Department for
Business, Energy
& Industrial Strategy

ECONOMIC IMPACT OF ROBOTICS & AUTONOMOUS SYSTEMS (RAS) ACROSS UK SECTORS

Methodological note accompanying the full report

BEIS Research Paper Number 2021/043

November 2021

A report for the Department for Business, Energy & Industrial Strategy (BEIS) by London Economics

Acknowledgements

This independent research report was produced by Daniel Herr, Moritz Godel, Ryan Perkins, Luke Pate and Teresa Hall from London Economics.

We would like to thank all individuals and organisations that contributed to this study for the valuable advice and information provided. London Economics would also like to acknowledge the useful guidance and feedback provided by the Department for Business Energy and Industrial Strategy (BEIS) throughout this research.

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Introduction

In May 2020, the Department for Business, Energy & Industrial Strategy (BEIS) commissioned London Economics (LE) to undertake an assessment of the economic opportunities of Robotics and Autonomous Systems (RAS) across UK sectors. This study will enable BEIS to understand where the key future economic opportunities lie for RAS uptake across the wider economy.

This methodological note accompanies the main report. It describes in detail the modelling approach employed in this study, including the key assumptions, evidence and data sources used, and key caveats of the analysis.

This note:

- First, discusses the approach used to select the chosen sectors examined in the study, including a detailed Red-Amber-Green (RAG) rating for all sectors considered.
- Second, provides a detailed description of the methodology used to derive quantitative results for each chosen sector, including the key assumptions, evidence and data sources used, and key caveats of the analysis.
- Third, provides a brief overview of the model of innovation diffusion used for the tipping point analysis and to extend RAS forecasts to 2035.
- Fourth, provides a brief overview of the methodology used by ABI Research to derive forecasts of the robotics markets on which estimates in this study are based.
- Fifth, provides the results of the tipping point analysis.
- Sixth, provides the economic baselines for each selected sector.

Details of approach to sector selection

Sectors included in the initial list of sectors considered were based on existing RAS literature. Noteworthy initial sources included:

- Council for Science and Technology: Science Landscape Seminar Series: Representative UK Robotics and Autonomous Systems (RAS) Infrastructure
    - Identification of Industrial Strategy Sectors: Life Science; Aerospace; Professional Business Services; Education; Nuclear; Oil and Gas; Automotive; Offshore Wind; Information Economy; Construction; Agri-tech
- BEIS existing information
    - Surgery; Long-term care; Space; Industry/Manufacturing; Agriculture; Extreme environments and infrastructure; Urban
- UK RAS White Papers
    - Manufacturing; Surgery; Space; Social Care; Agriculture; Emergency Response, Disaster Relief and Resilience, Resilient Infrastructure, Urban

Additional (or adjacent) sectors were considered as they were discovered in further exploratory reviews. The final list of sectors considered for further review was chosen based on the expected availability of literature as well as the potential of RAS for these sectors.

Additional background research focused on the following criteria; which formed the basis for a Red-Amber-Green (RAG) rating for each sector (see below):

Size of sector and the UK capability within this sector

- This criterion considered the relative size of each sector within the UK economy as well as the importance of the sector for the UK:
    - Sectors accounting for 10% or more of UK economic activity were given a green rating.
    - Sectors accounting for between 5% and 10% of UK economic activity were given an amber rating.
    - Sectors accounting for less than 5% of UK economic activity were given a red rating.
- A sector of a smaller size was given a higher rating if the sector was considered of particular importance to the UK, or had important UK capability.

Growth of the sector

- High growth sectors, as evidenced by an increase in the size of the sector of 20% or more over last five years (or similar trend) were given a green rating.
- Growth sectors, as evidenced by an increase in the size of the sector by less than 20%, were given an amber rating.

- Shrinking sectors were given a red rating.

Evidence of current and potential uptake

- This involved a comparison of available evidence on current adoption within each sector as well as evidence of future trends.
- A RAG rating was assigned based on the prevalence of RAS in each sector, and the quantity and quality of evidence of likely RAS uptake in the future.

Maturity of technology

- To make a judgment on the maturity of ‘smart robotics’ in each sector, research was undertaken on the prevalence of RAS use cases, either as prototypes or in business functions, within each sector was undertaken.
- A RAG rating was assigned based on the prevalence of RAS implementation as well as the nature of use cases within each sector.

Quality of Evidence

- The quality of evidence was judged based on the availability and nature of qualitative data sources.
- Sectors where evidence comprised a rich mix of sources including academic papers were given a green rating.
- Sectors where evidence was mostly comprised of consultancy, sector or industry papers (but with little academic literature) were given an amber rating.
- Sectors where evidence mostly comprised of blog posts, news articles, or other sources of a similar nature were given a red rating.

Overall assessment

An overall assessment was given to each sector based on the results of the RAG analysis. The final set of sectors to be explored in detail in the remainder of the study were chosen based on this overall assessment, as well as, policy considerations from BEIS.

The tables overleaf present the RAG ratings and overall assessment given to each sector considered. The following points are worth noting when considering the RAG assessment:

- Energy and infrastructure were initially considered as a single sector but were later considered separate due to the significance of each of these sectors as well as the varying nature of use cases.
- Transport and logistics were also initially considered as a single sector, but it was later decided to focus on non-transport logistics given the wide range of already existing evidence on autonomous. Nevertheless, important delivery and transport-focused use cases were highlighted in the qualitative section discussing the logistics sector where appropriate.

Sector selection research

Sector	Size of sector / UK capability	Growth of sector	Evidence of potential uptake	Maturity of technology	Quality of evidence	Overall assessment
Agriculture	Agriculture contributed less than 1% of the UK's GDP in 2018 (Statista). But this sector supports other economic activity, and the UK agri-tech industry is strong in terms of R&D and its ties with farmers.	GVA increased from 11,979 in 2013 to 13,508 in 2018 (£ million) (13%) (ONS)	Robotics is already common in dairy farming; uptake in arable farming is highly likely because of compelling social and economic drivers. RAS has potential to be transformative by allowing precision agriculture.	Robots are already well-established in the dairy industry in many countries. In arable farming, drone use is not yet widespread, especially in the UK. Robots for crop-harvesting are generally prototypes at present	Sources focusing on RAS in this sector included UK governmental and public bodies, a white paper from the UK-RAS Network, and news articles from reputable newspapers.	Opportunities are present. While the sector is relatively small, so that quantitative impacts are likely to be limited, it is an important one and one that the UK has particular strengths in.

Construction	The construction sector contributes around 6% of the UK's GDP (House of Commons Briefing Paper 2019)	GVA increased from 92,611 in 2013 to 115,978 in 2018 (£ million) (25%) (ONS)	While there is potential for RAS in this sector, the industry may be slow to capitalise on these (in part because of its structure)	A number of the underlying technologies for the industry (e.g. drones) are established in other contexts, but RAS is not yet well-established in this sector	Most sources focusing on RAS in this sector were blog posts and web articles. Some information was taken from consultancy papers and academic articles.	There is potential for RAS in this sector, but RAS is not yet well-established and uptake by fragmented firms may be slow.
Defence & military	The UK government spent 2.1% of GDP on defence in 2017 (UK government research and analysis)	Defence sector has grown 10% between 2010 and 2017 (ADS group)	Robotics already in use in military (e.g. military drones); future uptake likely given competitive imperative and reduction of exposure of military personnel. This means RAS' transformative potential in defence applications is significant by massively reducing the risk	High: this is perhaps the sector in which RAS applications are most well-established	Evidence for this sector mostly came from sources such as the Brookings Institute, the US Congressional Research Service, and the Hague Centre for Strategic Studies.	RAS is of increasing importance, but this importance is of a military and security not an economic nature.

			to human combatants			
Energy	Roughly 5% of GDP is contributed by energy sector (BEIS briefing paper). This is a critical sector that supports virtually all other economic activity £24bn in economic value created in 2016 (Energy UK)	Energy sector GVA has continued to increase since 2011 (where GVA was below £15bn), with an increase of £1.9bn between 2017 and 2018 to £33.5bn (6%) (Energy UK)	Future uptake in this sector is highly likely – BP has already committed to entirely automating deep-sea inspections, for instance. RAS has potential to be transformative by allowing for predictive, less disruptive maintenance – some applications (part. in decommissioning) are not possible without RAS.	Drones are well-established in the oil and gas industry. Other applications in this sector are not yet well-established.	The primary sources of information for this sector were public bodies.	This is a critical sector and one in which RAS uptake in the future is highly likely.
Food & drink	Food & drink is responsible for around a sixth of UK manufacturing GVA (Food and Drink Federation)	In 2018, sector contributed £28.7 billion in GVA, increase of 6.3% since 2016 (Make UK). There is high economic benefit to be attained from the incorporation of	Uptake has been slower in this sector due to the variation in products and packaging. Processing uptake is also limited but large efficiency	Advances in technology (such as advanced grippers) for robotics have increased the number of applications for robots, but	UK Gov Made Smarter Review, UK RAS white paper, Industry articles	Adoption of RAS in this sector is not yet widespread but there are significant opportunities for efficiency improvements

		digital technologies within the F&D sector (1.4% - 3% increase in productivity growth per year)	opportunities exist from increased automation	widespread implementation is not yet evident		from RAS adoption.
Health & social care	Healthcare and social care together account for more than 10% of GDP (ONS). Public spending on healthcare continues to increase to match with increasing demand.	Healthcare GVA increased from 81,206 in 2013 to 98,107 in 2018 (£million) (21%) (ONS). In Social Care, number of jobs has increased by 22% since 2009 (with an increase of 1.2% between 2017 and 2018). (Skills for care)	Several RAS applications have been introduced in limited capacity, future uptake is dependent on success of these initial trials and ease or replicability across different sites and contexts	Whilst care robots in the UK have limited maturity, other robots such as next-generation surgery robots capable of minimal access procedures and hospital AVs have continued to mature.	Papers commissioned by the Taxpayer's Alliance and the IPPR, Industry articles, news articles	There are strong societal and economic reasons that RAS has a lot of potential in this large and important sector

Hospitality	In 2014, the UK hospitality industry accounted for 9% of employment and nearly 4% of GDP (Oxford Economics) London's hotel sector continues to receive high levels of investment, suggesting a high level of resiliency	Increasing investment into London hotels in 2019/2020. RevPAR [revenue per available room] grew by 3% in third quarter of 2019 in London, 1% growth across UK.	The need for a 'human touch' in the hospitality sector means uptake has been limited; uptake from high-end establishments also estimated to continue to be limited in the future.	There are international hotels which are currently entirely robot-staffed or use robotic concierge and room service operators but are still seen as a novelty at this stage.	News articles of adoption use cases and technology prototypes.	While this is an important sector, it is unclear to what extent there is value for RAS adoption in this sector except in terms of novelty value. Therefore, we propose to exclude hospitality.
Industry & manufacturing	17.5% of the UK's GDP in 2018 came from manufacturing (Statista). Manufacturing accounts for 44% of UK exports (The Telegraph)	Manufacturing GVA increased from 170,757 in 2013 to 189,291 in 2018 (£million) (11%) (ONS); Britain expected to 'break into the top five industrial nations' globally in 2021 (The Manufacturer/The Telegraph)	Factory of the future of increasing importance in sector – though Batch-size 1 and fully automated factory unlikely to be seen on a large scale soon. Overall, sector has been slow to uptake robotics historically. – most likely scenario is robotics helping increase	Comparatively well-established technologies available – some international examples of factory of the future already exist (e.g. Siemens)	Extensive RAS literature for manufacturing available including Made Smarter Review and consultancy reports (e.g. BCG, McKinsey, PwC)	Manufacturing is a key benefactor of RAS – with many use cases applying here; though sector has been historically slow to uptake robotics.

			productivity of existing capabilities (rather than being truly transformative)			
Infrastructure	ONS estimates: Infrastructure investment by UK government was £18.9 billion in 2016, accounting for 36% of total government investment (of which over 85% was on transport infrastructure); and market sector investment was £10.3 billion in 2016 (of which £7.0 billion was by the energy industry). This sector bears on all other sectors.	Increased investment as part of government strategic plan (2020). £27bn into roads, £4.2bn into urban transport.	Uptake of RAS in this sector is highly likely in light of the compelling drivers in this sector. RAS has potential to be transformative by allowing for predictive, less disruptive maintenance.	Technologies in this sector are not yet well-established. At present, RAS in this sector are mostly prototypes or deployed for specific applications.	Evidence for this sector came mainly from academic articles, a UK-RAS Network white paper and information from other public bodies.	There are compelling reasons for future RAS adoption in this important sector

Life sciences	UK Life Sciences accounted for less than 1% (£16.7 bn) of UK GVA in 2016 (UK Parliament, Life Sciences Sector Report). This is a sector in which the UK globally 'punches above its weight', especially in terms of R&D	Over the period 2009 to 2018, the life sciences industry increased employment at a compound annual growth rate of 0.8% (an increase of 8% over 2009). Total industry turnover increased between 2009 and 2018 (£71.8bn to £73.8bn). Biopharma and Med Tech have decreased whilst service & supply have increased (UK Parliament, Office for Life Sciences)	Robotics already fairly common in labs, opportunity lies in high-throughput and drug-discovery robotics	Robots for use in drug discovery have been developed but use is currently limited and requires collaboration between researchers and well-funded industry companies	UK Gov Made Smarter review, industry articles, consultancy papers	Sector has historically not been shy to take up robotics and opportunities are available, but barriers remain, and life sciences sector size is relatively small in UK
Logistics & transport	Logistics contributed for 10% of UK non-financial business economy GVA, employing 2.7 million in the wider logistics industry (Santander 2019	GDP of Logistics has been continually increasing each year since at least 2014 (with annual percentage changes ranging from 1.4 to 3.1%)	Uptake in logistics is highly likely. Autonomous road vehicles are unlikely to be common in the near future, though	In logistics, there are relatively well-established technologies. Autonomous road vehicles are still at the	Evidence for this sector came from consultancy papers as well as news articles showcasing use cases	Especially in logistics, RAS technologies in this sector are relatively well-established and widespread adoption is likely

	Logistics Report). Logistics and transport play an important role in supporting other sectors	(Santander 2019 Logistics Report)		prototype stage		
Professional services & finance	Professional services account for 15% of UK GDP (PwC); financial services account for 6.9% (House of Commons Briefing Paper 2019) The UK services sector is globally competitive and remains one of the UK's main exports	Legal and accountancy sector GVA increased from 38,701 to 49,291 (£ million) between 2013 and 2018 (27%) Financial and insurance sector GVA increased from 122,797 to 135,078 (£ million) between 2013 and 2018 (10%) (ONS)	Applications in this sector are focused in software robotics and not in robotics with a physical dimension	AI/RPA already quite advanced and many solutions providers exist; but solutions are not always suitable for specific challenges faced. Some tasks require creative thought of the sort that robots are not yet capable of	Sector papers and consultancy papers only link to use of AI within industry, no evidence for physical robotics adoption	Little evidence of adoption potential of RAS with a physical dimension
Retail	The retail sector accounted for 5% of UK GDP and 9.5% of employment in 2017 (House of Commons	GVA of retail trade increased from 87,772 to 99,541 (£ million) between 2013 and 2018 (13%) (ONS)	Uptake of customer-service robots in near future appears unlikely; opportunities for non-customer-facing tasks such	Stock robots already in operation by players such as Ocado and Amazon; consumer facing robots more of a	While some information for this sector was drawn from UK governmental sources, much was taken from web	Potential is (at least in the near future) concentrated in non-customer-facing tasks. There are questions about how quick firms

	Briefing Paper 2019)		as stock monitoring	novelty at this stage	articles and blog posts	in this relatively large sector will be to respond to this potential
Space	The space sector accounts for less than 1% of UK GDP (2019 LE Size & Health report) Despite the small size of the sector, space is a critical national infrastructure for the UK. Moreover, satellite services support £300 bn in wider UK GDP (DIT). This is a sector in which UK capability is strong.	Since 2009/10, space has increased its share of UK GDP by 0.05 percentage points by 2016/17. (2019 LE Size & Health report)	Some applications such as surface missions and in-orbit maintenance require robotics technology to be carried out. These technologies are already in use	Robotics technology has been important aspect of space missions for a while; further technology development driven by space agencies such as NASA	Evidence for this sector mostly comes from UK governmental sources, a UK-RAS Network white paper, and an academic paper	RAS potential exists. Overall quantitative impacts will be small due to small size of sector, but this is an important sector where the UK has particular capability.

Source: London Economics

Quantitative analysis: Methodology

This annex describes the modelling approach employed in this study, including the key assumptions, evidence and data sources used. The modelling was undertaken in five steps. Each of these steps is discussed in further detail in this section; a brief overview is provided here:

- First, estimates of the current uptake of RAS and future adoption forecasts of RAS for each selected sector were derived.
- Second, estimates of how far along the adoption path each sector is and when the tipping point in shipments (i.e. when new robot shipments reach their peak) is likely to occur, given forecast adoption levels, were derived.
- Third, baselines (in terms of value added, employment and productivity) against which to assess benefits of RAS were constructed. This included taking account of the impact of COVID-19 and related public health measures.
- Fourth, the potential productivity impact of RAS under the baseline were estimated.
- Fifth, productivity impacts were translated to estimates of the potential benefits of RAS in terms of reduced employment needs and value added.

The central aim of the quantitative analysis was to provide comparable estimates of the potential opportunity across UK sectors, rather than precise forecasts of the uptake and corresponding benefits in any one sector. The estimates should therefore be interpreted in this light. Further, the following points should also be kept in mind when interpreting estimates provided throughout this section:

- Quantitative results presented in this study are based on current forecasts of future RAS adoption; that is, they are estimates given current adoption trends. In practice, adoption may differ from these estimates due to a wide range of factors, not least the evolving nature of RAS itself and the government's own public policy choices. Results should therefore be interpreted as plausible estimates given estimates of current adoption trends, not as forecasts.
- In practice, adoption may differ from these estimates due to a wide range of factors. The extent to which benefits can be delivered over and above the results presented in this study depend, in addition to advances in robot technology themselves, on the level to which uptake of robotics can be facilitated over and above current uptake forecasts, for example by mitigating barriers to uptake in key sectors.
- As with any estimates of future economic potential a number of assumptions had to be made in order to estimate future uptake of RAS across UK sectors and to translate estimated growth into economic benefits. Utmost care was taken to ensure assumptions chosen are sensible in order to derive the most robust and fair estimates of benefits. Nevertheless, the usual limitations and uncertainty present in any estimation of future adoption potential remain.
- It is further important to note that estimated impacts show the potential size of the economic impact relative to a plausible baseline of value added, employment needs, and labour productivity. The results do not make any claims about the overall growth of

value added itself; and the estimated impacts may be on top of baseline value added, or part of it, depending on whether RAS will provide additional growth on top of typical advances in technology already captured in the baselines.

The remainder of this section provides details, key assumptions, caveats and results for each step of the modelling.

Estimating the uptake of RAS across sectors

One of the key challenges for the modelling was the derivation of estimates of RAS uptake for the selected sectors. Potential uptake is uncertain and depends on a variety of factors. While forecasts for RAS uptake are available at the UK level, no (known) UK forecasts were available for the selected sectors. Moreover, data for the current stock of robots in each sector were also not available.

Estimating RAS uptake forecasts

Robot uptake under the scenarios used in this study was pegged to sectoral forecasts for RAS uptake, at the global level, by ABI Research (2020). Specifically, estimates of UK RAS forecasts at the sector level were derived by combining ABI Research forecasts for the UK as a whole with ABI Research sectoral forecasts at the global level (further details on the methodology used by ABI Research to derive these forecasts are provided in a later annex):

- First, the proportion of global robot shipments in each sector relative to overall shipments at the global level was calculated for each selected sector.
- Second, this proportion was applied to the overall UK total economy data to derive an estimate of potential uptake for each selected sector.

This analysis was undertaken separately for each robot category (industrial robots, collaborative robots, mobile robots, and exoskeleton).

Data for mobile robots was not available at the UK level. Therefore, this data was estimated, from EU shipments of mobile robots using the average share of UK shipments within shipments to Europe as a whole, across the other three robot groups (industrial robots, collaborative robots and exoskeletons).

Shipments rather than revenue was used as existing estimates of productivity improvements were based on robot stocks (or more precisely robot density, see derivation of robot density) rather than investments.

Caveats: As with any estimation, this approach makes a number of key assumptions. In particular, the approach assumes that sectoral breakdowns of shipments in the UK are similar to those seen globally, and that adoption in the UK, in each sector, will follow the same trend as the forecasted adoption globally for that sector. In addition, the estimation of UK mobile shipments from EU shipments assumes that the proportion of European mobile robot shipments that will be destined for the UK is similar to the UK share of the other RAS categories. These assumptions may not hold in practice. For example, the UK is lagging behind in manufacturing; therefore, it is likely that manufacturing shares are lower in the UK compared to the global share. Nevertheless, bearing in mind the significant uncertainty surrounding forecasts of RAS uptake in general (with uptake depending on a variety of factors), these estimates were deemed to present a plausible central scenario.

ABI Research data used for analysis

Data from ABI Research was not available for SIC sectors. Rather, ABI Research provides data for vertical markets. Therefore, a crucial part of the estimation of RAS forecasts for the selected UK sectors, was the reconciliation of data available from ABI Research with the chosen sectors. The table below provides the vertical markets for which data from ABI Research was available, and the assignment to selected sectors used in this study.

It should be noted that data for mobile robots and exoskeletons was only available at the overall manufacturing level rather than for food & drink manufacturing. Therefore, the share of food and drink manufacturing activities in UK manufacturing GVA was used to estimate the potential share of manufacturing shipments accruing to the food & drink manufacturing sector.

ABI Research data used for analysis

Sector	ABI vertical market	ABI definition of vertical market
Agriculture	Agriculture	Refers to robots deployed by farmers to perform specific tasks in farms, plantations and fields, such as weeding, fertilizing, watering, data collection, and fruit picking.
Construction	Construction	An industry plagued by low-productivity growth; construction has not historically been seen as a viable market for robots. However, a new round of companies is developing mobile systems for material handling, data collection, and task-based use cases for construction and have begun deploying in small numbers.
Food & drink service activities	Restaurants	Refers to robots deployed by Food and Beverage (F&B) operators either to serve dining guests or to prepare dishes.
Food & drink manufacturing*	Food, beverage and tobacco products	Refers to robots deployed by manufacturers in factories and plants to transport goods between production cells or lines.
Health & social care	Healthcare	Refers to robots deployed by healthcare institutions to transport goods within the healthcare facilities.
Warehouse logistics	Warehouse	Refers to robots deployed by Third-Party Logistics (3PL) providers in warehouse environment for goods transfer, picking, sorting, and palletization.

Sector	ABI vertical market	ABI definition of vertical market
Energy & infrastructure**	Energy & Utilities, and Infrastructure	Non-oil and gas utilities, like nuclear and renewable energy, will require robots to improve inspection, as will bridges, sewage systems, airports, and ports.
	Oil & Gas	Many robots are expected to be deployed for industrial inspection, monitoring, and other use cases in fossil fuel-related facilities.

Note: (*) For some robot types data was only available for the manufacturing sector as a whole. Data for food and drink manufacturing was estimates by using the share of food and drink manufacturing activities in manufacturing GVA. (**) Sectors were combined due to definitional and data issues.

Source: London Economics; Definitions of ABI's vertical markets obtained from ABI Research

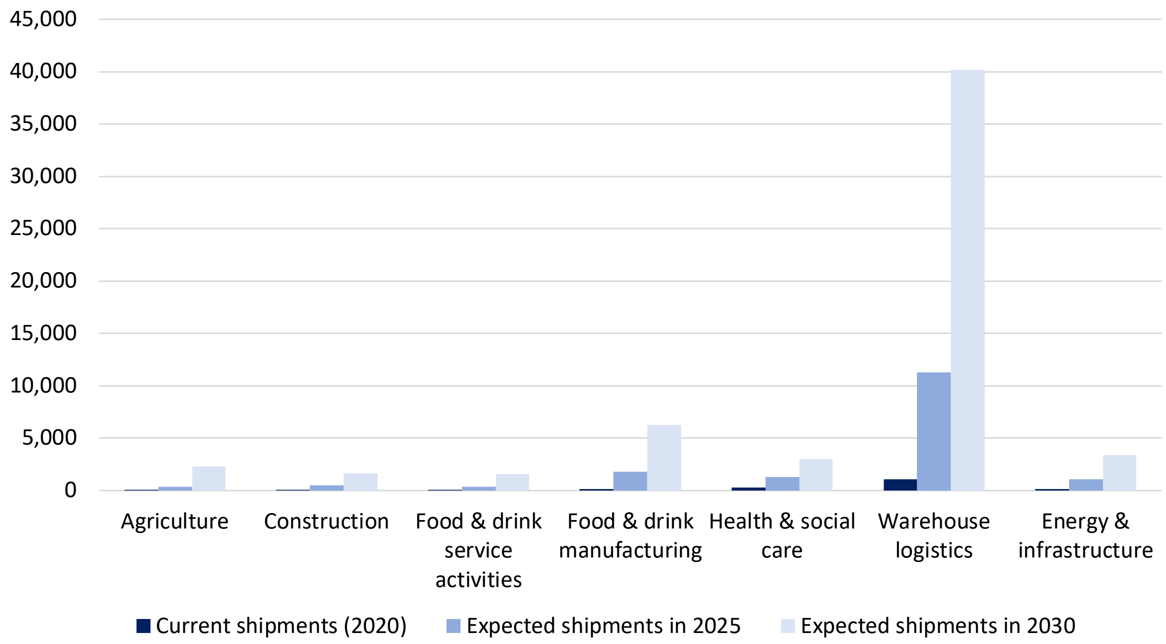
Caveats: SIC sectors and vertical markets do not necessarily align perfectly. Therefore, the quality of estimates derived in this study may be impacted by the quality of the match between ABI Research data and other data sources used.

Estimated robot shipments

The figure below shows the estimated shipment figures, for each selected sector, based on the analysis described in this section.

The uptake figures for the UK overall are provided in the main body of the report.

Estimated annual robot shipments for each selected sector



Source: London Economics analysis of ABI Research (2020) data

Estimating current stock of RAS

In addition to future forecasts of RAS uptake, it is important to get a sense of the current stock of robots in use in each sector. The reason for this is that a comparatively low number of annual shipments in a sector that already is employing a large number of robots is unlikely to deliver significant additional benefits. In contrast, a comparatively low number of annual shipments might represent a large increase in robot uptake in a sector with relatively low current levels of robot usage.

Unfortunately, as with forecasts of future shipments, estimates of the existing robot stock were not available for selected UK sectors. Therefore, the stock of robots for each selected sector was estimated in the following way:

- Data on the total stock of robots, in 2018, across the globe was obtained from the IFR (2019). Specifically, the IFR computed that the operational stock of robots stood at 2,439,543 units across the globe in 2018.
- To derive an estimate of the UK stock of robots, the share of UK shipments of industrial robots in 2018, based on data from ABI Research (2020), was calculated relative to global industrial robot shipments in 2018. This proportion was then applied to the global operational stock of robots by the IFR. This analysis indicated that the UK stock of industrial robots in 2018 stood at approximately 19,000 robots (or around 0.8% of the global stock)1.
- The proportion of total RAS shipments, in 2018, for each selected sector relative to UK RAS shipments was then used to derive estimates of the current stock of robots for each selected sector.

The results of this analysis are presented in the table below:

Estimated robot stock

Sector	% of world / UK	Robot stock
World		2.4 m
UK overall	0.8% of world	19,000
Agriculture	0.1% of UK	< 100

[1] Earlier estimates by the IFR (cited in Cheeseman, J., 2017), suggest that the UK robot stock stood at roughly 71 robots per 10,000 employees in the manufacturing sector. Using ONS employment data for the manufacturing sector suggests that this would translate to a slightly lower industrial robot stock of approximately 17,000. While these are older estimates which cover the manufacturing sector only, they provide additional confidence that estimates presented here are reasonable.

Sector	% of world / UK	Robot stock
Construction	0.1% of UK	< 100
Food & drink service activities	0.1% of UK	< 100
Food & drink manufacturing	4.8% of UK	900
Health & social care	0.1% of UK	< 100
Warehouse logistics	7.8% of UK	1,500
Energy & infrastructure	0.3% of UK	< 100

Note: Figures may not add up to total stock due to rounding.

Source: London Economics analysis of data obtained from IFR (2019) and ABI Research (2020)

Caveats: It should be highlighted that IFR (2019) estimates of the global stock of robots covers industrial robots only. It is therefore likely to underestimate the actual number of robots in use. At the same time, given the nature of industrial robots, they are unlikely to be in use in some selected sectors (such as food and drink service activities). Moreover, using shipment data to estimate the proportion of robots in each sector assumes that the sectoral distribution of historical shipments did not vary substantially to the current sectoral breakdown. However, given that a) shipments of non-industrial robots historically only accounted for a relatively small proportion of UK shipments, and b) the robot stock itself is not used in the analysis but only used as the basis to estimate the robot density (i.e. the number of robots per million hours worked), the impact of estimation error is likely to be negligible.

Tipping point estimation

The properties of technology diffusion have been widely studied. Diffusion (adoption) of new products (innovations) typically follows an S-shaped curve (see, for example, Golder, P. N., Mitra, G., D., 2018). This typical S-shaped nature of innovation diffusion was used to obtain a better understanding of how far along the adoption path each selected sector may be in a given period, as well as, when the tipping point in shipments – i.e. the point when new robot shipments reach their peak before slowing down – is likely to occur, given current shipment forecasts.

Many models have been developed to approximate the S-shaped diffusion process, ranging from very simple to very complex models. While more complicated models may capture more subtleties in the innovation process, these models also require the estimation of further parameters, adding further uncertainty. In practice, simple models have thus often been found to fit almost as well as much more complex models (Golder, P. N., Mitra, G., D., 2018).

For this reason, this study used a very simple model of innovation diffusion: The Bass Diffusion Model. The Bass Model is the most widely used mixed influence model and is backed up by a wide range of research and management applications (Boyle, 2010). To illustrate the previous point: Bass's original paper (Bass, F. M., 1969) was named, by the Institute for Operations Research and Management Sciences, as one of the top ten most influential papers in management science (Hopp, W. J., 2004) and, in 2006, was the most widely cited model for diffusion of innovation growth (Meade N., Islam T., 2006) - as of September 2019 the paper had 9,670 citations on Google Scholar. Moreover, while the model is simple and easy to understand, it has been found to be sophisticated enough to yield a realistic adoption process that "provides a good fit to the S-shaped curve" (Chandrasekaran and Tellis, 2007).

Given its widely documented characteristics, a detailed discussion of the Bass Diffusion Model is not reproduced in this annex. Rather, this section focuses on how the Bass Model was used in this study. Nevertheless, a short introduction to the BASS model has been provided in a later annex.

To approximate the S-shaped adoption process underlying the estimated robot uptake data in each selected sector, an OLS regression was fit to the shipment data derived earlier. Specifically, for each sector, the shipments in each year, between 2017 and 2030, were regressed on the total estimated robot stock in that year and the square of the total robot stock, as well as, a constant. The coefficients obtained from these regressions were then used to derive the Bass Model Coefficients characterising the shape of the S-shaped diffusion curve.

The table below provides the results of these estimations, for each selected sector:

Estimated Bass Coefficients

Sector	Coefficient of innovation (p)	Coefficient of imitation (q)	Market potential (M)
Agriculture	0.0004	0.40	30,649
Construction	0.0010	0.39	16,763
Food & drink service activities	0.0004	0.37	20,609
Food & drink manufacturing	(0.0028)	0.33	89,688
Health & social care	0.0021	0.34	34,175
Warehouse logistics	0.0002	0.34	544,942
Energy & infrastructure	0.0010	0.36	38,723
Typical range	0.0007 - 0.03	0.3 - 0.5	-

Note: The market potential represents the estimated total robot stock in a sector that could be achieved given current adoption trends. The coefficient of innovation factors influencing the adoption choice coming from external sources (such as innovators entering the sector). The coefficient of imitation factors influencing the adoption choice coming from internal sources (such as smaller or more cautious firms imitating larger or more innovative firms who adopt earlier).

Source: London Economics; Typical ranges for Bass parameters based on Mahan et. al. (1995) and Chandrasekaran and Tellis (2007).

The estimated S-shaped curve was then used in turn to extend forecasts based on ABI Research (2020) data in order to determine when adoption may reach its peak and subsequently slow. The estimated adoption curves are provided in a later annex. The curves and BASS model also form the basis for further analysis of the impact of accelerated adoption, i.e. shifts in the estimated adoption curves.

Caveats: The curves derived via this estimation are not forecasts, but rather approximations of where on the adoption curve each sector is likely to be if given adoption forecasts hold true. A significant number of factors influence adoption and actual adoption is therefore likely to be different than the curves derived via this exercise.

Constructing baselines

As with any estimation of economic benefits a key step is to define the ‘baseline scenario’ against which estimated productivity and economic benefits are assessed. The significant uncertainties of the current economic climate, as a result of the impact of COVID-19 and subsequent lockdown, presented significant challenges for the construction of economic baselines. In addition, the nature of some of the selected sectors (such as infrastructure) meant that they did not neatly map to the Standard Industrial Classification (SIC) for which official data is provided.

Given these challenges, the modelling took the following approach for the construction of the baseline:

- The selected sectors were matched to SIC codes, seeking to obtain matches that were as close as possible.
- Economic data on value added (in real 2018 terms, deflated using GVA deflators) and employment for the selected SIC codes was collected from the ONS.
- Historical value added and employment data was used to derive a historical labour productivity series (in real 2018 terms) by dividing real GVA in each year by the number of employees in that year.
- Baselines for future value added and labour productivity, over the study period, were constructed based on a linear trend estimation.
- More recent monthly GVA data for a number of high-level sectors, from the ONS, were used to take account for the economic shock presented by COVID-19.

- In order to avoid making controversial assumptions about the potential recovery from COVID-19, the Bank of England (2020) plausible economic scenario was used to model economic recovery under the baseline.

- The employment needs implied by the baseline, i.e. the number of employees needed to achieve the GVA baseline given the labour productivity baseline, were derived from the COVID-19 adjusted value added and labour productivity baselines.

The remainder of this section discusses key assumptions made and caveats of the baseline construction.

SIC sector matching

The table below shows the SIC-code alignment used for each selected sector:

SIC sector matches

Sector	SIC sector
Agriculture	A: Agriculture, forestry and fishing
Construction	F: Construction
Energy & infrastructure	D+E: Electricity, gas, steam + Water supply, sewerage and waste management
Food & drink manufacturing	CA: Manufacture of food, beverages and tobacco
Food & drink service activities	56: Food and beverage service activities
Health & social care	86+87: Human health + residential care
Warehouse logistics	52: Warehousing and transport support activities

Source: London Economics

Caveats: As the table shows, a reasonably good match could be made for most sectors. However, given definitional and data issues it was not possible to provide a satisfactory match for the food & drink, the energy, and the infrastructure sectors. The modelling therefore separated the food and drinks segment into its manufacturing and its services components; while, the energy and infrastructure sector were modelled jointly.

It should further be noted that the food & drink manufacturing sector match includes tobacco manufacturing, while the agriculture sector also includes fishing activities. More granular data was not readily available from the employment data obtained from the ONS. However, the more granular GVA estimates suggest that both tobacco activities and fishing only account for a small proportion of their sector matches. The inclusion of tobacco and fishing is therefore unlikely to have a significant impact on results.

Finally, employment data was not available from, the ONS, at the more detailed level needed for the sectors matched to SIC sub-sectors. In these cases, GVA data suggested that the sectors do not account for a large enough proportion of the overall activities of the SIC section and that use of data at the SIC section level would therefore skew the results. For this reason, data from the Business Register and Employment Survey (between 2015 and 2018) was used to estimate the proportion of total SIC section employment that can be attributable to the more detailed sector.

Adjustment factors used to apportion employment data to detailed SIC sectors

SIC section for which data was available	SIC sector match	Average share of sector in section (2015-2018)
A: Agriculture, forestry & fishing	A: Agriculture, forestry and fishing	100%
B, D, E: Mining, quarrying & utilities	D+E: Electricity, gas, steam + Water supply, sewerage and waste management	86%
C: Manufacturing	CA: Manufacture of food, beverages and tobacco	17%
F: Construction	F: Construction	100%
H: Transportation and storage	52: Warehousing and transport support activities	38%
I: Accommodation & food services	56: Food and beverage service activities	79%
Q: Human health and social work activities	86+87: Human health + residential care	76%

Source: London Economics analysis of BRES data

Accounting for COVID-19 shock

To account for the economic shock of COVID-19 more recent monthly GDP data capturing the period of March to May 2020 from the ONS (2020) was used to adjust the baselines.

Assumed impact of COVID-19

Sector	Closest sector for which more recent ONS data was available	Assumed Impact
Total economy	Whole economy	-19.1%
Agriculture	Agriculture	-6.3%
Construction	Construction	-29.8%
Energy & infrastructure	Mining, energy and water supply	-8.0%
Food & drink service activities	Accommodation and food services	-71.7%
Food & drink manufacturing	Manufacturing	-18.0%
Health & social care	Human health and social activities	-24.2%
Warehouse logistics	Transport and storage	-29.5%

Source: London Economics analysis of ONS (2020)

Caveats: It should be noted that his data was not available for the detailed sectors used. Therefore, the closest match, shown in Table 6, was used for each sector. In addition to these data availability issues, it is worth highlighting the significant uncertainty that continues to surround the impact of COVID-19. Much will depend on the length and severity of the ongoing pandemic as well as the public health measures put in place in response to the crisis. The assumptions used here should therefore be seen as plausible estimates at the time of modelling, not as forecasts.

Assumptions about the economic recovery from COVID-19

Significant uncertainty also surrounds the economic recovery from the ongoing pandemic. A wide range of differing projections have been made in recent months. In order to avoid making controversial assumptions about the potential recovery from COVID-19, the Bank of England (2020) plausible economic scenario was used to model the recovery under the baseline.

Specifically, the BoE scenario for the UK as a whole was used as the baseline on which estimates of economic recovery for each sector were based. In order to model recovery on a sectoral basis, the BoE scenario was adjusted by the magnitude of the COVID shock (see previous table). Labour productivity impacts were assumed to be constant across sectors.

Assumed recovery from COVID-19

Indicator	Sector	2020	2021	2022
Value added	Total economy	-14%	15%	3%
	Agriculture	-5%	5%	1%
	Construction	-22%	23%	5%
	Energy & infrastructure	-6%	6%	1%
	Food & drink service activities	-53%	56%	11%
	Food & drink manufacturing	-13%	14%	3%
	Health & social care	-18%	19%	4%
	Warehouse logistics	-22%	23%	5%
Labour productivity		-1%	2%	0%

Source: London Economics based on BoE (2020)

Caveats: Similarly to the impact of COVID-19, significant uncertainty continues to surround the recovery from the pandemic. Much will depend on the length and severity of the ongoing pandemic as well as the public health measures put in place in response to the crisis. The estimates presented here do not make any claim to be accurate forecasts of how recovery will actually play out and should not be interpreted in this way.

Estimating the employment needs implied by the baselines

The resulting value-add and labour productivity baselines constructed in this way were used as the basis to estimate the employment needs under the baseline. Specifically, value added for each year over the study period was divided by the corresponding labour productivity estimate in that year. The resulting baselines, for each sector, are provided in a later annex.

Estimating the potential productivity impact of RAS

As a new and evolving technology, significant uncertainty also surrounds the potential productivity effects that RAS may bring. Productivity impacts depend on a wide range of factors and may vary significantly across sectors or indeed across firms within sectors.

In order to estimate the potential productivity improvements from RAS, given the uptake forecasts derived earlier, this study made use of existing productivity estimates from the literature. Specifically, the analysis used productivity estimates from the Centre for Economics and Business Research (2017), which found that, in OECD countries between 1993 to 2016, a one-unit increase in robot density (defined as the number of robots per million hours worked) was associated with a 0.04% increase in labour productivity, as an anchor to derive sector specific productivity assumptions.

While other studies estimating labour productivity increases from RAS exist, these often use robot stock in a given sector to derive productivity estimates. While this works well when examining productivity improvements in a specific sector, the estimates do not generalise well when seeking to apply them to sectors of different sizes. In contrast, the use of robot density within the CBER analysis meant that the sector size is implicitly accounted for through the use of hours worked.

Caveats: Of course, the estimates from the CBER study do not generalise directly to the impact of RAS across UK sectors. First, as mentioned above, the impact of robotics may vary significantly across sectors. Second, the impact of robotics may vary significantly across countries. Third, the impact of robotics may vary significantly over time. Fourth, the impact of robotics may vary significantly by type of robot. In particular, historical robot uptake was mostly driven by industrial robots in the manufacturing sector. Impacts estimated from historical data are therefore likely to mainly capture automation of manual and routine tasks. In contrast, RAS has the capability to also deliver significant benefits for non-routine tasks.

To account for these difficulties, the analysis adjusts the CBER estimates in the following way:

- First, the CBER estimate of 0.04% is adjusted by the relative proportion of manual and routine tasks in each sector compared to the food and drink manufacturing sector. This is done to adjust the CBER estimate downwards in sectors where fewer tasks are manual and routine tasks (as 'traditional' robots would likely have had less impact on these sectors) and upwards where sectors had a higher proportion of manual and routine tasks. The resulting estimates are shown in the "productivity anchor" column in the table below.
- Second, the study uses the difference (or more precisely the ratio) between the proportion of manual and routine tasks in each selected sector, derived from PIAAC data (as described in the next sub-section), and data on the automation potential in each sector, from PwC (2018), to adjust the productivity anchor in order to account for productivity improvements from non-routine task automation.

The final productivity assumptions used in the analysis are shown in the table below:

RAS labour productivity impact assumptions

Sector	CBER productivity	Proportion of manual & routine tasks	Productivity anchor	Automation potential	Productivity assumption used
Agriculture	0.04%	28.2%	0.04%	30.0%	0.04%

Sector	CBER productivity	Proportion of manual & routine tasks	Productivity anchor	Automation potential	Productivity assumption used
Construction		20.6%	0.03%	38.0%	0.05%
Energy & infrastructure		16.2%	0.02%	39.3%	0.05%
Food & drink service activities		24.0%	0.03%	24.0%	0.03%
Food & drink manufacturing		29.8%	0.04%	45.0%	0.06%
Health & social care		17.0%	0.02%	21.0%	0.03%
Warehouse logistics		19.0%	0.03%	52.0%	0.07%

Note: Productivity estimates refer to the % increase in labour productivity for a 1 unit increase in robots per million hours worked.

Source: London Economics analysis of CBER (2017), PIAAC data and PwC (2018)

Caveats: Significant uncertainty surrounds the potential productivity effects that RAS may bring. Productivity impacts depend on a wide range of factors and may vary significantly across sectors or indeed across firms within sectors. As such, the analysis sought to derive assumptions that were plausible; but it is worth reiterating that productivity impacts in practice may differ. It is further worth noting that PwC estimates capture the automation potential within a sector as a whole. Their estimates also include automation through non-physical technologies such as Artificial Intelligence. Automation from RAS is therefore likely to be less than the automation potential. It could therefore be argued that the chosen scaling factor should be smaller than that implied by the ratio of manual and routine tasks to automation potential. At the same time, however, it is unlikely that 'traditional' robots would have been able to automate all manual and routine tasks in each sector. This would imply that the scaling factor should be larger than the factor used. Which of these effects is stronger in practice is difficult to establish.

Estimating the proportion of manual and routine tasks in each sector (PIAAC analysis)

The OECD conducts the Survey of Adults Skills as part of its Programme for the International Assessment of Adult Competencies (PIAAC). Data on responses to this survey for England and Northern Ireland was used in the analysis for this study (while data for Scotland and Wales was not available, it is unlikely that job characteristics for the same type of job are vastly different in Scotland and Wales compared to England and Northern Ireland).

The data contains, amongst other information, the sector in which each respondent works and the frequency with which the respondent performs certain types of tasks at work. Based on this information, work-time shares for different types of tasks were constructed from the frequency with which they were reported to be undertaken, using a similar methodology to that of Arntz, Gregory and Zierahn (2016). Specifically, tasks carried out:

- ‘Never’ were assigned a score of 0.
- ‘Less than once a month’ were assigned a score of 1/30.
- ‘Less than once a week but at least once a month’ were assigned a score of 1/7.
- ‘Every week but not every day’ were assigned a score of 1/2.
- ‘Every day’ were assigned a score of 1.

For each sector, the proportion of work that is accounted for by manual tasks was estimated by summing the work-time shares of manual tasks (i.e. tasks involving working physically for a long time or using skill or accuracy with one’s hands and fingers) in that sector and dividing this by the sum of the work-time shares of all tasks. To account for routine tasks, the share of tasks involving solving of simple (<5min) problems was used.

PIAAC data was available at 4-digit SIC level. Therefore, the granular SIC sector assignments (shown earlier) were used to derive the proportion of manual tasks for each selected sector.

Caveats: This analysis is based on the current nature of roles within each selected sector. As RAS is adopted, as well as with further technological advancement, it is likely that the nature of roles will change, and thus the proportion of tasks where RAS can feasibly be utilised may change too.

Estimating robot density in each sector

To translate the productivity assumptions, it was necessary to derive the current robot density for each sector, as well as, to translate the adoption forecasts into estimates of robot density in the future. To do this, the robot stock estimates derived earlier were combined with the COVID-19 adjusted employment baseline.

First the employment baseline, in terms of number of workers, was converted to an hours-worked baseline for each sector. To do this, data on the average number of weekly hours worked was obtained from the ONS. As with employment data, data was not available for detailed economic sectors. However, it seemed reasonable to assume that the average number of weekly hours worked in a sub-sector would be similar to that in the sector as a whole. Hours worked of the closest sector for which ONS data was available was therefore used as the basis for the analysis. As hours worked were relatively stable for the historical data obtained, the average hours worked over the most recent period was used to convert the future employment baseline to an hours-worked basis.

The table below shows the hours worked assumptions made for each sector:

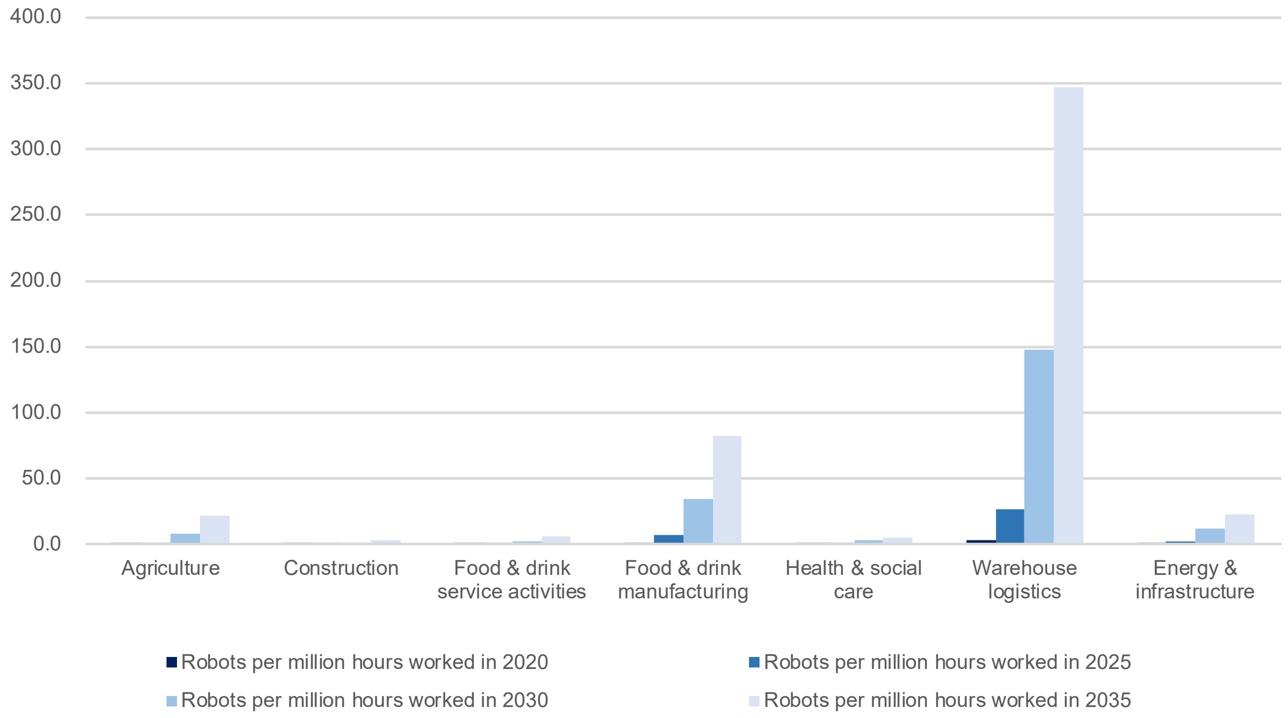
Assumed hours worked

Sector	Closest sector for which ONS data was available	Average weekly hours worked (2016-2019)
Total economy	Whole economy	32.1
Agriculture	Agriculture, Forestry and Fishing	43.9
Construction	Construction	37.3
Energy & infrastructure	Mining, energy & water supply	37.3
Food & drink service activities	Accommodation & food services	28.0
Food & drink manufacturing	Manufacturing	36.3
Health & social care	Health and Social Work	29.5
Warehouse logistics	Transport and Storage	35.9

Source: London Economics analysis of ONS data

The hours-worked baseline was then combined with the robot stock and annual shipment estimates to derive an estimate of the robot density in each sector over the study period:

Estimated robot density (robots per million hours worked under baseline) under current RAS adoption



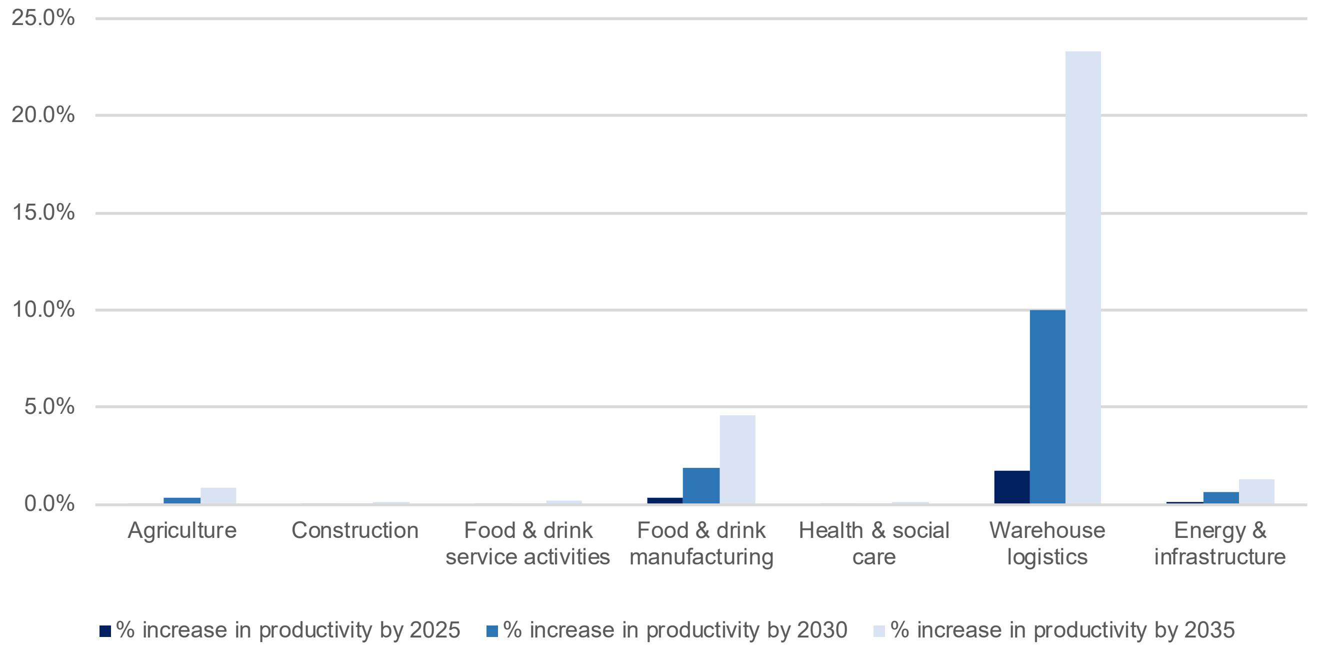
Source: London Economics

Estimating productivity improvements

Lastly, the estimates of robot density were combined with the productivity assumptions described at the beginning of this section. To do this, for each sector, the unit increase in robot density was calculated for each year over the study period. This was then multiplied by the respective productivity assumption to obtain an estimate of the potential improvements in labour productivity for each year.

The figure below shows the cumulative productivity increases, derived in this way, under current RAS adoption relative to the labour productivity baseline:

Estimated cumulative labour productivity increases, under current RAS adoption, relative to baseline



Source: London Economics

Translating productivity estimates into estimates of reduced employment needs and value added

The final stage of the analysis was the conversion of the labour productivity estimates derived in the previous section to estimates of the reduced employment needs and value added.

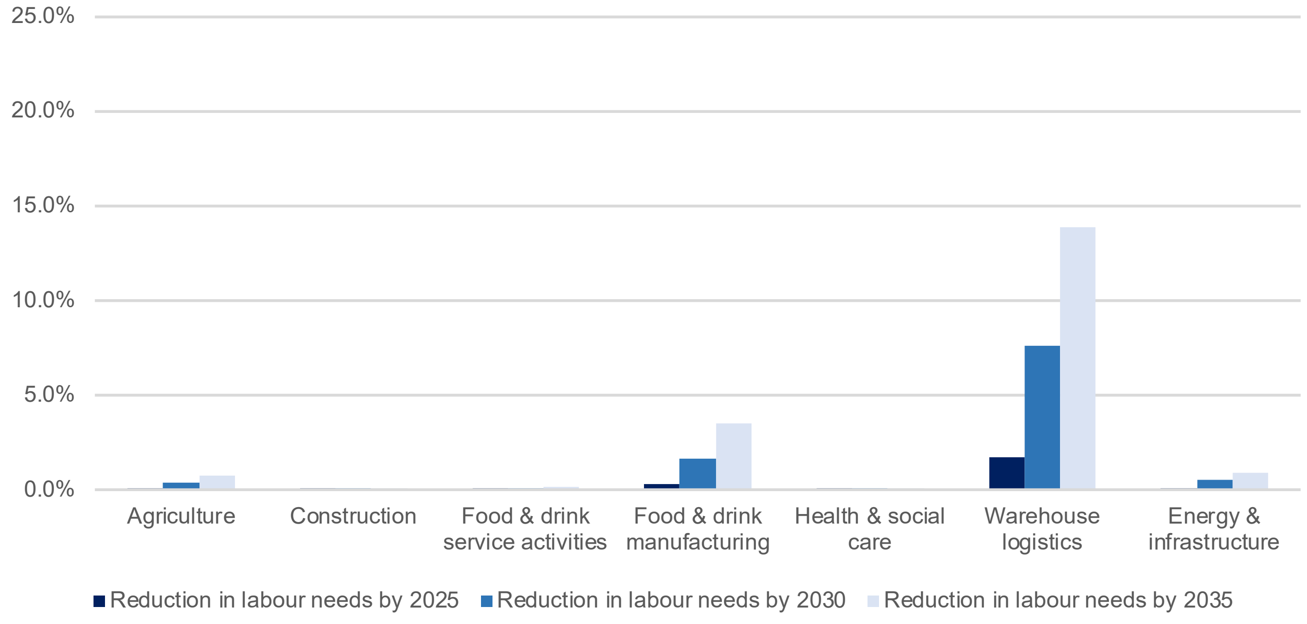
Step 1: Estimating the reduced labour need as a result of RAS

The first step was to translate the estimated productivity improvements into the potential reduction in labour needs RAS could help bring about. In other words, this step of the analysis looked at the reduction in the number of additional workers that need to be employed to meet GVA growth under current RAS adoption trends relative to the number of additional workers needed under the baseline.

To do this, the analysis first calculated a proxy for output under the baseline scenario by adding employment costs (calculated as discussed later in this section) to value added. The analysis then calculated the new (reduced) number of workers needed in order for output (proxied by the calculated output proxy) to remain constant, given productivity improvements under given RAS trends and the additional cost of RAS (the way in which RAS costs were derived is discussed later in this section). That is the scenario took the additional cost of acquiring robots, and the corresponding reduction in value-added, into account.

The resulting estimates of the reduced employment needs given current RAS adoption forecasts are provided in the Figure overleaf:

Estimated reduction in employment needs under current RAS adoption



Source: London Economics

Step 2: Estimating GVA impacts

The economic impact in terms of value added will depend on the level of displacement that RAS will bring; that is, what proportion of labour will be re-deployed to similar or higher value-add tasks, and what proportion of labour will be replaced. Therefore, in order to derive corresponding economic impacts, assumptions of the level of displacement likely to occur have to be made.

It is unlikely that all labour that is freed-up by the adoption of RAS will be re-deployed to similarly productive tasks. This is for two reasons: Firstly, the amount of labour available in the UK is unlikely to grow by as much as required under the baseline. Secondly, labour is not perfectly mobile between jobs, even similarly productive ones (either geographically or in terms of skills). Equally, it is also unlikely that none of the labour freed-up due to RAS is re-deployed.

However, there is significant uncertainty around the level of displacement likely to occur. This study uses estimates by PwC (2018) on the potential rates of job automation across sectors in order to derive plausible central estimates of economic impacts. The displacement assumptions made in the central case are shown in the table below:

Assumptions on labour displacement

Sector	% of workers re-deployed	% of workers displaced
Agriculture	70%	30%
Construction	62%	38%
Energy & infrastructure	61%	39%

Food & drink service activities	76%	24%
Food & drink manufacturing	55%	45%
Health & social care	79%	21%
Warehouse logistics	58%	42%

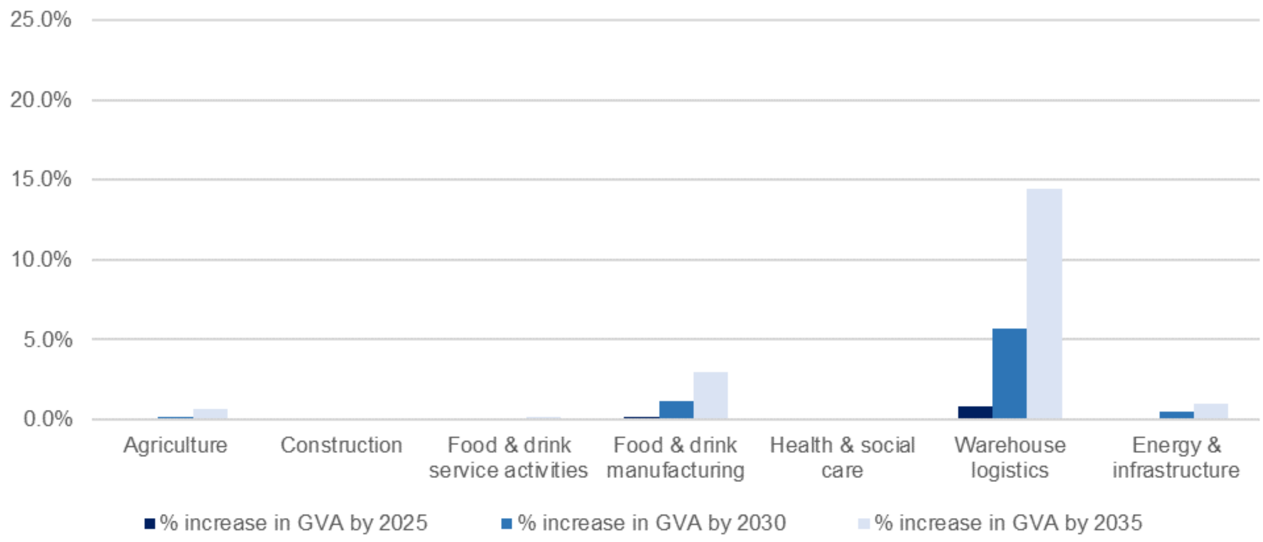
Note: The displacement assumptions apply to the reduced labour needs, not the total no. of workers. That is, a displacement factor of 30% entails that, of those workers whose tasks are replaced by RAS, 30% are displaced, while 70% are re-deployed to other tasks of a similar (or in practice higher) value-add.

Caveats: The displacement assumptions are of course oversimplifications in order to derive a reasonable central estimate. It is not clear what proportion of labour will be re-deployed and what proportion of labour will be displaced. The model therefore also provides estimates of the impact on value added under complete labour displacement and for the scenario where all labour is re-deployed.

Source: London Economics based on PwC (2018)

The displacement assumptions were then combined with the estimated reduction in labour needs, baseline employment, and improved labour productivity estimates under RAS in order to derive estimates of value-added under the central scenario; these estimates are shown in the figure below:

Estimated GVA impact under central scenario



Source: London Economics

Caveats: It is important to note that estimated impacts show the potential size of the economic impact relative to a plausible baseline of value added, employment needs, and labour productivity. The results do not make any claims about the overall growth of value added itself; and the estimated impacts may be on top of baseline value added, or part of it, depending on whether RAS will provide additional growth on top of typical advances in technology already captured in the baselines.

Calculation of labour costs

In order to estimate labour costs, the analysis combined the employment baseline, with the hours worked estimates, derived earlier, as well as, with estimates of the average labour costs per hour worked, obtained from the ONS.

The table below provides the labour cost assumptions, per hour worked, derived from ONS labour cost data. Similarly to hours-worked, future labour costs were assumed constant as given by the average labour costs over recent years. For consistency with the GVA numbers, the estimates were deflated using GVA deflators prior to taking the average.

Assumed labour costs per hour worked (in real 2018 terms)

Sector	Closest sector for which ONS data was available	Average labour costs per hour worked (2016-2019) in £ 2018 terms
Total economy	All industries	£20.4
Agriculture	Agriculture, Forestry and Fishing	£11.3
Construction	Construction	£18.9
Energy & infrastructure	Electricity, Gas and Water Supply	£24.8
Food & drink service activities	Accommodation and Food Service Activities	£10.2
Food & drink manufacturing	Food Products, Beverages and Tobacco	£16.7
Health & social care	Human health and social work activities	£17.0
Warehouse logistics	Transport and Storage	£19.5

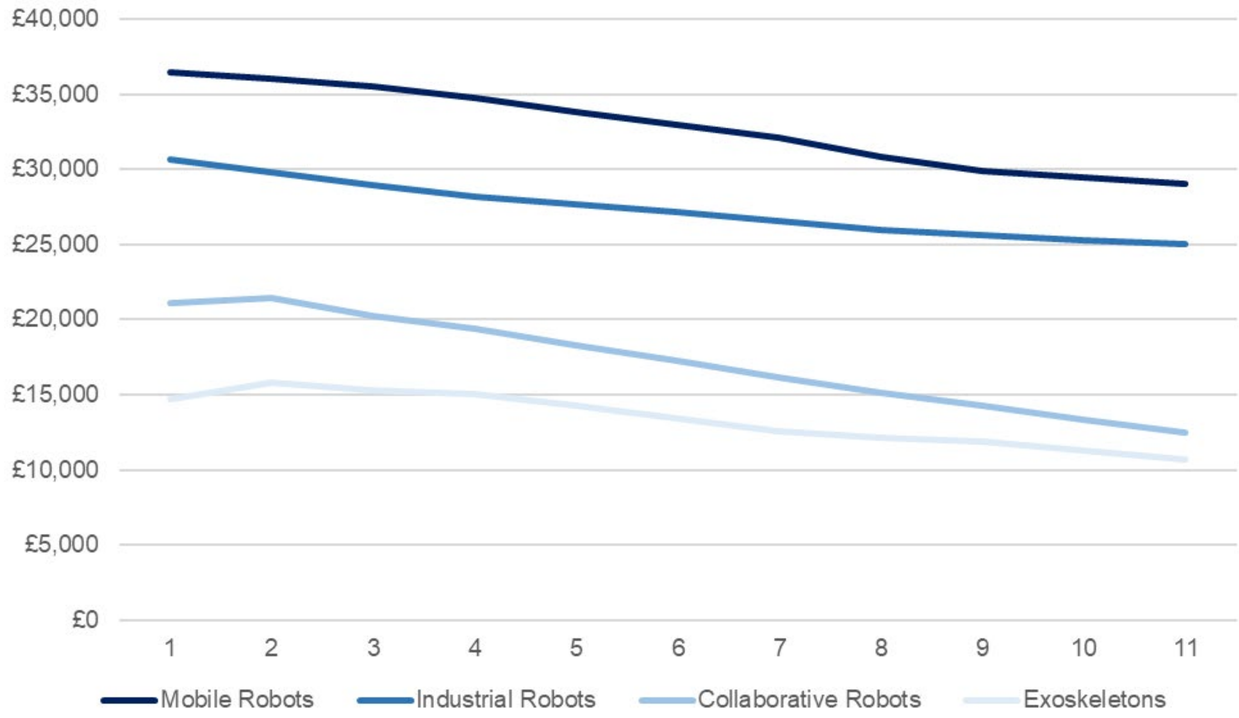
Source: London Economics analysis of ONS data

Caveats: This assumes that labour costs will remain constant over the study period. However, evidence suggests that in some sectors rising labour costs are a challenge. Labour cost savings assumed here may therefore be seen as conservative estimates.

Calculation of RAS costs

RAS costs were derived by first calculating estimates of unit costs from global ABI Research (2020) shipment and revenue forecasts, for each robot type for which data was available. A weighted average cost was then derived for each sector by multiplying estimated UK shipments for that sector by the derived unit cost. Costs beyond 2030 were estimated by applying a linear trend to the weighted average unit cost for each sector.

RAS unit cost assumptions



Source: London Economics based on data from ABI Research (2020)

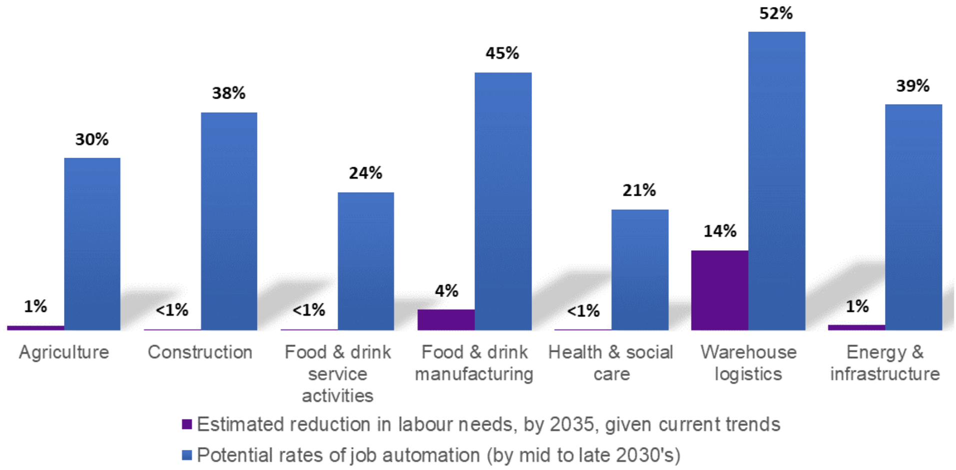
Caveats: RAS costs were estimated at a global level. Costs for UK companies may differ. Further note that RAS costs were not directly available and robot revenue was used as a proxy instead.

Deriving estimates of the ‘automation gap’ and the potential ‘size of the price’

In order to provide context to the estimated impacts, the analysis provides a rough analysis of the ‘automation gap’; that is, the approximate size of the difference between estimated impacts under current adoption forecasts and potential impacts.

First, the study compares estimates of the reduced labour needs with potential rates of job automation across sectors, from PwC (2018b):

Estimated vs. potential rates of automation across sectors

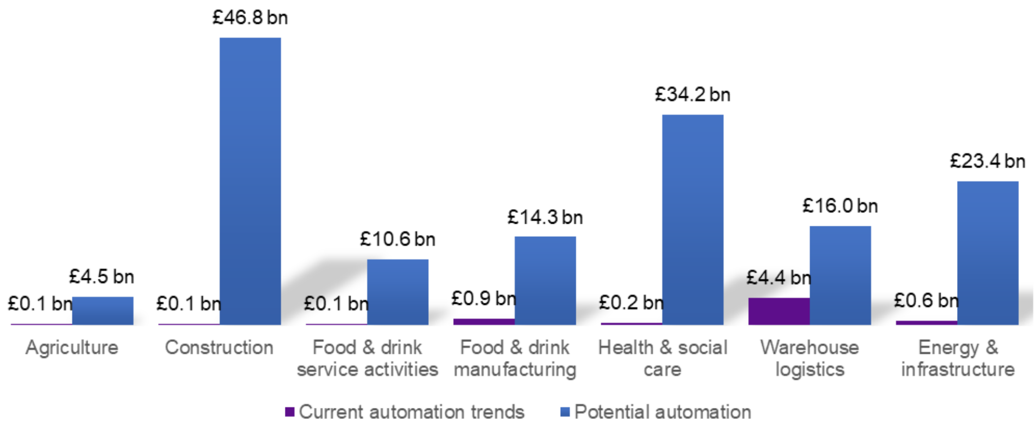


Note: The figure compares the estimated reduction in labour needs by 2035, given current estimates of future RAS adoption, and the potential rates of job automation in each selected sector. The potential rates of job automation across sectors is based on PwC (2018b).

Source: London Economics' analysis

To obtain an idea of the magnitude of the gap in terms of value, rough estimates of the potential economic opportunity in each sector were derived based on the potential rates of automation across sectors shown in the previous figure. These estimates were based on a simple calculation of 2035 baseline GVA, multiplied by the potential rate of automation from PwC (2018b). The resulting estimates are shown in the figure below:

The size of the price: Potential value of GVA that could be attributable to RAS, by 2035, if potential rates of automation were achieved



Note: The figure provides, for each selected sector, a rough estimate of the potential value of GVA that could be attributable to RAS, by 2035, if the potential rates of automation were achieved. These rough estimates are the result of a simple calculation multiplying 2035 baseline GVA by the potential rate of automation from PwC (2018b).

Source: London Economics' analysis

Caveats: PwC estimates capture the ‘automation potential’ within a sector as a whole, including automation through non-physical technologies such as Artificial Intelligence. Automation from RAS is therefore likely to be less than the automation potential. Moreover, as RAS further technological advancement are made, the proportion of tasks where RAS can feasibly be utilised may also change. Similarly, estimates of the magnitude of the gap in terms of value added are based on a very rough estimation (they ignore, for example, the potential additional costs of RAS in order to reach the potential). The comparison should therefore be seen as providing a rough guide to the magnitude of the gap only; they do not constitute a precise estimate.

The Bass Diffusion Model

The fundamental assumption of the Bass Model is that “the probability of adopting by those who have not yet adopted is a linear function of those who had previously adopted“ (Bass, F. M., 1969):

$$P(Adoption\ in\ t\mid not\ adopted\ yet)=\frac{f(t)}{1-F(t)}=p+\frac{q}{M}F(t)$$

Where:

f(t) = portion of the market that adopts at t

F(t) = the portion of the market that has already adopted at t

p = the coefficient of innovation representing influences from external sources

q = the coefficient of imitation representing influences from internal sources

M = the ultimate market potential representing the maximum possible adoption rate

The model is driven by two types of adopters:

- Innovators who are the first to seek out and adopt a new innovation
- Imitators who are more cautious and wait to see the experiences of others until choosing whether to adopt or not

In each year there are a fixed number of potential innovators (p), and a number of further potential adopters influenced by internal sources, i.e. imitating the innovators, (q/M · number of previous adopters). Each year a certain number of these potential adopters decide to actually adopt:

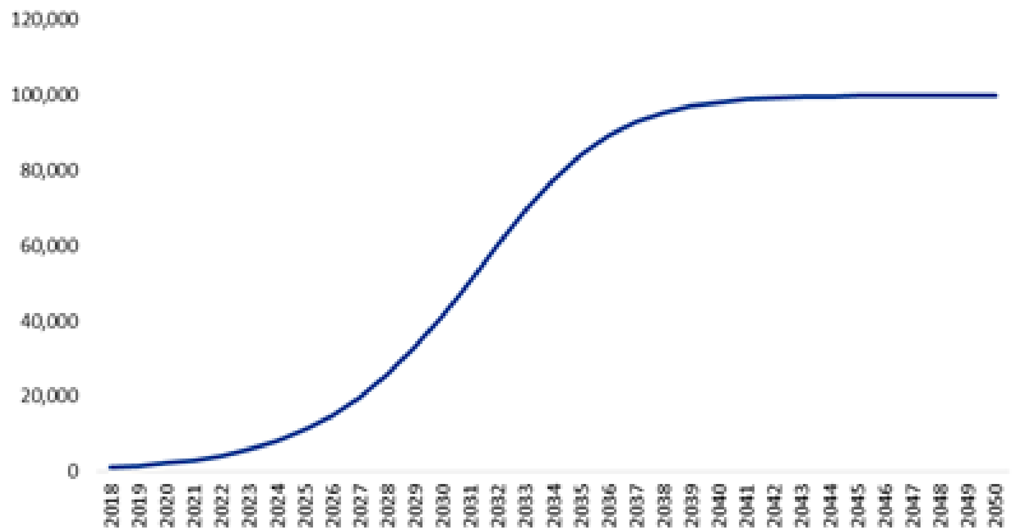
$$Adopters\ in\ t\ =\ p\cdot(M-\ all\ previous\ adopters)+\ q\cdot(1-1/M)\cdot all\ previous\ adopters$$

$$Adopters\ in\ t\ =\ Innovators\ in\ t\ +\ Imitators\ in\ t$$

As more and more organisations adopt the new technology, more and more organisations are tempted to jump on the bandwagon, and more of those tempted do actually adopt. Therefore, the number of imitators increases over time while the number of innovators decreases.

The ultimate market potential (M) imposes an upper limit on the potential number of adopters (adoption rate).

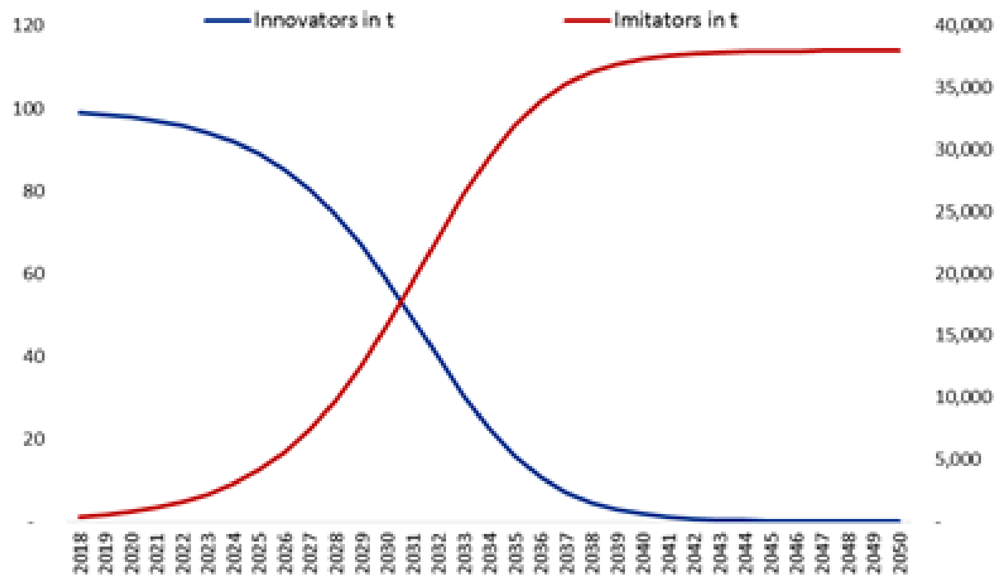
Total number of adopters by t



Notes: Graph based on an example process to illustrate the Bass diffusion model.

Source: London Economics

Number of innovators (blue) and imitators (red) adopting in t



Notes: Graph based on an example process to illustrate the Bass diffusion model.

Source: London Economics

Note on ABI Research methodology

Forecasts from ABI Research (2020) on the overall UK robotics trends as well as sectoral trends at a global level form the basis for the estimation of uptake of RAS as described in the earlier methodology annex. Given the central role of these forecasts play in the estimation, this section provides further details on ABI Research's methodology for deriving these forecasts. This methodological description was obtained from ABI Research' published market data sample[2], which contains further methodological information.

ABI Research Methodology:

"This market data examines the global industrial, collaborative, and commercial robotics market. The industrial robot industry is growing globally as companies look to lower manufacturing costs and increase the speed of product manufacturing. For this research, it is assumed that manufacturing trends continue according to historical industry norms without a major worldwide manufacturing disruption. The commercial robot market is relatively new compared to the industrial robot market.

[…]

The overall market size was derived from both top-down and bottom-up approaches. The top-down view was derived from industrial Gross Domestic Product (GDP)—both global and from companies—and industrial automation equipment by vertical market. On the other hand, the bottom-up approach was based on robotics platform revenue from the major industrial, collaborative, and commercial robotics companies worldwide.

This market data offering is the product of a quantitative assessment of the industrial, collaborative, and commercial robotics market, which was informed by, and further refined by, a qualitative analysis of the technological, business, and political drivers and constraints impacting the sector. The quantitative component was developed using a number of public and private sources. These include financial statements, earnings reports, corporate briefings, government/academic funding announcements, and association and industry publications, along with sessions at conferences and seminars and during private interviews with industry representatives, end users, and others involved with the industry value chain.

This market data offering also draws reference from various market data reports published by ABI Research, including Digital Factory Data (MD-IICT-104, https://www.abiresearch.com/market-research/product/1029891-digital-factory-data/), Wireless Connectivity Technology Segmentation and Addressable Markets (MD-WCMT-180, https://www.abiresearch.com/market-research/product/1033725-wireless-connectivity-technology-segmentat/), and IoT Market Tracker (MD-IOTM-106, https://www.abiresearch.com/market-research/product/1032132-md-iotm-iot-market-tracker/)."

ABI Research's Market Data (MD) model:

[2] See https://0d6ea3a143112fa73580-03f08f5fc1c22419d3b64e44df494fa7.ssl.cf1.rackcdn.com/eblast/deliverables/ABI-Research-Sample-MD-2020.xlsm

“ABI Research has created a dedicated Market Data (MD) model to help [their] clients assess market opportunities of robotics across different industry verticals and evaluate deployment of the technology up to 2030.

This MD provides forecasts reflecting on both volume and value attached to four different segments of the robotics market (industrial robots, collaborative robots, mobile robots, and exoskeletons). For each segment, ABI Research looks at shipments and revenue. ABI Research also breaks down the various robot types into sub-types to add further granularity.”

Forecasting Models Used:

“The MD primarily focuses on the hardware shipments and revenue, as well as service revenue for industrial robot, collaborative robot, mobile robot, and exoskeleton. These forecasts are based on ABI Research’s engagement with relevant robotics vendors, system integrators, chipset vendors, and technology implementers. The numbers of shipments are determined on a per company basis, with additional segmentations based on form factors, verticals, and business models. As the market is evolving rapidly across a number of new segments, this forecast reflects this change with an expansion in the number of form factors and verticals covered.

The granular segmentation provided by this model, together with the mix of expertise of analysts involved, mean that ABI Research has been able to provide reliable datasets based on top-to-bottom and bottom-up approaches reflecting on the balance of technology supply and market demand. This approach enables ABI Research to be unique in tracking both market and technology transformations across various industries. These have been based on dynamic changes in the typical characteristics of each market vertical, their relative pain points, and how the technology supply chain is aligned to solve these pain points.”

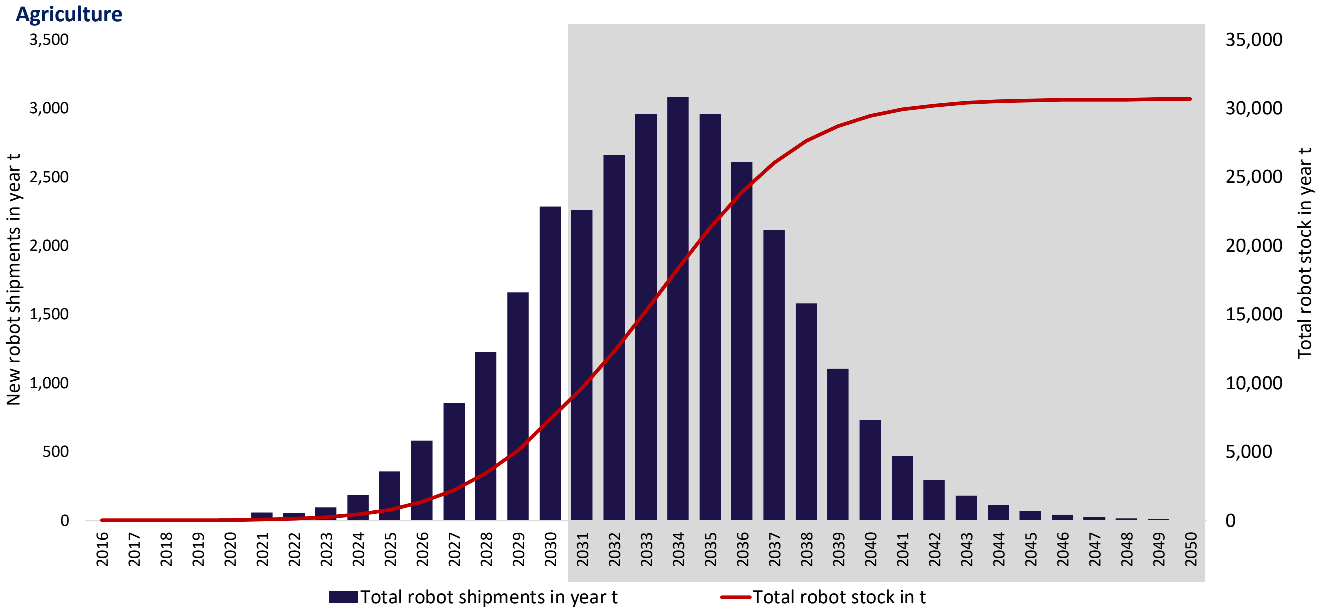
Data Validation:

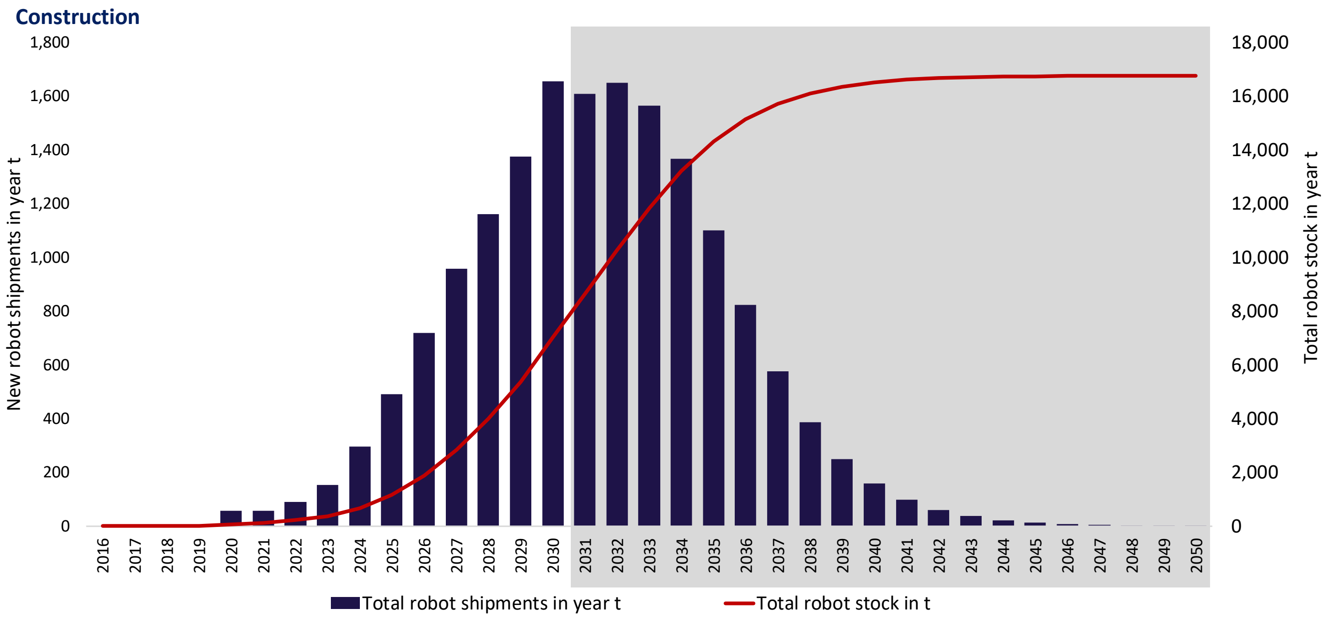
“Before publishing any output from ABI Research’s forecasting model, data have been shared with key industry players and stakeholders for validation. Feedback received from different parts of the value chain are then harmonized and the result enables ABI Research to tweak the modelling parameters and assumptions to align with overall industry expectations.”

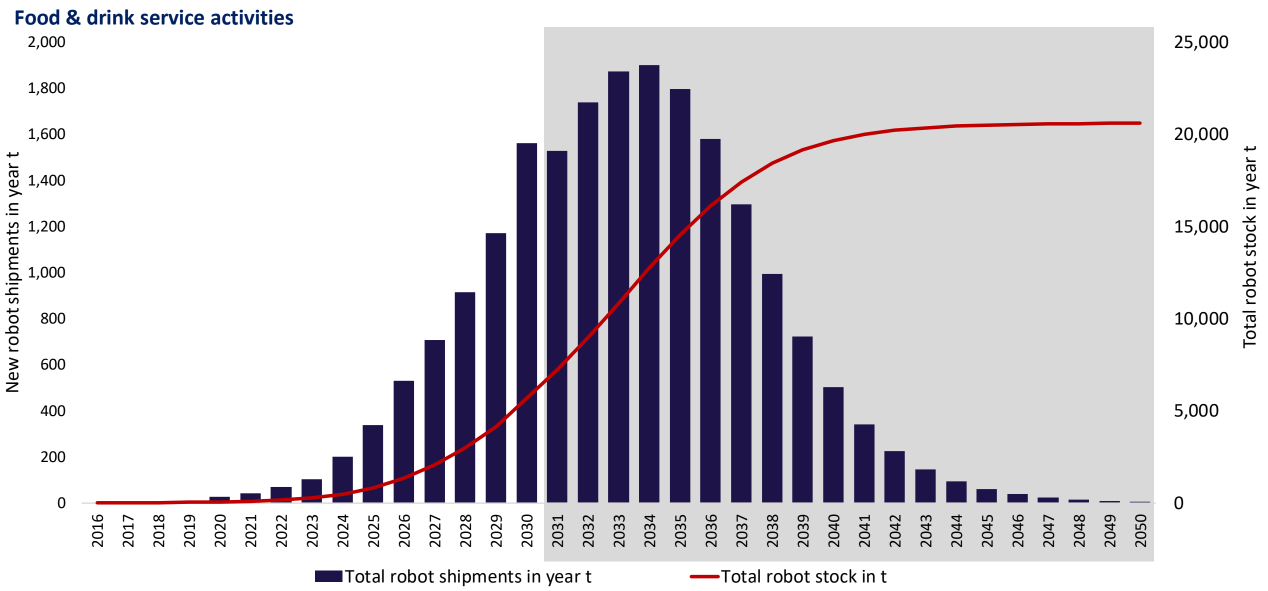
Tipping point analysis

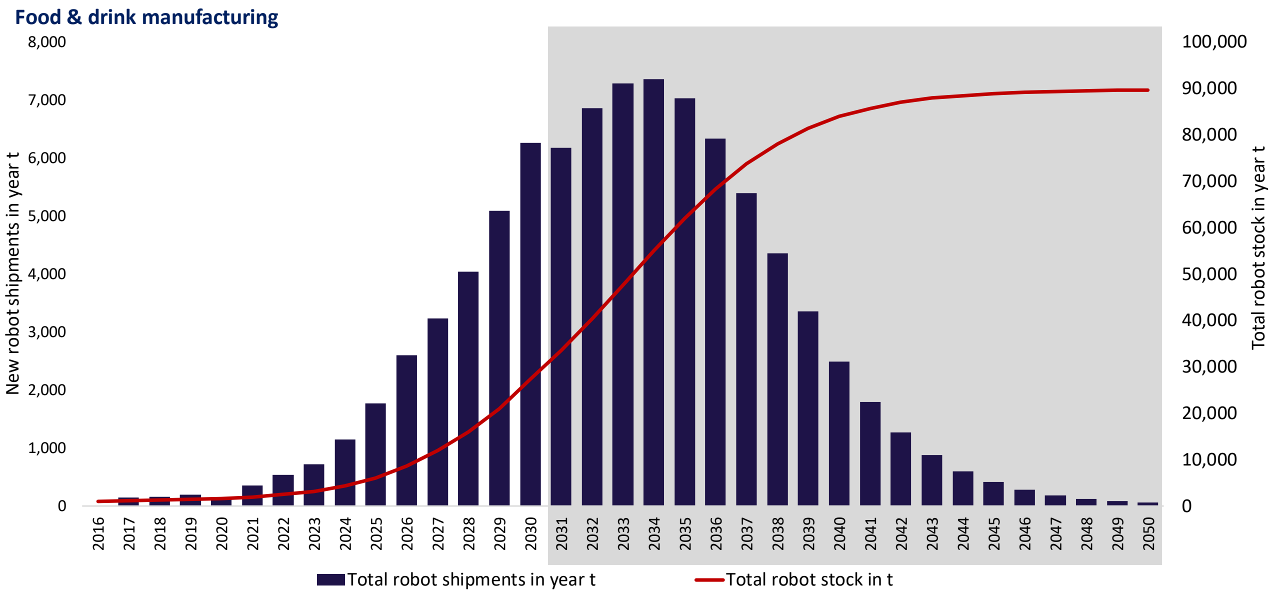
The figures below provide the results of the tipping point estimation discussed in the earlier methodological annex. It should be noted that these estimations are not forecasts, but rather approximations of where on the adoption curve each sector is likely to be if given adoption forecasts hold true. A significant number of factors influence adoption and actual adoption is therefore likely to be different than the curves derived via this exercise.

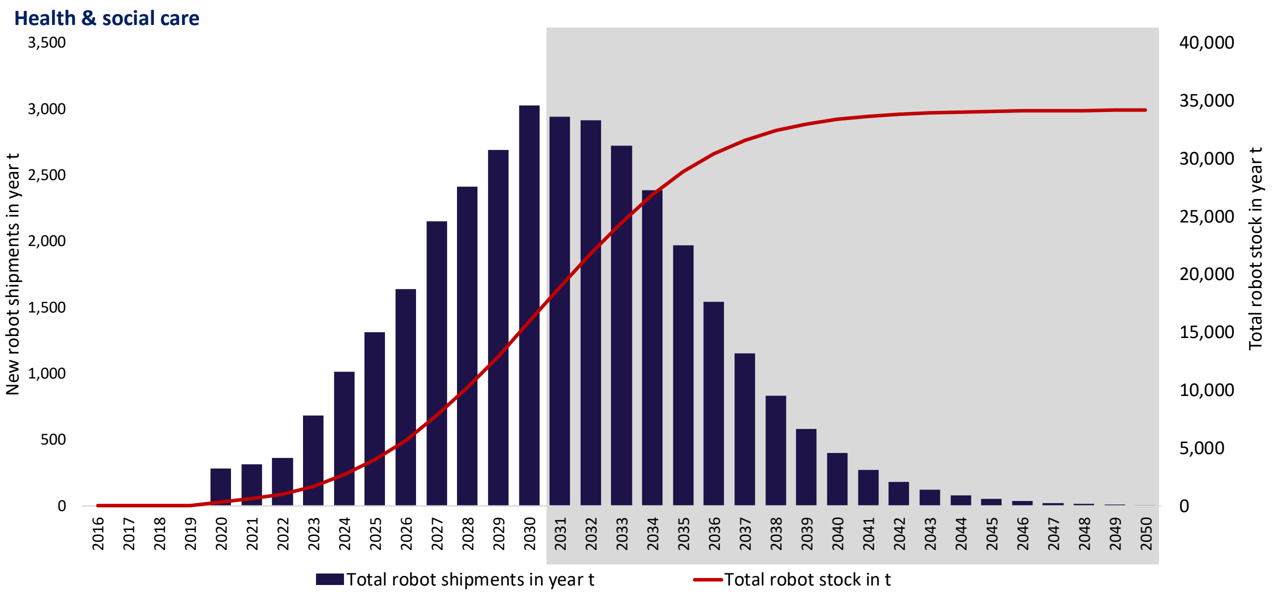
Forecasts up to 2030 are derived from ABI Research (2020) forecasts as described in the earlier methodological annex Forecasts from 2031 onwards (the grey shaded area) are based on the S-shaped adoption curve estimated based on this data.

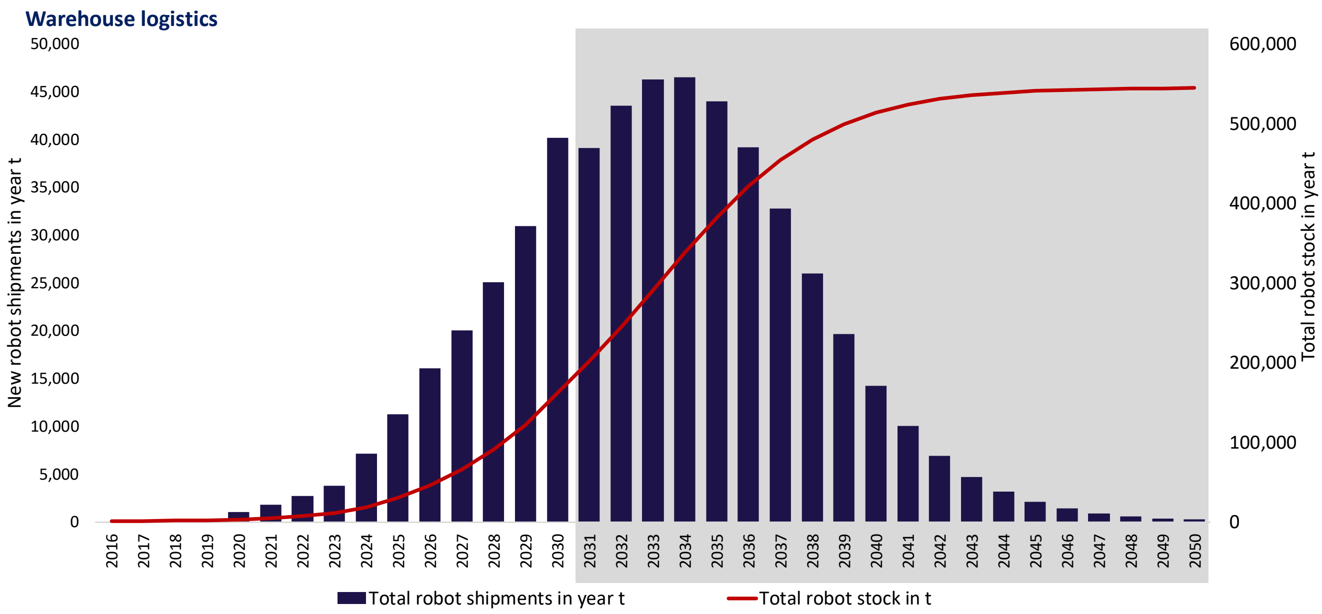


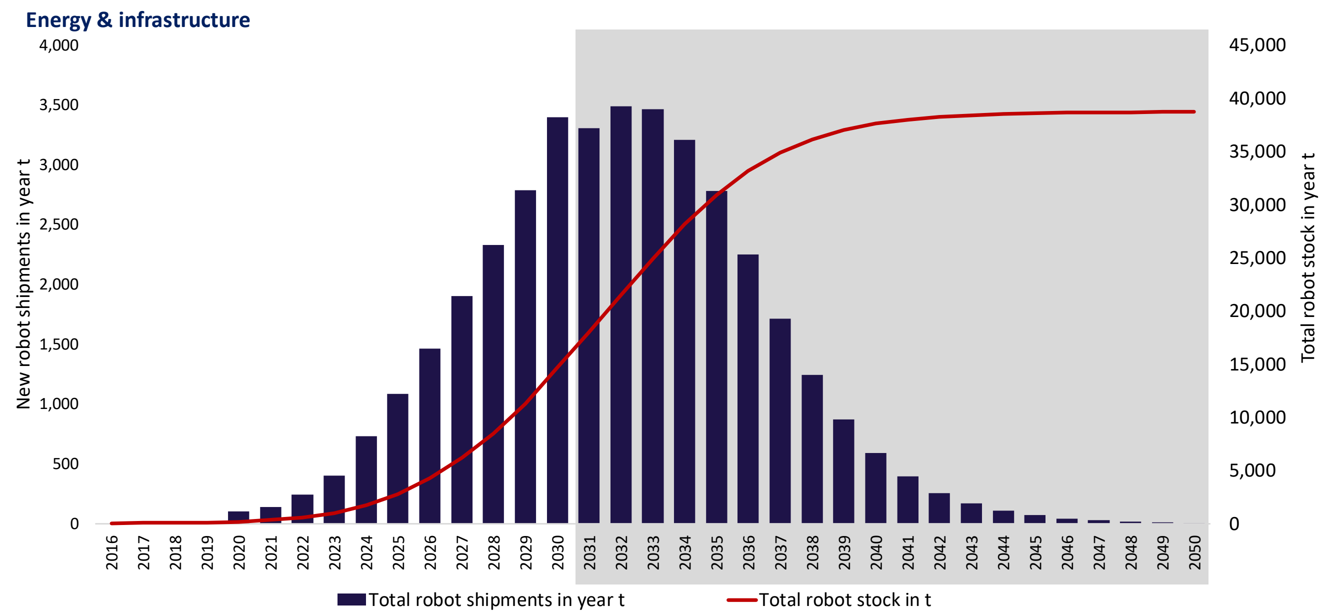



Food & drink service activities
New robot shipments in year t
Total robot stock in year t
Total robot shipments in year t
Total robot stock in t


Food & drink manufacturing
New robot shipments in year t
Total robot stock in year t
Total robot shipments in year t
Total robot stock in t

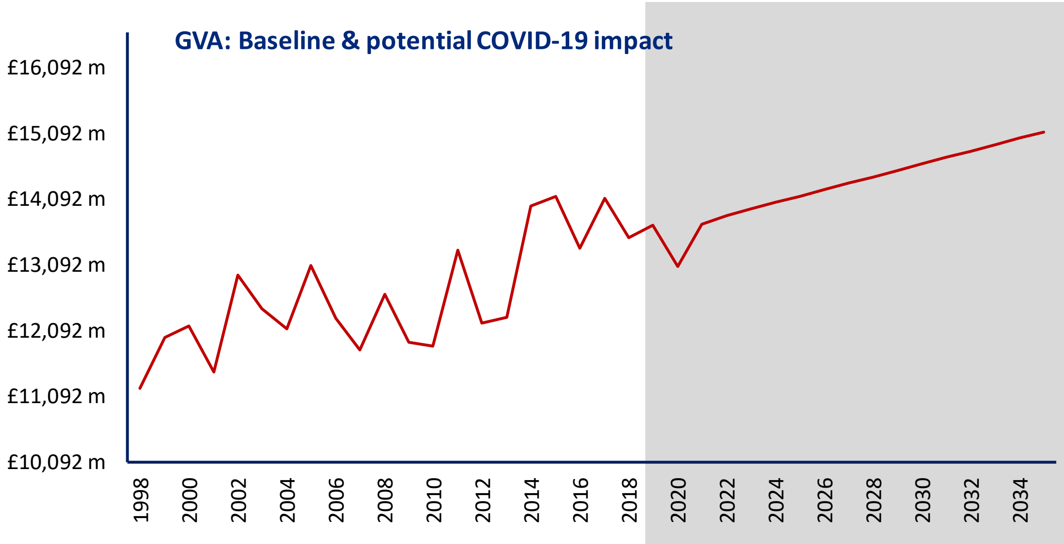

Health & social care
New robot shipments in year t
Total robot stock in year t
Total robot shipments in year t
Total robot stock in t

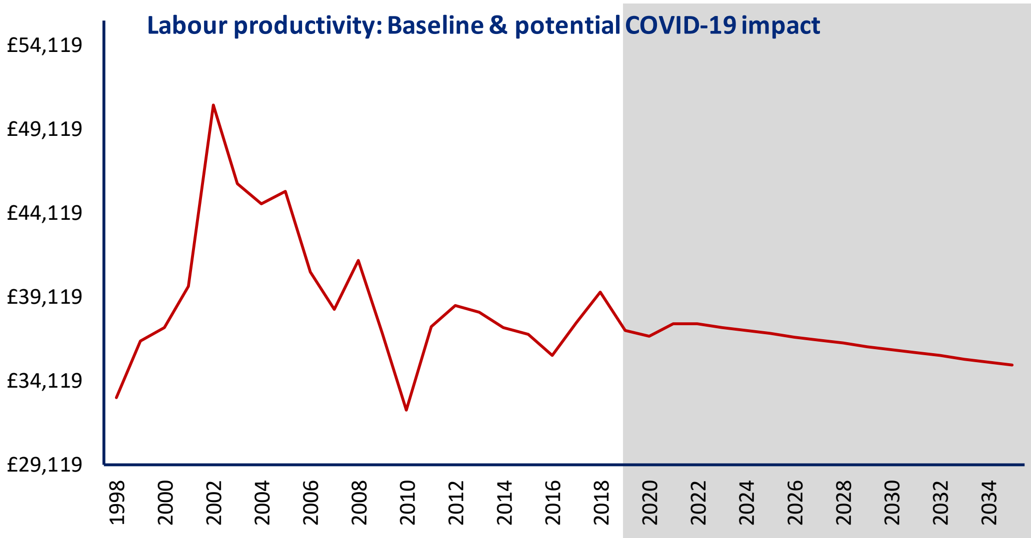

Warehouse logistics
New robot shipments in year t
Total robot stock in year t
Total robot shipments in year t
Total robot stock in t

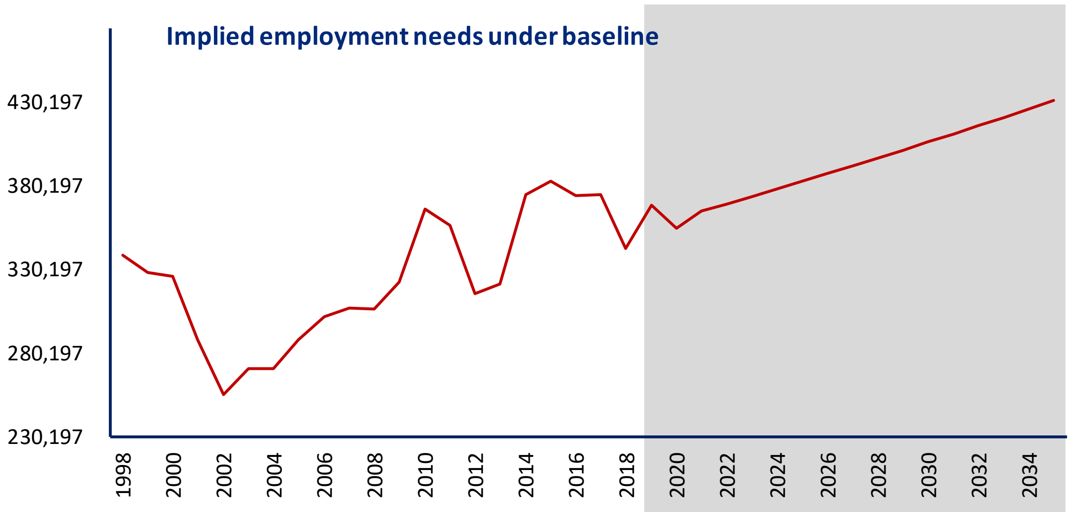

Energy & infrastructure
New robot shipments in year t
Total robot stock in year t
Total robot shipments in year t
Total robot stock in t

Baselines of economic variables

Baselines: Agriculture

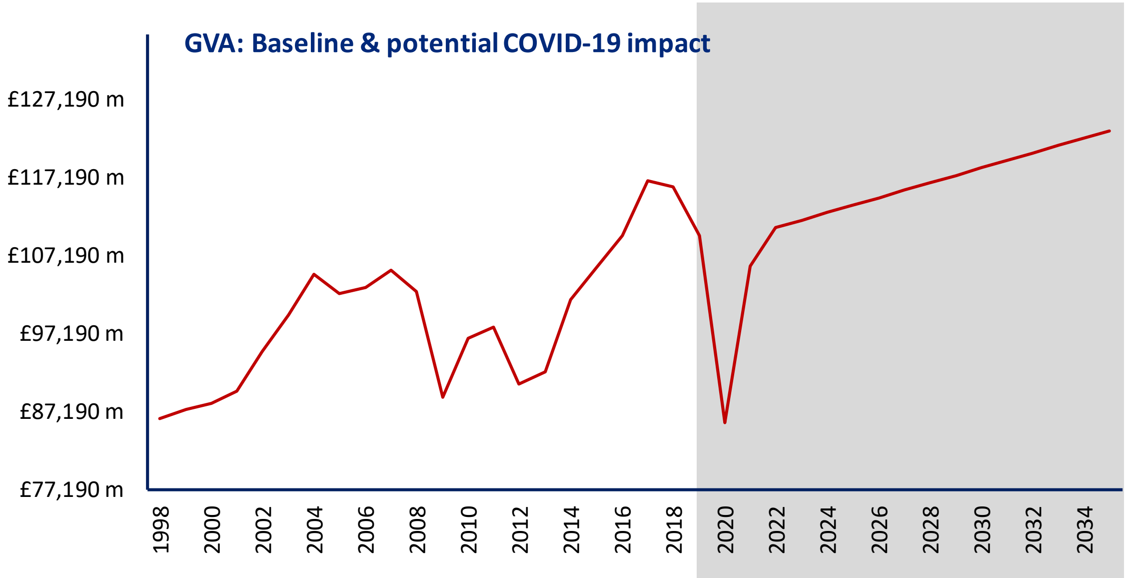


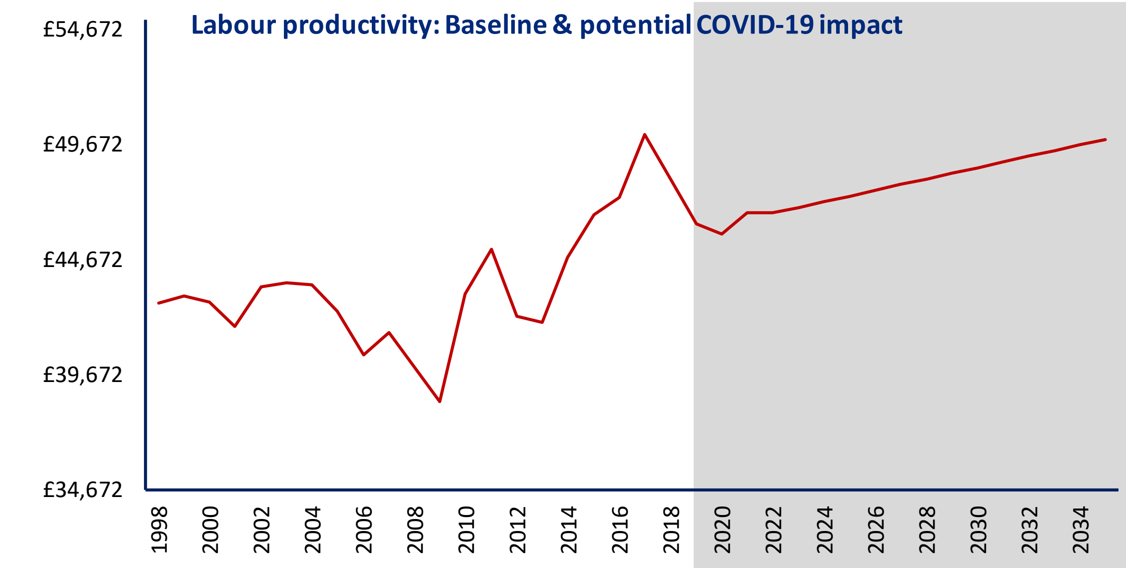


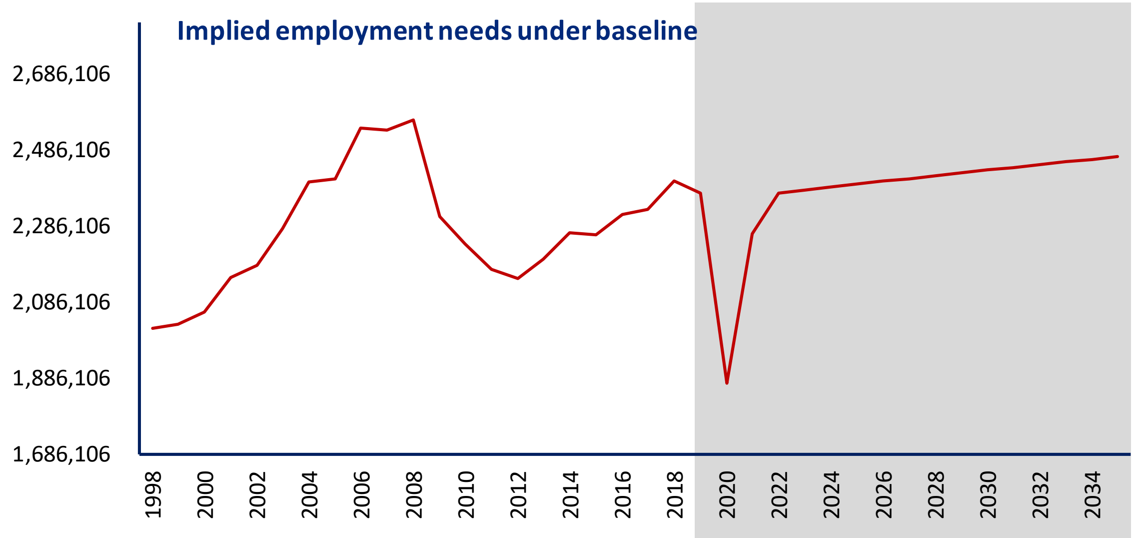


Source: London Economics

Baselines: Construction

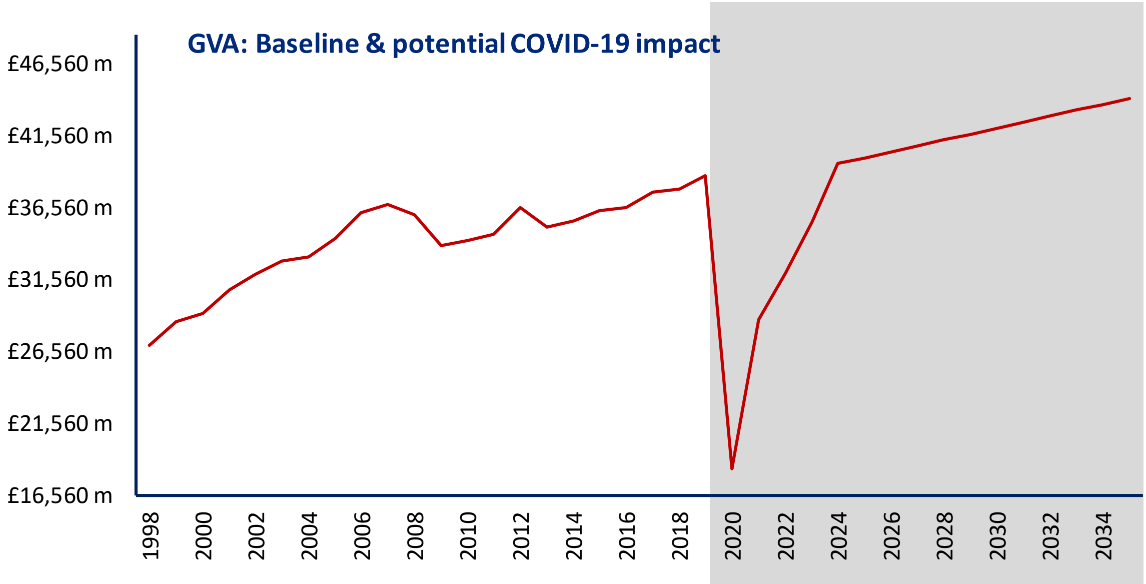


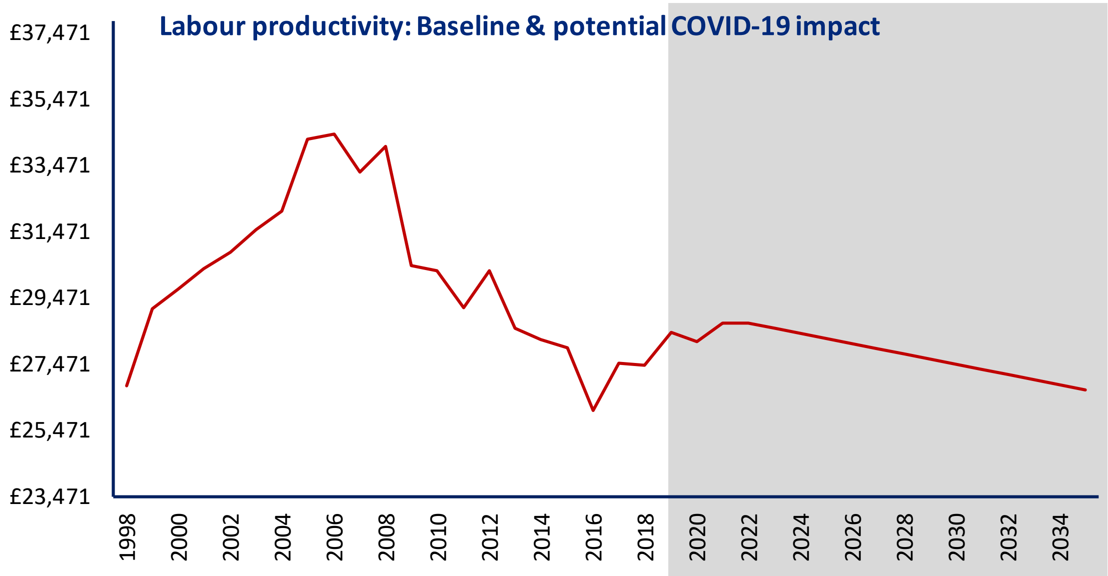


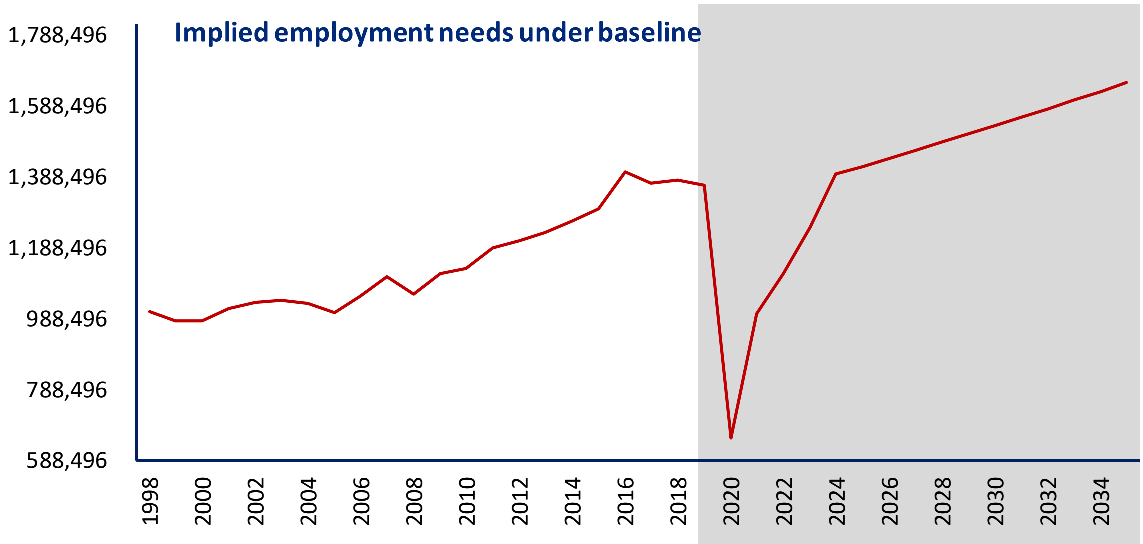


Source: London Economics

Baselines: Food & drink service activities

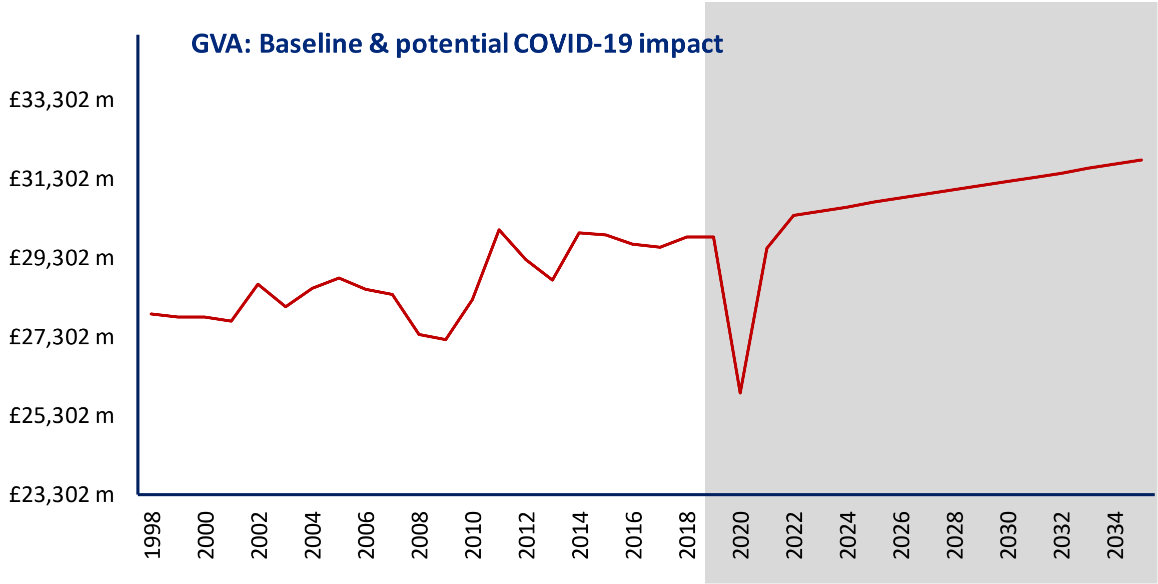


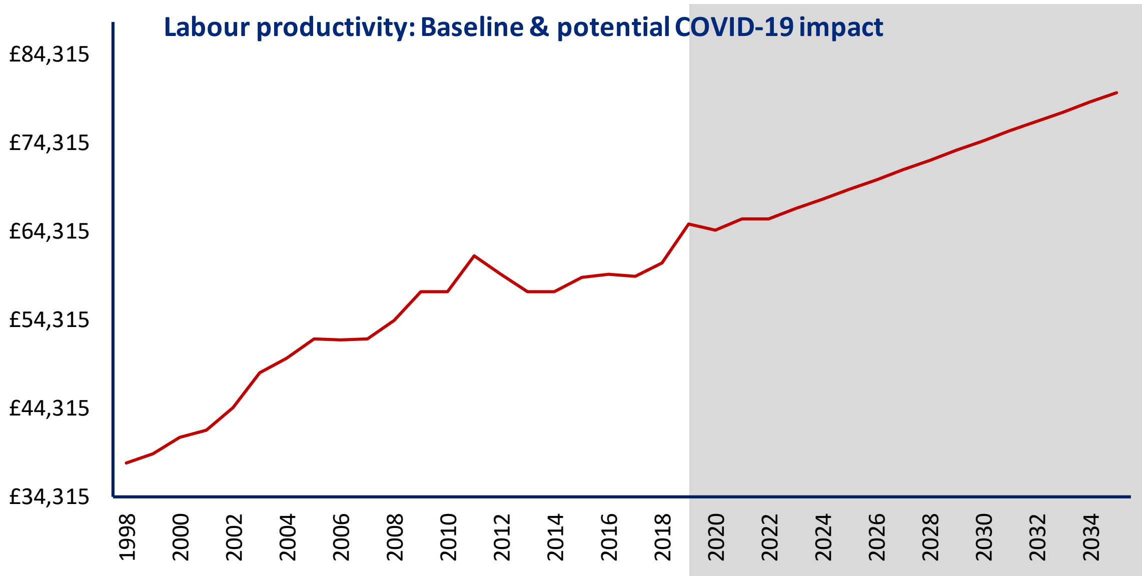


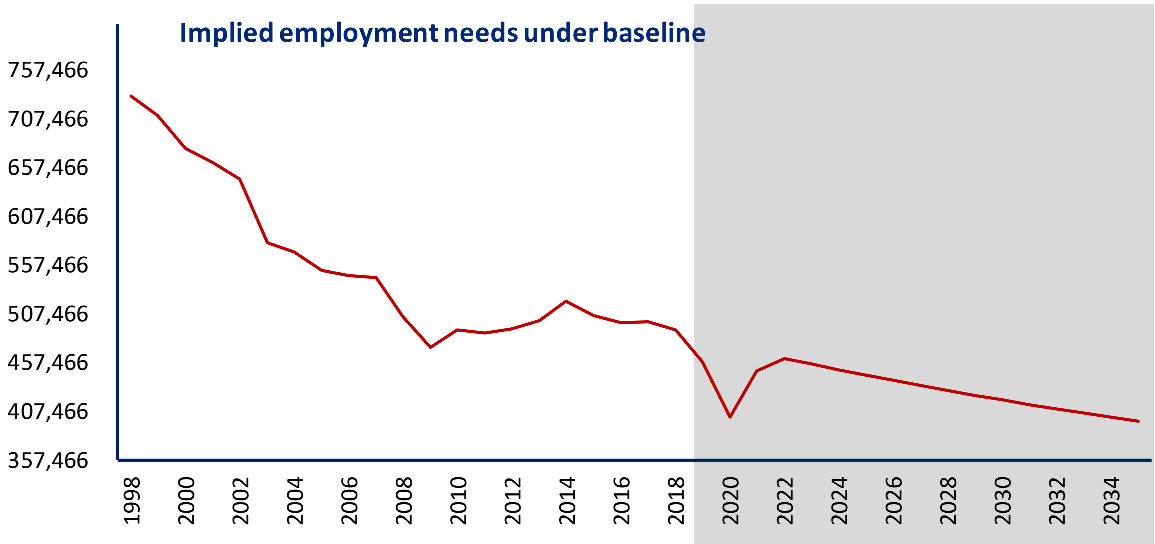


Source: London Economics

Baselines: Food & drink manufacturing

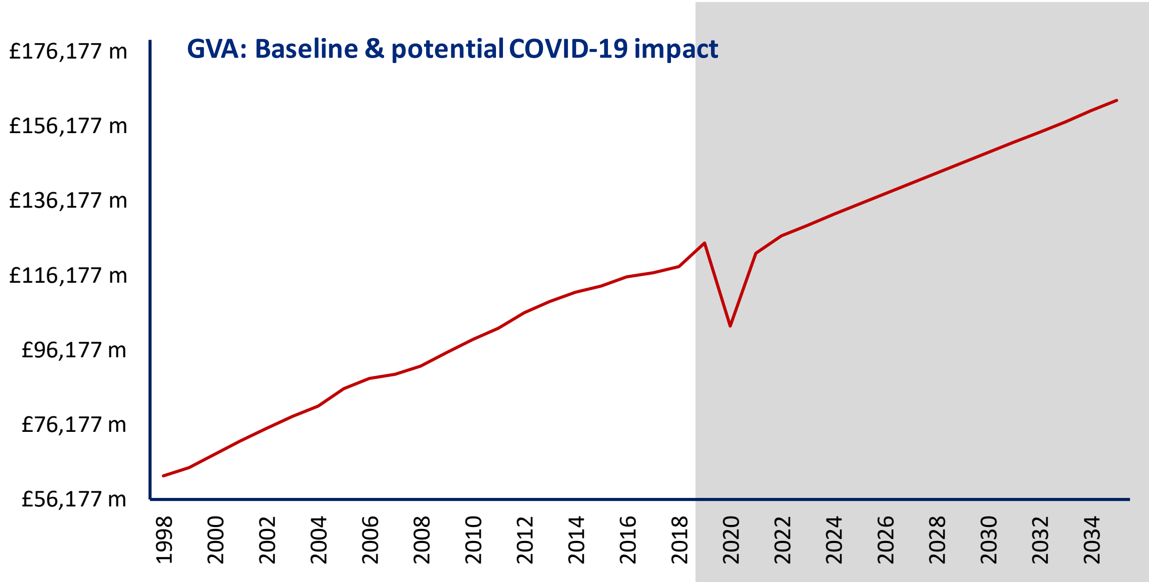


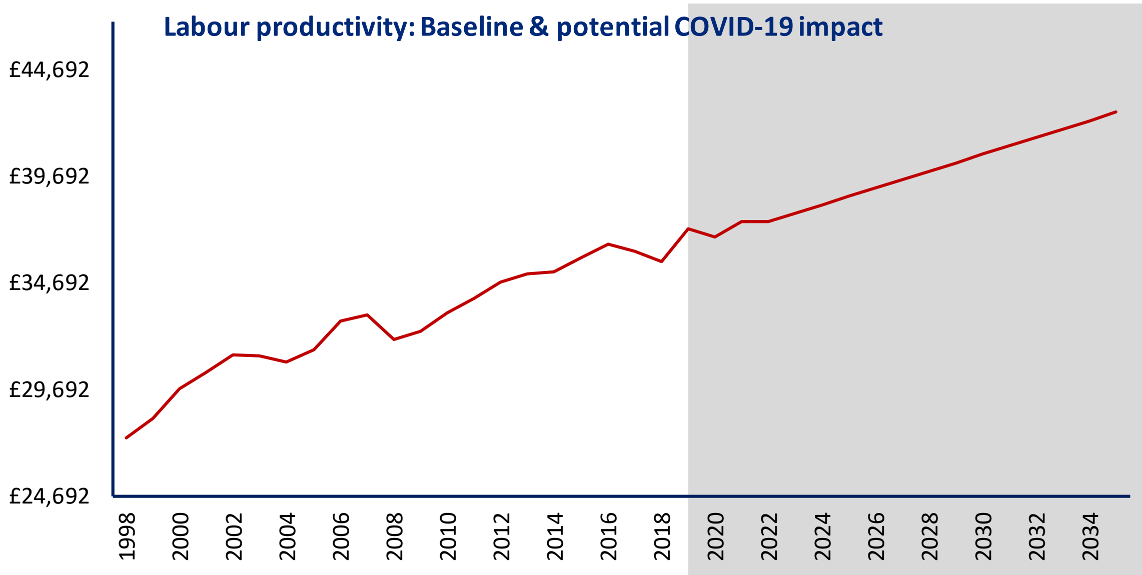


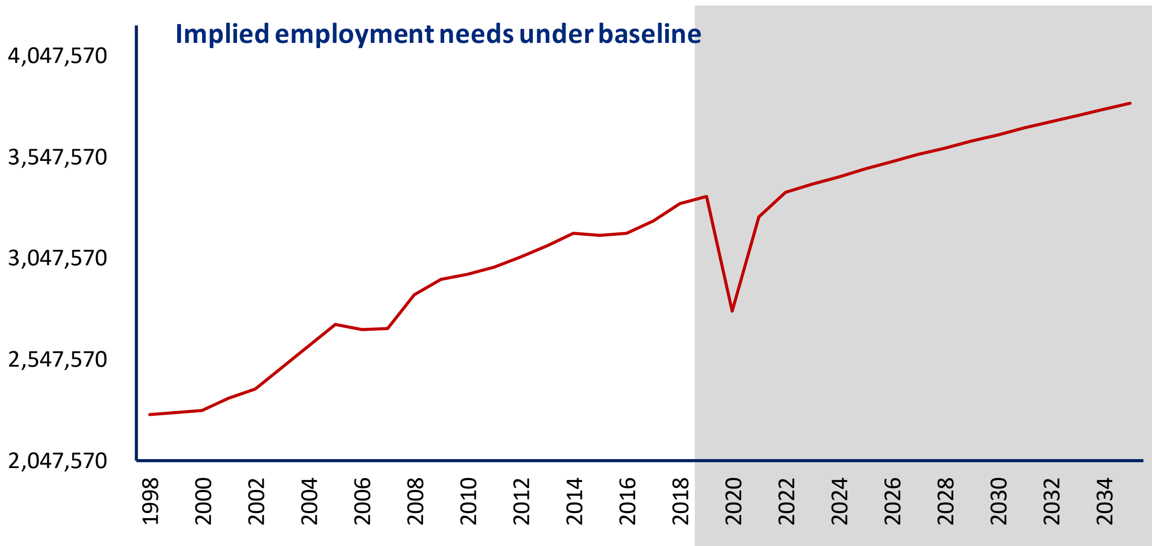


Source: London Economics

Baselines: Health & social care

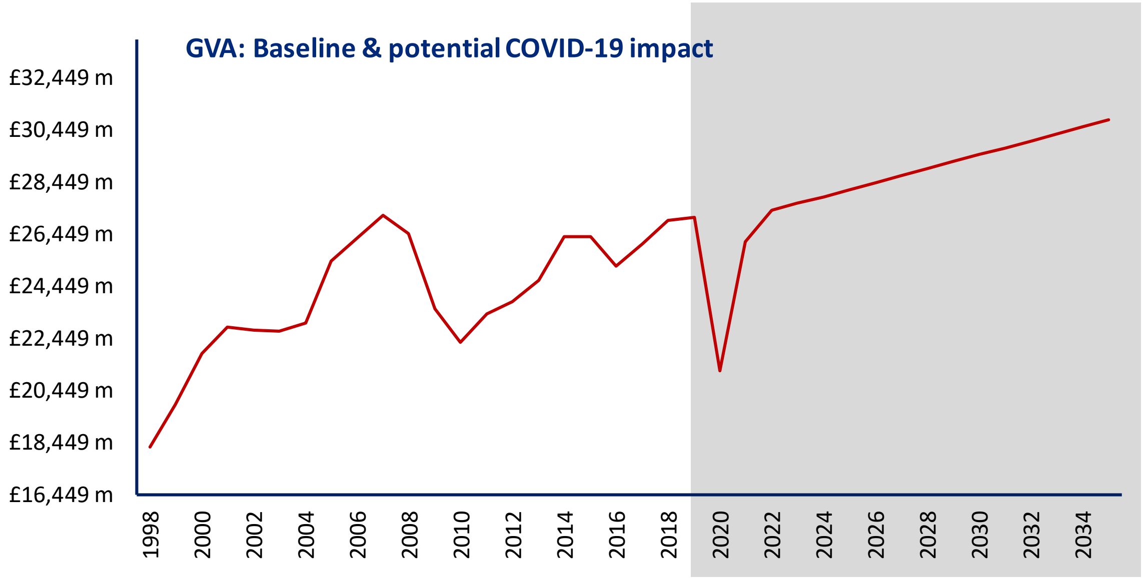


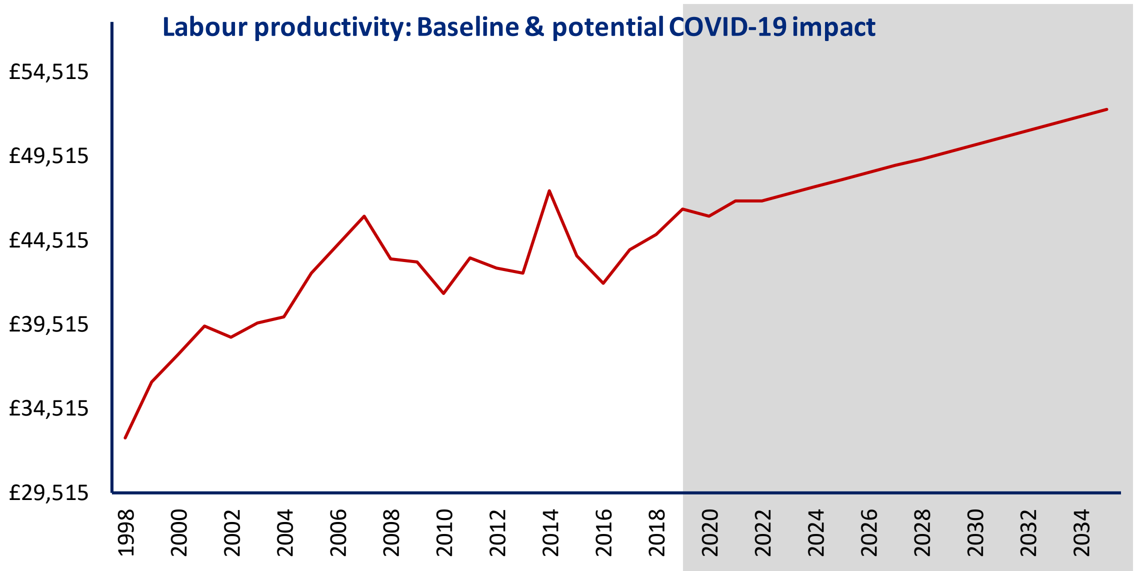


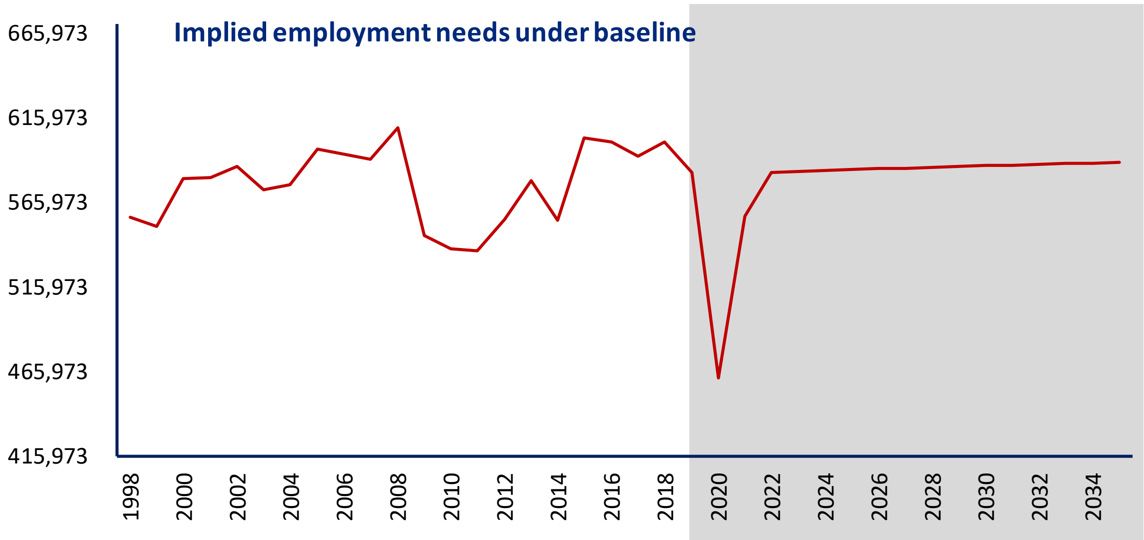


Source: London Economics

Baselines: Warehouse logistics

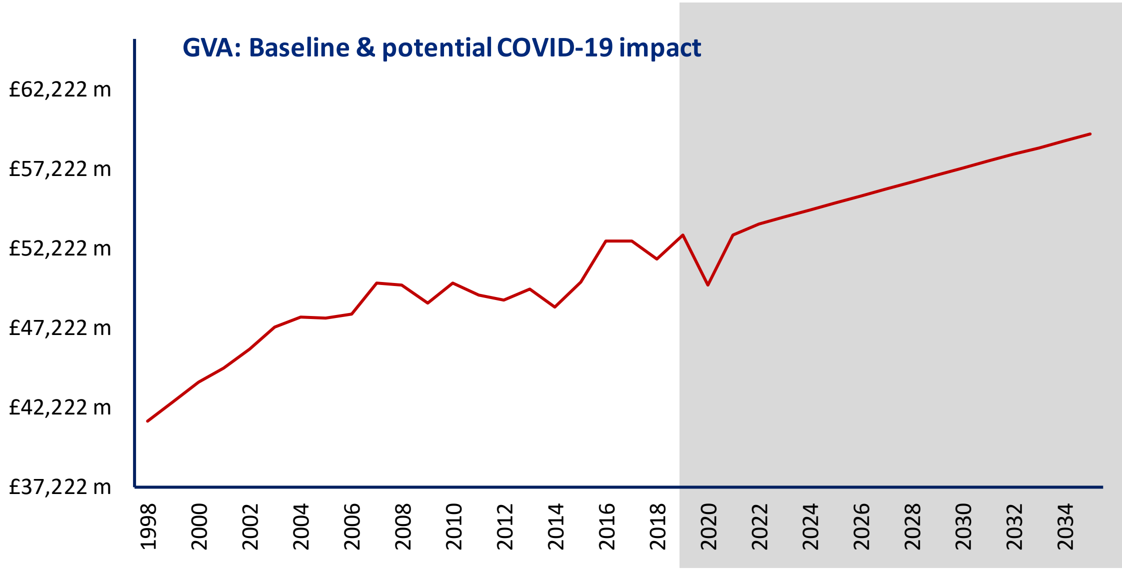


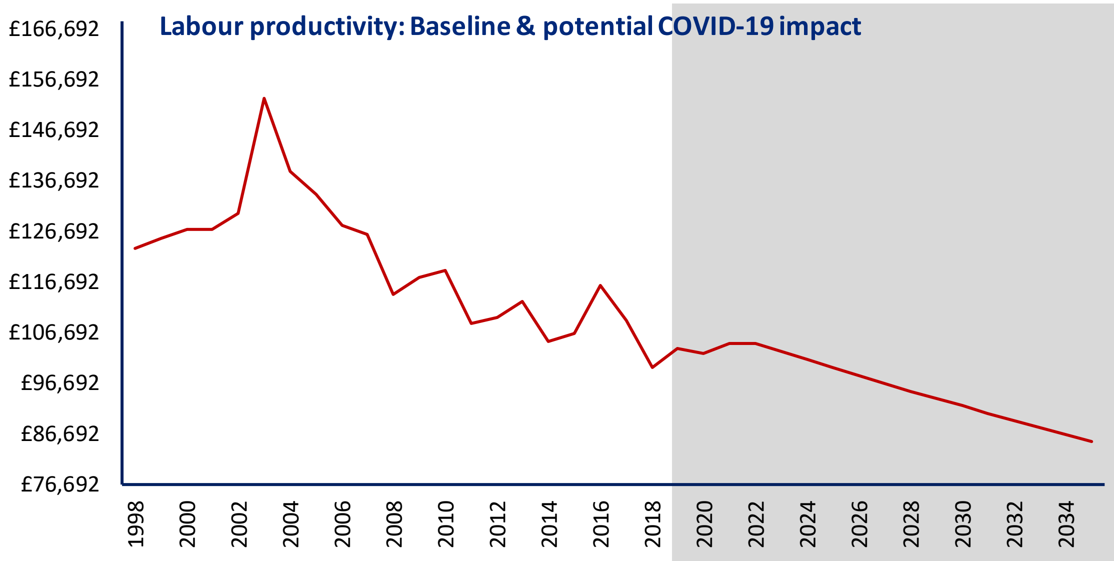


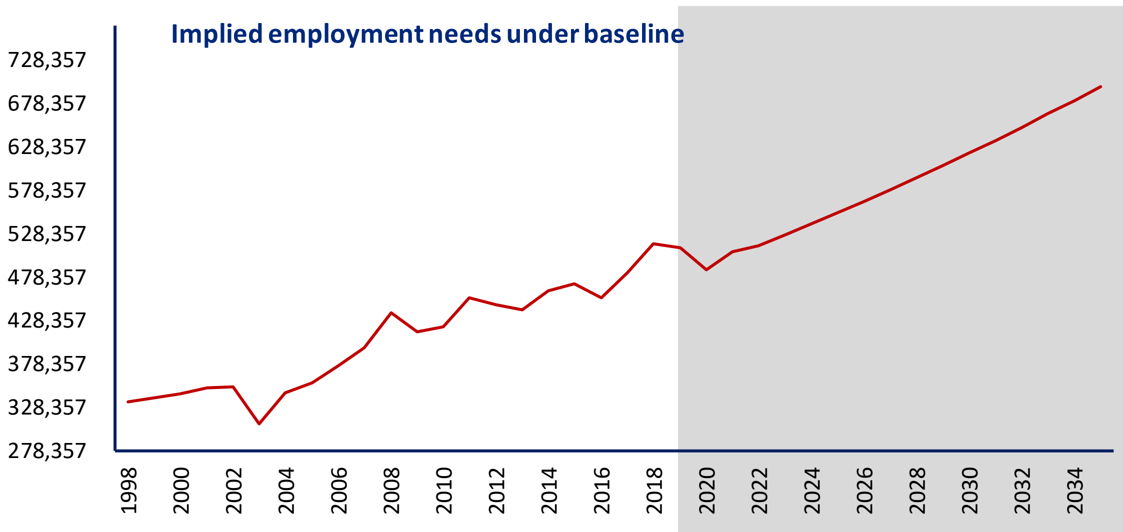


Source: London Economics

Baselines: Energy & infrastructure







Source: London Economics

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