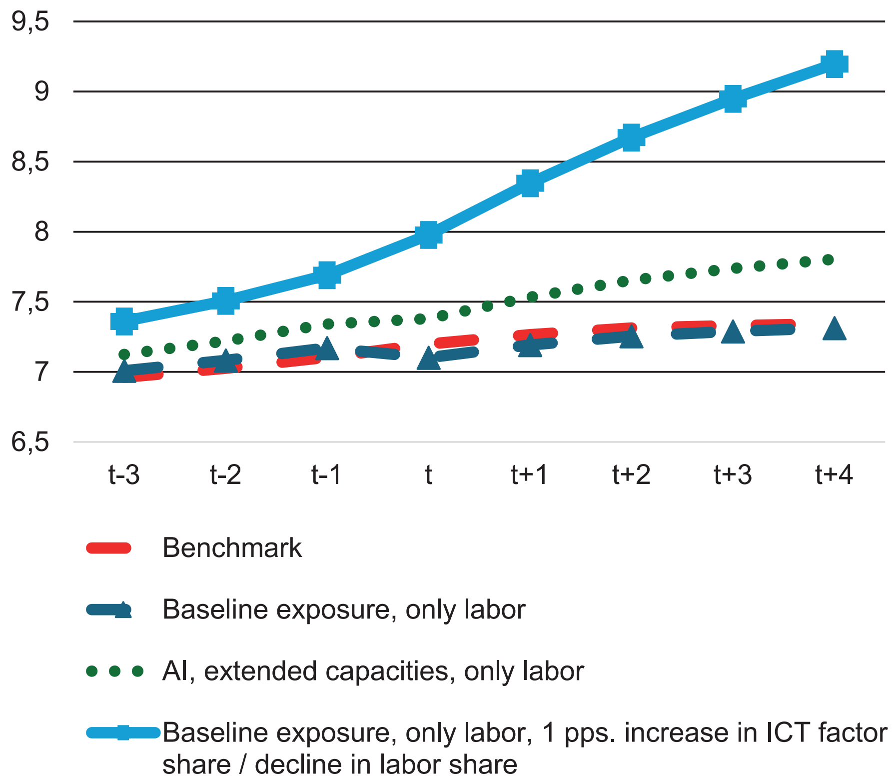

Figure 10. One-year real interest rate in different scenarios for different years. Period t marks the starting year of the GenAI shock (2023). Source: Own calculations.

	NIT sector investment per GDP,		Service sector investment per GDP		ICT sector investment per GDP		Aggregate investment per GDP		
	ICT	NIT	ICT	NIT	ICT	NIT	ICT capital	NIT capital	Total
Benchmark									
	0.4	3.2	1.6	8.7	0.6	1.8	2.5	13.7	16.2
Baseline exposure, only labor									
	0.4	3.2	1.6	8.6	0.6	1.8	2.5	13.6	16.1
Difference	0.0	0.0	0.0	-0.1	0.0	0.0	-0.01	-0.15	-0.2
Baseline exposure, labor and capital									
	0.4	3.2	1.6	8.5	0.6	1.8	2.5	13.5	16.0
Difference	0.0	0.0	0.0	-0.2	0.0	0.0	-0.01	-0.23	-0.2
AI, extended capacities, only labor									
	0.4	3.2	1.6	8.4	0.5	1.7	2.5	13.3	15.8
Difference	0.0	-0.1	0.0	-0.3	0.0	0.0	-0.03	-0.44	-0.5
Baseline exposure, only labor, 1pps increase in ICT factor share / decline in labor share									
	0.3	3.0	1.6	7.7	0.6	1.9	2.5	12.6	15.2
Difference	0.0	-0.2	0.0	-1.0	0.0	0.2	0.0	-1.1	-1.1

Table 6. investment rates in the scenarios. ICT = ICT related manufacturing and services; traditional services = other private and public services; NIT = other industries, excluding primary production. Source: Own calculations.

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Publisher: Taloustieto Oy

Tel. +358-9-609 900
www.etla.fi
firstname.lastname@etla.fi

Arkadiankatu 23 B
FIN-00100 Helsinki