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The Impact of AI on the Labour Market

Essays on Transformative Technology, Occupations, and Firms

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Abstract

The topic of this thesis is the economics of transformative technology, with the impact of artificial intelligence (AI) on the labour market as the primary focus.

Analysing German data, Essay I shows that occupational AI exposure was associated with wage gains, and an increased focus on knowledge-intensive tasks. There is a clear contrast between the types of work that are exposed to AI, versus robotics.

Essay II finds that AI exposure is associated with AI adoption and increased labour demand, as measured by job vacancy postings, in Swedish establishments/workplaces.

Essay III develops a novel measure of occupational AI exposure, called Dynamic AI Occupational Exposure (DAIOE). AI exposure is shown to be associated with upskilling at the firm level in Sweden, Denmark, and Portugal.

Essay IV analyses the labour market implications of the growing social and verbal capabilities of large language models (LLMs). Analysis of occupational data from O*NET and job ads provides a map of the most important types of social work tasks. Among social tasks, verbal communication tasks have the strongest association with occupational exposure to LLMs.

Essay V is about the impact of venture capital (VC) on start-up firms. Investment from both private and governmental VCs is found to increase sales with a 2-3 year delay, driven primarily by efficiency gains, and to some extent, capital investment. Governmental VCs are more likely to make follow-on investments in non-growing firms.

Keywords: Artificial intelligence, Technology, Labour market, Entrepreneurship

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[1] https://www.ai-econlab.com/

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Stockholm, February 2026

Erik Engberg

Stockholm, February 2026.

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List of Essays

This thesis is based on the following essays, referred to in the text by their Roman numerals.

I. "Artificial Intelligence, Tasks, Skills, and Wages: Worker-Level Evidence from Germany". Co-authored with Michael Koch, Magnus Lodefalk, and Sarah Schroeder. Published 2025 in *Research Policy*, 54(8), 105285.

II. "Artificial Intelligence, Hiring and Employment: Job Postings Evidence from Sweden". Co-authored with Mark Hellsten, Farrukh Javed, Magnus Lodefalk, Radka Sabolová, Sarah Schroeder, and Aili Tang. Published 2025 in *Applied Economics Letters*, 1–6.

III. "AI Unboxed and Jobs: A Novel Measure and Firm-Level Evidence from Three Countries". Co-authored with Holger Görg, Farrukh Javed, Hildegunn Kyvik Nordås, Magnus Lodefalk, Martin Längkvist, Natalia Monteiro, Giuseppe Pulito, Sarah Schroeder, and Aili Tang. Released 2024 as IZA Discussion Paper No. 16717.

IV. "Social Computers? LLMs and the Social Dimensions of Work".

V. "Direct and Indirect Effects of Private- and Government-Sponsored Venture Capital". Co-authored with Daniel Halvarsson and Patrik Tingvall. Published 2021 in *Empirical Economics*, 60, 701–735.

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Abbreviations

AGI	Artificial general intelligence
AI	Artificial intelligence
ASI	Artificial superintelligence
BIBB/BAuA	German employment survey
CEM	Coarsened exact matching
DAIOE	Dynamic AI occupational exposure
GVC	Governmental venture capital
ISCO	International standard classification of occupations
LLM	Large language model
MVC	Mixed (private and governmental) venture capital
NACE	European classification of economic activities
NLP	Natural language processing
O*NET	The Occupational Information Network
PCA	Principal components analysis
PES	Swedish Public Employment Service
PVC	Private venture capital
SCB	Statistics Sweden
SEM	Structural equation model
SNI	Swedish standard industrial classification
SOC	U.S. standard occupational classification
SSYK	Swedish standard occupational classification
VC	Venture capital

Introduction

At the time of writing this introduction in early 2026, artificial intelligence (AI) is beginning to have a significant economic impact, with widespread expectations that the impact could, over time, be transformative. Transformative technology is the common denominator of the five essays that make up this thesis. Four out of five essays (I-IV) focus on AI and its impact on the labour market. The fifth essay (V) is about innovation policy and the financing of entrepreneurship, and the conditions needed to nurture the kind of high-potential start-up firms that play an important role in making the technological transformation happen. The occupation is a central unit of analysis in the essays, followed in importance by the firm.

The rest of this introductory chapter features reflections on some of the main results, themes, and methods of the thesis. The final section includes a short summary of each essay.

Some High-Level Takeaways

This section summarises a couple of intuitive insights from the essays.

In the short to medium term, AI seems poised to have the biggest impact on white collar work (Essay III), including the knowledge-intensive services that have stood out as a thriving part of the labour market in developed economies such as Sweden in recent decades. Yet little evidence of overall labour displacement to date is found. On the contrary, AI exposure is found to be associated with increased wages in Germany (Essay I), increased hiring in Sweden (Essay II), and rising skill levels in Sweden, Denmark and Portugal (Essay III).

The higher AI exposure of white-collar work results from the fact that AI technology has thus far made more progress in replicating *cognitive* abilities such as language, reasoning, and vision, compared to *physical* abilities. This has been attributed to the difficulty of obtaining data for robotics (see Essay III), although progress is being made in applying AI to robotics in some areas such as self-driving cars. In Essay III we furthermore assume that socially intensive work is less exposed, all else being equal. Essay IV explores the nuances of this subject and finds that LLMs are applicable to verbal communication tasks. The least exposed jobs thus tend to be physically intensive (e.g. construction), or both physically and socially intensive (e.g. elderly care).

Another takeaway that can be gleaned from the Dynamic AI Occupational Exposure (DAIOE) measure from Essay III is that, while white collar workers are most exposed to AI, there is hardly any occupation that will be completely unaffected by AI. This is because AI replicates some basic cognitive abilities (language, reasoning, vision) that are needed to some extent in every job, even in jobs that DAIOE models as less exposed. Even in the absence of breakthroughs in AI robotics, blue-collar work can be affected by AI indirectly, through e.g. the development of new tools, or more efficient organisations, due to raised white collar productivity. While DAIOE reflects the potential of AI, realising that potential will require complementary investment and innovations.

Finally, to emphasise a point that will be repeated elsewhere in this introduction: while high exposure could suggest a risk of labour displacement this need not be the case. Some tasks and jobs will be automated, but it is also possible that raised productivity in some AI-exposed jobs will *increase* the demand for workers. Rather than just replicating what humans currently do, AI can be a powerful tool that extends their possibilities. AI will enable the emergence of new work tasks within jobs, and entirely new occupations, which offsets the automation of some tasks. Predicting how these different forces will play out, and the net effect on labour demand, is difficult even within one occupation, let alone for the labour market as a whole.

On the Value and Challenges of Doing Research About AI

AI is a phenomenon that continues to evolve rapidly, forcing us to constantly update our understanding of it and how it transforms the world. Because of the general-purpose nature of AI, its impacts on society are far-reaching and complex. Making sense of the flood of new developments in AI and its societal impact is a fascinating exercise but can at times feel overwhelming.

A rapidly evolving subject is fertile ground for research. But it also comes with some unique challenges. There is a risk that some research findings have a short "shelf life", as new facts emerge and the nature of the technology changes. Nevertheless, it is a worthwhile effort to document the changes that have occurred to date, and to try to make educated guesses about the future, applying the toolbox of economics. In doing so we accumulate knowledge, data, research tools, and theoretical frameworks that can have lasting value, and be built upon and adjusted when necessary.

AI is an important technology that will have a significant impact in the years to come. Even if progress in AI capabilities were to slow down, fully realising the potential of today's AI will take years. Further progress in capabilities would raise the potential even higher, and for now there are few signs of a slowdown. AI holds the potential to raise living standards in several ways. To name a few, it can raise productivity, making goods and services better and more abundant; it can accelerate science and innovation, thus helping to address societal challenges such as disease and climate change; and it can increase access to education.

On the other hand, a technology with such transformative potential also comes with some potential risks. We cannot rule out the possibility that adoption of AI will drive significant structural change in the future. Those changes can cause disruption, especially if they happen fast. Relatedly, AI can possibly exacerbate inequality. There are concerns about risks beyond the labour market, including misuse for fraud and cyberattacks, disinformation, applications in warfare, and in the most extreme case, existential risks from superintelligent AI (Center for AI Safety, 2023).

Social science can play a meaningful role in helping society to make sense of the changes that are being wrought by AI. By replacing confusion and speculation with the clarity of knowledge, research can facilitate discussions about the best way toward a future that captures the benefits of the new technology, while minimising the risks. This thesis aspires to contribute to that collective effort.

In general, given the potential for a fast pace of change and high uncertainty about the future, it seems prudent for society to devote resources to continuously monitoring the area. This is a key recommendation of a report for the US National Academy of Sciences (National Academies of Sciences, Engineering, and Medicine, 2025) that was coauthored by leading labour market experts and is echoed by me and coauthors in Lodefalk et al. (2025).

The next section provides an overview of the technological progress in AI.

The Rapid Progress in AI

Recent years have seen important breakthroughs in AI technology. A key development occurred in 2012, when an AI algorithm dubbed *AlexNet*, created by Krizhevsky et al. (2017), won the annual ImageNet image recognition competition. AlexNet used a type of AI algorithm based on deep convolutional neural networks (from a subfield of machine learning called *deep learning*) to achieve the highest rate of correctly classified images by a wide margin. Since 2012, deep learning has underpinned much of the progress in AI, enabling rapid progress across a wide array of applications such as language, vision, games, and robotics.[2] In recognition of the importance of this technology, 2024's Nobel prizes in both chemistry and physics were awarded for AI based on deep learning models. One of the laureates, Geoffrey Hinton, was a co-author of the AlexNet paper, which is one of the most widely cited in AI research.

Three key forces underlie the progress in AI: algorithms, compute, and data. There has been innovation in the **algorithms**, i.e. the design/architecture of the AI systems, where Krizhevsky et al. (2017) proved the potential of the deep learning approach. Another example of an algorithmic innovation is the transformer architecture (Vaswani et al., 2017), which played an important role in the growth of large language models (LLMs; more on this below).

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[2] In Essay III, we collect data on AI research during the years 2010-2023, providing an overview of the main areas of AI during those years.

Second, the declining cost of **computation**. The rapid, consistent growth in the computing power of computer chips for many years is known as Moore's Law, although there has been some discussion about whether the progress has slowed somewhat recently ('Jensen Huang Says Moore's Law Is Dead. Not Quite Yet', 2023).

Finally, AI models benefit from huge amounts of training **data**. Data availability has grown rapidly, owing to the growth of the internet and digitisation in general.

In recent years, much attention has been focused on the latest generation of AI technologies. *Large language models* (LLMs) are AI models that have been trained on vast amounts of text and can generate text in response to the user's instruction (the "prompt"). More broadly, *generative AI* refers to AI models that can create sophisticated content across several media, such as text, images, or audio.

The release of ChatGPT by OpenAI on November 30, 2022 became a watershed moment which greatly increased public interest in AI. ChatGPT grew explosively, reaching 100 million users in two months. A wave of excitement and investment was kicked off and has not diminished since then. As someone who had been watching the AI field since the beginning of my PhD studies in 2020, there is a stark contrast in the intensity of public attention to AI before and after the release of ChatGPT.

Notable developments related to LLMs in the last few years include the following:

- **Chat bots**: ChatGPT (2022-10-30) popularised the *chat bot* interface, where the user communicates with an LLM by exchanging text messages. Another key innovation by OpenAI, the company behind ChatGPT, was *reinforcement learning through human feedback* (RLHF). RLHF means that the chat bot is trained to behave in a user-friendly way by receiving feedback from humans on which responses the humans prefer.
- **GPT-4** (2023-03) represented a leap in performance over the previous iteration of GPT.

- **ChatGPT rivals** were released during 2023 by Anthropic (Claude, in March) and Google (Gemini, in December).
- **Reasoning models**: the Chinese LLM DeepSeek (chat bot version released in 2025-01) triggered a shift toward so-called reasoning models, which devote more computing power to "thinking" before giving an answer.
- **Agentic AI**: recently, LLMs have gained increasing ability to execute general tasks on a computer, moving beyond the chat bot interface. Notable product releases include Claude Code (public release 2025-05), OpenClaw (2025-11) and Claude Cowork (2026-01).

These developments all contributed to expanding the potential of LLMs.

The speed of the technological breakthroughs in AI in recent years have surprised many experts. The breadth of the capabilities of the most recent LLMs have caused some to pronounce that they represent a step in the direction of *artificial general intelligence*, or AGI, a hypothetical AI that would match all aspects of human intelligence. For example, researchers at Microsoft pronounced that GPT-4, the model released by OpenAI in early 2023, showed "sparks of AGI'" (Bubeck et al., 2023).

While AI based on deep learning seems to hold the most revolutionary potential, it should be noted that there has also been important innovation within machine learning methods that do not use deep learning. One of the most popular types of machine learning methods is *tree-based algorithms*. For example, Athey et al. (2019) propose a method dubbed *causal forest*, which can identify heterogeneous effects in econometric analysis. An example of a Swedish paper applying the causal forest method to Swedish administrative data is Athey et al. (2023). *XGBoost* is a well-known algorithm that has become popular in private sector use for predicting various outcomes in structured/tabular data (Chen & Guestrin, 2016). Deep learning models, in contrast, are distinguished by their ability to process *unstructured* data, such as text or images.

As the 2030s approach, a central question is what trajectory the technological progress will take in the years and decades ahead. Will AI continue the current trajectory of rapid progress for many years to come, or will it reach a plateau? For example, constraints on further progress could arise if the decline in the cost of compute fails to keep pace with the growing demand, leading to rising costs of computer chips and energy. In summary, uncertainty about the future is high.

Even if we could somehow predict with certainty what will happen with the foundational technology, predicting its economic effects adds another layer of complexity and uncertainty. In the next section, we turn to research on the economic effects of AI, with a focus on the labour market.

Research on AI and the Labour Market

The growing ability of computers to carry out tasks that previously could only be done by humans has led to a great deal of speculation about what the economic implications of this technology could be. Here follows a broad, but not exhaustive, overview of the economics literature on AI and the labour market.

One strand of research has focused on measuring the adoption of AI. Several data sources have been used for this purpose. **Online job ads** are a valuable source of information about what kinds of skills, such as AI-related skills, are demanded by employers. Job ads provide detailed coverage of the labour market, and each job typically contains a textual description of the job, from which information can be extracted with natural language processing (NLP) techniques. Examples of such studies include Acemoglu et al. (2022), Alekseeva et al. (2021), and Squicciarini & Nachtigall (2021). In this thesis, job ads are used to measure AI adoption in Essay II. Additionally, job ads are used in Essay IV, but for the purpose of analysing the social skill requirements of jobs, as opposed to AI adoption.

Another source of data on AI adoption is **surveys to workers or firms**, as in Bick et al. (2024), Humlum & Vestergaard (2024), Pulito et al. (2026), and Lodefalk, Engberg, & Tang (2025a). Survey data on AI adoption by Swedish firms are used in Essay II.

Studies affiliated with the top AI labs OpenAI and Anthropic have used data directly from **users' conversations** with the respective chat bots ChatGPT and Claude (Chatterji et al., 2025; Handa et al., 2025). Key use cases include decision support, coding, writing, learning, and searching for information.

Since ChatGPT was first released, several **experimental studies** have been carried out. These studies have used experimental study designs (*randomised controlled study*, RCT) to test the impact of large language models on specific occupations and work tasks, such as professional writing tasks (Noy & Zhang, 2023), management consultants (Dell'Acqua et al., 2023), software developers (Cui et al., 2024; Peng et al., 2023) and customer service (Brynjolfsson, Li, et al., 2025). The strength of these studies is that their experimental design facilitates interpretation of the causal impact of AI, and their ability to give early hints about the likely future, and wider impact of AI. A key limitation lies in external validity; while they can provide high quality evidence on narrowly defined contexts, the results cannot be easily used to predict the aggregate labour market effects.

The most striking aspect of these studies is that they all find significant productivity gains, within the tested occupations and tasks. The gains manifest themselves as AI enabling workers to complete tasks faster, and with maintained or higher quality, compared with workers not using AI. This seems to suggest that even today's generative AI technology has significant potential for raising productivity, once widely implemented. It should be noted, however, that the experimental studies tend to focus on occupations that have high AI exposure. They thus represent an upper bound; for many occupations, the potential of AI will be lower than what is estimated in those studies.

The studies furthermore provide interesting nuance on how AI impacts work in different contexts. For example, Dell'Acqua et al. (2023) identify two types of AI users: "centaurs", who delegate specific tasks to AI, and "cyborgs", who integrate the AI throughout their workflow. They also find that current AI technology can do some tasks well, but not others, creating a "jagged frontier" which provides opportunities for human-AI collaboration. Several of the experimental studies, including Brynjolfsson et al. (2025), Dell'Acqua et al. (2023), and Noy & Zhang (2023), find that less-productive workers gained the most from using AI tools, whereas it did not make as much of a difference for the most productive.

Another interesting category of experimental studies uses **LLMs as experiment participants**. It has been envisioned that if LLMs can accurately simulate human behaviour, then one could potentially use them to run digital ("in silico") social science experiments (Anthis et al., 2025; Horton, 2023). Evidence on the ability of LLMs to accurately simulate human behaviour, discussed in Essay IV, is provided e.g. by Manning et al. (2024), Strachan et al. (2024), and Weidmann et al. (2025).

Several studies have taken a **theoretical macro perspective**, attempting to model the impact of AI on the economy as a whole. Acemoglu (2024) takes the experimental studies noted above as a starting point. He then argues that those studies indicate marginal gains, to a subset of tasks, among the most-affected occupations. He concludes that AI will have quite limited effects on the economy, raising aggregate productivity by less than one percent over the coming ten years.[3] A contrasting perspective is provided by Korinek & Suh (2024), who attempt to analyse the economic implications of an AGI scenario where AI surpasses humans in all work tasks. One of their key findings is that if research and development could be automated with AI, then this could lead to large and broad-based wage growth. Brynjolfsson et al. (2021) describe a "productivity J-curve", where costly complementary investments must be made before the full potential of a general-purpose technology such as AI can be harnessed. Complementary investments to AI are discussed in Lodefalk, Engberg, & Tang (2025a), where we discuss the obstacles to harnessing the potential of AI in the public sector.

[3] On the other hand, Acemoglu has also said that he believes that AI may have large effects in the long term. In an interview with a Swedish newspaper, he stated that "I think that much of our social and economic lives will be fundamentally changed by it within maybe 20 years" (von Seth, 2024).

Some studies use observational data on labour market outcomes, such as hiring, employment, or wages, to try to measure the relationship between AI and labour market changes. These studies contribute **empirical evidence on how AI has impacted the labour market to date**. Essays I, II and III belong to this category of the literature. As discussed above, the explanatory variable, AI, is measured in various ways in the literature including job ads, surveys, and occupational AI exposure measures (more on this below). A study in this vein which has received attention recently is Brynjolfsson, Chandar, et al. (2025), who find evidence of reduced hiring of junior workers in AI exposed roles. More research is needed to determine whether young workers really are the "canaries in the coal mine" that have suffered an early negative shock to labour demand from AI. Teutloff et al. (2025) study an online platform for white-collar gig workers, and find evidence for a reduction in demand, after ChatGPT, for some tasks that are exposed to LLMs automation. On the other hand, demand for tasks requiring AI skills increased. While these studies provide insights on the overall labour market effects, key challenges lie in measuring the impact of AI and proving causality.

Another genre within this literature has been to develop **exposure measures**, which seek to model and quantify the relationship between occupations and AI. Because this approach plays an important role in this thesis, the next section takes a closer look at it.

Modelling Occupational Exposure to AI: Strengths and Limitations

Constructing the Measures

Essays I-IV all make use of measures of occupational AI exposure. We develop our own measure, DAIOE (see essay III), which is used in essays I and IV.

Measures of occupational AI exposure have been a notable genre in the research on AI and the labour market. An early, influential study was Frey & Osborne (2017). Other highly cited studies include Brynjolfsson et al. (2018), Felten et al. (2018, 2021), and Webb (2019). More recently, exposure to LLMs specifically was modelled by Eloundou et al. (2024) and Felten et al. (2023). All these studies aim to generate a measure which quantifies and ranks the AI exposure of all occupations in a taxonomy.

The approach is similar in spirit to Autor et al. (2003), a seminal study when it comes to the impact of computer technology on the labour market, in the sense of empirically examining different types of work and how they relate to technology.

While exact approaches vary, exposure measures typically use the following three main kinds of data as inputs:

1. **Data on AI capabilities**. DAIOE follows Felten et al. (2018) in using AI performance benchmarks from AI research. Webb (2019) uses the texts of AI patents. Eloundou et al. (2024) and Felten et al. (2021) use crowd-sourced expert judgments on what AI can do. Eloundou et al. additionally use LLM prompting to predict task exposure to LLMs.
2. **Data on the work content of occupations**. O*NET, the database on occupational data maintained by the U.S. Bureau of Labor Statistics, is used in most cases. Studies may use different parts of O*NET; for example, DAIOE uses *abilities* and *social skills*, whereas Eloundou et al. use *tasks*.
3. **Some way to connect the AI capability data to the occupation data**. DAIOE uses the *mapping matrix* from Felten et al. (2018), where experts rated the relatedness of AI applications (e.g., language modelling) to worker abilities. Webb (2019) uses NLP techniques to link patent texts to work descriptions.

Interpretation, Strengths, and Limitations

What does AI exposure mean, exactly? In the interpretation of several studies (Eloundou et al., 2024; Engberg et al., 2024; Felten et al., 2021), AI exposure means that AI is *highly applicable* to a particular type of work. This implies that there is a greater *potential for productivity gains* of applying AI, meaning that AI enables the good or service to be produced with higher quantity and/or quality for the same amount of input.

Many would like to know how AI adoption will impact labour demand. Will AI fuel layoffs and wage cuts? Who will be the winners or losers? It is a key limitation of most exposure measures that they cannot provide satisfactory answers to these pressing questions. The authors all say that their exposure measures are agnostic as to the impact on labour demand. As analysed by Acemoglu & Restrepo (2019), productivity gains from technology adoption in an occupation can manifest themselves in several ways, with different implications for labour demand. Most creators of exposure measures have judged it as too difficult to predict those outcomes.[4] An exception is Gmyrek et al. (2023).

The great strength of exposure measures, on the other hand, is that by providing an exposure score for every occupation in a taxonomy (such as SOC, ISCO, or SSYK), they provide a bird's-eye view of how AI relates to the labour market *as a whole*. The value of being able to say something about how AI relates to every occupation is reflected in the interest that the media has shown in the occupation exposure rankings.

The occupation-level exposure data can be merged with other sources of labour market data that feature occupation codes, opening vast opportunities for analysing how AI relates to the economy. For example, it can be combined with linked employer-employee registry data (LEED), providing both a macro perspective and the possibility to delve into granular detail. Starting from the level of the individual worker, exposure can be aggregated to other units of observation, such as the establishment, firm, industry, region, etc. In Lodefalk, Engberg, Lidskog, et al. (2025), for example, we use this approach to undertake a detailed analysis of the AI exposure of the Swedish public sector. Worker-level outcomes are studied in Essay I; establishments

[4] For a framework for predicting the wage impacts of automation, see Autor & Thompson (2025). They argue that technology can depress wages when it automates the "expert" parts of the job, thus lowering the skill level needed to carry it out.

in Essay II (aggregating from both job ads and registry data); and firms in Essay III.

Exposure measures predict *potential* productivity gains, rather than observed ones. As with any economic model, exposure measures add value by providing a framework for thinking about certain economic phenomena, highlighting key mechanisms. Reality is more complex than any model. There are inevitably some factors that influence AI adoption that lie outside the model, such as organisational or institutional factors. Other exogenous factors are raised by Svanberg et al. (2024), who point out that some occupations have more economic value than others, and/or are easier to automate, and thus are more likely to receive investments in new technology.

Nevertheless, exposure can serve as a useful benchmark, a rough guide to where to expect the greatest impact of AI in the short to medium term. In the appendix to Essay III, we show that DAIOE is strongly positively correlated with AI adoption on the occupation level, as measured by the share of AI-related job ads within the occupation. To the extent that adoption diverges from exposure, it can be fruitful to analyse the discrepancies, to understand what factors outside the exposure measure are inhibiting AI adoption from reaching its potential.

It is a fundamental limitation that the exposure measures are based on the occupations and work content that constitute today's labour market. It is important to keep in mind that new tasks and occupations will emerge in the future, some of which will be possible only thanks to AI.

Finally, as with other models, a benefit is that we can study the inner working of the model, to understand the mechanisms at play.

The rest of the introduction summarises the five thesis essays, as well as two related research projects that were conducted in parallel but are not included in the thesis.

Summaries of the Essays

Essay I: Artificial Intelligence, Tasks, Skills, and Wages: Worker-Level Evidence From Germany

The essay leverages longitudinal labour market data from Germany to analyse changes in the skill and task content of occupations over time, as well as wages, and how those changes relate to technology in the form of AI exposure (measured by DAIOE from Essay III) and robotics exposure.

We document a clear contrast in the skill and task profiles of occupations that are AI exposed, versus robotics exposed. This suggests that the labour market impact of AI adoption will be quite different from that of robotics, the 21st-century impact of which has been studied extensively before.

Looking at changes within occupations, we find that more AI exposed occupations tended to become increasingly focused on knowledge-intensive, cognitively demanding skills and tasks.

We further show how workers' earnings evolve and find that workers in AI exposed occupations experienced higher wage growth than workers in non-exposed occupations.

Essay II: Artificial Intelligence, Hiring and Employment: Job Postings Evidence From Sweden

This essay aims to provide empirical evidence on the relationship between AI and labour demand. We study the relationship between AI exposure and hiring on the firm level, using a combination of online job ads and registry data on workers and firms from Sweden during the years 2014-2022.

We find that AI exposure is associated with increased hiring of workers in AI roles, a sign of adoption of AI technology. This finding is supported by an analysis of survey data from Statistics Sweden, which showed that AI exposed firms are more likely to consume AI services.

In contrast to evidence from the United States (Acemoglu et al., 2022), we find no signs of reduced hiring. We interpret the results as an indication that, during the 2014-2022 period in Sweden, AI adoption was not associated with labour displacement, but with establishment growth.

Essay III: AI Unboxed and Jobs: A Novel Measure and Firm-Level Evidence From Three Countries

The essay develops a measure of occupational exposure to AI which we call *Dynamic AI Occupational Exposure* (DAIOE).[5] It builds on the work of Felten et al. (2018, 2021), who mapped the main areas of AI research to worker abilities in O*NET.

We contribute by collecting year-by-year data on 140 performance benchmarks from AI research papers, allowing us to quantify AI progress during the years 2010-2023, making the index *dynamic* (time-variant). In addition to overall AI exposure, we create 11 sub-measures which reflect exposure to specific areas of AI. We also allow the importance of social tasks in work to play a significant role in the model. In our interpretation, exposure predicts a potential for applying AI but is agnostic as to the ultimate impact on labour demand.

A key takeaway is that *cognitive* work is most exposed, while *social* and *physical* work is less exposed, all else being equal. This tends to place white collar occupations at the top of the AI exposure spectrum, and blue collar occupations at the bottom.

We bring DAIOE to linked employer-employee micro data from Sweden, Denmark and Portugal. Estimating regression models at the firm level, we find that AI exposure is associated with skill upgrading. We find no significant associations with changes in employment.

[5] DAIOE data and information can be found at: https://www.ai-econlab.com/ai-exposure-daioe

Essay IV: Social Computers? LLMs and the Social Dimensions of Work

The essay takes as its starting point the assertion that AI, in the form of large language models (LLM), marks a breakthrough in the ability of computers to process natural language and social interaction. The difficulty of earlier generations of computers to master verbal and social skills had previously been identified as key constraints on their labour market impact (Autor et al., 2003; Deming, 2017). LLMs therefore transform the exposure to computerisation of social tasks, which play an important and growing role on the labour market (Deming, 2017). There is great variety among social tasks, however, and it is not immediately obvious which social task traits matter most for the impact of LLMs.

To generate some insights on this topic, the essay has two objectives. The first is to develop a data-driven, multidimensional characterisation of social tasks. The second objective is to analyse how the identified *social dimensions of work* relate to LLMs, as measured by occupational LLM exposure.

To measure exposure, I make use of the language modelling sub-index of DAIOE (developed in Essay III), and two LLM exposure measures from Eloundou et al. (2024). To characterise social tasks, I apply principal components analysis (PCA) to 55 social O*NET variables and interpret the six principal components. Additionally, I apply semantic clustering on social skill terms from job ads and identify 14 social skill clusters.

Analysing the relationship between social dimensions and LLMs, I find that verbal communication is the social task that is most consistently associated with occupational LLM exposure. The social task types of leadership, service, and negotiation are associated with lower LLM exposure.

Essay V: Direct and Indirect Effects of Private- and Government-Sponsored Venture Capital

The final essay departs in part from the focus on AI, and studies *venture capital* (VC), i.e. equity investment in start-up firms. As emphasised by Schumpeter (1942) in his theory of *creative destruction*, innovation and structural change is often driven by the emergence of new businesses that adopt fresh practices and renew the economy. Providing a favourable environment for entrepreneurial activity is therefore important for an economy's ability to dynamically adapt and realise the transformative potential of new technologies such as AI.

VC plays a significant role in providing funding as well as non-financial resources, such as management advice and access to networks, to high-potential start-ups, often in high tech sectors such as IT or life science.

The essay studies how private- and government sponsored VC investments impact the receiving firms. To this end we draw on data on VC investments in 699 Swedish firms, as well as registry data on the firms' finances, employees, etc. We create a matched control group of similar firms that do not receive VC and apply structural equation modelling (SEM) to allow for different impact channels.

We find that, for both private and government-sponsored VCs, VC investment is associated with a significant increase in sales 2-3 years after the investment. The main impact channel is efficiency gains ("direct effects" on sales), followed by capital investments ("indirect effects"), whereas employment effects are minimal. We also observe that governmental VCs are more likely to make follow-up investments in non-growing firms.

The essay includes a discussion of how differences in investment behaviour and outcomes between private and governmental VCs should be interpreted. Notably, private VCs tend be to more purely focused on profit maximisation. Governmental VCs, on the other hand, may have limits on how much profit they are allowed to make and instead have other objectives, such as promoting innovation, entrepreneurship, or employment.

Honourable Mention Essays

I would like to take the opportunity to mention two additional research projects that were conducted during my doctoral studies. They are related to the other essays but are not included in the thesis.

AI and the Public Sector

The first of these is on the topic of AI in the public sector, co-authored with Rolf Lidskog, Magnus Lodefalk, Fredric Skargren, and Aili Tang. This project applied many of the data sources and research tools that had been built up within AI-Econ Lab over the previous years: the DAIOE measure, registry data on workers and firms, job ads, surveys to workers and firms, and more.

A centrepiece of the study is a scenario simulation exercise inspired by Bailey et al. (2023). We combined data on occupational AI exposure from DAIOE, registry data on public sector organisations and their workers, and employment forecasts, to simulate several scenarios of productivity growth in the public sector over the coming 20 years. Our main scenario predicts a significant potential for productivity gains, especially in administrative functions of the public sector. The predicted potential is smaller in physically and socially intensive services such as elderly care but rises when we assume significant adoption of AI robotics.

In addition to the scenario simulations, the report draws on a variety of sources including interviews with experts on the public sector to identify key obstacles to implementing AI in the public sector. We point to digital infrastructure, data, human capital, legal aspects, leadership and continuous monitoring of the area, given how quickly things are moving and the uncertainty about the future. All in all, significant resources must be invested to realise the potential of AI in the public sector, which is consistent with the J-curve hypothesis of Brynjolfsson et al. (2021).

Originally published as a working paper (Lodefalk, Engberg, Lidskog, et al. (2025), the study is forthcoming in Digital Society. A version was published as a report (in Swedish) by the Expert Group on Public Economics (ESO) which is attached to the Swedish Ministry of

Finance (Lodefalk, Engberg, & Tang, 2025a). An article was also published in the journal Ekonomisk Debatt (Engberg et al., 2025), and an editorial in the business daily Dagens Industri (Lodefalk, Engberg, & Tang, 2025b).

New Work, Exiting Work, and Artificial Intelligence

This paper is co-authored with Hildegunn Kyvik Nordås, Magnus Lodefalk, and Radka Sabolová. It has not been published yet, so the findings are preliminary. In a similar vein as Autor et al. (2024) and Lin (2011), we analyse the entry and exit of occupations, and the relationship of these structural changes to AI. The emergence of new occupations is an important part of structural change in the long run; Autor et al. (2024) find that most of the employment today is in occupations that did not exist 80 years ago.

We rely primarily on job ads to identify fine-grained occupations that entered or exited the Swedish labour market in recent years, during the 2010s. While covering a shorter time span than some previous studies, we leverage the job ads combined with registry data to delve into more detail.

We characterise the new and exiting (disappearing) jobs, and find that new work tends to be associated with cities and knowledge-intensive services, especially IT. This is consistent with findings from Autor et al. (2024), Kalyani et al. (2025), and Lin (2011). Exiting work, on the other hand, is associated with rural areas and with low-skilled administrative and manufacturing roles. New work is more likely to demand AI skills, although we do not observe any new dedicated AI job title up to the year 2022.

Compared to exiting work, new work is more likely to demand the following skills: technology, software, social, cognitive, language, and creativity. AI related jobs put additional emphasis on data, software, creativity, and business systems.

All in all, these observations from the “leading edge” of structural change provide clues about the direction of the Swedish labour market’s evolution, and its relation to AI.

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