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AI-enabled Automation, Trade, and the Future of Engineering Services

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Abstract

This paper studies the role of trade for the joint uptake of AI-enabled automation in manufacturing and engineering. It develops an agent-based model (ABM) where the agents are heterogeneous manufacturers and engineering firms. The model features two technology-related business models: engineering as a face-to-face consultancy service and engineering as automated software. Switching to the software technology is costly for both manufacturers and engineers, but the cost declines with the number of firms having made the leap due to network effects. The simulations start with a scenario where all firms are in the consultancy business model and trace out the path of software adoption over time. The software adoption rate follows an S-shaped curve for manufacturers and a boom and bust cycle for engineers. Trade affects the cut-off productivity rate at which manufacturers switch technology, the shape of the adoption rate curve, and the incentives for engineers to develop software. In a two-country model with a high and low-wage country, the low wage country adopts software early and import consultancy services from the high-wage country, a pattern similar to China's trade and AI development.

Keywords: Technology adoption, Automation, Trade, Agent Based Modelling
JEL Codes: C63, F16, O33.

1 Introduction

In a recent paper, Baldwin and Forslid 2020 predicted that white collar jobs will be swept away at a faster pace than previous episodes of automation. The paper strikes a chord in the popular debate on "how AI is coming for your job"[1]. As AI capabilities for language, speech and image recognition pass human levels, AI-enabled software can perform white collar tasks previously done exclusively by high-skilled humans. Furthermore, white collar jobs in rich countries could face a double whammy.

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[1] see for instance https://www.ft.com/content/c4bf787a-d4a0-11e9-a0bd-ab8ec6435630

Not only may AI-enabled automation transform such jobs, but digitized tasks can also be traded over electronic networks such that an engineering job in, say Germany, can be performed remotely in India. For the double whammy scenario to come to bear, AI-enabled automation must be broadly adopted and professional services widely traded. Furthermore, imported services and AI must replace local professionals faster than new jobs are created.

So far fear of disruption and mass unemployment in white collar jobs seems not to be supported by facts. To the contrary, despite a substantial increase in imports of professional services and high exposure to AI, employment in professional services has grown steadily in the OECD area, both in absolute and relative terms.[2] A possible explanation for continued job growth is that AI creates new jobs and complements rather than substitutes for work in professional services, which have seen rising demand for AI-related skills (Alekseeva et al. 2021). Another explanation is that AI is still not broadly adopted. For instance, recent surveys in Sweden and the United States show that less than 10% of firms use AI in these countries.[3]

This paper analyses the joint uptake of AI in manufacturing and engineering. AI is a major technology that cannot easily be woven into existing production processes. Rather, it typically requires a major restructuring of production (T. Bresnahan 2019). Engineering plays a major role in production design in manufacturing and also constitutes essential inputs to manufacturing firms (Rock 2019; Hitomi 2017). We study the interaction between engineering and manufacturing in technology adoption using a dynamic Agent-Based Model (ABM) and simulate the uptake of AI-enabled automation software in an open economy where trade in engineering services affects both the opportunity cost of AI-enabled automation and access to AI applications. ABM simulations are well suited for capturing interaction between heterogeneous agents in a rapidly changing environment where agents make decisions under imperfect information.

Our model features two types of agents and two business models. The two agent types are manufacturing agents and engineering agents while the two business models are consultancy and AI-driven automation software, hereafter *software*. The consultancy business model is characterized by engineering agents providing technical support and problem solving to manufacturing agents through face-to-face on-site consulting. Such support may involve product and process design, supply chain management and quality management. In the software model, these activities are supported or replaced by AI-driven automation software. At the outset of the ABM simulations all agents are in the consultancy business model. In subsequent periods each agent decides independently whether to switch to the software business model.

The switch implies a leap to a different way of organizing production for both types of agents. Engineering agents reassign the engineers from consultants to software developers. Manufacturing

[2] Professional services, particularly engineering, are among the highest-ranking occupations on an AI Occupational Impact index developed by Felten, Raj, and Seamans 2019.

[3] See `https://www.scb.se/contentassets/4d9059ef459e407ba1aa71683fcbd807/uf0301_2019a01_br_xftbr2001.pdf` for Sweden and Zolas et al. 2021 for the US.

agents making the switch restructure production around licensed software and the employment of systems integration engineers. We model this as a discrete switch from one production function to another. For both types of agents the transition entails considerable current cost and uncertain future gains. In a market where each agent acts on its own, there is no guarantee that the technology shift is synchronised between the two types of agents. Indeed, our simulations generate an S-shaped uptake of automation among manufacturers, starting with the most productive firms, while the engineering sector exhibits a boom-bust cycle of AI application development.

Our paper contributes to the literature in three major ways. First, it combines insights from the literature on cross-border technology diffusion through trade in intermediate inputs (Caselli and Coleman 2001; Francois 1990; Markusen 1989; Xu and Wang 1999) with the literature on technology adoption under uncertainty (Kyvik Nordås and Klügl 2021; Stoneman and M.-J. Kwon 1994; Stoneman and M. J. Kwon 1996; Unel 2013). We add to this literature cross-border network effects from technology adoption. These stem from cross-border knowledge diffusion in the consultancy business model and cross-border data flows in the software business model. Our analytical framework offers a rich context for studying the impact of trade, technology and skills policies in the adoption of AI-driven automation technology.

Second, we address the wide gap between AI capabilities in the laboratory and their application in manufacturing (Agrawal, Gans, and Goldfarb 2021; T. Bresnahan 2019; Zolas et al. 2021). Commanding the knowledge to create industrial applications from technology developed in labs, engineers play an important role in bridging this gap (Rock 2019). Furthermore, they typically understand client potential for benefiting from the applications better than the clients themselves. Our dynamic ABM simulates the interaction between heterogeneous engineering and manufacturing agents under imperfect and asymmetric information, tracing out the AI-adoption path in an open economy setting.

Third, our paper contributes to the literature on the interaction between trade, technology adoption and jobs. The model depicts technology-driven upheavals in the skilled labor market and traces reallocation of engineers from consultancy to software development and system integration engineering in a skills-intensive restructured manufacturing sector. The discrete shift from one production technology to another is a novelty in our paper which picks up the insights from e.g. Brynjolfsson and Hitt 2000 that complementary organizational and skills investment are needed when adopting a new technology. Our model also exhibits scarcity of engineering skills as a constraint on technology adoption in some scenarios.

Previous work on technology diffusion through trade in intermediate inputs generates productivity gains in importing firms from lower cost or better quality of inputs as well as deepening specialization (Keller 2004; Halpern, Koren, and Szeidl 2015; Sharma 2014).[4] In our model low-

[4]There is also a large body of research studying technology spillovers related to cross-border transactions where knowledge travels with traded products as a positive externality of trade (Keller 2004; Savvides and Zachariadis

cost imported intermediate inputs make the consultancy business model more attractive and thereby raises the productivity threshold for AI-adoption in manufacturing firms. An additional channel linking trade to technology adoption in our model goes through cross-border licensing of automation software. Exporting engineering agents harvest data from foreign clients, and use it for development and upgrading software, which stimulates its uptake by local manufacturing agents. Thus, imports of low-cost consultancy services delay uptake of software by local manufacturing agents, while exports of AI-enabled software lower the productivity threshold for technology adoption at home.

The literature on technology adoption considers technology as a given that can be bought from the shelf, or is embodied in machinery or intermediate inputs.[5] By explicitly modelling the role of engineers in technology adoption our paper offers additional insights. Thus, our model generates a boom and bust cycle in engineering, similar to what is commonly observed in technology sectors during periods of rapid technology changes (Doms et al. 2004), but rarely captured in models of technology adoption. Furthermore, we are able to analyse the interaction between cross-border trade, cross-border software licensing, AI-adoption and jobs, and thus explore the double whammy problem described in Baldwin and Forslid 2020.

The prominent role of engineers in technology adoption in our model also reflects a departure from the recent literature on AI and jobs (Acemoglu and D. Autor 2011; Felten, Raj, and Seamans 2019). As emphasised by T. Bresnahan 2019 and Agrawal, Gans, and Goldfarb 2021 AI rarely substitutes for workers at a task level. Furthermore, it is well documented in the literature that AI - and ICT before it - requires complementary investment in machinery, skills and often also organizational changes (D. H. Autor, Levy, and Murnane 2003; Berman, Bound, and Machin 1998; Bessen et al. 2018; Brynjolfsson, Rock, and Syverson 2019; T. F. Bresnahan, Brynjolfsson, and Hitt 2002). Such adjustment costs can be an order of magnitude larger than the initial investment in the new technology (Brynjolfsson and Hitt 2000). The labour market effect is a change in the role of engineers from consultants to software developers in engineering firms while new roles as systems integration engineers in manufacturing firms is created. For all reasonable parameter values, shortages of engineers delay the adoption of AI in manufacturing. However, depending on the parameters of the model, demand for engineers in the manufacturing-engineering supply chain may decline as software adoption levels off.

Ours is not the first paper to use an ABM for simulating technology adoption. A considerable body of literature exists analysing the diffusion of ICT and industry 4.0 in specific countries, including studying the impact of different policy interventions (Prause and Günther 2019). To the best of

2005).

[5]The seminal paper by Katz and Shapiro 1986 features a technology sponsor which promotes technology to which it has ownership. This paper is concerned with technology choice in the presence of network effects and lock-in of the technology that arbitrarily attracted early adopters. Our paper takes a different approach as we study the leap from one technology to another involving fundamental changes in the organisation of production.

our knowledge there are no published papers using ABM to analyse the interaction between trade and technology adoption, however. The methodology adds new insights on the path to universal adoption of AI-enabled automation software and the volatility of markets along that path. The model also entails policy relevant parameters related to trade costs, restrictions on cross-border data flows as well as technology switching costs, and provides a rich framework for policy analysis.

The rest of the paper is organised as follows. Section two presents the model, while its ABM implementation is described in section 3. The ABM experiments and results are presented and discussed in section 4, while section 5 concludes.

2 The model

2.1 Intuition

We propose a dynamic model consisting of two types of agents, two business models, and several countries. Manufacturing agents produce final goods according to a production function which combines a firm-specific asset and services inputs sourced from engineering agents. We distinguish two types of relationships between the engineering agents and the manufacturer agents: consultancy and software.

The consultancy model involves consultants from the engineering agents working with the client, on-site, face-to-face, to solve problems and perform a set of tasks. The problems are client-specific and the ability to solve them rests with the consultant. An engineering agent and a manufacturing agent enter a contract which specifies the tasks the consultant is to perform and the payment, which is an annual fee per consultant. In the software model, the manufacturing agent licenses software from an engineering agent and pays an annual licensing fee. Trade in services is possible in both types of relationships. In the consultancy case, engineers visit foreign clients, but may face additional costs relative to working in the home country. These include travel costs and entry costs related to complying with regulation in the other country.[6] In the software case, engineering agents licence software to foreign clients subject to an annual license fee, which may differ from the fee offered by local providers, if any. To focus on engineering and technology adoption, we assume that all agents are prices takers.[7]

Consultancy services are not standardised so each agent offers its unique variety and builds a reputation that commands a mark-up over marginal cost. This captures common features in professional services such as occupational licensing where engineers may have exclusive rights to

[6]In some countries engineers need a license to operate. In others they need to demonstrate that they have qualifications equivalent to local requirements. Standards and regulations on products and processes may be different from the home country and the engineer needs to invest time and sometimes engage a lawyer to comply with foreign regulation.

[7]Thus, we assume that the agents operate in a competitive market for inputs and outputs and engineers may find alternative employment outside the manufacturing-engineering supply chain at the going wage.

perform a predefined set of tasks and in some countries the professional body may limit the number of licenses issued and thereby create scarcity.[8] We assume that consultants gather experience from working with clients. The accumulated knowledge helps them improve services over time and to standardise and digitise the tasks performed with clients. There are thus dynamic economies of scale in the consultancy business model.

In the software business model the engineering agent establishes an R&D department where, using existing AI technology developed in labs, it develops software applications that automate services. The R&D activity requires a given number of engineers and their salaries constitute a fixed cost which the engineering agent recuperates through the licensing of the resulting software. Once developed, the software can be licensed to an unlimited number of clients at home and abroad. Furthermore, the software generates client data which the engineering agent harvests and uses for incremental improvements and updates of the software. Thus, there are both dynamic and static economies of scale in the software business model.

If client data are transferred across borders for processing and use, there may be regulatory hurdles regarding cross-border data flows. These can be related to privacy, security or data localisation requirements when the foreign country does not recognise the home country's regulations in these areas. Licensing to foreign clients may also carry additional cost of translating instructions and manuals to the local language, and adjustment of products to local technical standards.

On the client side, manufacturing agents are heterogeneous in terms of productivity. Before they enter the market they draw a productivity level from a Pareto distribution, which comes with a set of firm-specific fixed assets that do not appreciate. Switching business model from relying on external consultants to using software involves restructuring of production around the automation software and employing in-house systems integration engineers. There are network effects in the adoption of software stemming from more data generated to improve the software as well as a thicker market for client support.

The ABM model starts with drawing a random productivity level from a Pareto distribution for the manufacturing agents and allocating assets to manufacturing agents proportional to their productivity level. At the outset all agents are in the consultancy business model. The ABM next simulates the choice of business model and matches engineering consultants or software suppliers to manufacturers within and across countries in each subsequent period. At the end of each period the model updates the level of experience gathered by each consultancy agent and data gathered through software licensing and adjusts the number of surviving agents in each business model.

[8] It is beyond the scope of this study to model the pricing behaviour of engineering agents. Suffice to note that the source of market power and mark-up pricing in the engineering sector is related to engineering services being experience goods and engineering firms building a reputation for quality and licensing that restricts entry into the sector.

2.2 Formal model

2.2.1 Environment

There are two factors of production in manufacturing; intermediate engineering services and a bundle of assets which is allocated to firms in proportion to their productivity draw. The two factors are denoted L_v and S_v respectively where $v \in [h, f]$ and h and f represent the home and foreign countries respectively. For simplicity of exposition the formal model presented here has two countries while the ABM simulations also exhibits a multi-country framework. Engineers are perfectly mobile across firms and sectors within a country. Across borders they are mobile subject to trade costs as consultants, but they cannot take up employment abroad.[9]

2.2.2 Manufacturing agents

Manufacturing agents, indexed i, are heterogeneous in terms of productivity denoted θ_i, which follows a Pareto distribution. The probability density function of the Pareto distribution is given by $g(\theta) = k(\theta_{min})^k(\theta)^{-(k+1)}$ where θ_{min} is the scale parameter, which we set to unity, and k is the shape parameter, which we tentatively set to 2.2.[10] The corresponding cumulative density function is $1 - \left(\frac{\theta_{min}}{\theta}\right)^k$.

The manufacturing agents produce final output, denoted Y, using the asset factor indexed l and engineering services, indexed s. Engineering services can be provided by local or foreign consultants; or production can be automated using AI-based software, which in turn could be licensed from local suppliers or sourced from abroad. Switching to the software model is risky, and it is more risky if the vendor is foreign. We model this by adding a stochastic term to the cost function for software.

There are four possible cost functions for the manufacturing agent depending on business model and location of engineering suppliers. Total costs for the consultancy and software business models for manufacturing agent i respectively when sourcing from home are:[11]

$$TC_{i,c,hh} = \left[\frac{w_{l,h}}{\alpha} + \frac{\varphi_h w_{s,h}}{\beta_c \theta_i}\right] Y_i \tag{1}$$

$$E\left[TC_{i,softw,hh,t}\right] = \frac{A_{h,t}}{\theta_i} w_{l,h}^{1-\beta} w_{s,h}^{\beta} Y_{i,t} + \delta_h + E_i[\gamma_{i,hh}] \tag{2}$$

Total costs for the consultancy and software models respectively, when sourcing from the foreign

[9] In trade policy terms, countries are open to trade through mode 4, i.e. temporary movement of natural persons, but their labor markets are closed.

[10] This is close to empirical estimates of the shape parameter of productivity distribution from firm level data (Feenstra 2018). A shape parameter larger than 2 ensures that the variance of the distribution can be identified.

[11] The corresponding production functions for the consultancy and the software models are $Y_{i,c} = \min\{\alpha L_{i,c}, \beta_c \theta_i C_i\}$ and $Y_{i,softw} = \frac{\theta_i}{A_t} L_{i,softw}^{(1-\beta)} S_{i,sofw}^{\beta}$ respectively.

country are:

$$TC_{i,c,hf} = \left[\frac{w_{l,h}}{\alpha} + \frac{\tau\varphi_f w_{s,f}}{\beta_c\theta_i}\right] Y_i \tag{3}$$

$$E\left[TC_{i,softw,hf,t}\right] = \frac{A_{h,t}}{\theta_i} w_{l,h}^{1-\beta} w_{s,h}^{\beta} Y_{i,t} + \delta_f + E_i[\gamma_{i,hf}] \tag{4}$$

TC represents total cost of production. The two business models are indexed c and *softw* respectively. The location of the firm is indexed h for home and f for foreign. A firm located in the home country sourcing inputs from the foreign country is indexed *hf*. Time-variant variables are indexed *t*. For both business models we apply constant elasticity of substitution production- and cost functions. In the consultancy model we use the extreme case of a Leontief specification where inputs are perfect complements, while in the software model we apply the Cobb-Douglas functional form. These particular functional forms are not critical for the results, but represent two different production technologies and corresponding cost structures. They have the property that the Leontief function has the lowest costs - or equivalently produce more output with the same inputs - at low levels of productivity and high levels of the scale factor, while the Cobb-Douglas function exhibits the lowest cost for high productivity levels or a low scale factor. The cost functions are the same for manufacturing agents in the foreign country, although we allow parameter values to differ across countries (Figure 1).

Variables and parameters: α represents the L-factor intensity of production while β_c depicts the consultancy input intensity of production. Factor prices are denoted by $w_{v,l}$ and $w_{v,s}$ respectively, while the mark-up rate that engineering agents obtain for their consultancy services is φ_v. These parameters may differ across countries, depending on the income level and the strength of competition in each market. Providing engineering consultancy services in a foreign country involves trade costs, which we denote τ. The trade costs are of the iceberg type, which implies that in order to sell C units, τC units must be shipped.[12] A scale parameter $A_{v,t}$, the license fee for software, δ_v and a stochastic element γ are additional parameters in the cost function for manufacturing agents that opt for the software model. The stochastic element γ is normally distributed across firms $\gamma_i \sim \mathcal{N}(\mu_v, \sigma_v^2)$. It reflects the risk related to changing business model and we assume that this risk is higher when sourcing software from abroad than when sourcing from a local firm.

Manufacturing agents will be in the market for software if the expected cost of switching to software is lower than continuing with the consultancy model.

[12] Some of these costs, for instance recognition of qualifications, are fixed and do not depend on the volume exported. We do, however, not distinguish between fixed and variable trade costs here but lump them together into an exogenous ad-valorem equivalent trade cost.

A manufacturing agent will switch to software if:

$$\min\{TC_{i,c,hh}, TC_{i,c,hf}\} > \min\{E\left[TC_{i,softw,hh,t}\right], E\left[TC_{i,softw,hf,t}\right]\} \tag{5}$$

and will source from abroad if foreign software is cheaper, better or available before it has become available in the home market. The condition for sourcing abroad is:

$$\delta_h - \delta_f \geq E[\gamma_{i,hf}] - E[\gamma_{i,hh}] \tag{6}$$

The right hand side of the condition is mostly positive, since the risk of sourcing software abroad is higher than for sourcing software at home.[13] Thus, agents will rarely source from abroad unless foreign software suppliers charge a lower license fee or software is not available at home.

Figure 1: The four cost functions

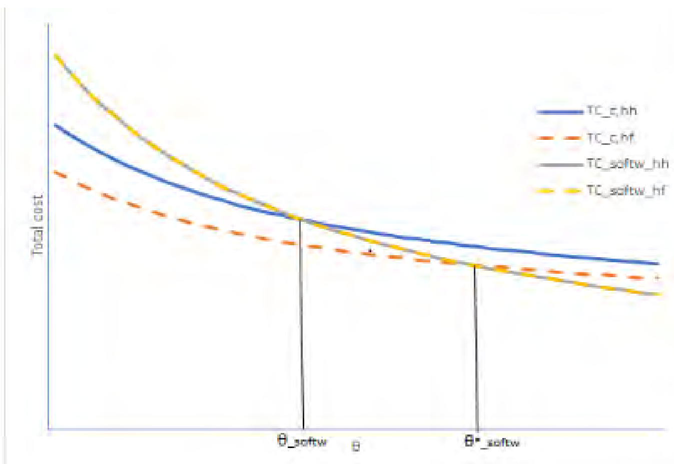


Figure 1 illustrates the case when the cost of engineering consultancy services is lower in the foreign country while the cost of software is the same in both countries. With the sourcing of lower-cost imported services, the cut-off productivity level for switching to software (θ^*_{softw}) is higher compared to a situation where no trade is possible (θ_{softw}). As opposed to Baldwin and Forslid 2020's double whammy story, trade with a low-cost country in our model makes automation less attractive and fewer agents will automate.

There are indirect network effects related to the switch to the software model as adopters on the manufacturing side benefit from a thicker market of software suppliers. The more manufacturing agents in a country adopt AI, the thicker the market for software and the more knowledge spillovers

[13]However, since the stochastic elements are independent of each other and partly overlap, there is also the possibility that for some draws, the realised stochastic cost element is higher when sourcing software at home.

across adopting agents. We capture this by modelling the scale parameter A to be a declining function of the number of firms that have switched to software with one period lag:

$$A_{h,t} = \frac{A_{h,t-1}}{(n_{softw,h,t-1} + \nu_{netw} n_{softw,f,t-1})^{\rho_{netw}}} \tag{7}$$

where $0 < \rho_{netw} < 1$. The network effect is weaker across borders, but still positive as captured by $0 < \nu_{netw} < 1$. As we will see in the simulations, the network effect plays a decisive role for the speed of technology diffusion and we therefore run extensive sensitivity simulations for the values of ρ_{netw} and ν_{netw}. Demand for engineering consultancy services from each manufacturing firm choosing that model is given by:

$$C_i = \frac{Y_i}{\beta_c \theta_i} \tag{8}$$

Manufacturing agents source consultancy services from home if $\varphi_h w_{sh} < \tau \varphi_f w_{sf}$ and from abroad if $\varphi_h w_{sh} > \tau \varphi_f w_{sf}$ and randomly from home or abroad if $\varphi_h w_{sh} = \tau \varphi_f w_{sf}$ as long as there are consultants available in the respective country. Thus, agents will import consultancy services if the trade costs are compensated by foreign suppliers having lower wages or mark-ups (or both). Manufacturing agents that have switched to the software model in country v will seek to employ engineers according to the demand function:

$$S_i = \frac{A_t}{\theta_i} \left[\frac{\beta}{1-\beta} \frac{w_l}{w_s} \right]^{(1-\beta)} Y_i \tag{9}$$

2.2.3 Engineering agents

Engineering agents, indexed over j hire engineers which are deployed to client firms on a contractual basis in the consultancy business model. The contract covers one period and its value varies across clients, depending on their size and productivity as indicated in equation 8. The engineering agents may sell to clients at home and abroad. All their costs are in terms of wages. Each engineering agent offers a customised service and charge clients a mark-up factor of $\varphi > 1$, which may differ across countries. The consultancy revenue is thus $\varphi_h w_{s,h} \sum C_{i,h} + \frac{\varphi_f}{\tau} w_{s,h} \sum C_{i,f}$. We choose units such that one unit of consultancy services corresponds to the input of one full-time consultant for one period, and $C_{i,f}$ represents units shipped. Engineering agents in the consultancy business model hire engineers before they enter contracts with manufacturers. At the point of hiring engineers, expected profits are:

$$E[\pi_{c,j}] = (\varphi_h - 1) w_{s,h} \sum E[C_{i,h}] + \left(\frac{\varphi_f}{\tau} - 1 \right) w_{s,h} \sum E[C_{i,f}] \tag{10}$$

Clearly, engineering firms will export consultancy services only if the mark-up factor in the foreign market is larger than the trade cost factor, i.e., $\varphi_f > \tau$.

Experience, denoted λ, accumulates from working on-site and face-to-face with manufacturing clients. Furthermore, engineers gain more experience from working with the most productive manufacturers. An engineering agent j's accumulated experience is thus a function of the productivity of the most productive manufacturer it has worked with in the previous period. Hence, more productive customers are also more demanding and offer more challenges and learning through the co-creation of solutions.

$$\lambda_{j,t} = \lambda_{j,t-1} max[\theta_{i,j}]^{\eta} \tag{11}$$

In the software model, engineering agents establish an R&D department and divert S_F/λ engineers to staff it. S_F corresponds to a minimum number of inexperienced engineers needed to successfully develop automation software, i.e. a fixed cost, while λ_t captures experience from working with clients. Thus, a smaller team of experienced engineers can obtain the same result as a larger team of inexperienced engineers. The total cost of switching for the engineering agent is the wage costs for the engineers working in the R&D department and the foregone profits from no longer deploying them to clients as consultants. Revenue in the software model will be the licence fee δ_v times the number of local and foreign manufacturers that license the software from agent j; $n_{softw,j,v}\delta_v$. Expected profits from the software model is thus:

$$E_t[\pi_{softw,j,h,t}] = E_t[n_{softw,j,h,t}]\delta_h + E_t[n_{softw,j,f,t}]\delta_f - \frac{w_{s,j} S_F}{\lambda_{j,t}} \overline{\varphi} \tag{12}$$

where $\overline{\varphi}$ is the average of the mark-up factor on sales at home and abroad. The engineering agent knows the cost of developing software, but at the point of deciding whether to develop it, the number of clients that will take up the software is unknown. The engineering agent does, however observe the productivity of the manufacturing agents and thus can estimate how many of them are sufficiently productive to gain from switching to software. For simplicity, there is no discounting in the model (i.e. the discount factor is one). It is clear from equation 12 that profits from switching to the software model is lower the higher the mark-up factor φ, predicting that engineering agents operating in a less competitive market, for instance a market with occupational licensing, are less innovative than firms operating in a competitive market which limits the ability to charge a high price. Engineering agents will switch to software if $E_t[\pi_{softw,j,h,t} > 0]$

The engineering agents' R&D department use available AI-based platforms and data sets together with customer data, applying machine learning (ML) to create software applications that accomplish the functions previously offered through consultancy. After successfully licensing the software, the engineering agent harvest data from customers, which helps the agent maintain, update and improve the software. AI-enabled automation software depreciates fast, and we assume that it lasts T periods. Each period between its development and obsolescence a fraction ζ of the number of engineers required to develop the software is needed to maintain it. However, engineering agents benefits from harvesting data from software using clients and the fraction is adjusted as follows:

$$\zeta_{j,h,t} = \frac{\zeta_{j,h,t-1}}{(n_{softw,j,h,t-1} + \nu_{data} n_{softw,j,f,t-1})^{\rho_{data}}} \tag{13}$$

where $0 < \nu_{data} < 1$, $0 < \rho_{data} < 1$. Note that we allow for the possibility that data extracted from foreign customers is less valuable, for instance because of restrictions on cross-border data flows.

Demand for engineers is given by:

$$S_{d,h,t} = \sum_{i,c,h} S_{i,h} + \sum_{i,c,f} S_{i,f} + \sum_{j,softw,new,h} \frac{S_F}{\lambda_{j,t}} + \sum_{j,softw,maint,h} \zeta_{j,h,t} \frac{S_F}{\lambda_{j,t}} + \sum_{i,softw} S_{i,h} \tag{14}$$

The first term represents consultants deployed to local manufacturers, the second term deployment of consultants to foreign manufacturers, the third employment in R&D developing software, the fourth employment in maintaining software and the fifth direct employment at manufacturing agents that have switched to the software business model (equation 9). Supply is exogenously given by S_v.

These 14 equations, representing supply and demand for engineering services in two business models, constitute the conceptual core of the ABM. The forces that drive the adoption of software are engineers' accumulated experience from working with clients and network effects from its adoption. What holds back the development of software is comfortable profits from the consultancy model on the part of the engineering agents, uncertainty about how many manufacturers will buy the software once the cost of developing it is sunk, and uncertainty about the gains from the switch to software on the part of manufacturing agents. These countervailing forces ensure a gradual adoption of software in the economy. The speed depends on the size of the economy, the endowment of productive assets and engineers, the level and dispersion of productivity among manufacturing agents as well as policy-induced factors including occupational licensing affecting the mark-up, protection of intellectual property rights affecting the license fee, and restrictions on cross-border data flows.

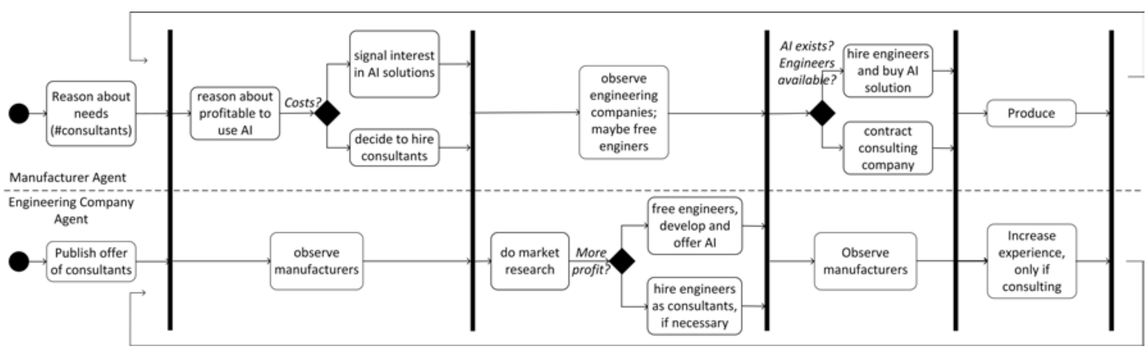
3 The ABM setup

Translating this abstract model into an agent-based simulation requires to change the model's perspective from a top-down view to the perspective of the participating engineering and manufacturing agents. Simulated individual actors make decisions which have an impact on others' decisions and on the overall outcome. An actor can just take decisions based on available information and expectations generated from that information. Thus, a particular challenge is the timing and sequencing of the decision making processes on the agent level. Decisions need to be rolled out in a synchronized and coordinated way. This involves additional assumptions to be explained and justified in the following subsections.

For implementation, the simulation platform *SeSAm*[14] was used due to its support for complex agent decision process modeling, providing a visual programming interface for agent behavior. One of the features of SeSAm that may impact on model implementation outcome concerns the particular design of the virtual parallelism for agent update: during one simulated time step, all agents are individually updated in a random sequence. Thus, the modeler cannot determine which of the agents is updated first. Update is complete, that means that agent actions have immediate effect on its environment. For example, a manufacturing agent hires engineers. Those engineers are then not available for being hired by other subsequently updated agents. That means the agents that are by chance updated first, may acquire resources, those who are updated last, may find no available resources left.

Figure 2 illustrates the coordinated sequence of decision making of manufacturing and engineering agents.

Figure 2: Decision making process of the simulated agents



The full cycle as given in Figure 2 corresponds to one simulation cycle, or "year". Decisions of manufacturing agents and engineering agents need to be synchronized, which is expressed by the black vertical lines in the figure: all agents can only continue with their decision making process, if all other agents have reached a synchronization bar.

While rolling out the formal model given above, certain details about the decision making processes had to be assumed. These additional assumptions are discussed in the following.

[14]www.simsesam.org

3.1 Assumptions in the decision making of engineering firm agents

Engineering agents either offer consultancy services or software, never both. The consultancy model hereby means that the agent offers the service of all its employed engineers. The manufacturers select an engineering agent to contract for as many engineers as necessary or possible. An engineering agent doing consulting may have too few engineers left to fulfill the demand of the manufacturer. If there are available engineers on the labour market, the engineering agent hires as many as possible to be able to send the demanded number of consultants.

It may happen that an engineering agent does not receive contracts that would cover all of its employed engineers. In such cases engineers are not immediately laid off, but kept on board until the agent decides to develop software, even if that implies making a temporary loss. If an engineering agent makes a loss with software, it returns to its old way of doing business. This is a way of modelling exit due to bankruptcy and entry of new engineering agents while keeping the number of agents constant.

Before engineering agents decide whether to switch to software, manufacturing agents assess whether they would gain from using software. The engineering agent is – due to some market research – able to count the number of potential software clients in each country in which it plans to sell the software. For each country, the agent draws a random market share up to m, the maximum market share and uses this as expected number of manufacturers that may license the company's software $n_{softw,j,v}$ in formula 12.

3.2 Assumptions in the decision making of manufacturing agents

When contracting for consultancy services, a manufacturing agent selects one engineering agent to fulfill its demand as much as possible using the following precedence order:

1. select the *cheapest* offer from all engineering companies who can fulfill the full demand.

2. select the engineering company who can provide the *highest* number of engineers after hiring more engineers.

As a consequence, a manufacturing agent would accept a higher price rather than to contract a lower number of consultants. Not managing to contract enough consultants results in adapting the number of assets that can be used during production and as a consequence lowering output. If a manufacturer is not able to contract any consultants, it does not produce anything in this year. We do not assume that manufacturers leave the market, but simply try to setup production again in the next cycle.

A manufacturer, who decided to license software and learnt that software is actually available for licensing, tries to recruit systems integration engineers to support its usage. This recruitment can only be done on the domestic labour market. If this is not possible because the full number of necessary engineers is not available, the manufacturing agent turns to consultancy as a fall back solution. If recruitment is successful, the manufacturing agent actually selects software randomly weighted with the suppliers experience λ among domestic appliers and foreign suppliers fulfilling equation 6.

When a manufacturing agent buys software, the switching costs (γ) are drawn from a normal distribution. The parameter of the distribution depends on in which region the manufacturing agent and the engineering agent are located.

Manufacturing agents re-decide every year whether and from which supplier to license software or use consultancy services. As a consequence, software may licensed from different suppliers every year.

3.3 Specification of the baseline parameter settings

Table 1 summarizes all parameters and their values in the baseline setting. Sensitivity analysis was performed for all parameters, particularly interesting results are found in the appendix,

Table 1: Exogenous variables and parameters, baseline symmetric case

Symbol	Parameter	Value in the baseline case
	Number of countries	2
	Number of manufacturers per country	100
	Number of engineering companies per country	30
L	Units of assets per country	3000
S	Number of engineers per country	1000
w_l	unit cost, assets	1
w_s	salary, engineer	1.5
α	asset intensity, manufacturing, consultancy model	1
β_c	consultant intensity, manufacturing, consultancy model	1.5
β	engineer intensity, manufacturing, software model	0.2
θ_i	productivity level, manufacturing firm i	Pareto distributed
A_0	scale parameter, manufacturing, software model	3
ρ_{netw}	strength of network effects using software	0.007
ν_{netw}	border impact on network effects of using software	0.5
ρ_{data}	strength of data collection effects from licensing software	0.007
ν_{data}	border impact on data collection from software	0.5
δ	license fee, software	10
γ	stochastic switching cost, manufacturing	normally distributed
μ	mean, normal distribution, risk of switching to software	1
λ_0	initial experience, engineers	1
η	update factor for λ	0.1
m	max when estimating future market share	0.4
φ_h	mark-up rate, consultancy	1.3
φ_f	mark-up rate, consultancy to foreign country	1.3
S_F	number of engineers needed to develop software	18
ζ	Software maintenance cost relative to development cost	0.5
T_0	lifespan of software, years	5
τ	Iceberg trade costs consultancy services	1.0

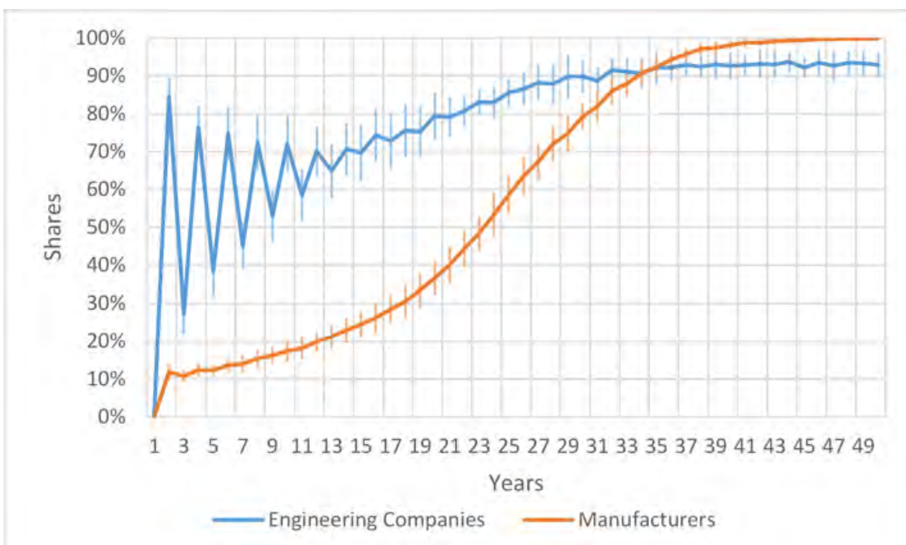
4 Experiments and Results

Each experiment is repeated 30 times. Diagrams show the average value over those 30 repetitions and the standard variation over the 30 runs. In the initial cycle, all agents apply the consultancy business model. At the end of the first cycle, engineering agents decide whether to develop software and manufacturing agents decide whether to switch to automation software. We start by analysing the uptake of software in an integrated world economy as a benchmark. We next introduce international borders across which services can be traded and software can be licensed, while engineers cannot take up employment abroad.

4.1 Technology uptake in an integrated economy

Before discussing scenarios that deal with trade, we study the general dynamics of the model in one integrated world economy endowed with 6000 units of productive assets, 2000 engineers, 60 engineering firms and 200 manufacturing firms. The parameters of the experiment are given in Table 1. The simulated uptake of software is depicted in Figure 3.

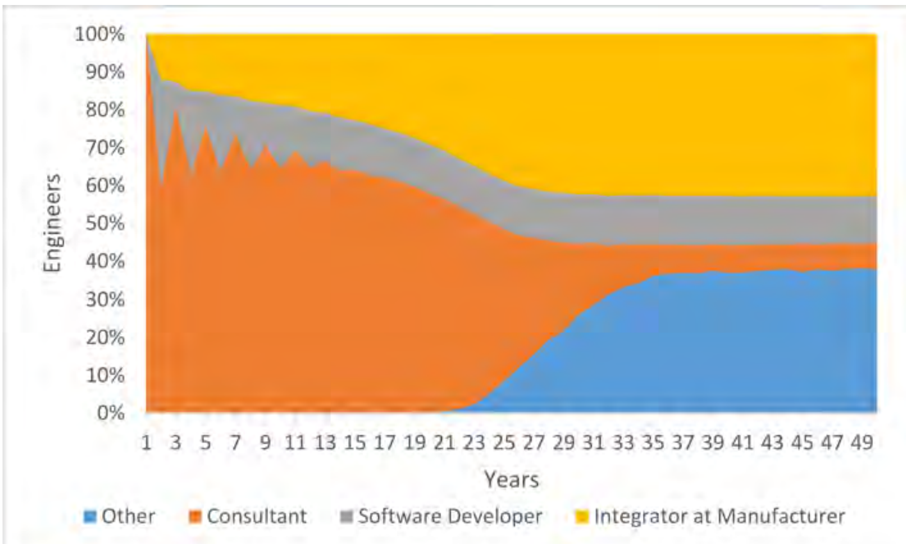
Figure 3: Percentage of companies having switched to software automation



We first observe that the uptake of software in manufacturing is S-shaped, corresponding to previous studies on the uptake of technology over time (Gort and Klepper 1982; Hall and Khan 2003; Kyvik Nordås and Klügl 2021). The adoption path starts with the most productive manufacturing agents switching to software automation. As network effects kick in and reduce the cost of switching, more firms make the leap and after 39 years 99% of the manufacturing agents have switched.

The engineering agents' change of business model follows a boom and bust cycle. Having observed the potential market for software, engineers form expectations about profit.[15] However, many fail to find customers the first year and revert to consultancy and try to enter the software market again in later periods until most engineering agents have transformed themselves to automation software providers and maintainers. Our model thus reflects a similar boom-bust cycle as for instance observed during the dot.com bubble in the 1990s (Doms et al. 2004).

Figure 4: Dynamics of allocation of engineers



The uptake of AI is associated with a drastic upheaval in the jobs market for engineers as reported in Figure 4. At the outset all engineers are employed as consultants with engineering agents. Over time, engineering agents reinvent themselves as automation software developers and the engineers change jobs from consultants to software developers, while some of those leaving the engineering agents find jobs in the manufacturing firms that have switched technology and need in-house systems integration engineers to manage the new production process. In our baseline scenario, shortage of engineers delays the uptake of software in some manufacturing agents in the early periods. Furthermore, during the first technology hype, a few manufacturers also have difficulties finding consultants and must temporarily halt production. As the transition progresses, however, shortages turn to abundance, and some engineers exit to other sectors.[16] The job dynamics

[15]Recall that engineering firms observe the productivity of manufacturers and therefore know how many firms could be ready to switch. However, there is a stochastic element to manufacturers' switching cost. We capture engineering firms expectations about their share of the software market by assigning a random number between zero and 0.4 in the baseline scenario. Sensitivity analyses show that a lower share dampens the boom-bust cycle and a higher share amplifies it, but the boom-bust cycle remains for all max market shares. See appendix Figure 15.

[16]As noted, all agents are price-takers in our model, which reflects a market outside our setting which absorbs

is sensitive to the value of β. Our baseline value reflect the employment share of engineers and other technical professionals and mangers in manufacturing agents according to Eurostat. It is, however, quite possible that β could be higher in more high-technology manufacturers and that the parameter might increase over time. Sensitivity to the value of β is presented in the appendix. Indeed the software uptake curve is flatter the higher is β (see Figure 13).

The sensitivity of the simulations to key parameter values is illustrated in the next charts. We first tested different values for φ and δ, which relate to the cost facing manufacturing agents in the two business models. Figure 5 a) and b) show a scan through different values of φ, while keeping $\delta = 10$. As predicted by comparing equations 1 and 2, the cost advantage of software is higher the higher the mark-up rate. Thus, when contracting engineers as consultants, manufacturers pay a mark-up over their wages, while when employing engineers in the new function as systems integration engineers, they pay the going wage. With the highest mark-up rate (2.5), it takes only 13 years for 99% of the manufacturing agents to switch to software, while with a mark-up rate of 1.1, it takes as much as 47 years to reach a 99% uptake. It is also notable that the volatility of the software market is higher in the first years and stabilizes earlier the higher is the mark-up rate. The mark-up rate reflects the strength of competition in the engineering sector, including barriers to competition stemming from occupational licensing. Our results thus suggest that when the uptake of AI is driven from the manufacturing demand side, occupational licensing accelerates the uptake of AI. Trade also introduces more competition and put downward pressure on the mark-up rate. Trade would in such cases raise the cut-off productivity level for switching to software and hence delay technology adoption.[17]

Figure 5, c) and d) show a scan through different δ values while keeping $\varphi = 1.3$. Obviously, all else equal the cost advantage of software is smaller the higher is δ. When the license fee is 5, it takes 37 years before 99% of manufacturers have switched to software. If the fee increases to 10, it takes 39 years. Beyond that, it takes more than 50 years and thus beyond the time horizon for the simulations. Engineering agents would be keen to develop software if they could charge a high license fee, but they also realize that the market will be smaller the higher the fee. Therefore, volatility in the software market is smaller the higher the license fee. The license fee reflects the level of competition in the software market including protection of intellectual property rights. Strong protection of intellectual property rights which allows engineering agents to charge a high license fee slows down the uptake of AI in our simulations where the adoption rate is determined from the demand side.

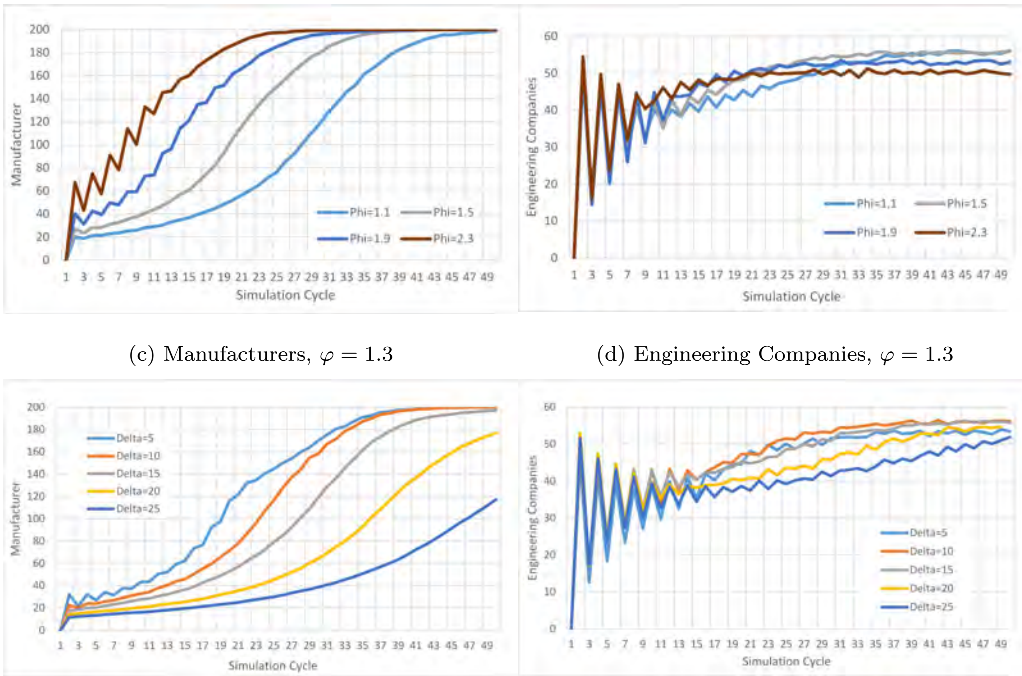
Figure 6 shows the combined effect of of scanning the values for φ consultancy markup costs and δ software licence fee.

The network effect of switching to the software model is an important driver of the simulation

idle engineers.

[17]The mark-up rate is exogenous in our model and this effect is not captured as an endogenous outcome in the simulations.

Figure 5: Scanning δ and φ



(a) Manufacturers, $\delta = 10$

(b) Engineering Companies, $\delta = 10$

(c) Manufacturers, $\varphi = 1.3$

(d) Engineering Companies, $\varphi = 1.3$

results. Figure 7 shows a scan through different values of ρ on both sides of the baseline value. Clearly, the uptake of software is slower the weaker the network effects, and the results are highly sensitive to the strength of the network effects.

The amplitude of the boom-bust cycle of the software market is also sensitive to the fixed cost of developing software, S_F, and the maximum expected market share of the engineering agents, m. The volatility is higher the smaller is S_F and the higher is m. See the appendix for details.

4.2 Baseline: Identical countries, no trade costs

In this section the integrated world economy analysed in the previous section is split into identical countries. Engineering services and software are freely traded, but engineers can only seek employment in their home country. In the baseline scenario with two countries this does not change the uptake paths of software in manufacturing and engineering much. It takes two more years for 99% of all manufacturing agents to switch to software, which is due to the reduced network effects of software adopted abroad. Qualitatively, the adoption paths and employment effects are the same as for one integrated world economy. About half of consultancy services as well as software are

Figure 6: Number of years before 99% of manufacturers have switched technology

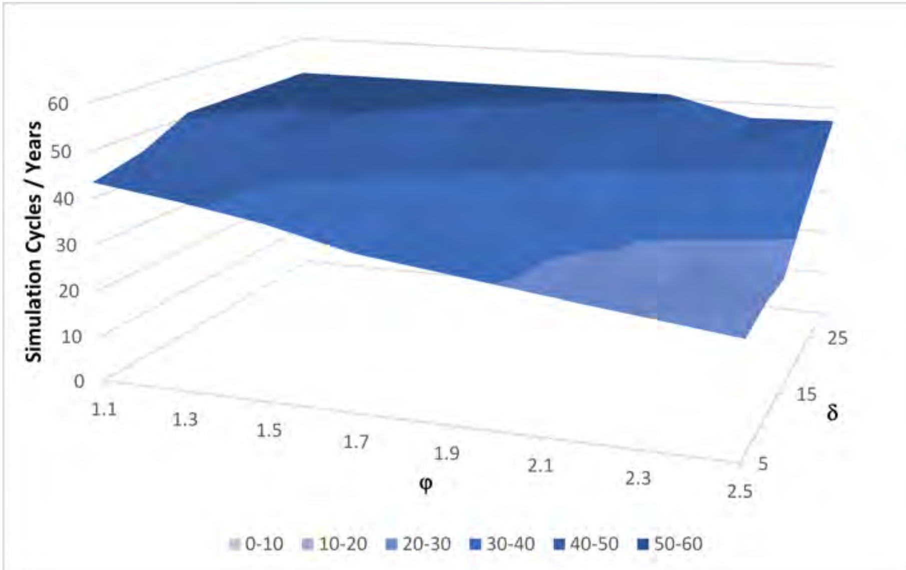
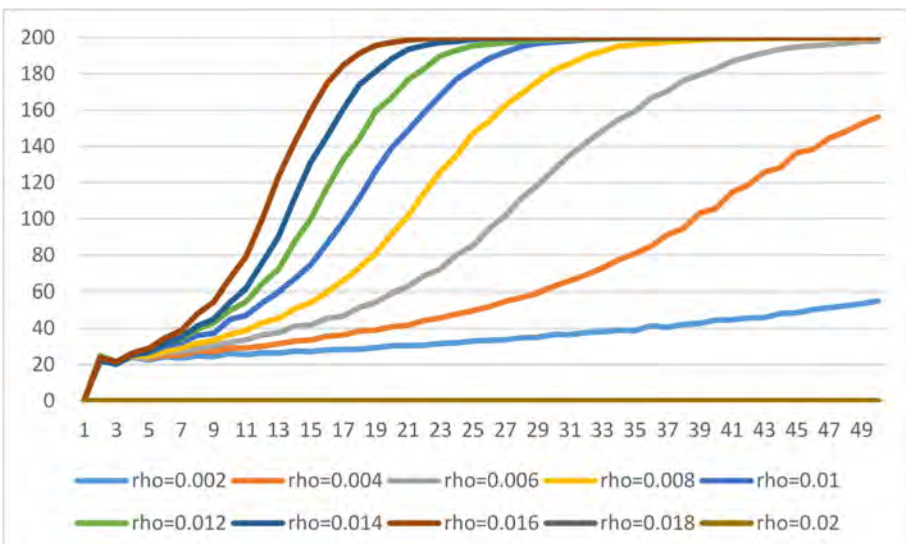


Figure 7: Technology uptake by manufacturers ρ_N settings



sourced from abroad as one would expect when there are no trade costs.

The most significant difference between an integrated world economy and individual countries is the network effect, which is weaker across borders than inside a single country (see equation 7). To study the interaction between market fragmentation, cross-border spillover effects and uptake of software, we ran simulations with different values of ν first for two identical countries, next four identical countries and finally eight identical countries. The combined size of the identical countries is always the same as the integrated world economy simulated in the previous section. The share of manufacturers having adopted software halfway through the simulations - after 25 years - are reported in Table 2. Clearly, fragmented markets slow down technology adoption. Since the network effect is stronger the larger the home market relative to all foreign markets, small countries lose out when markets are fragmented. Conversely, policies aiming at market integration would substantially speed up the adoption of automation technology in manufacturing.

Table 2: Share of manufactures adopting automation after 25 years

ν_{netw}	2 countries	4 countries	8 countries
0.2	42	32	28
0.4	44	39	36
0.6	49	45	42
0.8	54	52	50
1.0	58	56	53

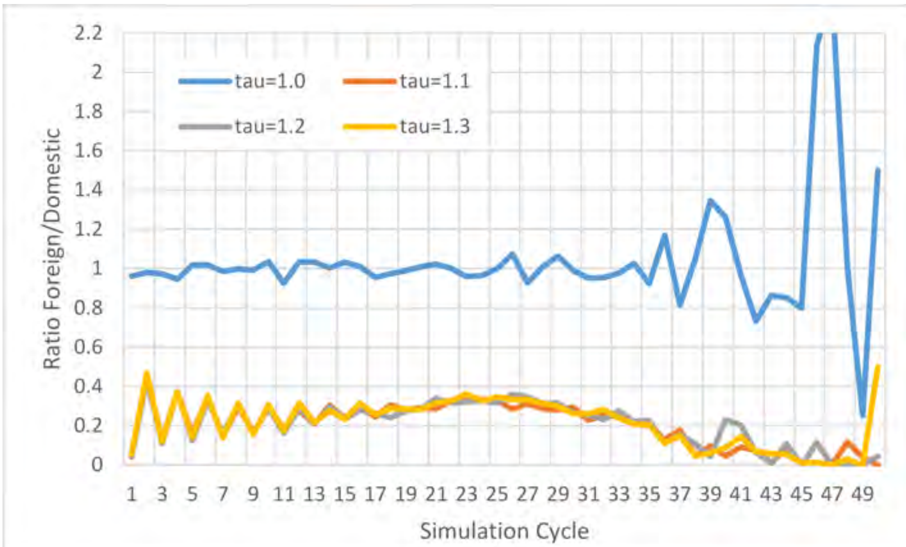
Policy measures that could raise the network effect could be common standards such that experience gathered in one country would be directly relevant in another country.

4.3 Identical countries with trade costs

This section presents simulations of different values of the iceberg trade costs τ for two identical countries and baseline parameters. As evident from equation 10, trade costs exceeding the markup rate will be prohibitive and no trade will take place when $\tau > \varphi_f$. Further, the technology switch decision is based on the minimum of production cost from sourcing from home or from abroad. With identical countries and trade costs, production costs are always lowest when sourcing from home (equation 5), and one would not expect to see trade in consultancy services at all. However, due to the dynamics of agent interaction and the sequencing of decisions, we observe trade in consultancy services even in this scenario. Trade happens when manufacturers remaining with the consultancy model cannot find a local consultancy firm with sufficient capacity. The Leontief production function implies that demand for consultants is fixed by the firm's asset and productivity level, and by assumption the consultancy contract cannot be split between several engineering agents. During technology booms on the engineering side at home, local manufacturers may fail to find local consultancy firms with sufficient capacity and source from abroad instead.

As can be seen in Figure 8, when $\tau = 1$, the sourcing of local and foreign consultants is arbitrary and the ratio of imports to local sources is around one. Towards the end of the simulation period, when 99% of manufacturers have already adopted software, the remaining consultants are few and not always available locally. Hence the wide swings towards the end of the cycle. For trade costs between 1 and 1.3, local suppliers are always preferred, but not always available and the foreign share is relatively low, but positive.

Figure 8: Ratio between manufacturers using foreign consultants and using domestic consultants.



4.4 Trade between countries at different wage levels

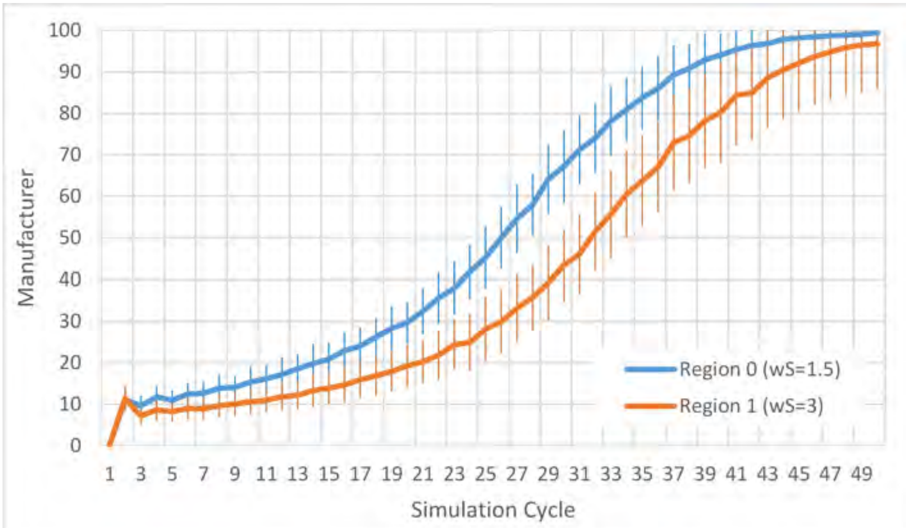
This section explores the interaction between trade and technology adoption when the countries have different wages for engineers. We run the simulations for $w_{s,f} = 1.5$ and $w_{s,h} = 3$. To focus on the impact of income differences, there are no trade costs in this simulation.[18] Figure 9 shows technology uptake in manufacturing in the two countries.

As predicted in Figure 1, and equation 5 the cut-off productivity level for switching to software is higher in the high-wage country and technology uptake is consequently slower than in the low-wage country. The high-wage country stays with the consultancy model for longer for two reasons. First, the cost advantage of consultancy is larger because the country has access to low-wage consultants from abroad. Second, the cost disadvantage of switching to software is larger because manufacturers must pay the higher wages of local systems integration engineers in the software scenario. In the low-wage country in contrast, the cost advantage of software stems from higher costs of imported consultancy services, and lower cost of employed systems integration engineers.

Reallocation of engineers across industries and functions is portrayed in Figure 10. Consistent with the technology uptake pattern and manufacturing demand for systems integration engineers, the employment of engineers in manufacturing picks up more quickly and stabilizes at a higher level

[18]Simulations with trade costs show a similar pattern for the key variables of interest.

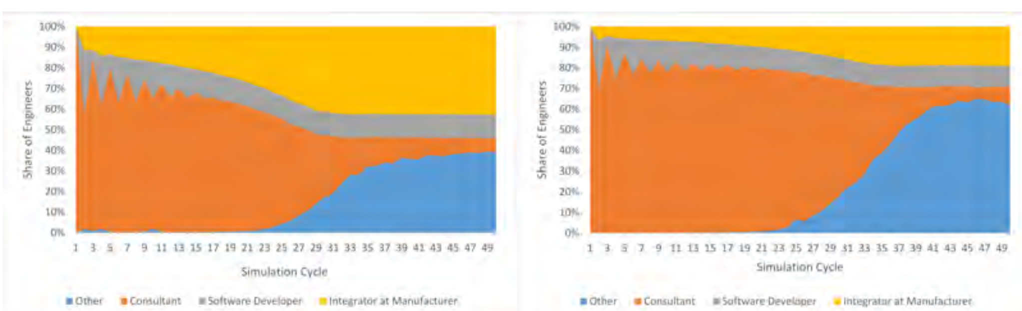
Figure 9: Technology uptake trade in countries of different w_s.



in the low-wage country. In the high-wage country, employment as consultants remain high until most manufacturing firms have switched to software. The lower employment of systems engineers in manufacturing stems from equation 9, implying that demand for engineers are lower the higher their wages.

Figure 10: Employment countries of different w_s

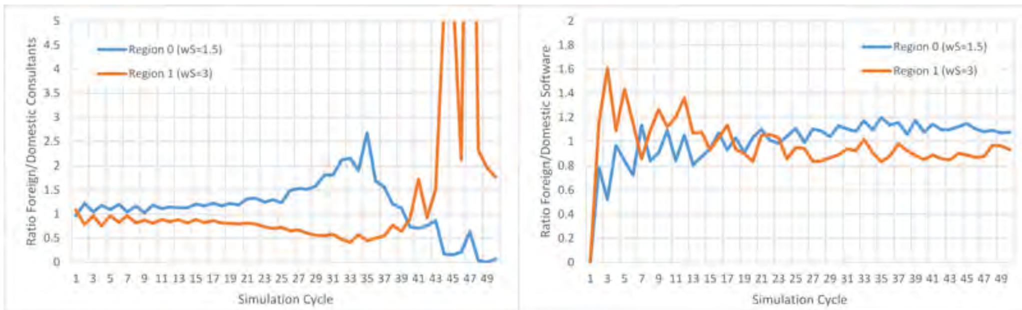
(a) $w_s = 1.5$ (b) $w_s = 3$



Trade between the two countries are depicted in Figure 11. The ratio of foreign to local suppliers of consultancy services is depicted in panel a) while the ratio of local to foreign software suppliers is reported in panel b). We first notice that trade is prevalent during the entire transition period as the ratio is close to one for both the high-wage and low-wage country. Moreover, the ratio is above one in the low-wage region and below one in the high-wage region, which is counter-intuitive

Figure 11: Trade flow of consultants and software

(a) Ratio foreign/domestic consultants (b) Ratio foreign/domestic software



at first sight. The explanation is grounded in the ABM decision making process. The agents take the decision to switch to software independently based on equation 5, where the left-hand side is the same for firms in the two countries, while the right-hand side is larger in the high-wage country. Therefore, the low-wage country will shift to software earlier than the high-wage country, and in the process engineers move out of consultancy and into software development and systems integration in manufacturing. The supply of consultants in the low-wage country goes down substantially as a consequence. The manufacturers still in the consultancy model will compete for the remaining consultants in both countries. They all prefer the low-cost consultants, but they also prefer high-cost consultants to closing down. Given this, the matching of consultants to manufacturers is random. Since there are more consultants in the high-wage country, the foreign to local ratio is higher in the low-wage country.

Cross-border licensing in software runs from the low-wage country to the high-wage country in the early phase of the adoption trajectory since the low-wage country switches to software earlier than the high-wage country. The head-start in technology adoption is reinforced through the harvesting of data from the foreign software clients. The license fee is assumed to be the same at home and abroad and the ratio of local to foreign licensing fluctuates around one for both countries as the uptake of software progresses.

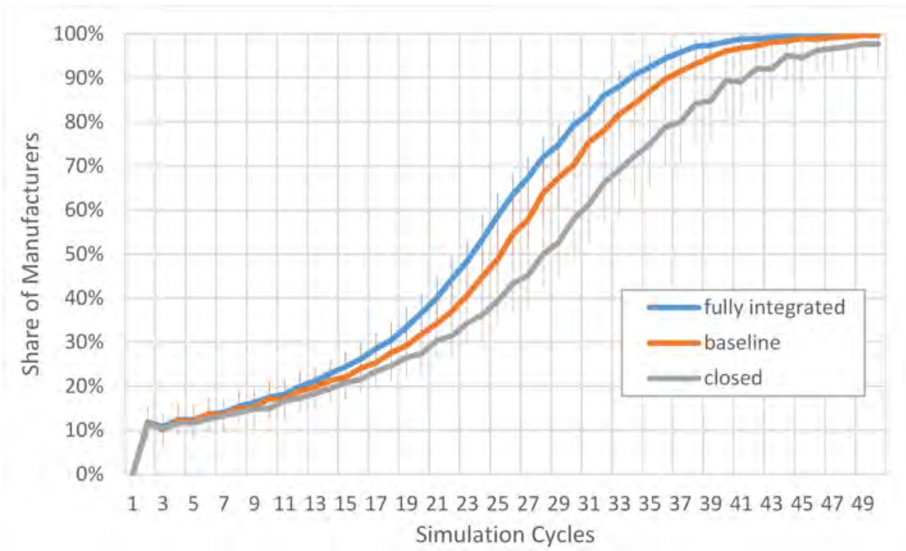
The trade scenario may seem counter-intuitive for trade economists. It does, however resonates with some recent trends. For instance, China was until 2019 a net importer of other business services from the US, while it has taken the lead in AI development and adoption in some fields.[19]

[19] See WTO BATIS database for trade data. Services trade data are available at a rather aggregated level. Engineering services are part of the aggregate "other business services". See Zhang et al. 2021 for a description of advances in AI.

4.5 Technology uptake in a closed economy

In this section the world economy is divided into two symmetric countries. They are the same as those explored in Section 4.2, but here services are not traded at all.[20] Comparing the simulations in this section to those in section 4.1 amounts to comparing an integrated world economy with autarky. We also compare to the free trade scenario with two symmetric countries of the same size as the closed economy studied here.

Figure 12: Technology uptake in closed economy



The first thing to notice is that software uptake is much slower in the closed economy than in the economy of similar size but open to trade, while the fastest uptake is in the integrated world economy. While about 60% of manufacturers had switched to software after 25 years in the integrated economy scenario, half had done so in the free trade with two identical countries while only 39% had switched after 25 years in the closed economy. The main explanation for the slower uptake is the lack of network effects from foreign technology adoption.

5 Conclusion

This paper has analysed the interaction between engineers and manufacturers in the adoption of AI-enabled automation software using an ABM model. The model draws on insights from international trade theory, the theory of technology adoption and qualitative information on the role

[20]Trade in engineering services and automation software could for instance be blocked by nationality requirement and residence requirement for engineers, and prohibition of cross-border data flows.

of engineering in bringing AI from the laboratory to industrial applications. The ABM's bottom-up approach where multiple agents take decisions independently and based on imperfect information generates new insights. Four predictions stand out as novel. First, the simulations depict scenarios with an S-shaped technology adoption path, with only the most productive manufacturing agents adopting the software in the early stages. Second, the supply of automation software follows a boom-bust cycle, replicating market volatility during rapid technical change as observed for instance during the dot.com bubble. Third, trade with low-wage countries delays technology adoption in high-wage countries. High and low wage countries could represent emerging versus rich countries - or countries with occupational licensing versus countries with unregulated professions. Fourth, low-wage countries adopt AI-enabled automation technology earlier than high-wage countries, while exporting automation software and importing engineering services - replicating trade and technology adoption patterns observed in recent years between China and major OECD countries.

A scenario presented in recent literature is one where professionals face a double whammy from automation and competition from highly skilled workers working remotely from low-wage countries. So far, the double whammy scenario has not materialized for engineers. To the contrary AI-adoption has been slow and engineering - and professional services in general - have boasted the fastest job growth among occupations despite rising exposure to import competition. However, our model does predict abundance of engineers after about two decades when AI-enabled software is widely adopted in the baseline scenario.

Our paper offers a rich framework for policy analyzes in the areas of professional licensing and mutual recognition of qualifications, intellectual property rights in an international trade context and restrictions on cross-border data flows as well as data localization requirements. For such policy analysis the parameters of the model can be calibrated to specific countries.

Limitations of our analysis are first, the setup has a fixed number of agents. This prevents scale economies to be fully exploited in the software sector and we cannot study a scenario where one or a few software firms become dominant. We believe that this is less of a problem in the market for automation software for manufacturing than it is in consumer-oriented software. The market for automation software is quite specialized with many suppliers. Nevertheless, more work is needed to introduce endogenous entry and exit of agents to further explore the dynamics of technology adoption. Second, our work offers numerical simulations based on a theoretical framework which we believe captures the essence of AI-enabled automation software adoption as a process driven by joint but independent actions by engineers and manufacturers. Nevertheless, more work based on in-depth case studies and interviews with decision makers about the drivers in the adoption process and their roles will inform future work in this area.

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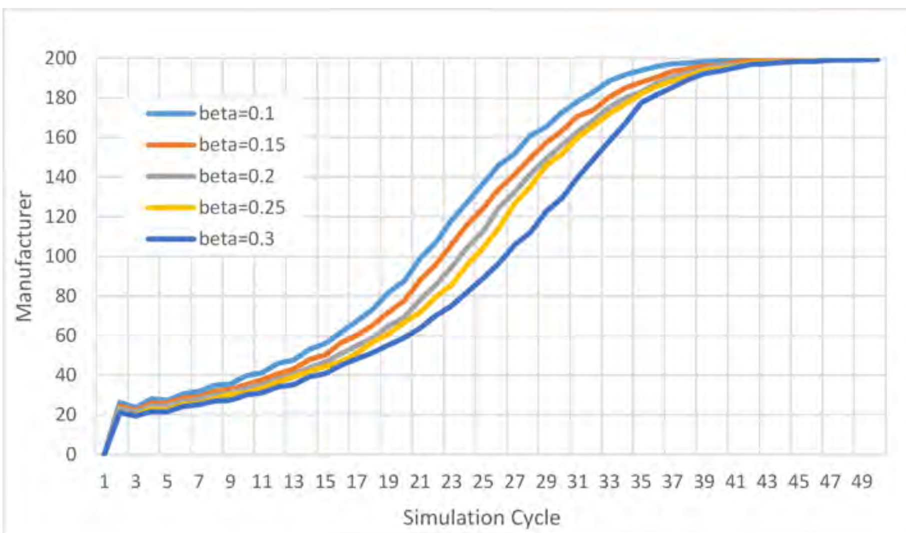
A Appendix: Sensitivity Experiments

A.1 Intensity of engineer employment in manufacturing, software business model

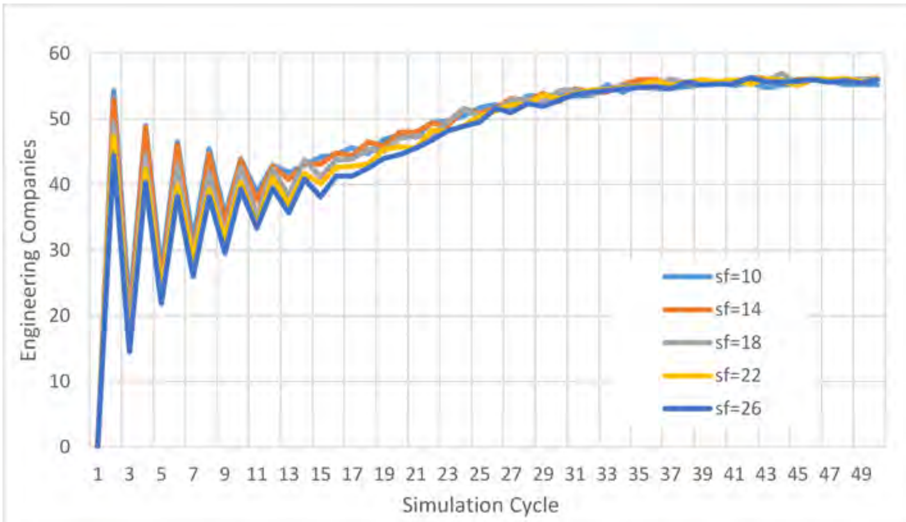
Figure 13: Technology uptake in manufacturing, sensitivity to the value of β.



The value of β represents the intensity of systems integration engineer employment in manufacturing in the software business model. The higher it is, the higher the relative costs of the software business model. The impact comes from the direct costs of using software depicted in equations 2 and 4 and the corresponding demand for systems integration engineers in equation 9.

A.2 The fixed costs of developing AI-enabled automation software

Figure 14: Software development in engineering, sensitivity to the value of S_F



The fixed cost of developing software S_F is an important factor for engineering agents to switch to software development. The lower it is, the more engineering agents will develop software. However, since number of engineering agents offering software does not influence the decision of the software users, i.e. the manufacturing agents, the volatility of the software market is higher the lower is S_F. The fixed costs have an impact on the path of software developing engineering agents, but not the endpoint which is full adoption by all agents.

A.3 Software developers' max expected market share

In the ABM implementation of the model, engineering agents have expectation about the market share they could take. This is a random number with an exogenous ceiling, m. The higher the ceiling, the more volatile the software market. If the ceiling is as low as 10%, the boom and bust cycle is quite muted.

Figure 15: Software development in engineering, sensitivity to expected market share