

**Agent Based Modelling of the UK Economy:
Investigating the first and second-order effects of
placing the UK population under lockdown in
response to the COVID-19 Pandemic**

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Abstract

This paper analyses the effect of lockdown and the closure of non-essential industries on the UK economy in response to the COVID-19 pandemic. The paper makes a case for the use of agent-based modelling for policy-making decisions.

Owing to the broad scope of the project, it aims to provide a proof of concept that establishes a methodology for creating an agent-based model, which expands upon the existing literature by modelling households and employment dynamics in greater detail.

The model gives insights into five key areas:

1. The ways in which lockdown affects key parts of the UK economy
2. How people in the UK are affected by multiple rounds of lockdown
3. How the effect on people propagates through the economy and affects households
4. How the adjustments impacted households make to their spending affect industries
5. How different industries adjust to lockdown conditions

These insights form a useful starting point for further exploration of what an optimal economic policy response to the crisis should look like.

Thirteen different economic scenarios are presented in the paper. The response of the UK economy to the imposition and removal of lockdown conditions, as well as the closure of non-essential industries is examined across the thirteen scenarios.

The model scenarios show that the economy is most sensitive to the amount by which people cut their household expenditure when they feel poorer and that industries will cut workforces aggressively in response to lockdown and the closure of non-essential industries. The model scenarios also show that all industries are not affected equally by the lockdown.

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Introduction

The UK economy is a complex non-linear system. Within it, there are numerous networks and interacting agents, each with different rules governing their behaviour. The behaviour of the UK economy is difficult to predict in normal times. When unforeseen events, such as the coronavirus pandemic strike, predicting how the economy may respond is especially difficult. In spite of its difficulty, having a model of the economy forms the basis for understanding the complex system and for making policy decisions. Deciding how to re-open the economy and understanding who may be most affected by the closure of industries can be greatly aided by the use of a model, for instance.

Mainstream economic analysis has long been conducted using techniques that make large assumptions about the nature of agents within economies. Many have made the case that these assumptions, such as the rational agent assumption, which assumes that people make rational economic decisions, are not realistic. These assumptions can “cause models to differ profoundly from reality in some cases and lead policy-makers astray” - Farmer and Foley (2009). Other econometric models may use forms of linear and non-linear regression analysis to estimate the drivers of aggregate quantities, such as Gross Domestic Product, and their significance in order understand and predict how the economy will behave. This form of analysis is not suited to answering low-level questions about economies.

Agent-based Models (ABMs) are a fundamentally different way of modelling complex systems. They aim to build simulations of complex systems. Agent based economic models build economies from the ground up, modelling the agents that comprise them, their attributes and their dynamic behaviour. The choice of agent depends on the scope of an ABM. Baptista et al (2016), for instance, made an economy comprised of three agents: households, banks and a central bank agent, in order to investigate the UK housing market. Further examples of agent based models are presented in the related work section.

The degree of heterogeneity across agents depends on how much complexity and variation the modeller wants to capture. Having a sufficiently broad range of agents can allow for more non-linear dynamics to be captured and allow the behaviour of more nuanced segments of the economy to be examined in response to different conditions (Baptista et al 2016).

This paper describes an ABM of the UK economy. The aim is to investigate the short-term economic impact of lockdown measures on UK industries and households, taking into account the networked relationships between agents in order to understand the first and second-order effects of such an economic shock.

Related Work

Researchers have approached the problem of modelling the economy in a variety of ways. Whilst some, such as Baptista et al (2016) and Gilbert et al (2008), have focused on modelling key markets to determine the state of an economy, others have focused on alternative areas of the economy, which can also be argued to be key determinants of the state of an economy.

The housing market is given considerable attention in research due to the fact that “housing is the largest asset class in the world” (Baptista et al 2016). Baptista et al argue that the econometric modelling approach used in several Dynamic Stochastic General Equilibrium (DSGE) models was limited because it treated the housing market as a homogenous market – they did not differentiate between different agents within the housing market, opting to model aggregated quantities within the market instead.

Baptista et al (2016) aimed to study the impact of macro-prudential policies on key housing market indicators. Their approach expanded upon the work of Axtell et al (2014). They overcame the limitations of the housing market DSGE models they criticised by including different types of agents within their model and by programming them to make decisions and exhibit other dynamic behaviours that were consistent with empirical data. Their agents included first-time buyers, home owners, buy-to-let investors and renters. Their model also incorporated a household lifecycle, which modelled the formation and destruction of households over time, the construction of houses, market clearing (a housing market to match buyers and sellers of houses and determine the settlement price between transacting parties), financial markets where homeowners take out mortgages with banks, and a central bank to set the benchmark interest rate.

In their 10,000 agent model, each household was assigned an income randomly selected from an income percentile distribution. Households then spent this income on non-housing consumption, made financial choices about whether to rent or own and about whether to pay housing expenses or save their money. Households died according to an age-dependent distribution and, when they died, a randomly selected household inherited their property.

Gilbert et al (2009) focused on the interactions between spatially distributed agents within the housing market in order to investigate dynamics that arose from their behaviour. Unlike Baptista et al (2016), who sought to understand the impact of policies on the housing market, Gilbert et al (2009) aimed to investigate the impact of endogenous shocks on the housing market. An endogenous shock is one that originates within the system, as opposed to outside of it. By way of example, an interest rate policy shock affecting the housing market would be considered an exogenous (external to the system), as it occurs because factors external to the agents who make up the housing market itself, whilst a housing market collapse due to excessive speculation by agents purchasing homes, would be classed as an endogenous shock.

The basis of their modelling approach bears some similarities with Baptista et al (2016). Their stylised model attempted to represent realistic behaviour of agents, but was not

initialised on empirical data of the UK economy. Their model consisted of households, geography, sellers, estate agents, buyers, transactions, construction and demolition of houses and macroeconomic variables. However, the modelling approach diverges from Baptista et al (2016) with respect to how Gilbert et al (2009) modelled the housing market and the emphasis they placed on incorporating spatial dimension into their ABM.

Gilbert et al explicitly modelled financial intermediaries in the form of estate agents. Furthermore, unlike Baptista et al (2016), their model accounted for spatial variations within the UK housing market. This was a key feature of their ABM. They captured spatial information by distributing houses on a grid. Towns were made up of clusters of houses in defined areas within the grid. Towns had vacancy rates, housing densities and initial house prices. The initial house prices were either randomly distributed or set based on the distance of a given house from south-west corner of its grid space. This reflected the zonal nature of house prices in certain areas. Additionally, the offer price of houses was based on the prices that other houses in the locality were sold at. Households were able to relocate to different areas based on factors such as changes to their incomes and changes in their mortgage price. The estate agents within the model operated at a local scale, with each being allocated three areas of a town to cover. Most houses in the model were covered by two estate agents, however.

Tian et al (2020) similarly made a model that accounted for spatial variations across agents. Their study focused on household energy consumption in China. Their model consisted of regions, households, energy-devices and fuel types, but unlike the aforementioned models, they did not account for changes in housing stock or extensively model the financial transactions of households. Household income was viewed as an important determinant of the energy consumption habits and energy device ownership. It was also assumed to be a key mechanism driving behavioural change in energy consumption habits, as were technological developments and government subsidies. Tian et al modelled changeable household behaviour, to reflect how households may change their energy consumption habits in response to changing income as well as the availability of new technologies. As with Axtell et al (2014) and Baptista et al (2016), the parameters of the functions and distributions governing dynamic behaviour were fitted to empirical data.

Axtell et al (2014), on the other hand, made a model of the Washington DC area, which was capable of running at 1:1 scale, “with one agent for each household” (Axtell et al 2014). They believed that calibrating the individual agents within their model on empirical data would enhance the usefulness of their model and cited this as a shortcoming of Gilbert et al (2009). Their model contained a large number of households with “homogenous rules of behaviour but heterogeneous realised behaviour since decisions depend on local household characteristics” - Axtell et al (2016). They aimed to see if they could create a model that generated internal dynamics comparable to those observed in the Washington DC area.

Their model consisted of two main agents: banks and households. A single representative bank agent was used owing to the lack of data on banks. This agent’s primary behaviour was awarding fixed rate, adjustable rate and interest-only loans to households. As well as

including different types of loans, the model also included buyers, sellers, investors and renters – agents that represented the main parties involved in transactions. Unlike Baptista et al (2016), Axtell et al allowed households to go bankrupt and properties to be foreclosed.

Households were modelled in a manner similar to those outlined by Baptista et al (2016). However, Axtell et al used historical loan and housing data to derive mathematical functions and distributions governing household behaviour instead of using rules of thumb. They specified an expenditure function that captured the observed variations in expenditure across households of different income levels. The function they fit reflected the fact that “higher-income agents spend a smaller fraction of income on housing”. The empirically derived functional behavioural rules allowed the model to better reflect the reality it attempted to model. This contrasts the approach taken in the stylised model proposed Gilbert et al (2009).

The aforementioned models have the benefit of capturing more detailed household dynamics than models with just one agent used to represent all households. They are limited, however, in their ability to answer wider questions about the economy. Though using the housing market as a proxy for the economy as a whole is a valid approach, it is an approach best used to analyse the causes and effects of housing market dynamics or when the origin of shocks is assumed to be the housing market. This approach has limited use when the housing market is not the primary driver of economic shocks, as is the case with coronavirus. It also fails to consider other critical economic agents that exist in economies, such as industries.

One approach researchers have taken to address this shortcoming is by explicitly modelling industries. Chanona et al (2020) used a quantitative model to make predictions about the likely impact of the COVID-19 pandemic on the US economy, focusing specifically on industry dynamics as a key driver of economic changes. Their research estimated only the first-order impacts of the pandemic. They determined that different industrial sectors responded differently to external shocks. They asserted that industries may be hit by demand-side shocks, which affect the level of demand for the goods and services produced and also by supply-side shocks, which affect their supply chain and constrain their output levels. A key finding of theirs was also deriving a Remote Labour Index, which indexed occupations based on their ability to work from home. By way of example, they found that construction and extraction workers have a lower ability to work from home than education, training and library occupations as classified by the Standard Occupation Classification. By quantifying the ability to work from home for different occupations, Chanona et al (2020) were then able to plot the range of remote labour indices within different industries on a box plot and derive the ability of the average worker in each industry to work from home.

Hallegatte (2008) proposed a modelling framework to “investigate the consequences of natural disasters and the following reconstruction phase” - Hallegatte (2008). Hallegatte’s model contained households and industries within a regional economy. Hallegatte’s model also included a labour market, which provided a key income distribution mechanism between industries and households. The model was based on input-output tables, which were used to model the supply chains of different industry sectors. By modelling this network of sectors and their input from other sectors (their supply chains), it became possible to compute how shocks emanating from the demand side (consumers) propagate through the system and affect

suppliers and producers downstream of the shock. Hallegatte's criticism of this approach was that it did not allow shocks propagating from the supply-side due to limited supply of inputs to the production process (in Hallegatte's case, due to the destruction of working capital by Hurricane Katrina) to be computed. This was because the input-output table, also known as the Leontief production function, assumed a fixed combination of inputs needed to produce a given unit of output. This assumption did not allow the essential reality of supply constraints to be captured. In reality, suppliers may adjust to supply constraints by changing the quantities of inputs they use to produce outputs. Such a change necessitates having more alternative Leontief production functions to reflect changes made to the production recipes.

Hallegatte attempted to overcome this limitation by accounting for changes in the amount of machinery able to produce output in order to impose a constraint on production levels. If this was below the level of production implied by the input-output table, industries would be forced to cut their level of output due to a lack of productive capital, even if they were able to source inputs in their usual quantities.

Inoue et al also used an ABM approach to model an economy, this time to simulate the impact that placing Tokyo under lockdown for a month would have on production levels in neighbouring regions whose economies are dependent on Tokyo's. Their model placed a particular emphasis on the attributes of firms and their supply chains. Like Axtell et al (2014), they ran a simulation with a high agent count. Theirs contained 1.7 million firm agents and 5.6 million total links in the supply chain network that connected the 1.7 million firms.

Like Hallegatte, their model also used input-output tables to model the supply chain and assumed a fixed production recipe. However, they extended upon Hallegatte's methodology by incorporating firm inventory levels, which impact how firms satisfy demand and the volume of new orders industries they place with their suppliers. These inventories were randomly assigned at firm level by sampling from a distribution. Their inclusion allowed for more nuanced supply chain dynamics within the model. For example, in their model, firms experiencing supply shortages could choose to maintain current levels of production by running down their inventories instead of reducing their output levels.

Inoue et al also accounted for constraints on productive capacity by computing three key values: the maximum potential output a firm was capable of, the maximum it can produce with its current supply levels and the current level of demand for a firm's output. The minimum value of these three constrained the production levels. When firms were unable to meet demand due to constraints, they did not fill all orders and then decided which of the existing orders to fill. Inoue et al allocated their output by placing orders in descending order volume and then filling orders in this order. Under this rationing scheme, smaller orders would not be filled. This approach contrasts the smeared approach, which evenly distributes output across all orders and ensures that everyone who places an order receives some output.

The work of Pichler et al (2020) expanded upon the work of Inoue et al (2020) and Chanona et al (2020). This model examined the economic consequences and likely spread of COVID-

19 under different scenarios. A key aim of their work was to find a good re-opening scenario that balanced the trade-offs of re-opening with managing the spread of the virus.

Their model included industries and households and also used an input-output table. Critically, unlike Inoue et al (2020) and Hallegette (2009), Pichler et al (2020) did not assume that inputs used by industries remain fixed over time. Under lockdown conditions in their model, producers were able to change their production recipes, eliminating any inputs that were not absolutely essential, which gave a more accurate representation of behaviour at industry level that other models had been unable to capture.

Their model also included a feedback mechanism between unemployment and consumption, as opposed to modelling consumption as a fixed quantity relative to the person or household in question. Importantly, they modelled households as homogeneous, having only one representative household. They also modelled all workers within a given industries as homogenous by assuming that they all earned the same wage. This is a shortcoming of their model, which the ABM presented in this research paper attempts to address.

Model Specification

The modelling approach used in this research piece follows a similar methodology to that used by Pichler et al (2020). It formulates key agents as households, people and industries, as these have been identified as the main entities that experience the first-order effects of a pandemic shock. It also incorporates a dynamic input-output matrix to reflect changing supply constraints and sourcing decisions by industries.

Its main contribution to the literature is that it expands upon the input-output ABMs discussed in the related work section, which do not model households to the same degree of detail as they do industries. This is a consequential. The model in this research piece explicitly models the heterogeneity between household agents so that the effects of COVID-19 on subsets of households can be observed. It builds a clearer picture of the types of households within the economy by placing particular emphasis on employment data and modelling different states of employment among agents and, households, by extension.

It also models employees as having occupations and wages that are empirically derived, which, again, expands upon Pichler et al (2020), in which all employees within an industry were assumed to earn the same wage. The model proposed also presents a methodology that can be extended in order to incorporate multiple regions to allow future models to address questions about differences in the impact of lockdown conditions across regions.

By taking this approach, the model is able to give insights into five key areas:

1. The ways in which lockdown affects key parts of the UK economy
2. How people in the UK are affected by multiple rounds of lockdown
3. How the effect on people propagates through the economy and affects households
4. How the adjustments impacted households make to their spending affect industries
5. How different industries adjust to lockdown conditions

Owing to the scope of the model, it is largely a proof of concept.

Project Requirements:

1. System must allow users to view aggregated household agents by their different properties, such as income level or region
2. System must allow users to view aggregated industry agents by their different properties, such as sector and supply and demand
3. System must allow users to input different starting variables to investigate different scenarios
4. System should be calibrated using UK economic data and should contain an approximate scaled model of the UK economy in each simulation it runs
5. Deliver a proof of concept that an integrated approach to modelling the economy in the proposed manner is possible

Choice of Programming Language

The choice of programming language used to create this agent based model was a critical early decision. It was determined that this agent based model required a statically-typed imperative programming language in order to achieve the high degree of complexity that was required to make the network of agents.

Whilst the model was ultimately coded entirely in Java without the use of software frameworks, there were two strong candidates software candidates for the project: Repast Simphony, a Java agent-based modelling framework, and NetLogo, a Logo-based dynamically typed language designed for agent-based modelling.

Repast Simphony, was rejected as a candidate framework on the grounds that it had too steep a learning curve for a project of such short duration. NetLogo was rejected because of its more limited data structures and dynamically typed, script-based nature, which made it unsuitable for a complex model of this kind.

Sources of Model Complexity

Much complexity arose from the fact that the economy is a large, complex network of interacting agents with many dependencies, or, in object-orientated programming terms, tightly-coupled objects. The code base reflected this. This also led to complexity around organising the code.

The complex, highly-coupled nature of the network also made it difficult to debug. Complexity also arose from agents having a large number of state variables and therefore mutable states.

Data Used

The majority of data used in this model were taken from the Office for National Statistics (ONS). Key household data on the variation of spending patterns by decile and key industry data on employment, occupations and median wages across different industries were taken from the ONS. Population data, household formation data and demographic data was also taken from the ONS. This data was incorporated into the model so that each run was a scaled representation of the UK economy in terms of demographics, households, occupations, industries and employment and spending habits (see bibliography for ONS data sources).

Industry input-output data used to determine how much each industry should produce, known as the Leontief production function, was taken from the Pichler et al data set (2020). The remote labour index (RLI) data used to quantify the ability of people in different occupations to work from home was derived by mapping the RLI data compiled by Rio-Chanona et al data set (2020) for occupations defined by the International Standard Classification of Occupations to their approximate counterparts defined using the Standard Occupation Classification.

Economic Model

Economy assumptions

The model economy models the portion of the economy above working age. This includes the economically active portion (those aged between 16 and 64) and the retired portion of the UK economy. It assumes that these two groups are the primary drivers of economic activity. It also assumes that 20% of the population is comprised of children under the age of 16 and does not model them explicitly. These assumptions were made using population and demographic data from the Office for National Statistics.

The model focuses exclusively on changing employment dynamics across people who are actively seeking employment or already in employment. It assumes that people who are long-term unemployed and retired remain so throughout and that it is only those who are classified as short-term unemployed who may become employed.

Initialised Economy

The model economy has three types of agent: industries, households and people. Each agent has a mutable state that is based on a number of its attributes.

The class diagram in figure 1 illustrates some of the attributes and interrelations between agents.

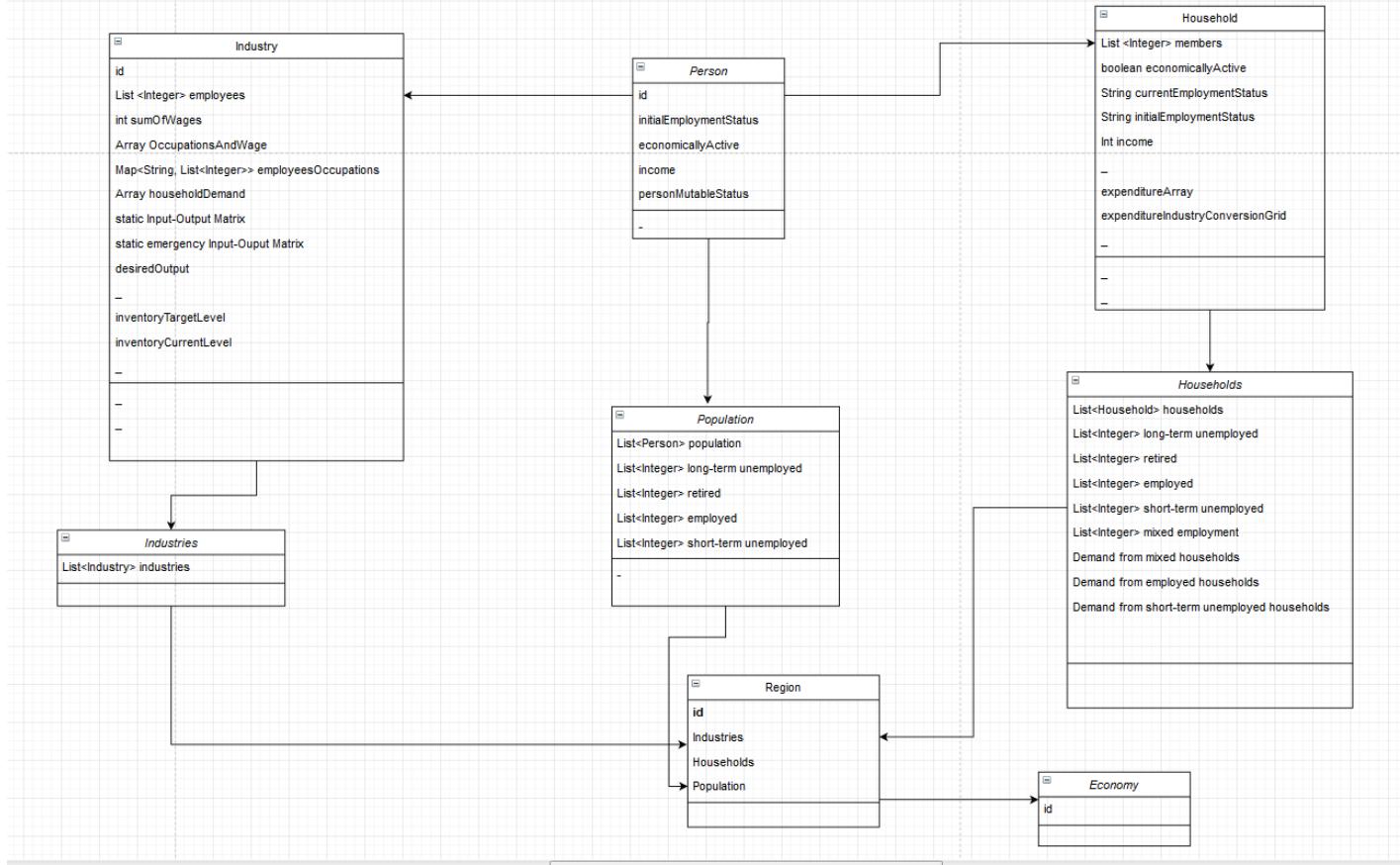


Figure 1: Truncated class diagram showing agents' attributes and their relationship with other agents

People have occupations, which allow them to earn an income from an industry. Each person belongs to a randomly allocated household, which has between 1 and 3 members. It is at the household level that spending decisions are made.

There are many ways of formulating households, such as by age or by income. Employment was decided to be a key driver of household income, so households were divided into retired and economically active households. The state and behaviour of economically active households that have members who are either short-term unemployed or employed can change as their employed members become unemployed and their unemployed members become employed, as shown in figure 2. These changes to employment affect a household's overall income, which in turn may cause them to adjust their spending patterns.

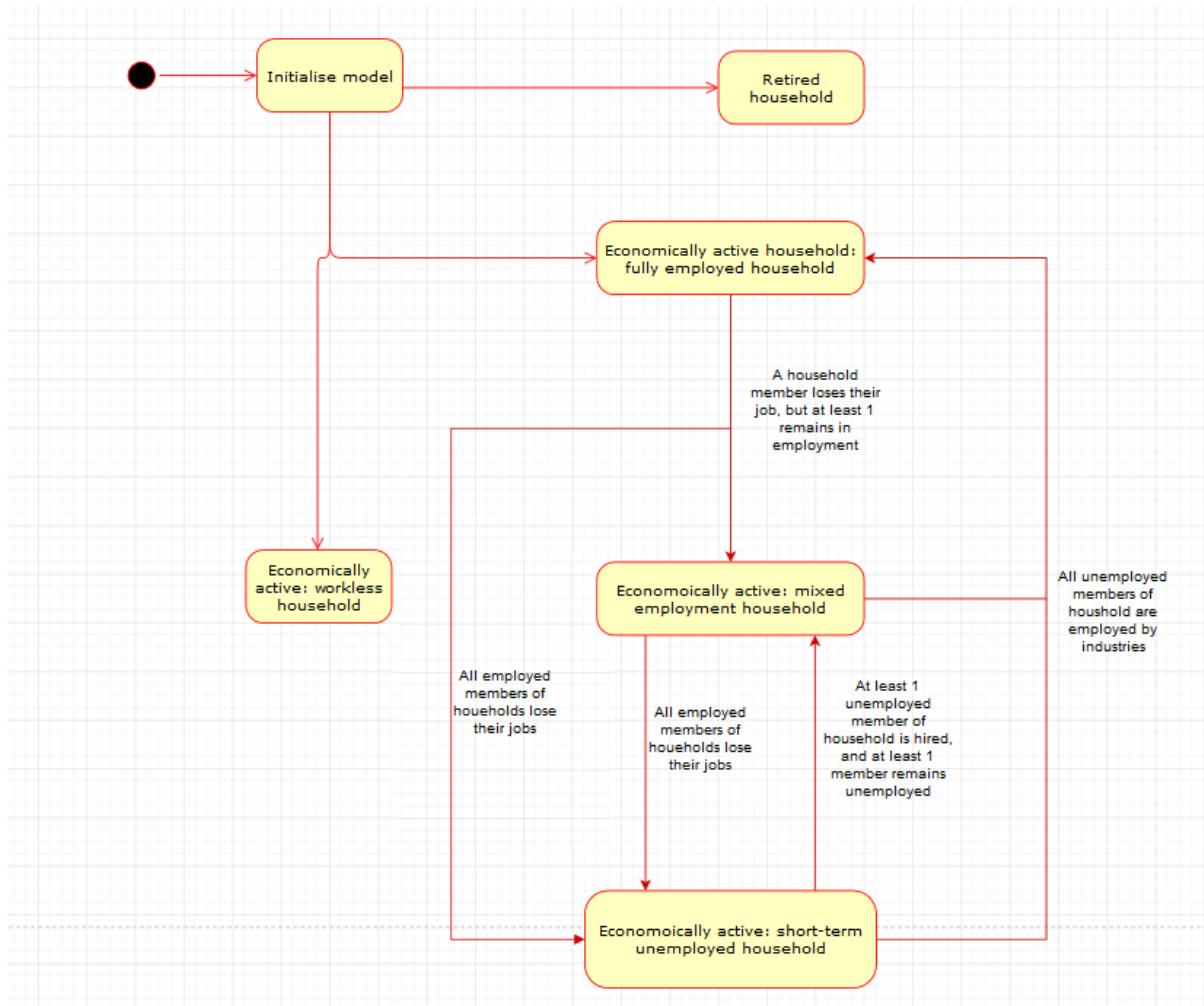


Figure 2: A household state diagram

Other factors affecting household spending patterns are a household's intrinsic financial optimism. This attribute affects how households respond to changes in the total income of their members. Households with a higher intrinsic financial optimism are more optimistic. They are less likely to change their spending patterns when a member is made unemployed, instead assuming that the member will soon find a job. Conversely, those with a lower intrinsic financial optimism have a less optimistic outlook and are more likely to respond to drops in their income by reducing their expenditure. This has knock-on effects on industries, which are reliant on household demand.

There are 20 industries in the model as defined in the ONS Annual Population Survey. The 21st industry, extraterritorial organisations, was neglected from the model.

Each industry differs in terms of the occupations it requires and in the proportion of its workers that belong to each occupation. The proportion of workers belonging to occupations within a given industry was also derived from the ONS Annual Population Survey. Related to each occupation is an annual median wage taken from the ONS's Annual Survey of Hours and Earnings (see figure 3).

	A Occupation	B Median Wage
1		
2	Corporate Managers And Director	£43,913
3	Other Managers And Proprietor	£29,699
4	Science, Engineering, Tech Professional	£41,897
5	Health Professional	£30,580
6	Teaching And Educational Professional	£35,008
7	Business, Media And Public Service Professional	£38,000
8	Science, Engineering ,Tech Associate Pro	£29,031
9	Health And Social Care Associate Professional	£23,002
10	Protective Service Occupation	£38,191
11	Culture, Media And Sports Occupation	£23,255
12	Business, Public Service Associate Pro	£33,282
13	Administrative Occupation	£20,218
14	Secretarial And Related Occupation	£15,726
15	Skilled Agricultural And Related Trade	£20,083
16	Skilled Metal, Electrical, Electronic Trade	£31,333
17	Skilled Construction And Building Trade	£27,828
18	Textiles, Printing And Other Skilled Trade	£19,707
19	Caring Personal Service Occupation	£14,677
20	Leisure, Travel And Related Personal Servi	£15,679
21	Sales Occupation	£12,097
22	Customer Service Occupation	£19,239
23	Process, Plant And Machine Operative	£23,135
24	Transport And Drivers And Operative	£25,564
25	Corporate Managers And Director	£20,482
26	Other Managers And Proprietor	£12,880
27		

Figure 3: A table of all occupations in the model and the wage they pay

Incorporating this data was critical to modelling detailed income differentials across people in employment.

Dynamic Behaviour

Once initialised, agents interact with their environment and each other through their dynamic behaviour and the state of the model evolves over the simulation steps.

Households

The dynamic behaviour of households is encapsulated in figure 4.

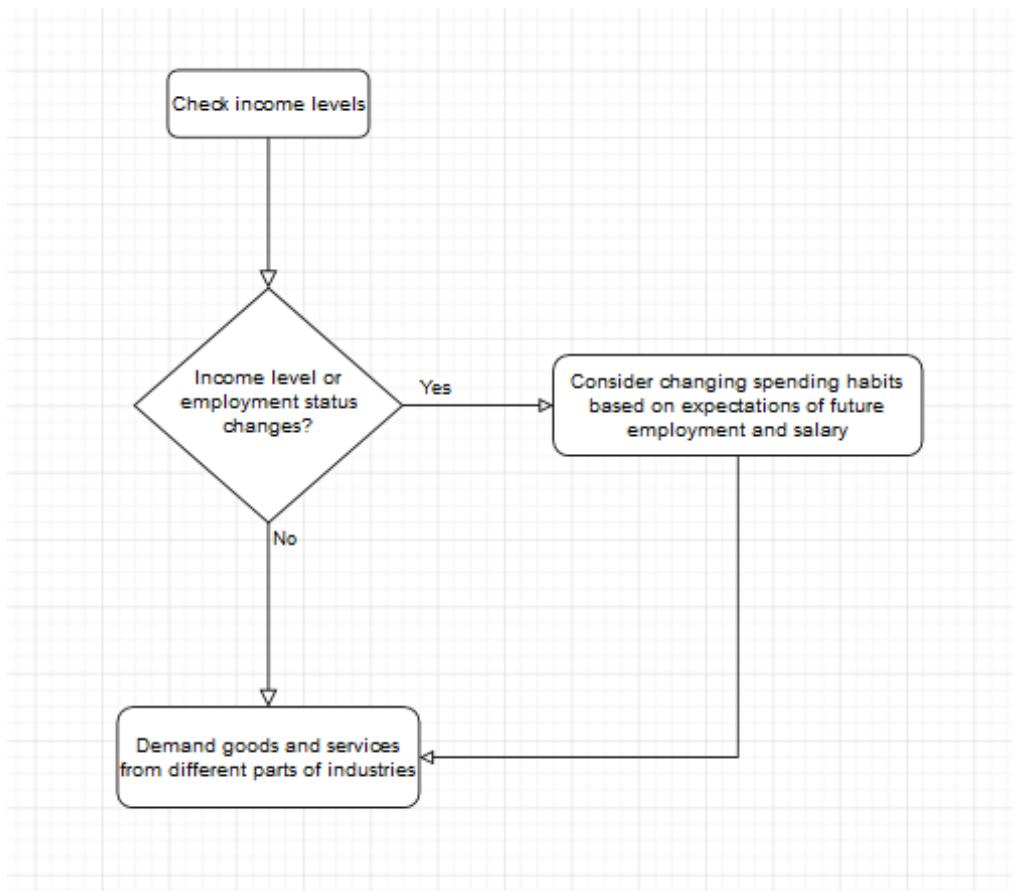


Figure 4: A flow diagram showing the dynamic behaviour of households

At each time step, households check their income levels. It is at this step that the likelihood of feeling poorer given a change in their income is computed using each household's intrinsic financial optimism. Each household's demand for goods and services is then computed by mapping household demand along 36 expenditure categories to 55 industry categories. This is discussed in greater detail in the next section covering the dynamic behaviour of industries. The proportion of household income spent on each expenditure category is derived from the ONS's Detailed Expenditure and Trends.

Industries

Industries must calculate how much they need to produce to satisfy demand, they must hire and fire employees in different occupations to adjust the size of their workforce to required levels and they must pay their employees. More detailed dynamic behaviour of industries is shown in figure 5.

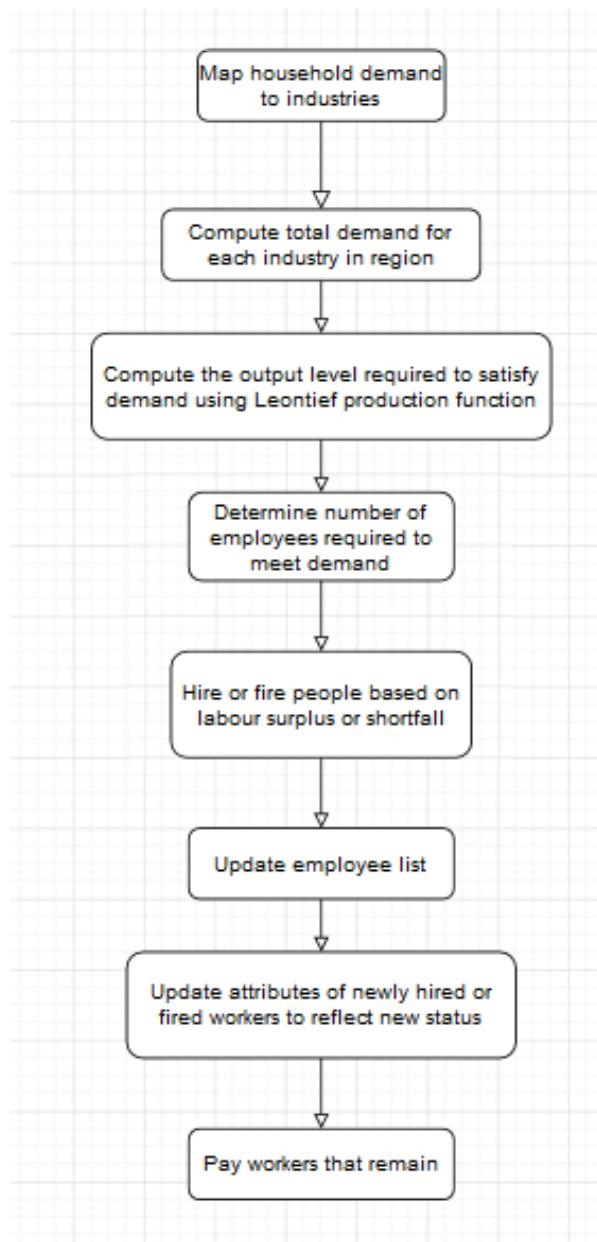


Figure 5: A flow diagram of the dynamic behaviour of industries at each simulation step

In order to be useful, the household expenditure categories must be mapped to the 20 industry categories used in the model. This process involves an intermediate step of mapping the 36 default household expenditure categories to their related industry categories in terms of 55, not 20, industry categories. The map was derived from the Office for National Statistic's Supply and Use Table.

36 household expenditure categories	55 industry expenditure categories	20 industry expenditure categories
Food	Products of agriculture, hunting and related services	Agriculture, forestry and fishing
Non-alcoholic beverages	Products of forestry, logging and related services	Mining and quarrying
Alcoholic beverages	Fish and other fishing products; aquaculture products; support services to fishing	Manufacturing
Tobacco	Coal and lignite	Electricity, gas, air cond supply
Narcotics	Extraction Of Crude Petroleum And Natural Gas & Mining Of Metal Ores	Water supply, sewerage, waste
Clothing	Other mining and quarrying products	Construction
Footwear	Mining support services	Wholesale, retail, repair of vehicles
Actual rentals for households	Preserved meat and meat products	Transport and storage
Imputed rentals for households	Processed and preserved fish, crustaceans, molluscs, fruit and vegetables	Accommodation and food services
Maintenance and repair of the dwelling	Vegetable and animal oils and fats	Information and communication
Water supply and miscellaneous dwelling services	Dairy products	Financial and insurance activities
Electricity, gas and other fuels	Grain mill products, starches and starch products	Real estate activities
Furniture, furnishings, carpets etc	Bakery and farinaceous products	Prof, scientific, technical activ.
Household textiles	Other food products	Admin and support services
Household appliances	Prepared animal feeds	Public admin and defence
Glassware, tableware and household utensils	Alcoholic beverages & Tobacco products	Education
Tools and equipment for house and garden	Soft drinks	Health and social work
Goods and services for household maintenance	Textiles	Arts, entertainment and recreation
Medical products, appliances and equipment	Wearing apparel	Other service activities

Figure 6: Lists of the 36 household expenditure categories, the 55 industry expenditure categories and the 20 industry expenditure categories used to map household expenditure categories to industry expenditure categories

Once the map to 55 industries has been computed, the total demand for each industry is then computed across the UK by mapping each household's demand to these categories. This is a critical input that is needed to in order to compute the level of output that each of the 55 industries must produce if it is to satisfy the demand.

Industries determine how much to output to produce to satisfy incoming demand by solving equation 1 for x. This is what is known as the Leontief production function.

$$x = Cx + d$$

Equation 1: Leontief production function

$$x = (I - C)^{-1} + d$$

Equation 2: Equation 1 re-arranged to solve for x

, where C is a square 55x55 input-output matrix (also known as the production recipe), which relates an industry's required inputs to its output, I is a square 55x55 identity matrix and d is a 55x1 matrix of total household demand for each of the 55 industries.

The input-output matrix, C, is what changes under lockdown conditions as industries change the quantity of inputs they use to produce their outputs in response to supply constraints. The production recipes used in Pichler et al (2020) and were obtained from the data set they provided.

Once industries have decided on the amount they need to output to satisfy demand, they then proceed to adjust the size of their workforce to the size required to produce the output. Hiring occurs when a larger workforce is needed to produce the output. The industry determines how many additional employees from each occupation are needed for production and interviews a multiple of the additional workers required by sampling randomly from the list of people who are currently short-term unemployed. Industries only hire workers if the worker they interview has the required skills (expressed as having an occupation that matches the occupation that is being searched for). On the other hand, industries fire employees by removing them from their list of employees, adjusting their wage to reflect the income they receive as an unemployed person, setting their industry to null and placing them in the short-term unemployed list. These changes at an industry and person level are reflected at a household level by updating the status of households to reflect any changes in the employment status of their members. The workers that remain are then paid their income, setting up the next simulation step.

Implementation: Data Structures and algorithms

The large scope of the project and its speculative nature as a proof-of-concept necessitated a software design approach that focused on delivering a product, as opposed to designing for efficiency.

The primary data structures used were arrays and array lists, where dynamic data structures were needed. Java collections were used wherever groups of similar objects needed to be contained in one location. For instance, the population of the UK was contained within an array list of type Person. Other array lists containing important information about the system were derived from this, for instance, an array list containing the unique identifier of each person who was classed as being short-term unemployed. Importantly, to avoid replicating people and making it harder to track changes in the code, people were kept in one location and were referred to elsewhere by their unique identifiers.

Arrays were used where the number of objects within a particular data structure was fixed, such as in the array containing the names of all available occupations.

In order to speed up the running of the code, critical data structures containing the agents were sorted and kept in sorted order. Doing this benefitted the model's performance by increasing the search efficiency of these array lists.

Testing

Debugging ABMs is known to be a difficult task, again, because, in many cases, they are representing messy real-life networks that are tightly-coupled and necessarily difficult to represent compactly. Finding errors in such a network is not an easy process.

Code organisation was an important aid in the debugging process. Combined with the extensive use of comments, ensuring that each method was limited in scope and building complexity from small, specific methods helped to highlight areas of code that were producing bugs.

The code was written using a spiral software development approach to help deal with its complexity. As a result, the approach taken to testing was to build the network incrementally and sequentially, testing the program each time a new method was added.

Naturally, there are a number of areas where improvements can be made to the organisation of the code. In future iterations, greater focus will likely be placed on increasing code re-use by writing more stand-alone methods to perform repeated operations, such modifying the list containing the unique identification numbers of short-term unemployed people. Further potential improvements to the code are discussed in the results and evaluation section.

Project Management

The project has been managed largely through the selection of an appropriate software development approach. Sensible project management was a natural consequence of choosing a spiral approach to modelling this proof-of-concept. This approach enabled the project to be approached in a sequential manner, which helped to constrain the complexity, which made the problem tractable. This was a tremendous advantage due to the fact that there was no clear model or framework for implementing such a model. Thus, it had to be accepted from early on that it was not possible to specify many components of the project ahead of time. It was necessary to hope that, with rigorous, thoughtful software design at each stage, the ABM would work as intended when fully connected. This is the approach which must be taken when one is working to solve a problem that is not yet well-understood or which does not yet have formally accepted methodologies or approaches to tackling, especially if the programmer has no prior experience of making such a model, which was the case on in this project.

Results and Discussion

In this results section, thirteen model scenarios are compared and contrasted. Each scenario has been generated by running a model simulation on a population of 10,000 people. The output graphs have been selected to show how the key model quantities evolve during each of the model runs. The outputs include the annual sum of household demand across all industries, the level of output that industries produce in response to household demand, changes in employment, the related changes in household classification and the overall workforce within industries.

Model scenarios	1	2	3	4	5	6
Expenditure if feel poorer	0.3	0.8	0.3	0.8	0.3	0.8
Behaviour change threshold	0.1	0.1	0.1	0.1	0.1	0.1
Unemployed income	1000	1000	1000	1000	1000	1000
Retired income	20000	20000	20000	20000	20000	20000
Long-term unemployed income	12000	12000	12000	12000	12000	12000
Number of people to interview multiple	10	10	10	10	10	10
Selected lockdown recipe	1	1	2	2	3	3

Table 1: A table containing the model parameters used to run model scenarios 1 to 6

			12 lockdown periods	12 lockdown periods	36 period lockdown	36 period lockdown	12 lockdown periods
Model scenarios	7	8	9	10	11	12	13
Expenditure if feel poorer	0.3	0.8	0.3	0.8	0.3	0.8	0.5
Behaviour change threshold	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Unemployed income	1000	1000	1000	1000	1000	1000	1000
Retired income	20000	20000	20000	20000	20000	20000	20000
Long-term unemployed income	12000	12000	12000	12000	12000	12000	12000
Number of people to interview multiple	10	10	10	10	10	10	10
Selected lockdown recipe	1	1	1	1	1	1	1

Table 2: A table containing the model parameters used to run model scenarios 7 to 13

The output graph from model scenarios 1, 2, 6, 7, 8, 9, 11 and 13 can all be found in the appendix. The outputs of scenario 10 are discussed later in this section in greater detail.

Model scenarios 1-6 all experience the effects of lockdown as an impulse that lasts for a week that is then removed. The lockdown is extended to last for 12 weeks in model scenarios 9 and 10 and 36 weeks in model scenarios 11 and 12.

The parameters in each model run have been set to reflect a range of economic scenarios. The ‘expenditure if feel poorer’ parameter sets how aggressively people cut their expenditure if the environment or their own personal conditions make them feel poorer. This may happen under lockdown conditions or if one loses their job. In scenario 1, for example, when any person feels poorer, they cut their expenditure to 30% of its usual amount. Whilst this may not be a realistic assumption due to ongoing property payments, it is useful for assessing the sensitivity of the model.

The ‘behaviour change threshold’ parameter determines the level at which household spending patterns are likely to change. It is linked to a household’s intrinsic financial optimism. Varying this threshold determines the extent to which the population adjusts their spending patterns and feel worse off. Households with a likelihood of feeling poorer that is lower than the behaviour change threshold do not change their spending habits when lockdown is imposed or when they lose their jobs.

The unemployed, retired and long-term unemployed income parameters set the incomes of agents with these states. The ‘number of people to interview multiple’ determines how many people each industry interviews when looking for people to hire and the ‘lockdown recipe’ parameter determines which input-output matrix to use in the Leontief production function

when computing how much output each industry must produce in order to meet the household demand. There are three potential lockdown recipes that can be used across industries. These vary by the number and quantity of inputs used. The more stressed the recipe, the more sparing it is. Of the stressed lockdown recipes, all of which make significant changes to the normal production recipe, recipe 1 is the least aggressive, recipe 2 is the second most aggressive and recipe 3 is the most aggressive in terms of cutbacks. Recipe 3, the most aggressive production recipe, only included the inputs that were definitely required by each industry in stressed conditions according a survey conducted by Pichler et al (2020). This variant omitted all inputs which survey respondents expressed some uncertainty over, whereas recipe 1, the least aggressive of the 3, included these inputs. Recipe 2 also included the uncertain inputs, but in a smaller quantity than in recipe 1.

Runs 5 and 6 used the most aggressive production recipe. Surprisingly, changing the production recipe to a more aggressive variant had a negligible effect on industry-wide production levels. This negligible difference between runs with different production recipes can be observed between the output of model scenario 2 and model scenario 6, which, but for their lockdown production recipes, are identical.

The first and second model scenarios show that the model results are very sensitive to the cuts households make to their expenditure when they feel poorer. Cutting expenditure by 70% compared to cutting it by 20% results in a large divergence between the total household demand across the two models. Household demand in model scenario 2 recovers considerably faster than it does in model 1, so much so that it approaches its pre-lockdown levels across most industries. In model scenario 1 on the other hand, household demand remains anaemic, hardly recovering after lockdown is removed.

Apart from having a higher behaviour change threshold (which raises the number of households that feel poorer and change their spending habits when faced with adverse conditions), scenarios 7 and 8 are identical to scenarios 1 and 2 respectively. The model does not show a comparable level of sensitivity to the ‘behaviour change threshold’ parameter, as varying the behaviour change threshold in models 7 and 8 had a negligible effect on the model outputs when compared to those of scenarios 1 and 2.

The model scenarios are sensitive to the duration of lockdown up to a point. When lockdown remains in place sufficiently long, the household demand levels reach a steady state and stop changing. This can be seen in scenarios 9 – 12, where household demand levels fall sharply and then plateau at their steady-state levels when under lockdown. It is only when lockdown is lifted that demand picks up. This contrasts scenarios 1-7, where lockdown is applied over 1 week. This scenario does not give industries much time to adjust to lockdown conditions before they are lifted, meaning that the full effects of a prolonged lockdown are felt neither by industries nor households. This is why employment levels, household demand as well as output do not fall to the levels seen in scenarios 9-12. According to scenarios 9-12, it takes approximately 4 weeks for the effects of lockdown to fully manifest. Beyond this point, the models do not show any appreciable changes until lockdown is lifted. Thus, the model implies that all lockdowns lasting over 4 weeks have the same destructive effect on the economy. It is for this reason that scenarios 9 and 11 show practically identical rates of change of household demand, employment levels and industry production levels after lockdown is lifted, in spite of the 24 week difference in the duration of lockdown between the scenarios. Whilst the model captures changes in the behaviour of households under lockdown, it does not sufficiently capture further changes in behaviour under extended

periods of lockdown. The non-linearities that emerge from this would likely affect households' intrinsic sentiment and further alter their spending patterns.

Model scenario 10 is analysed in greater detail with the aforementioned model sensitivities in mind. Its parameters arguably best represent a reasonably likely lockdown scenario, where lockdown lasts for 12 weeks, where over half of all households are likely to feel poorer under lockdown conditions and change their behaviour and where the households that do feel poorer cut their expenditure by 20%.

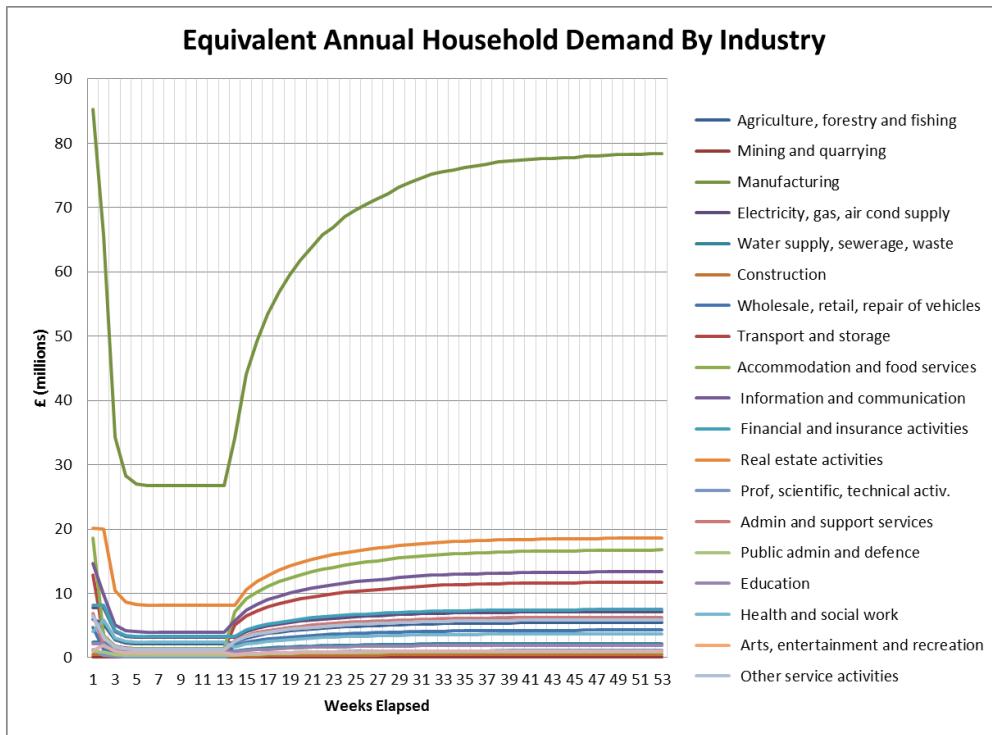


Figure 7: A graph of the equivalent annual household demand for all industries in model 10

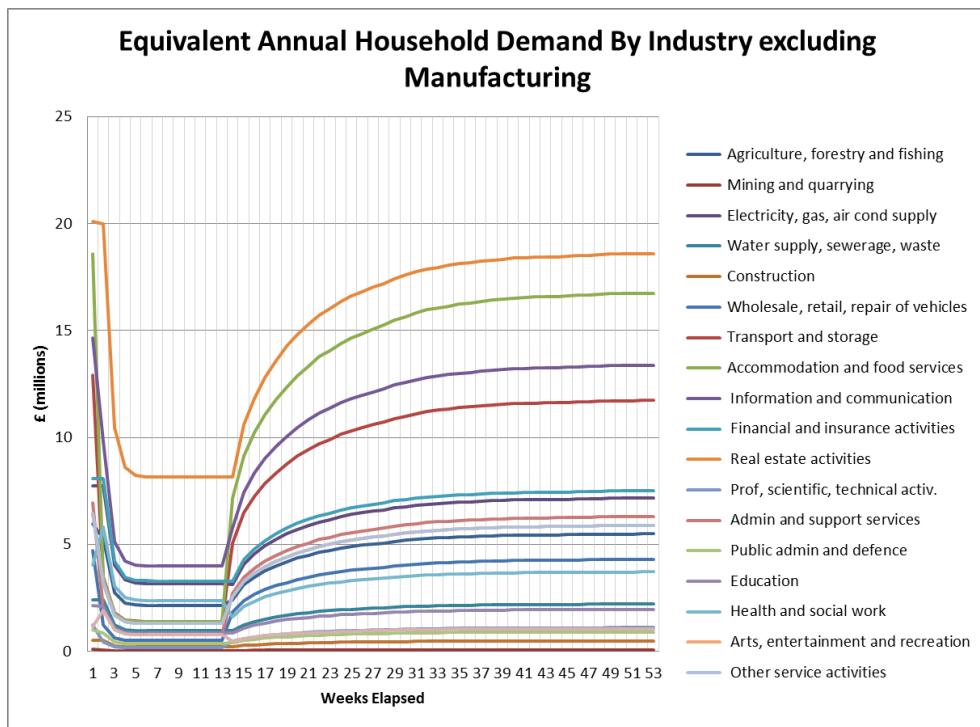


Figure 8: A graph of the equivalent annual household demand excluding demand for the manufacturing industry in scenario 10

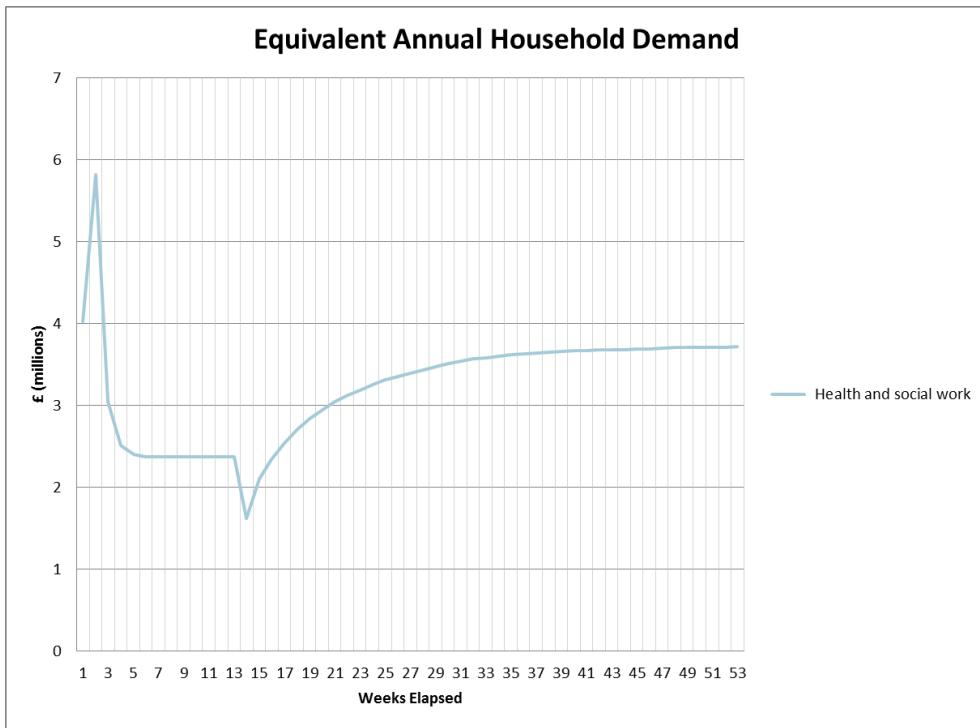


Figure 9: A graph of the equivalent annual household demand for the health and social work industry in scenario 10

The equivalent annual household demand in figure 7 shows that manufacturing is most sensitive to household demand, exhibiting the largest drop of all industries due to the imposition of lockdown. This is primarily due to the fact that the manufacturing industry has large sub-industries. Looking at the chart which excludes manufacturing in figure 8, it can be

seen that sharp drops across all industries are observed under lockdown. The main exception to this is the health and social work industry (shown in figure 9), which shows a sharp initial rise in demand under lockdown followed by a sharp drop in demand. The subsequent sharp fall in demand for this industry's goods and services was surprising and is probably a shortcoming of the model. This is probably due to the fact that the transmission of COVID-19, the primary driver of the rise in household demand for healthcare services, has not been modelled.

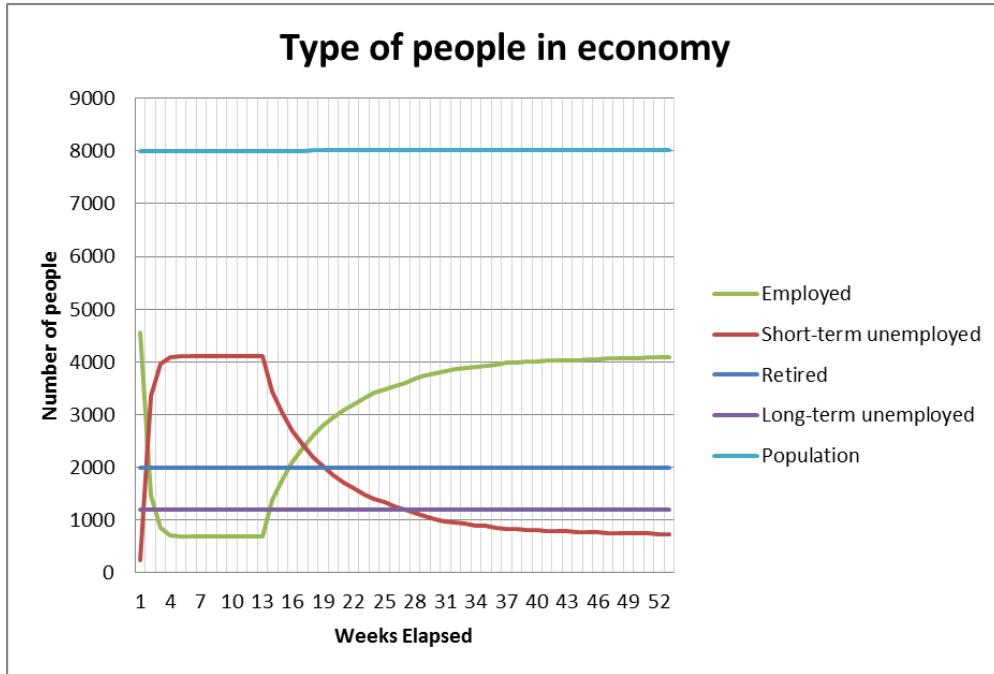


Figure 10: A graph of the changing employment dynamics within the population in scenario 10

Employment dynamics and the resulting household status dynamics behave as expected in this model scenario, as shown by figure 10. The number of people who are short-term unemployed rises sharply as people are fired after lockdown is imposed and non-essential industries are closed. The model suggests very high unemployment levels under a sustained lockdown, with the number of people who are short-term unemployed rising to nearly 5000, close to equal the number of people who were initially in employed. This might be a realistic approximation and could explain the importance of the government's furlough scheme to deter industries from laying people off en masse and precipitating the alarming levels of unemployment suggested by the scenario 10.

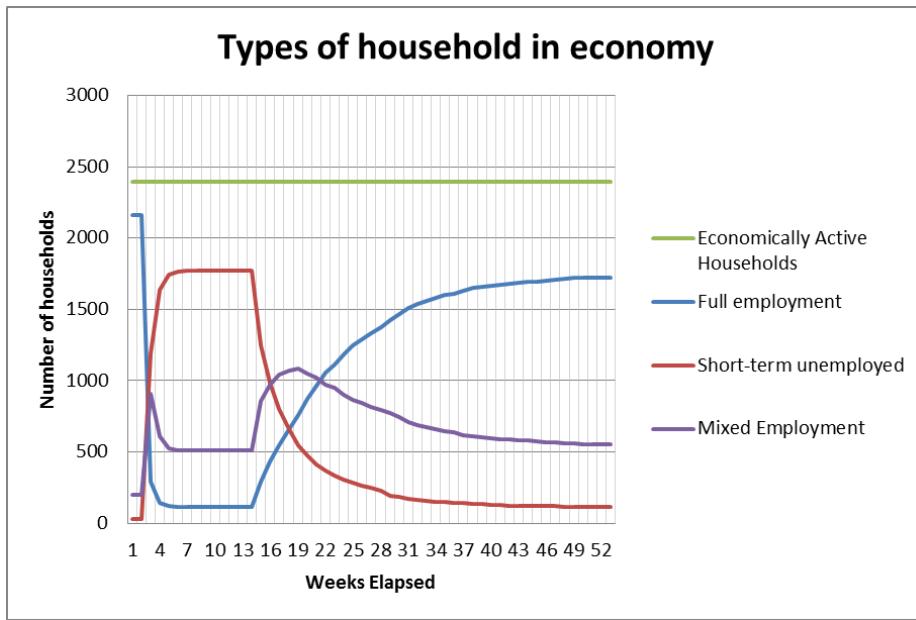


Figure 11: A graph showing the varying quantities of household types in the economy

The status of households in the economy evolves in line with the changing employment dynamics in figure 10. As more people are fired, the number of mixed and short-term unemployed houses rises sharply. Figure 11 shows that the number of short-term unemployed households only declines when lockdown is lifted.

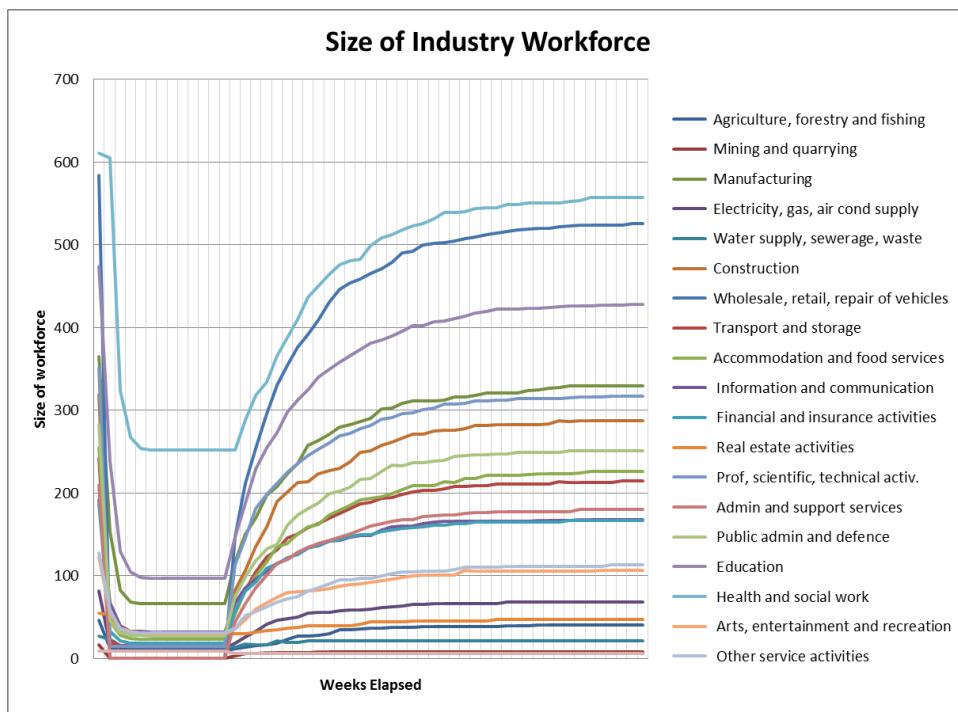


Figure 12: A graph showing the changing levels of employment within each industry in scenario 10

Workforce dynamics are in line with the sharp rise in employment levels, as the vast majority of industries fire employees to adjust to the lower levels of demand for their output. The noteworthy observation here is that the figure 12 suggests that the ‘wholesale, retail, repair of

vehicles' industry is hit very hard by lockdown, and has to fire most of its workers. However, it also recovers rapidly when lockdown is lifted (as seen by its steep gradient), which suggests an accelerated rate of hiring when lockdown is lifted).

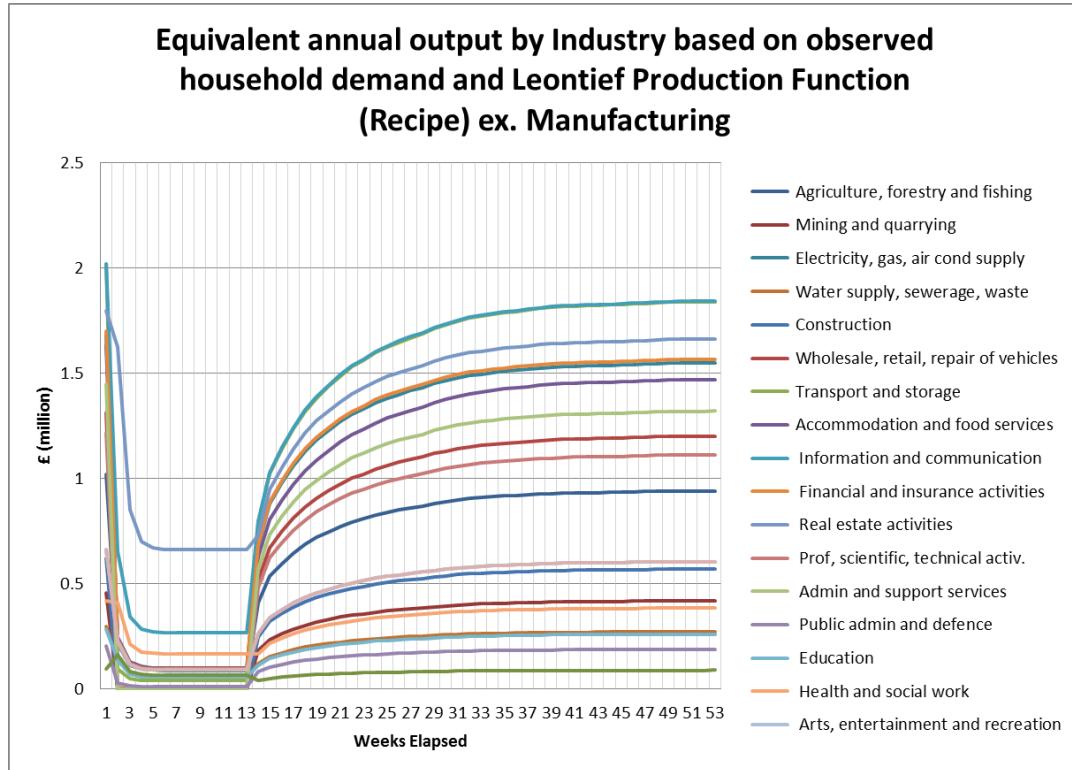


Figure 13: A graph showing the levels of output of each industry in response to levels of household demand in scenario 10

The output industries decide to produce is also consistent with changing household demand in the scenario 10. However, the order of magnitude of production is surprising. The £-volume of output is roughly 10 times smaller in magnitude than £-volume household demand. This is strange. Linear algebra was used to compute the output matrix, which yielded this result. Further testing is needed to see if this is a result of the matrix decomposition scheme that was chosen or some other phenomenon.

Project Deliverables

When measured against the project's deliverables, the model scores as follows:

1. System must allow users to view aggregated household agents by their different properties, such as income level or region. **PASS**
2. System must allow users to view aggregated industry agents by their different properties, such as sector and region and supply and demand. **PASS**
3. System must allow users to input different starting variables to investigate different scenarios. **PASS**
4. System should be calibrated using UK economic data and should contain an approximate scaled model of the UK in each simulation it runs. **PASS**
5. Deliver a proof of concept that an integrated approach to modelling the economy in the proposed manner is possible. **PASS**

By this measure, the model meets all of the project's objectives. It should be stressed, however, that this is a proof of concept and that there is much room for improvement. Given more time, the next iteration of the model would make improvements to the algorithmic speed of the model so that it can run at larger scales. It currently takes roughly 8 minutes to run a simulation for a population of 10,000. Simulations for populations of 100,000 or more take in excess of 6 hours to complete. The latency is largely due to the hiring and firing methods within the model. These would have to be optimised significantly in order to improve the run times. Such an overhaul would likely necessitate the creation and use of more efficient data structures that have good insertion and search times.

Lastly, as discussed in the related work section, industries would also be extended to include stocks of finished products to better reflect the reality of today's complex supply chains. The model would also be extended to incorporate different regions of the UK. A novel approach would be required here, as none of the literature presents a way of accomplishing this. A feasible approach to this problem could be to connect separate regions together in a network using matrix equations similar to those used to connect industries together to form a supply chain network.

Conclusion

To conclude, the model shows that lockdown and the closure of non-essential industries triggers downturns across the board in terms of household demand and industry output. As this is the case, the policy response should prioritise lessening the negative impacts of conditions under lockdown. It should do this by targeting the sensitive model parameters as well as the agents that are shown to be most sensitive to lockdown.

The model scenarios imply that the economy is most sensitive to the amount by which people cut their expenditure when they feel poorer and that industries will cut workforces aggressively in response to lockdown and the closure of industries. Whilst cuts to expenditure are largely driven by a person's disposition, they can be influenced by government communication. Government should move to swiftly to propose plans to help re-assure people and stop their spending levels from plummeting. On this note, whilst the current government furlough scheme may be somewhat effective in propping up household demand, it may overlook the critical role that having a job plays in making people feel as though they

are not significantly worse off. It may well be the case that people placed on furlough feel worse off in spite of the fact that they have technically not been made redundant. If this is the case, it calls the efficacy of the government's furlough scheme into question.

The model scenarios also show that industries are not affected equally by the lockdown and disrupted supply chains. The 'wholesale, retail and repair of vehicles' industry is most sensitive to lockdown from an employment perspective. It exhibits the sharpest fall in employment and the sharpest recovery post-lockdown. Other sensitive industries include the manufacturing industry, the professional, scientific and technical activities industry and the education and health and social work industry. These industries should be closely monitored and a strategy should be formulated to try and soften the negative effects on these industries and speed up the ensuing recovery.

The paper has made the case for the use of agent-based modelling for policy-making. The insights it provides about the impact of lockdown and the closure of non-essential industries on households and industries in the economy form a useful starting point for further exploration of what an optimal economic policy response to the crisis should look like.

Bibliography

- Rob Axtell, J. Doyne Farmer, John Geanakoplos, Peter Howitt, Ernesto Carrellla, Ben Conlee, Justin Goldstein, Matthew Hendrey, Philip Kalikman, David Masad, Nathan Palmer and Chun-Yi Yang (2014). An Agent-Based Model of the Housing Market Bubble in Metropolitan Washington, D.C.
- Rafa Baptista, J Doyne Farmer, Marc Hinterschweiger, Katie Low, Daniel Tang and Arzu Uluc (2016). Bank of England Staff Working Paper No. 619. Macroprudential policy in an agent-based model of the UK housing market.
- J. Farmer and J. Foley (2009). The economy needs agent-based modelling.
- Nigel Gilbert, John C. Hawksworth & Paul A. Swiney (2009) . An Agent-Based Model of the English Housing Market.
- Stephane Hallegatte (2008). An Adaptive Regional Input-Output Model and its Application to the Assessment of the Economic Cost of Katrina.
- Hiryasu Inoue and Yasuyuki Todo (2020). The Propagation of the Economic Impact through Supply Chains: The Case of a Mega-City Lockdown against the Spread of COVID-19.
- R. Maria del Rio Chanona, Penny Mealy, Anton Pichler, Francois Lafond, & J. Doyne Farmer. (2020). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective
- R. Maria del Rio Chanona, Penny Mealy, Anton Pichler, Francois Lafond, & J. Doyne Farmer. (2020). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective [Data set]. <http://doi.org/10.5281/zenodo.3751068>
- Office for National Statistics: Annual Survey of Hours and Earnings, All, <https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/previousReleases>
- Office for National Statistics: Annual Population Survey, Industry 18-19, <http://www.ons.gov.uk/ons/guide-method/method-quality/quality/quality-information/labour-market/index.html>
- Office for National Statistics: Input-output supply and use tables, Household Final Consumption Expenditure 2016 <https://www.ons.gov.uk/economy/nationalaccounts/supplyandusetables/datasets/inputoutputsupplyandusetables>
- Office for National Statistics: Population estimates for the UK, England and Wales, Scotland and Northern Ireland: mid-2019, using April 2020 local authority district codes, MYE1: Population estimates <https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland>
- Office for National Statistics: Workbook 1 – Detailed Expenditure and Trends, 3.2 Detailed household expenditure as a percentage of total expenditure by disposable income decile

group,

<https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/datasets/familyspendingworkbook1detailedexpenditureandtrends>

- Anton Pichler, M. Pangallo, R. Maria del Rio Chanona,, Francois Lafond & J.Doyne Farmer. (2020). Production networks and epidemic spreading: How to restart the UK economy?
- Anton Pichler, M. Pangallo, R. Maria del Rio Chanona,, Francois Lafond & J.Doyne Farmer. (2020). Production networks and epidemic spreading: How to restart the UK economy? [Data set] <https://zenodo.org/record/3834116>
- Shanjun Tian and Shiyan Chang (2020). An agent-based model of household energy consumption.

Appendix

3rd party Libraries and Code Used

What used?	Source	Where used in code?
Apache Commons Maths	http://commons.apache.org/proper/commons-math/download_math.cgi	industry.RegionIndustries.computeRequiredOutput - industry package - RegionIndustries Class - computeRequiredOutput method
CSV parser	@author Michael Lihs. Modified by Y. Ogunyemi	usefulMethods.CsVParser.readCSVtoStringList - usefulMethods Package - CsvParser class - readCSVtoStringList method

- The Apache Commons Maths package was used to perform linear algebra operations in order to compute the required output of industries.
- The readCSVtoStringList method in the CSVParser package used lines of code by Michael Lihs that were posted on stackoverflow. These were then modified and extended when writing the readCSVtoStringList method

File Structure of Code

The source code can be found in the following git repository:

https://github.com/yeCodes/UK_Economy_ABM_Final

The code in the git repository is contained in the folder entitled, ‘UK_Economy_ABM_Final’. The source code can be found within the ‘src’ folder. There are three important folders within this, the ‘peopleHouseholds’ folder, which contains the classes defining person agents, household agents and regional household agents. The industry package contains the industry class, which defines industry agents and the class which defines regional industry agents. It is this ‘RegionIndustries’ class that contains the main method, which initialises and runs the simulation.

There are numerous CSV files within the ‘industry’ and ‘peopleHouseholds’ packages. These are used for model initialisation.

Running the Model

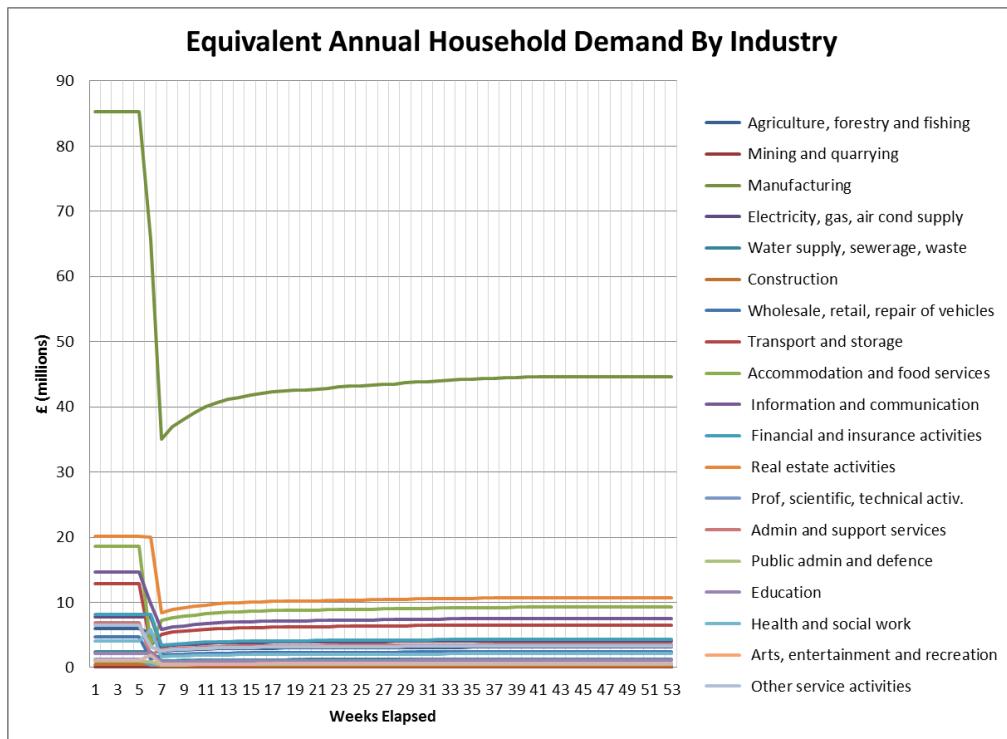
To run the model, go to the main method found in ‘~/industry/RegionIndustries’ and enter the model parameters, which are to be found between lines 125 and 140 of the class. Lastly, to vary the duration of lockdown, go to line 224 within the main method and vary the number of ‘imposeLockdown’ for loops. Do the same on 232, this time within the ‘liftLockdown’ loop, to set the number of simulations cycles to run after lockdown has been removed.

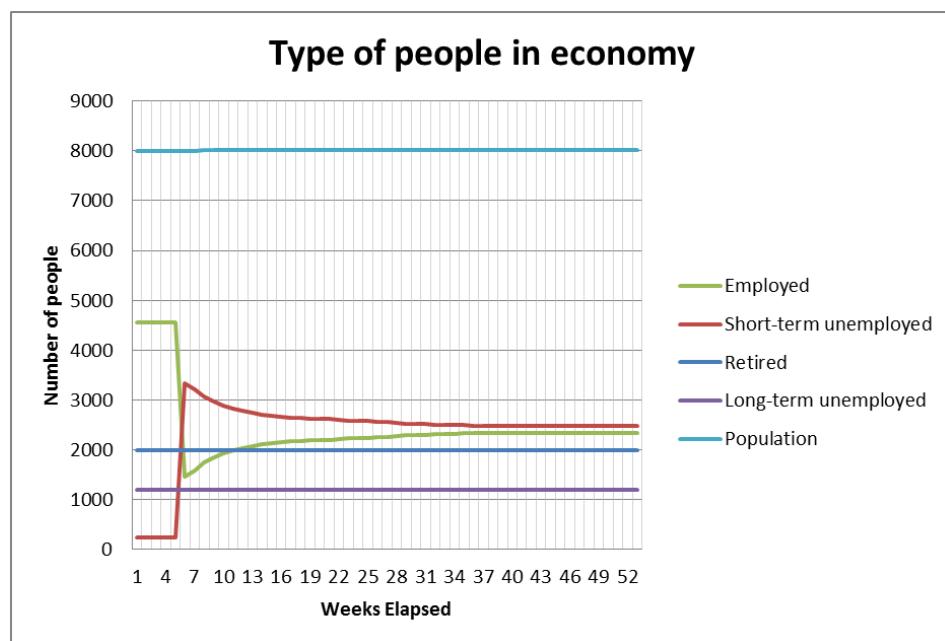
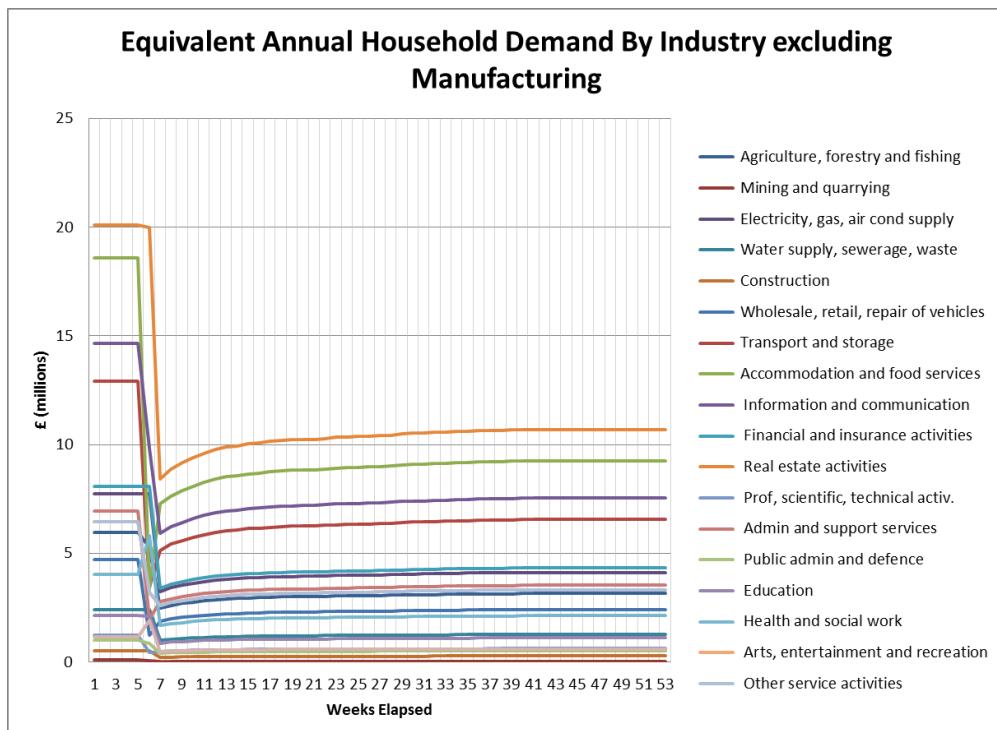
The ‘Results’ folder at the top of the file directory contains the results of the 13 model scenarios that have been commented on in this project.

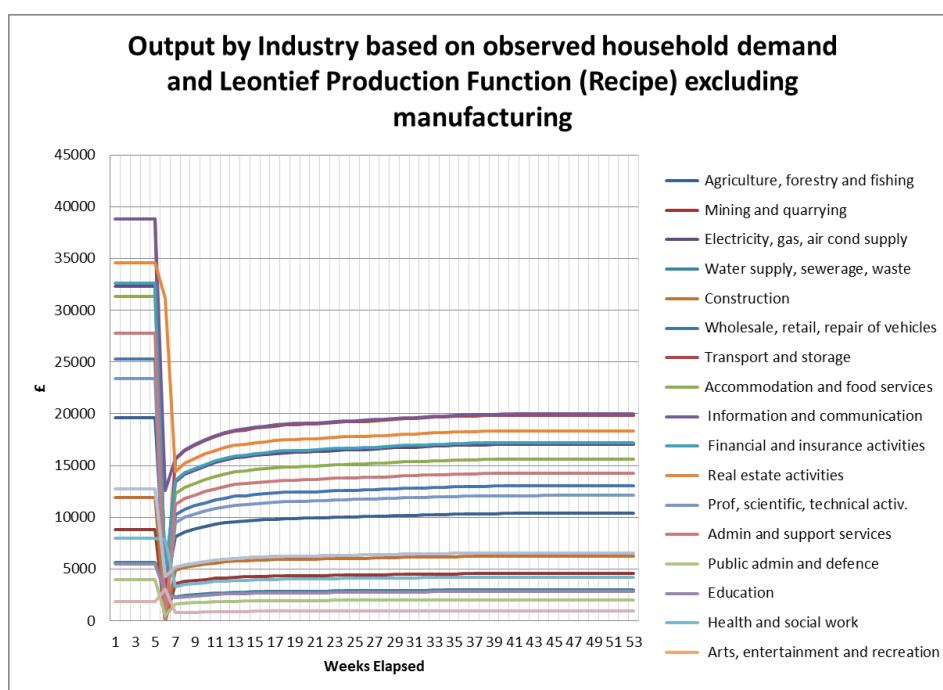
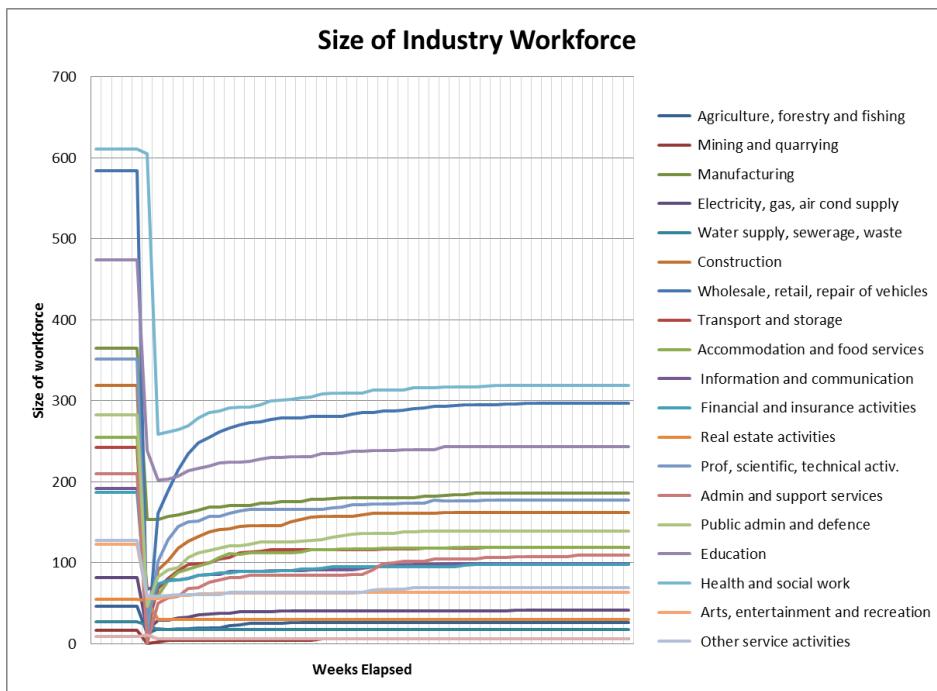
The model outputs all the results of a simulation to CSV files at the highest level of the file directory (the level of the ‘src’ and ‘Results’ folders). Before running subsequent scenarios, the results should be manually transferred to the ‘Results’ folder and given column and row headers that are consistent with the labelling conventions used in the other scenario within the folder.

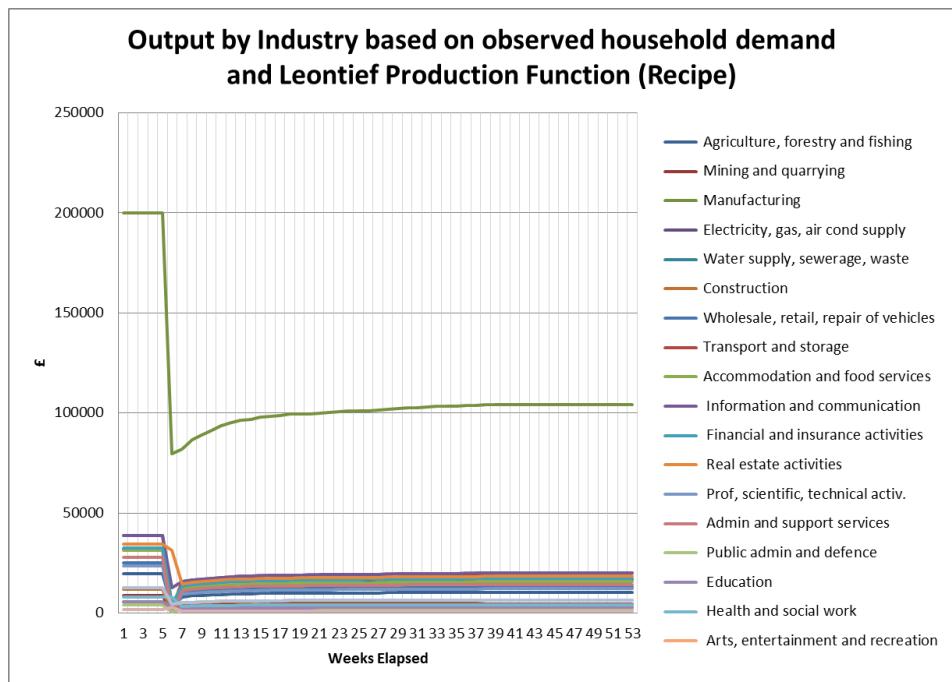
Model Scenario Outputs

Scenario 1

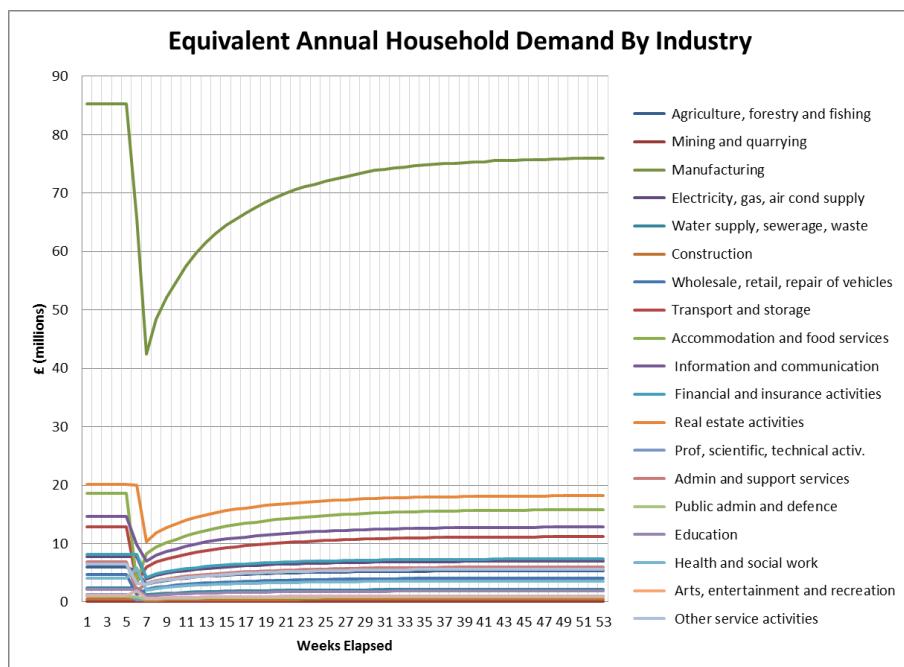




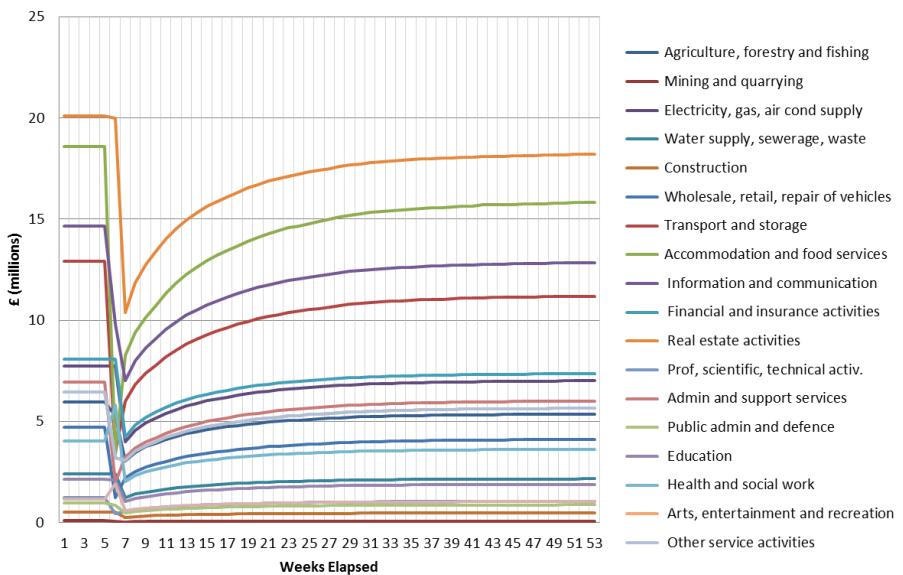




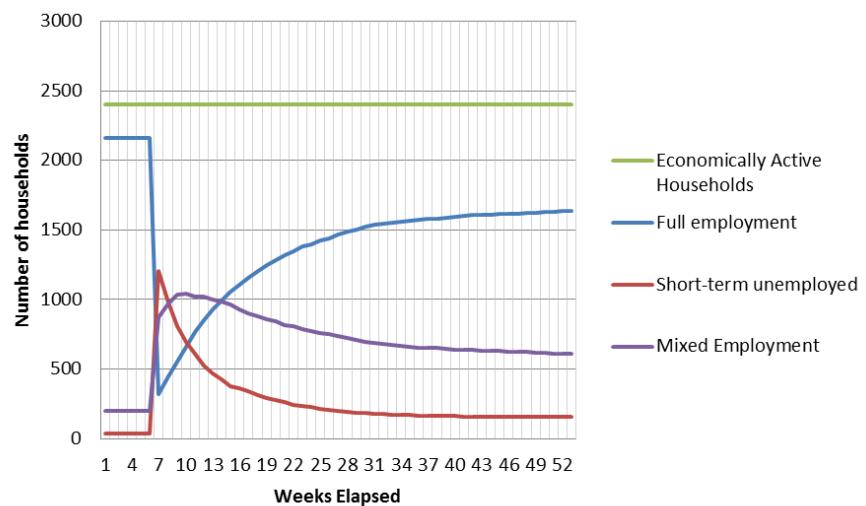
Scenario 2

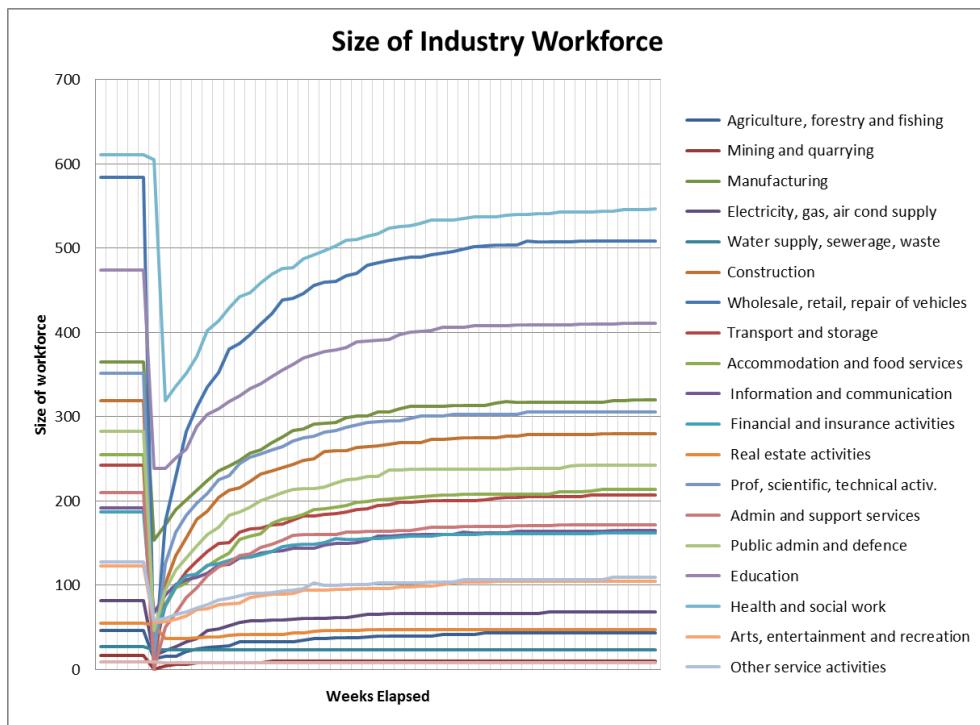
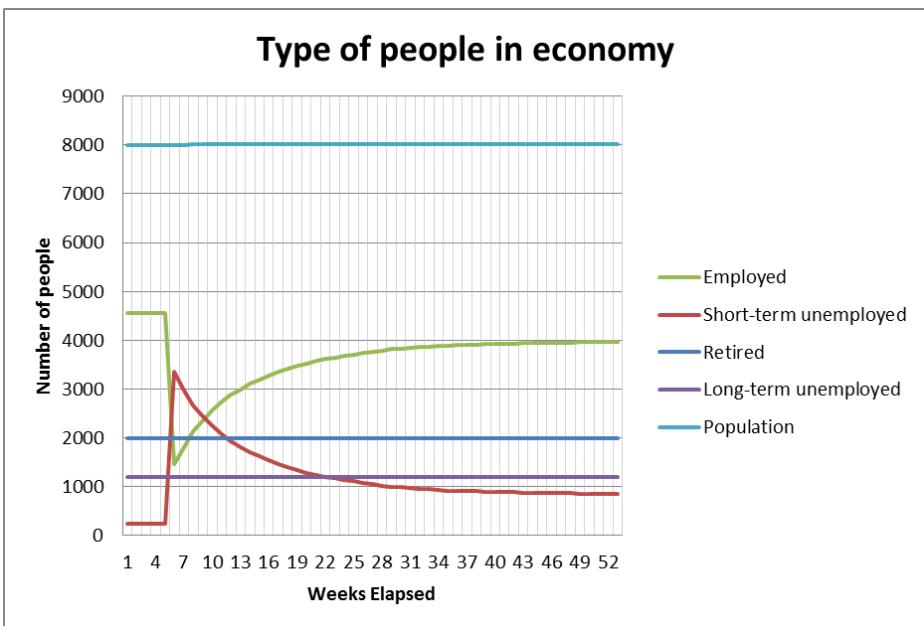


Equivalent Annual Household Demand By Industry excluding Manufacturing

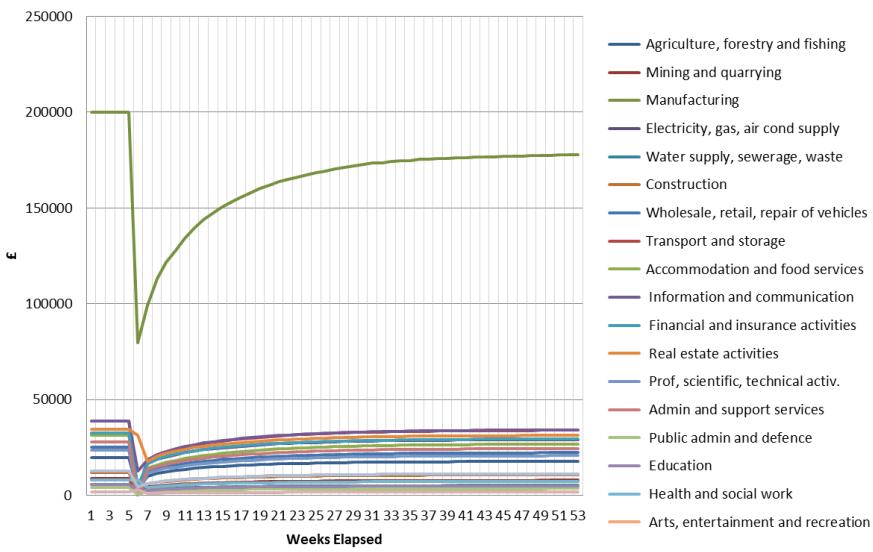


Types of household in economy

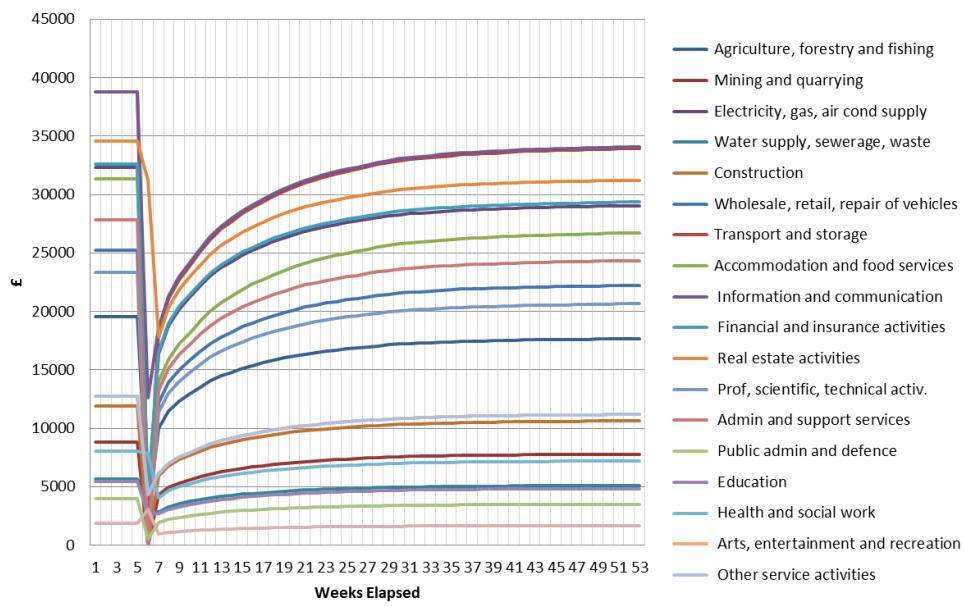




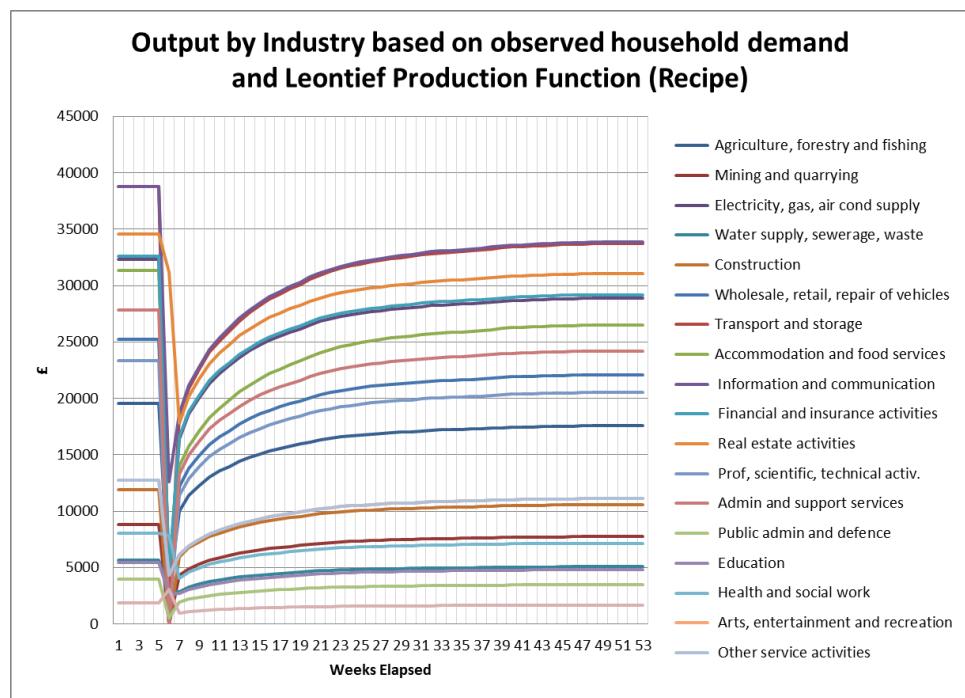
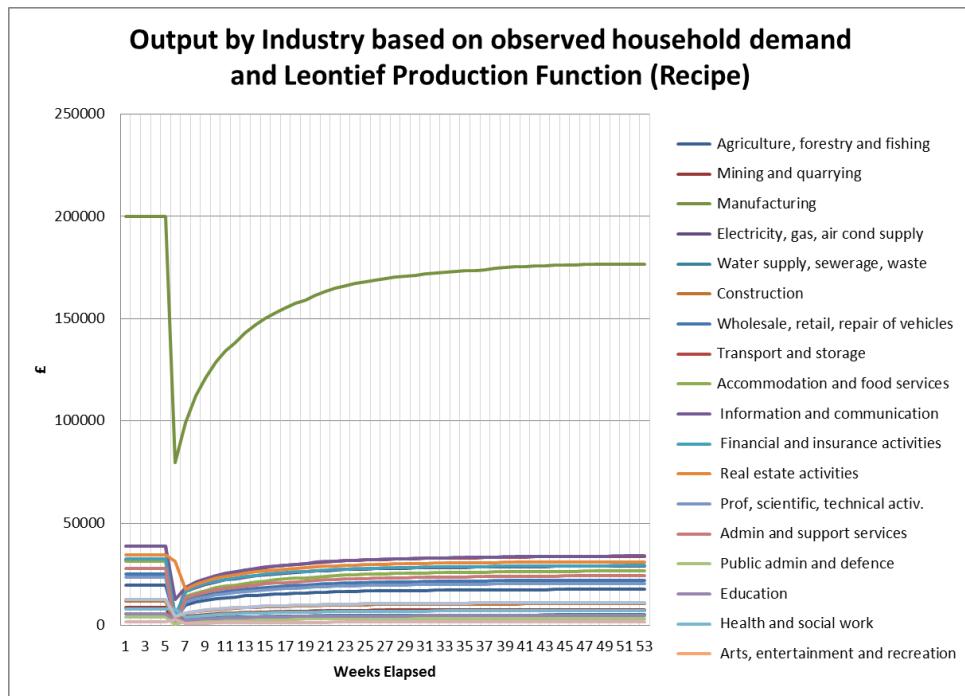
Output by Industry based on observed household demand and Leontief Production Function (Recipe)



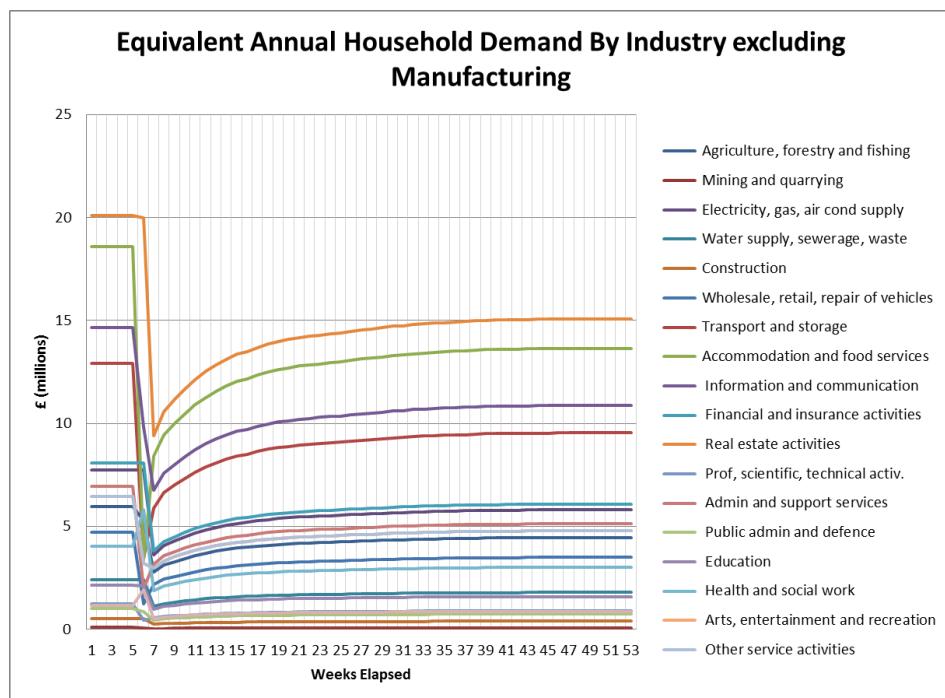
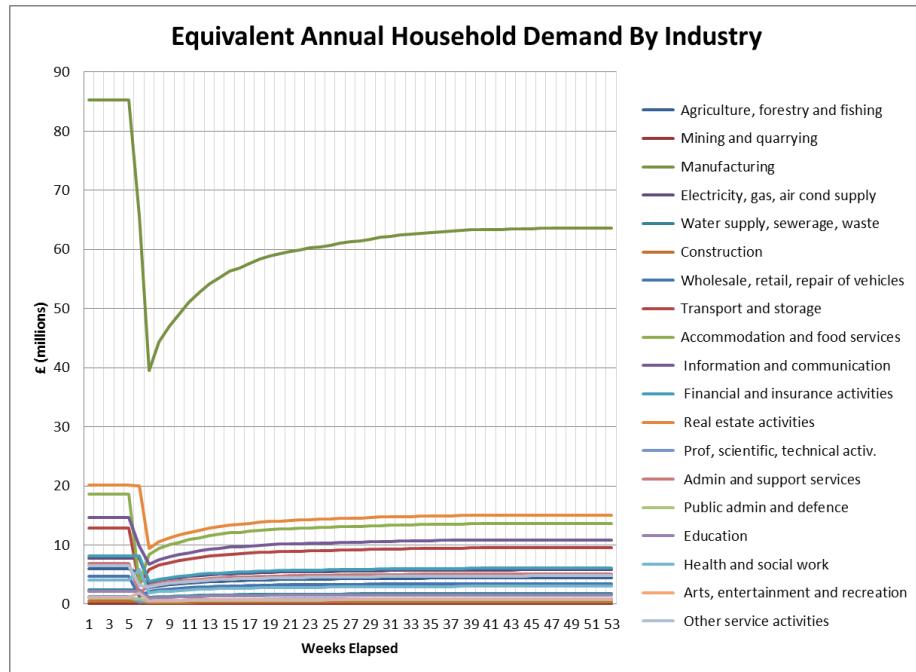
Output by Industry based on observed household demand and Leontief Production Function (Recipe)

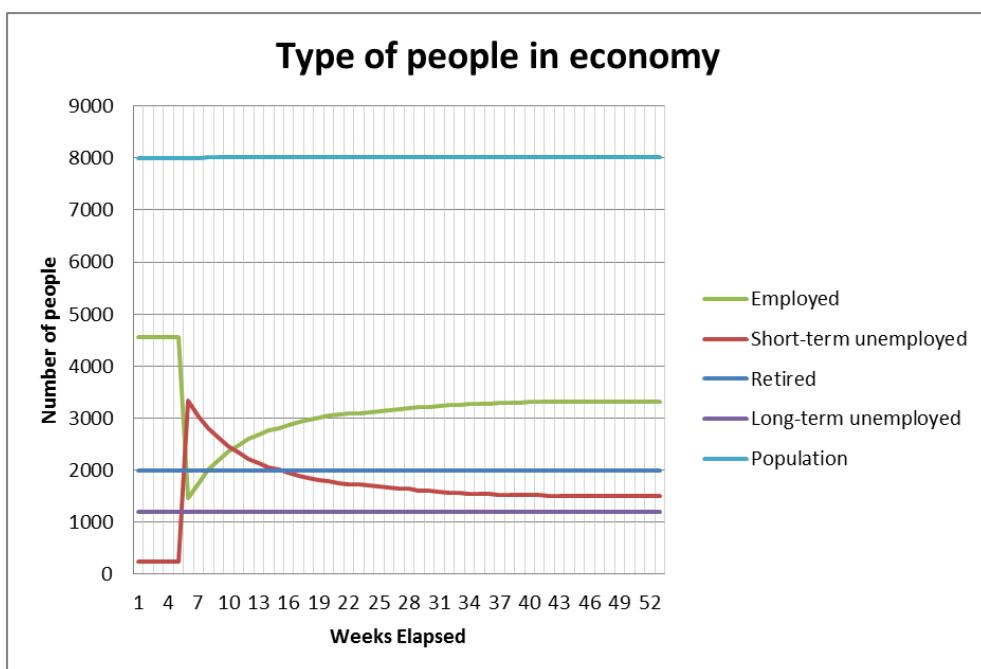
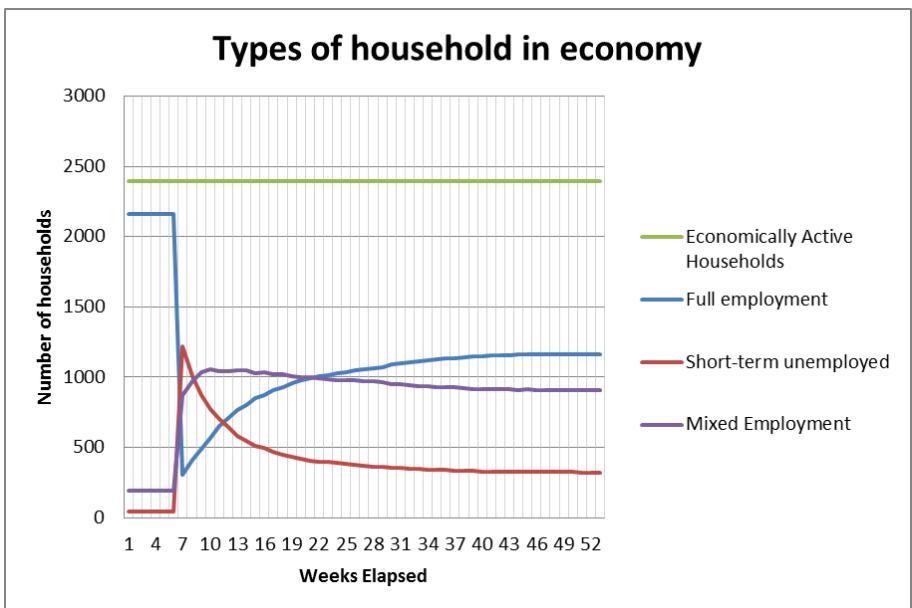


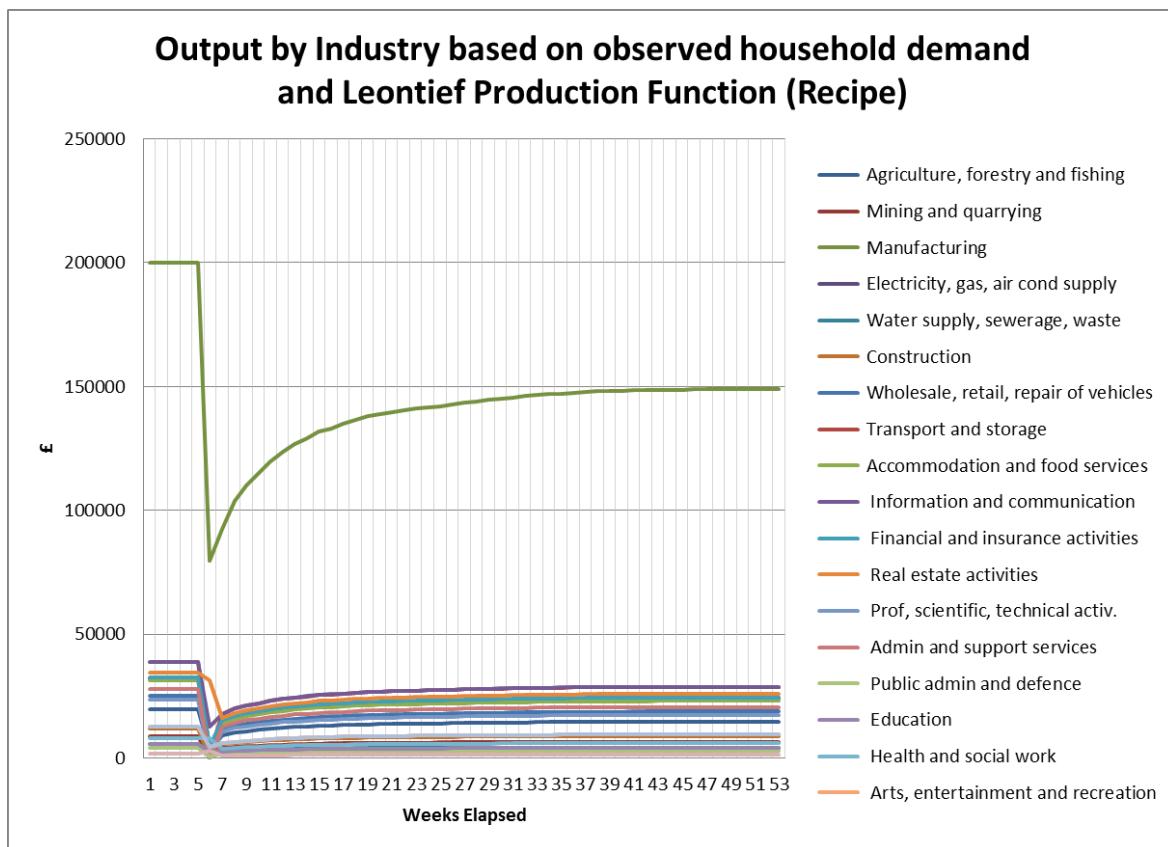
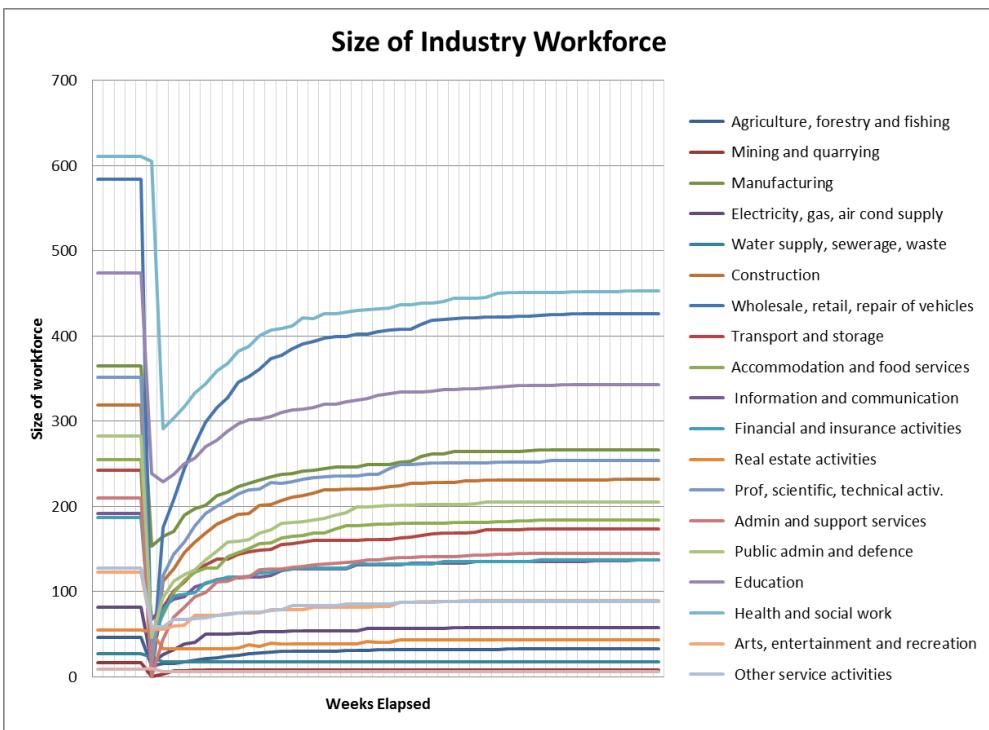
Scenario 6

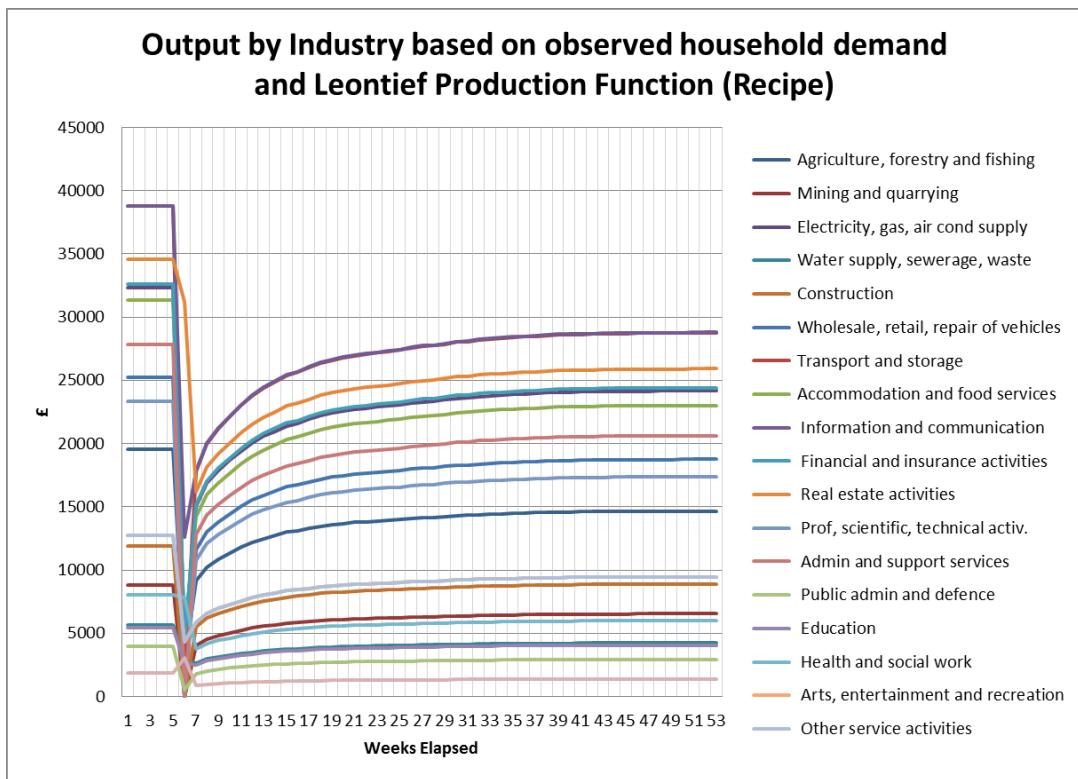


Scenario 7

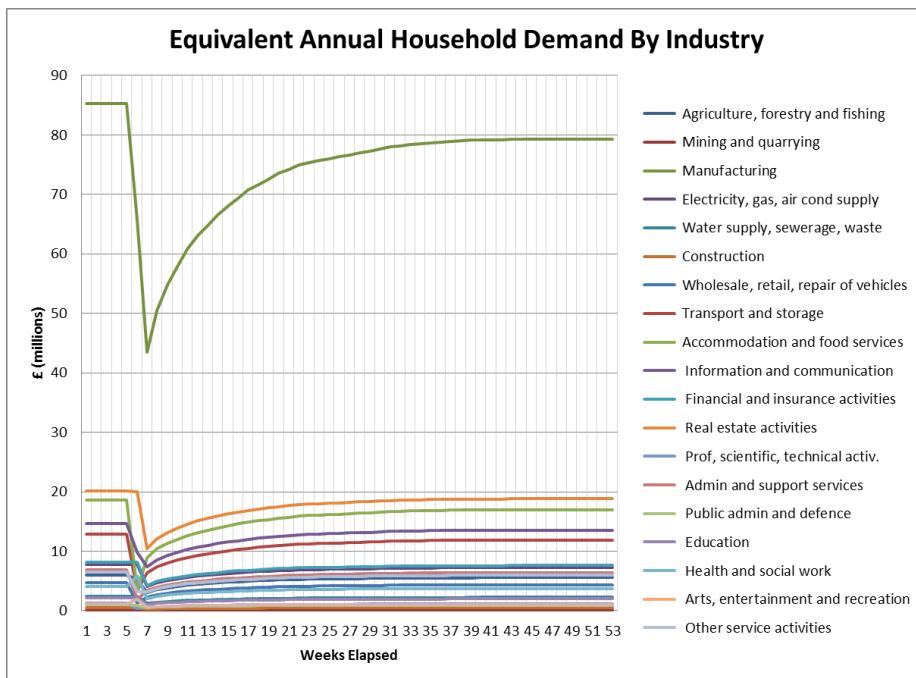


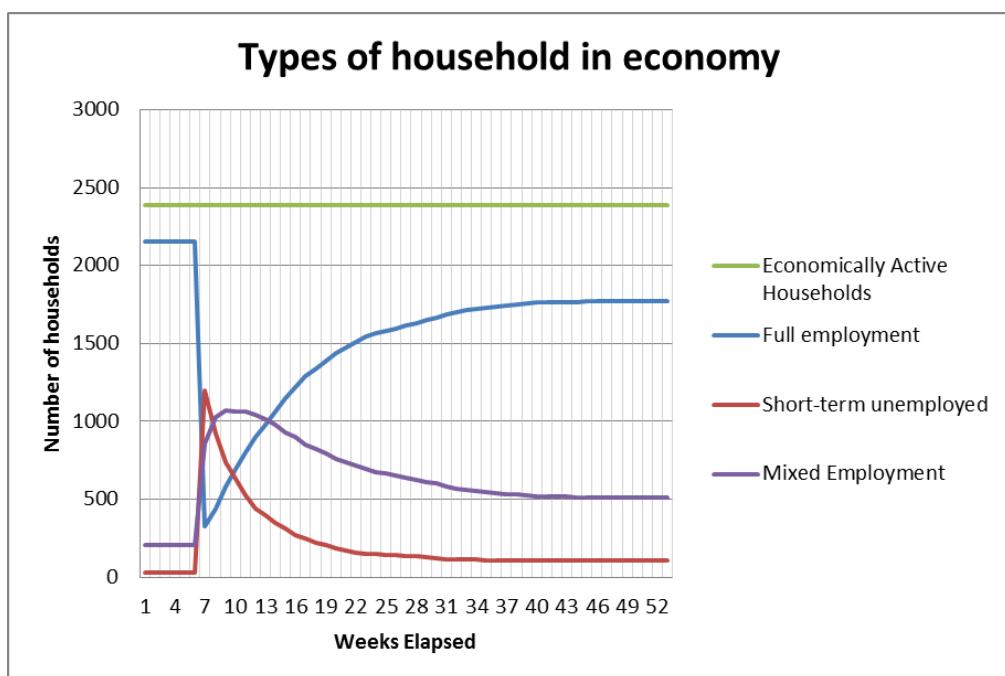
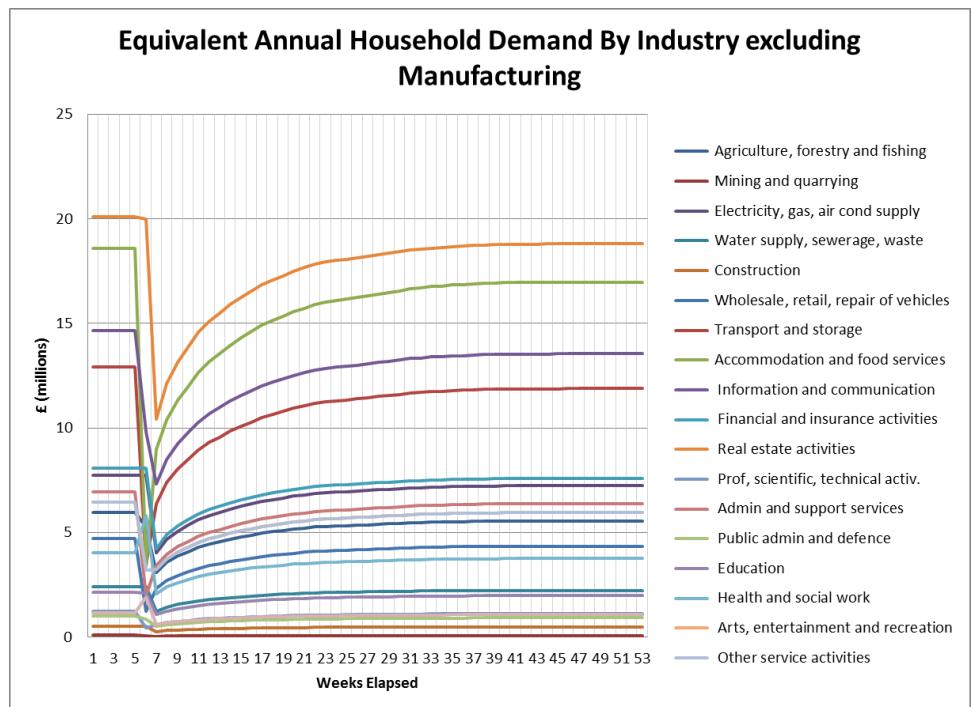


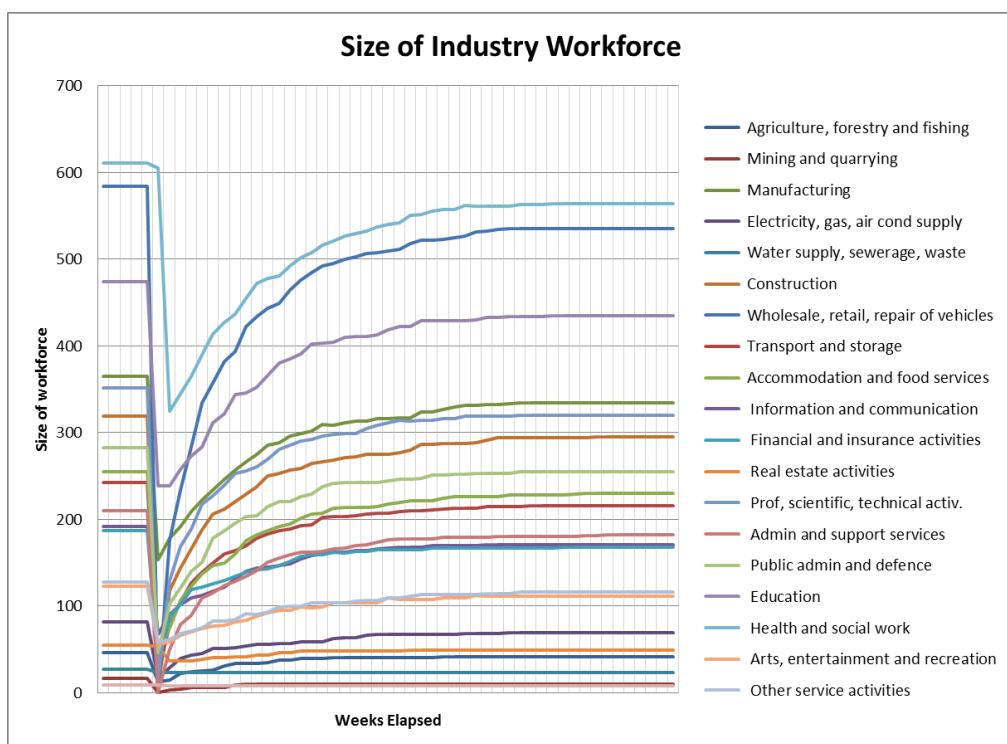
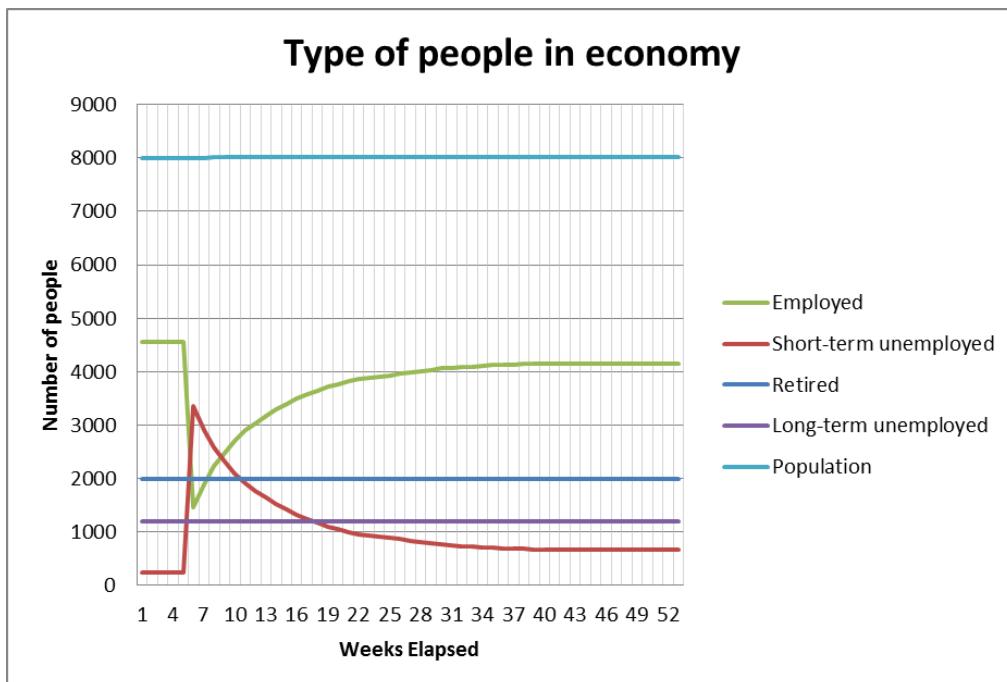




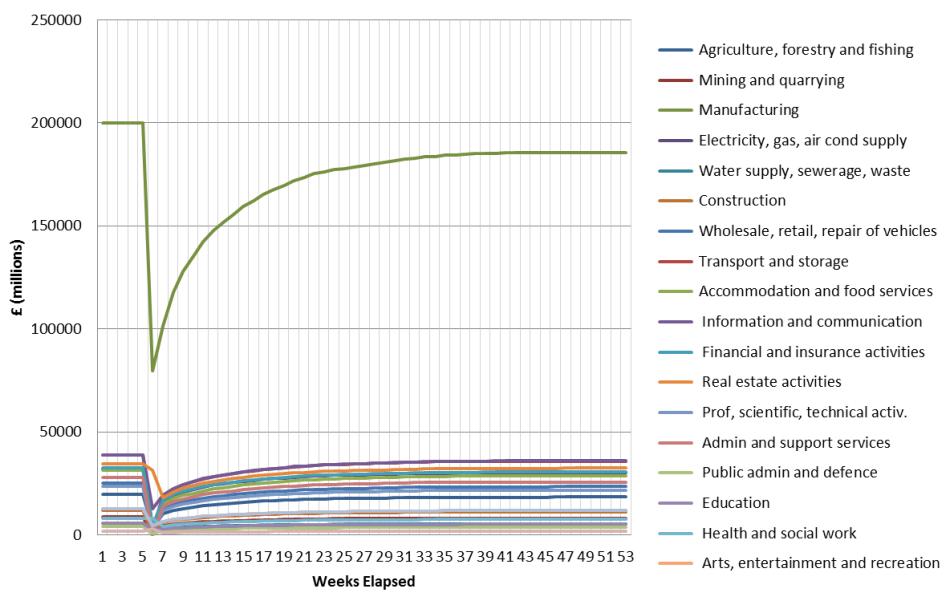
Scenario 8



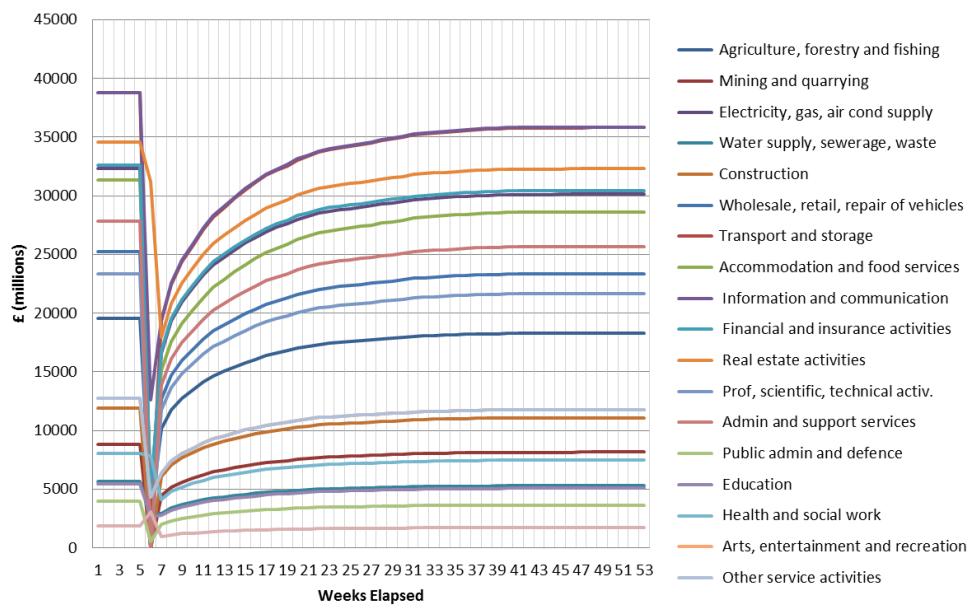




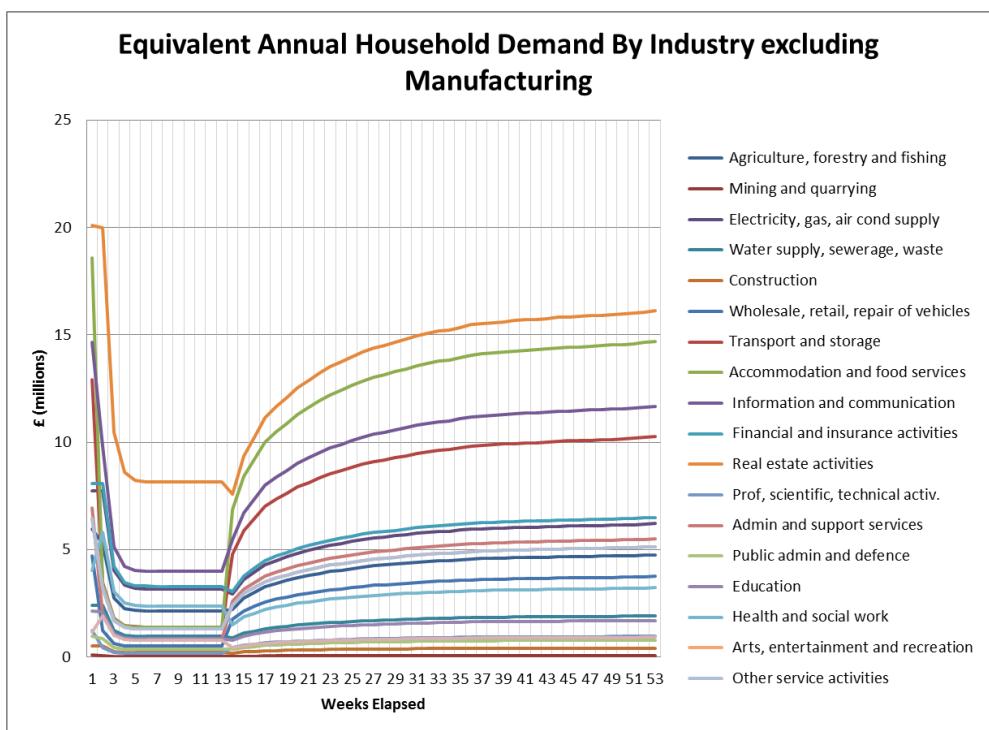
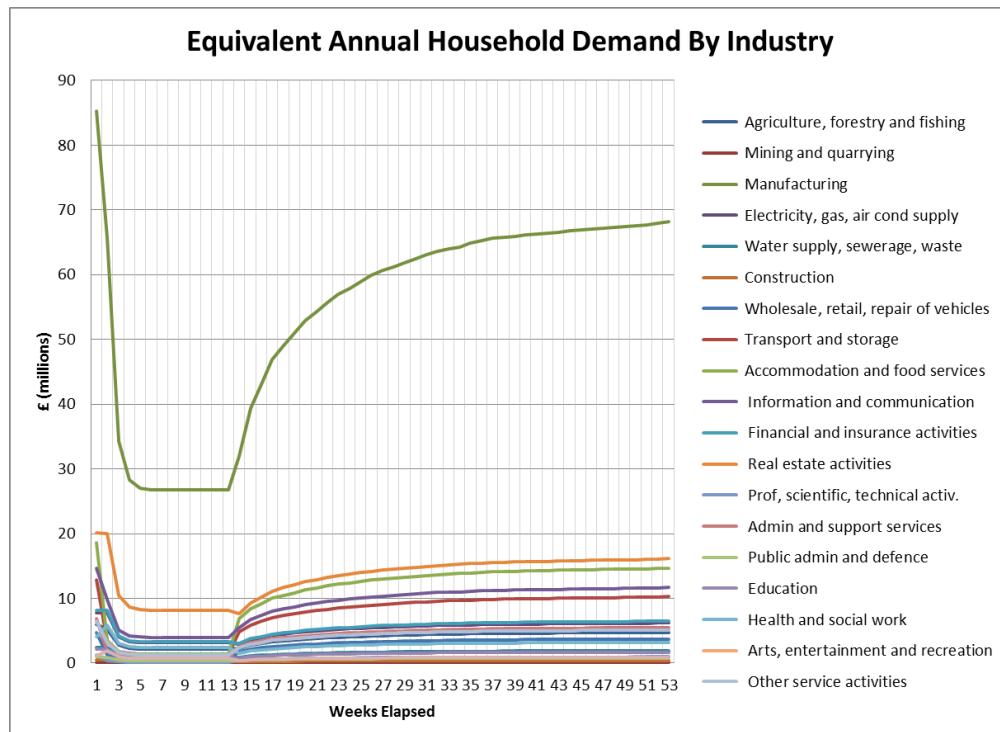
Output by Industry based on observed household demand and Leontief Production Function (Recipe)



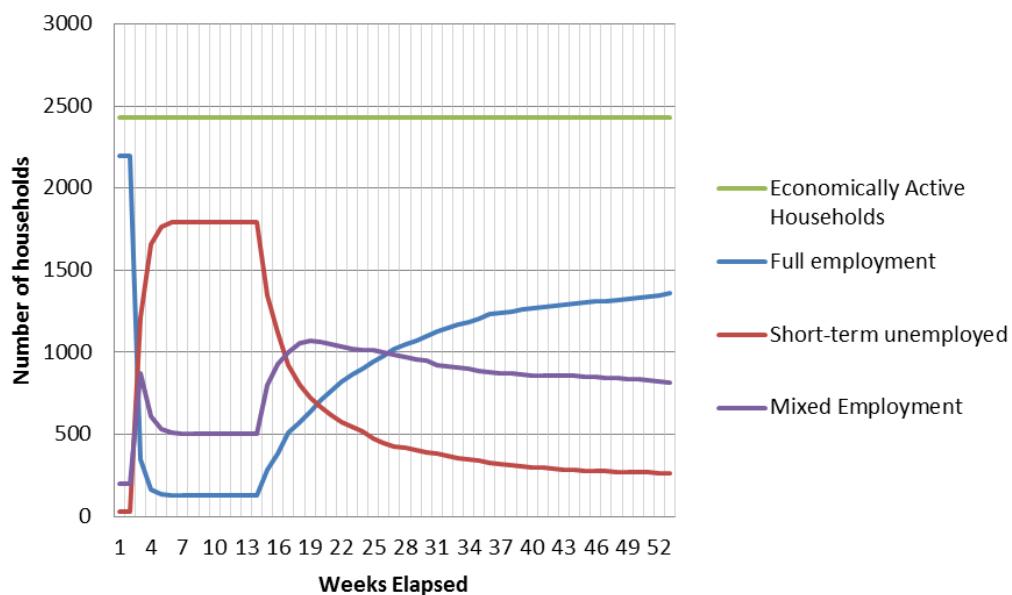
Output by Industry based on observed household demand and Leontief Production Function (Recipe)



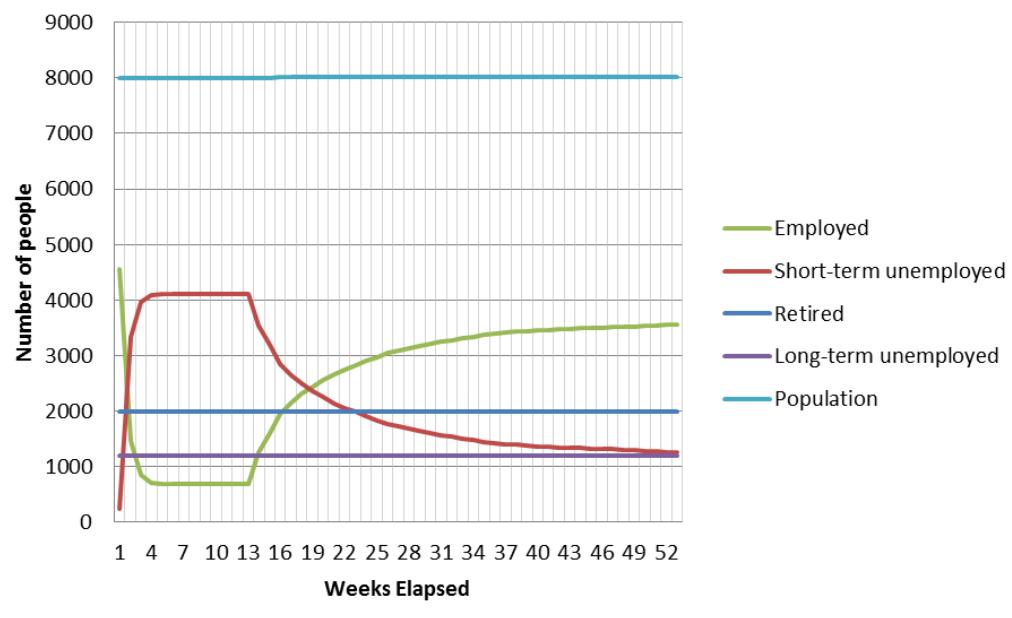
Scenario 9

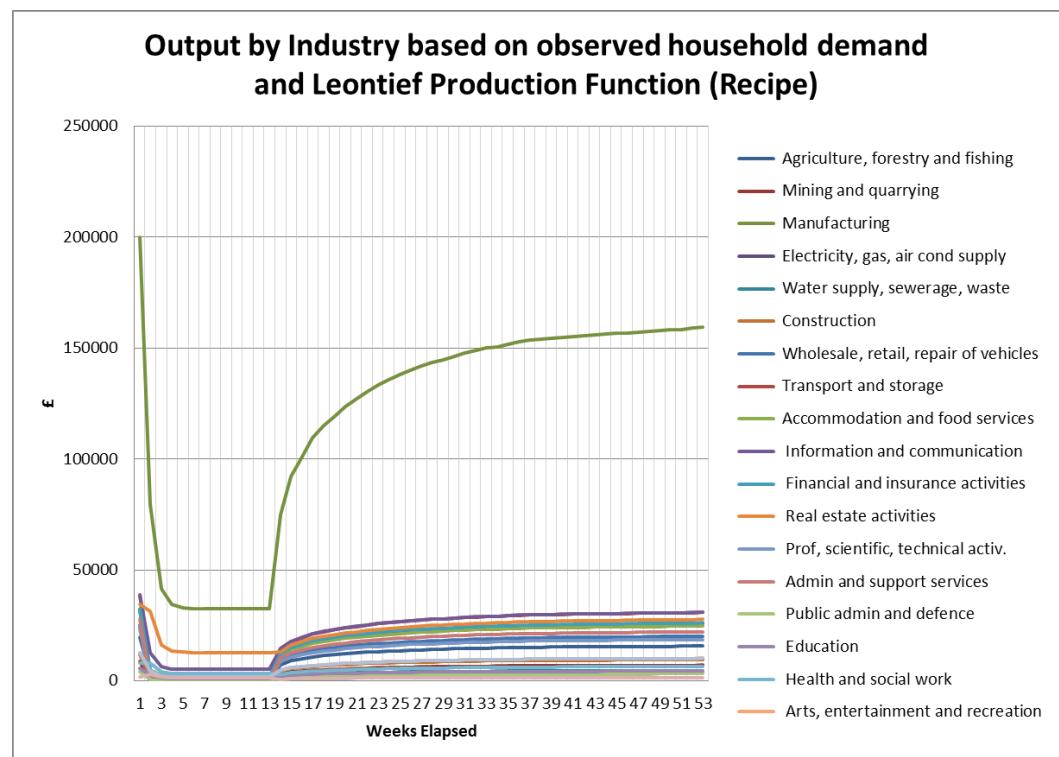
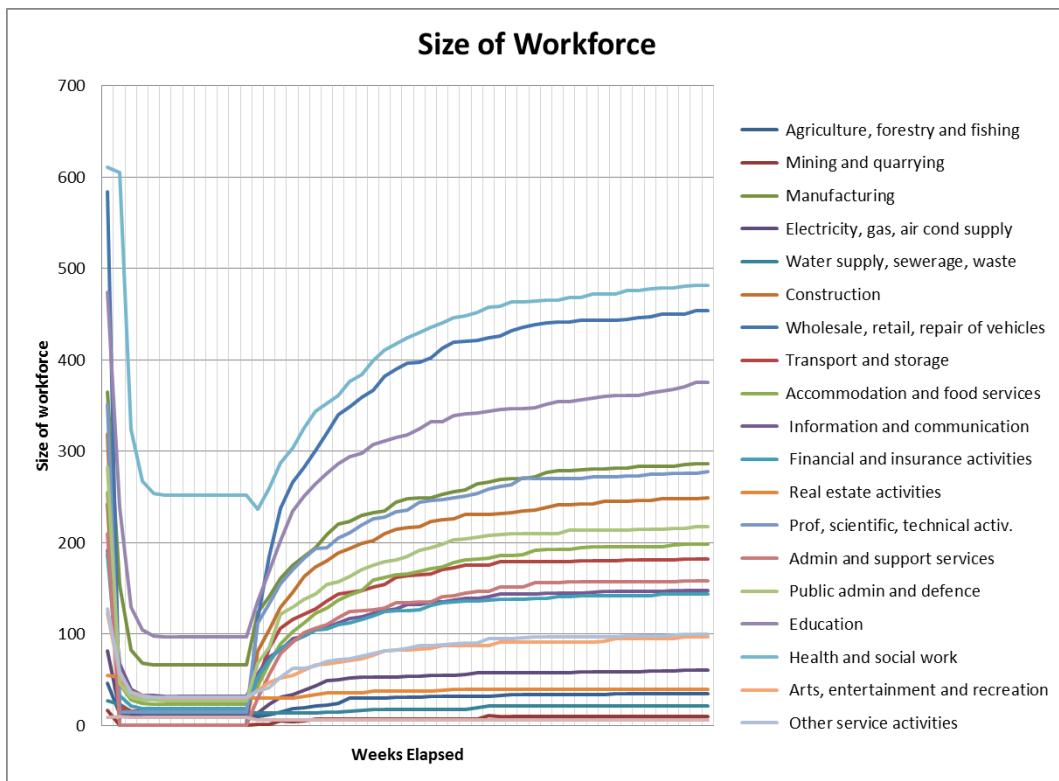


Types of household in economy

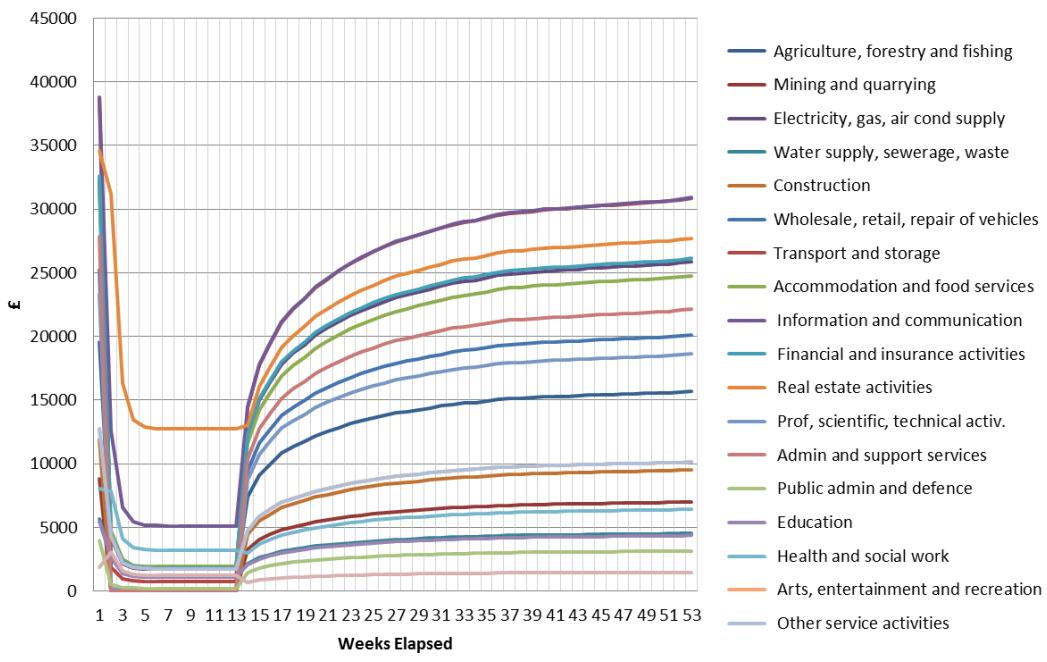


Type of people in economy

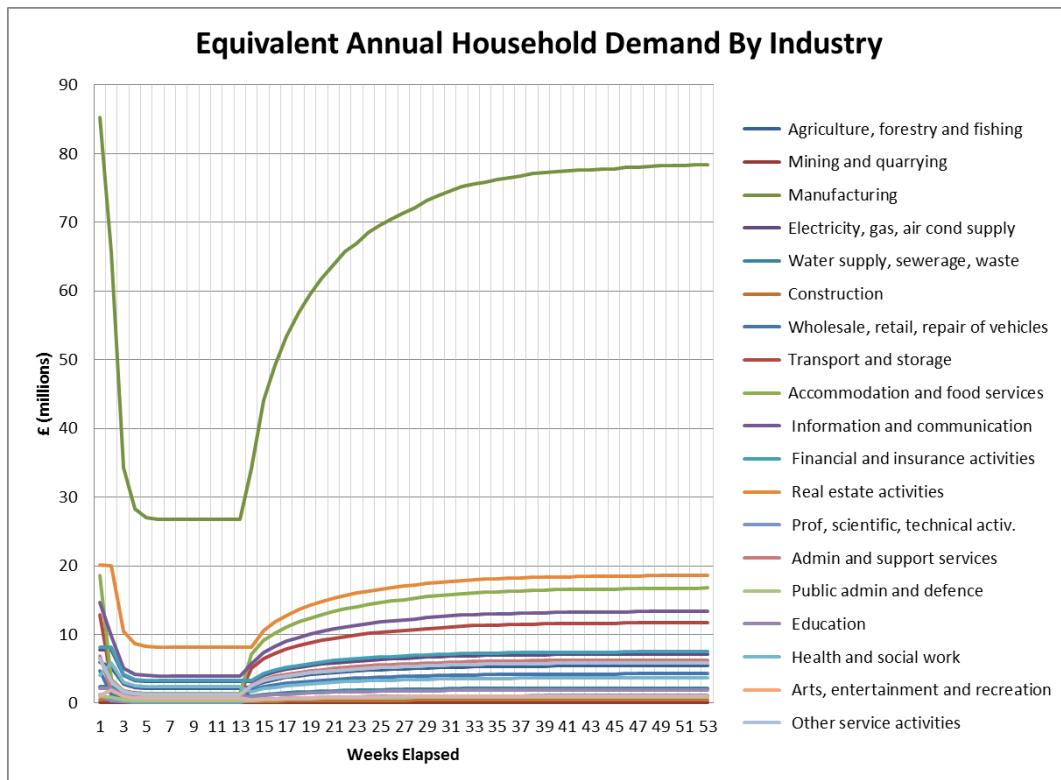




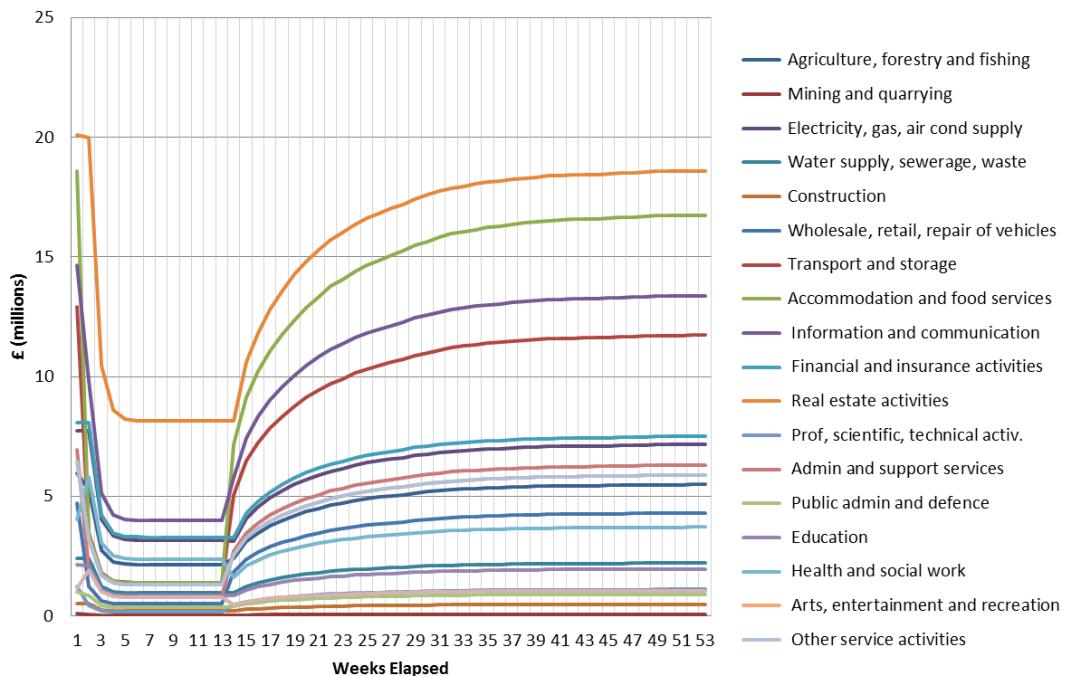
Output by Industry based on observed household demand and Leontief Production Function (Recipe)



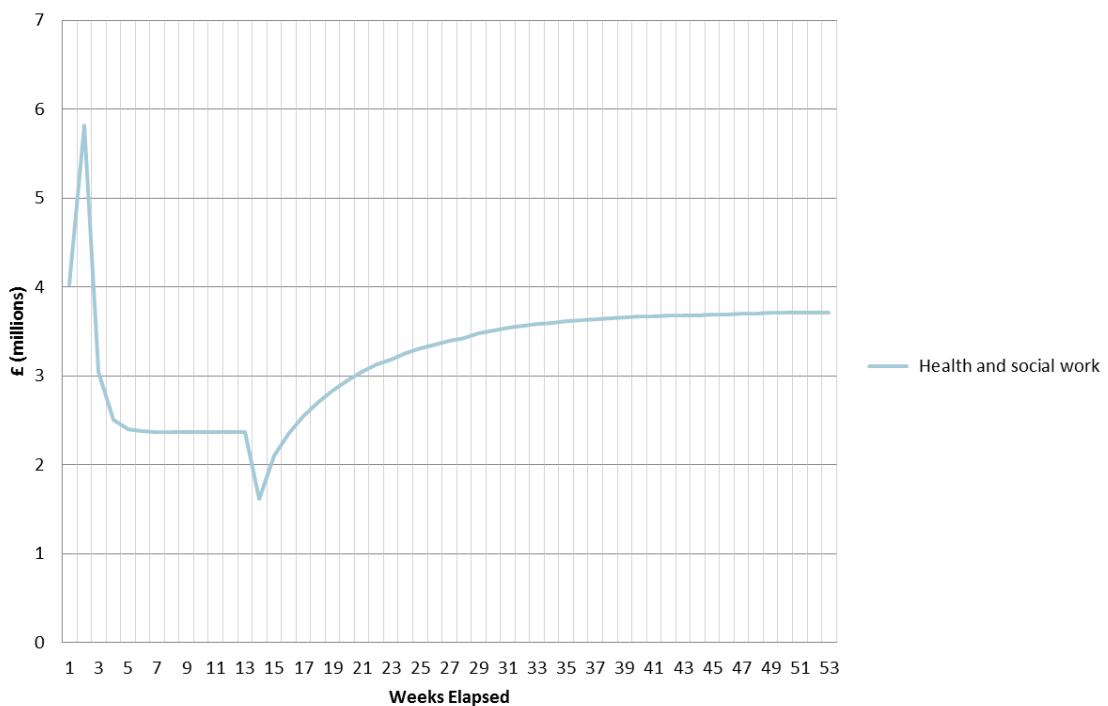
Scenario 10

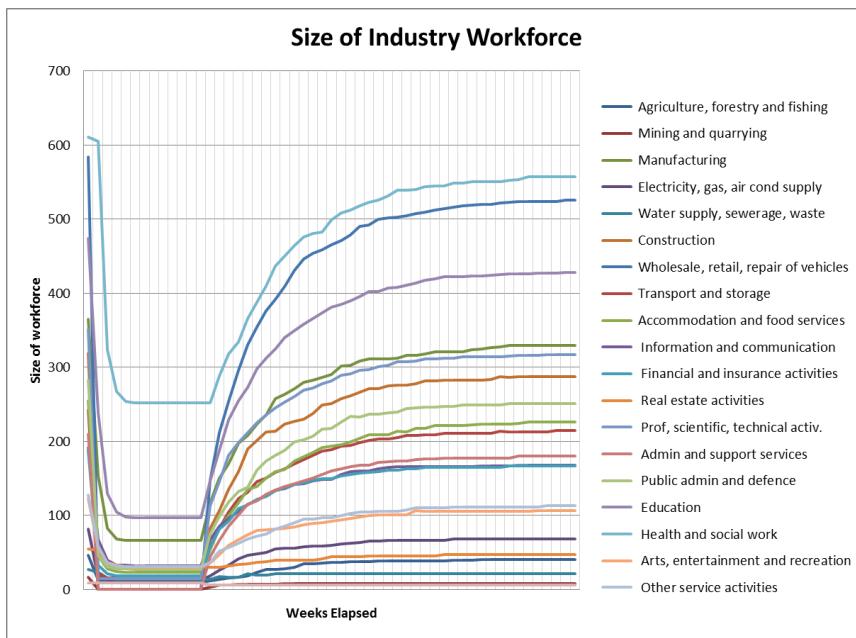
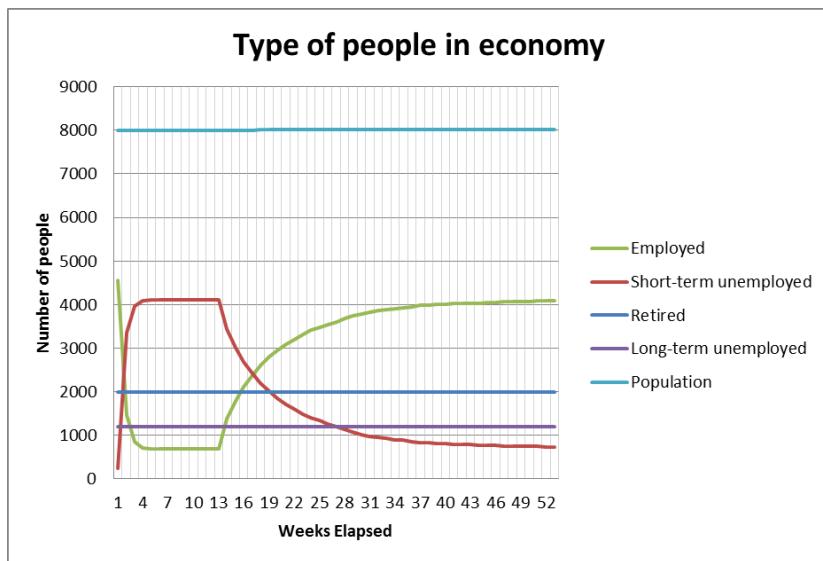


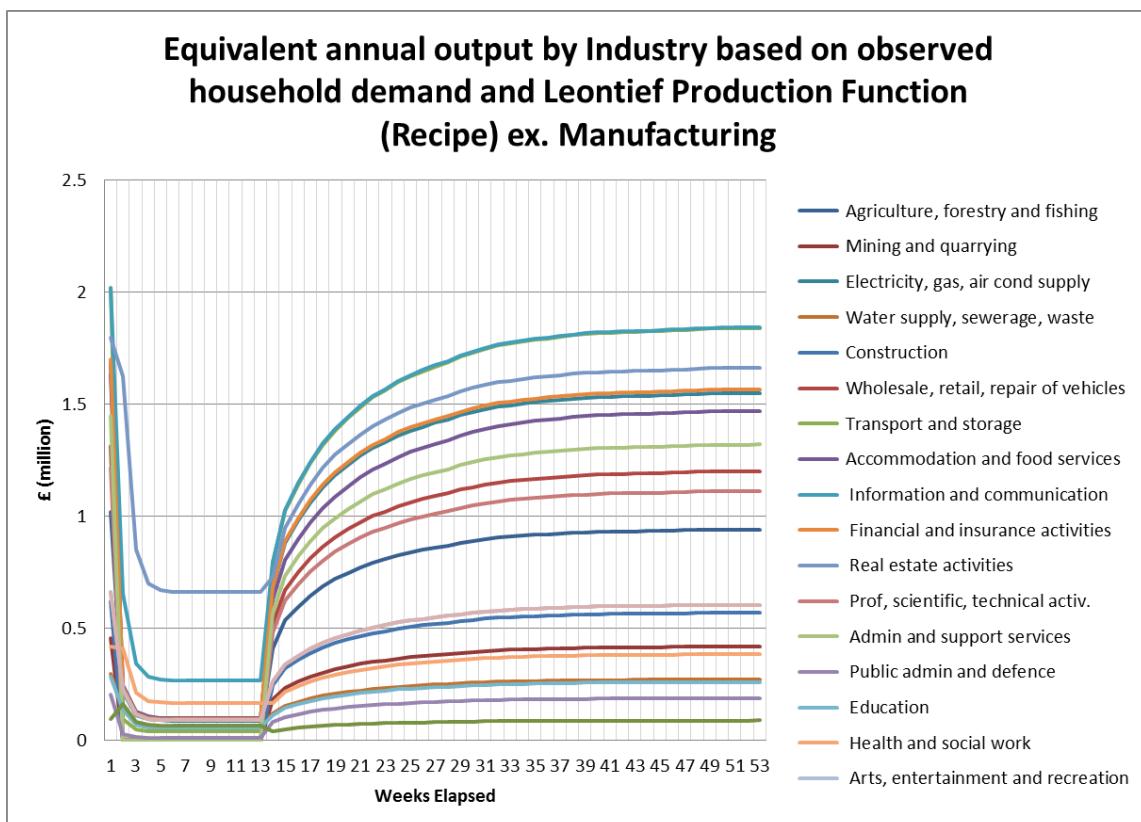
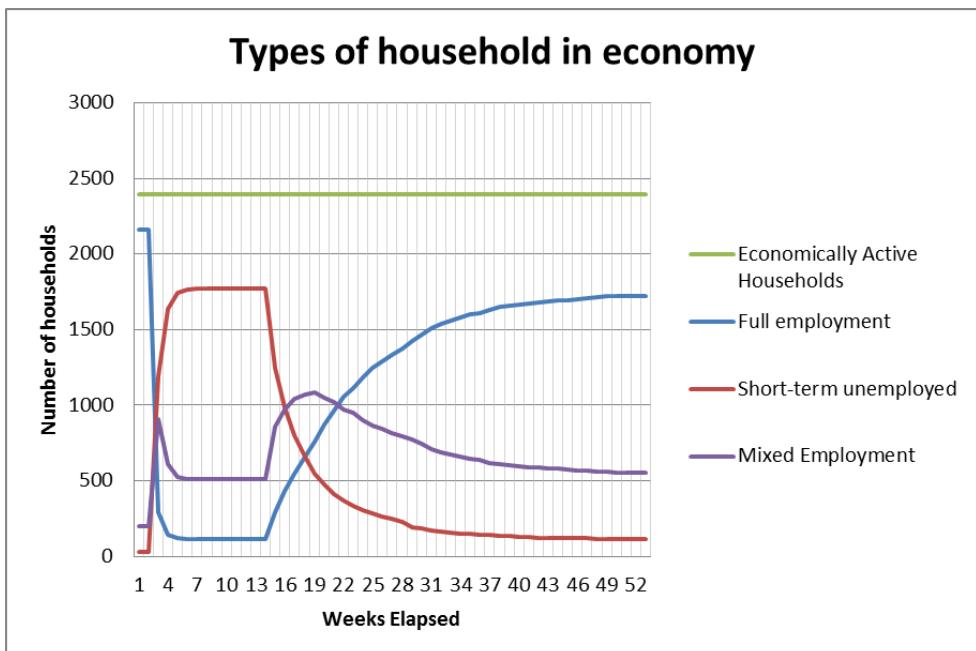
Equivalent Annual Household Demand By Industry excluding Manufacturing



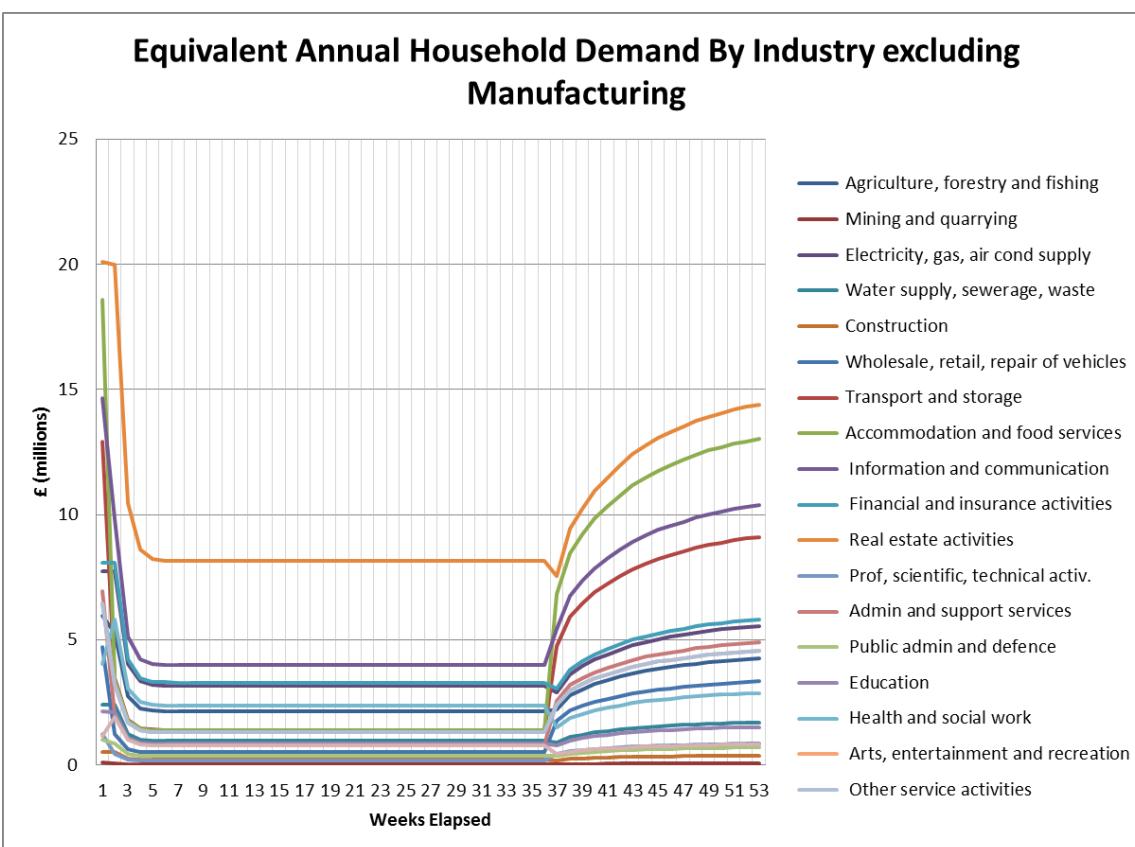
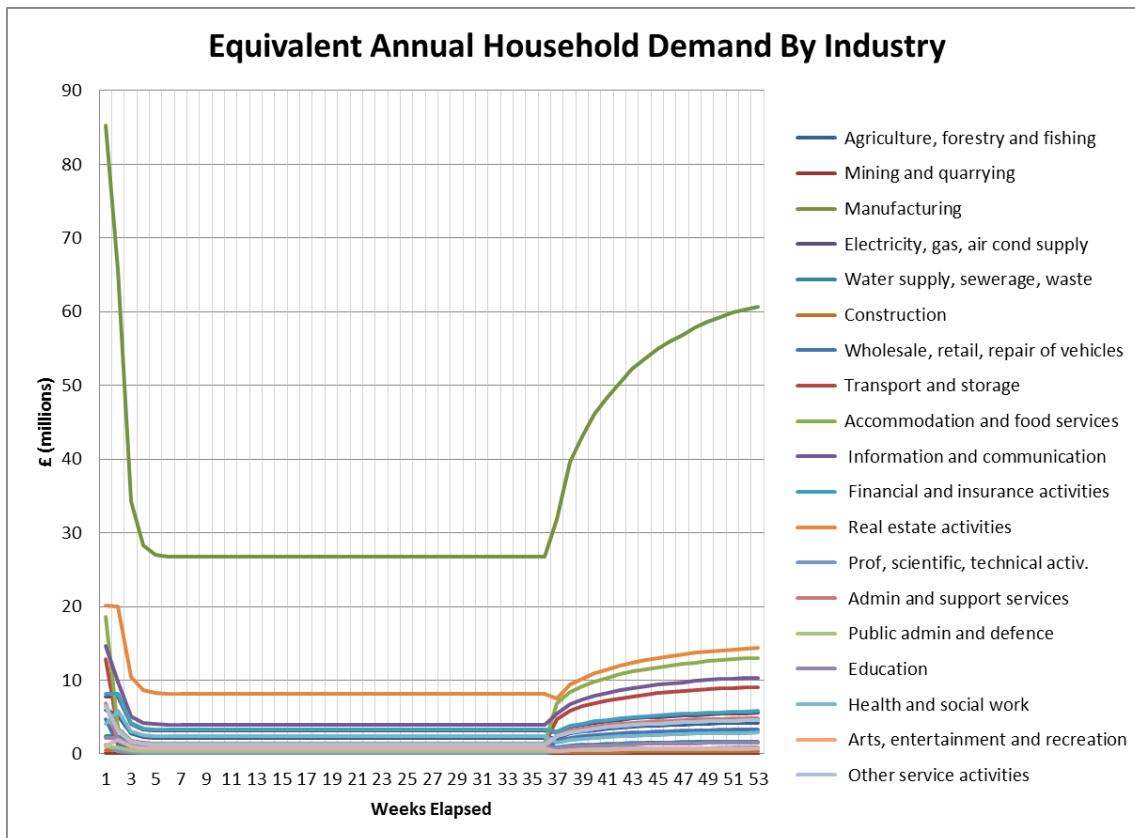
Equivalent Annual Household Demand By Industry excluding Manufacturing

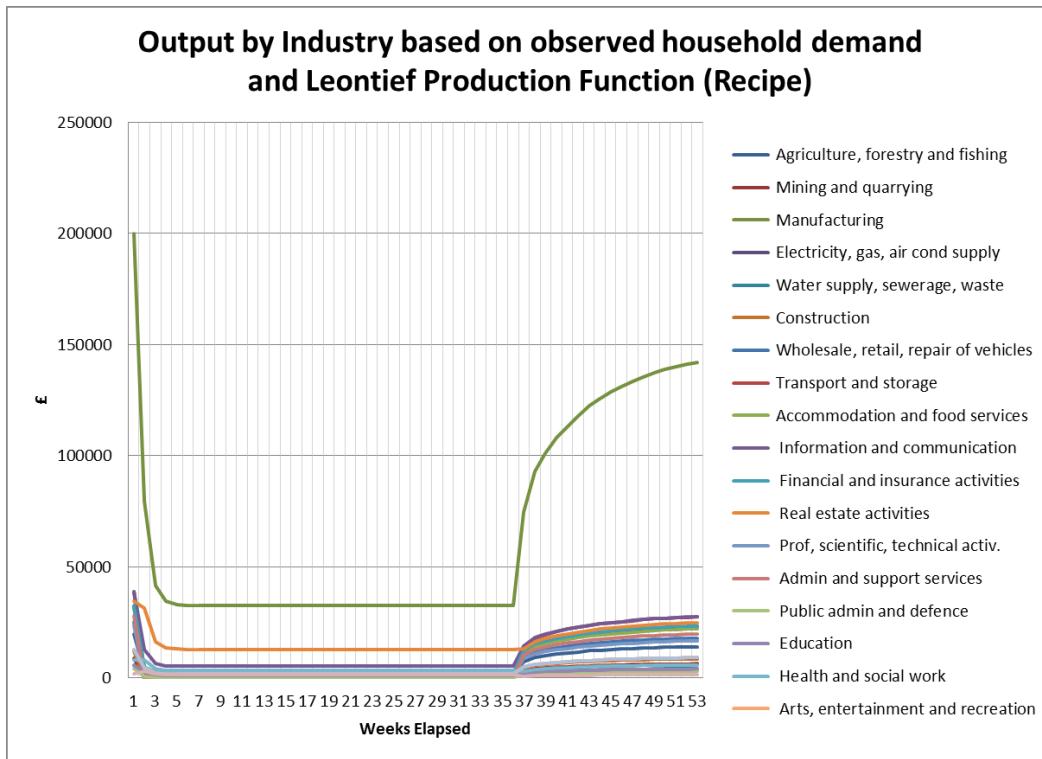
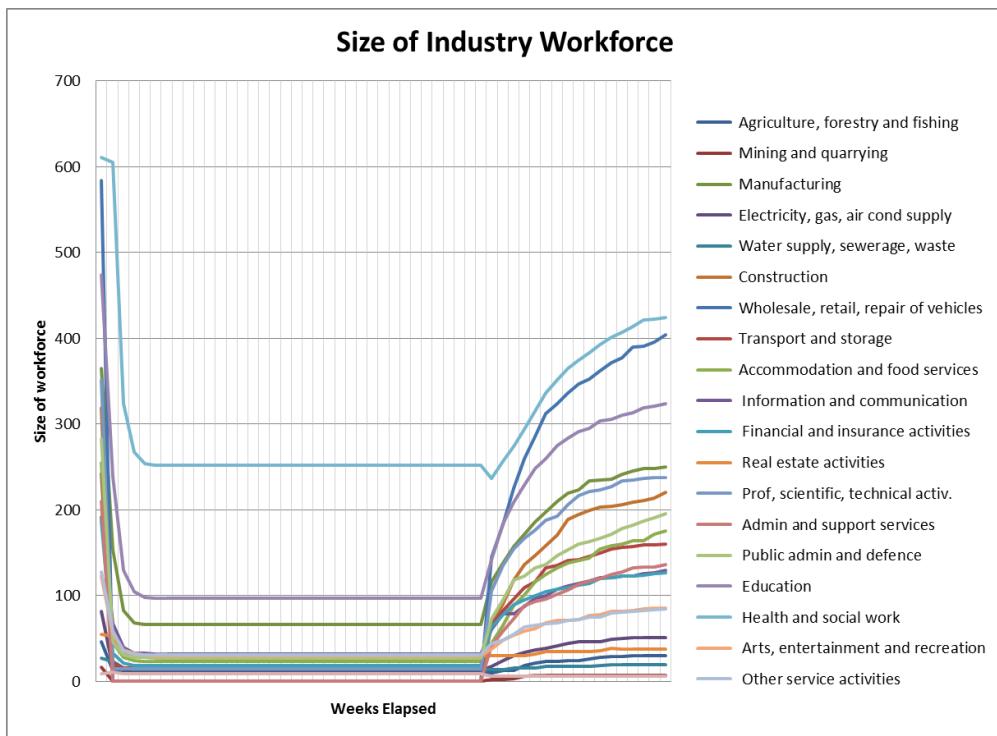


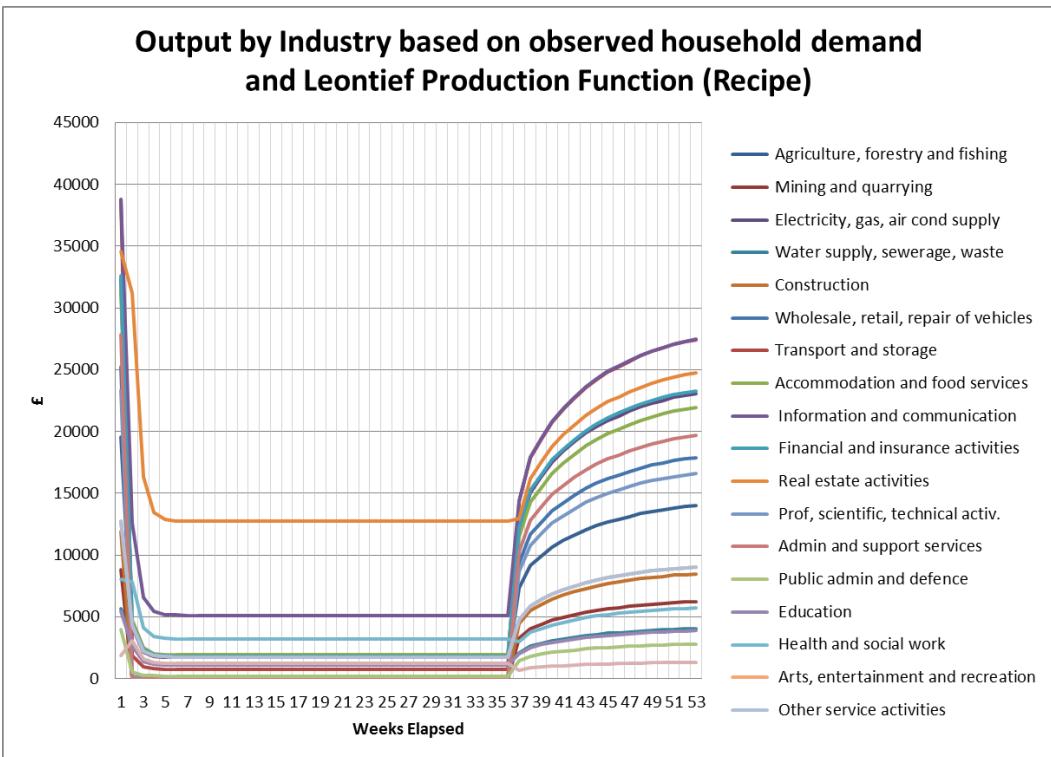




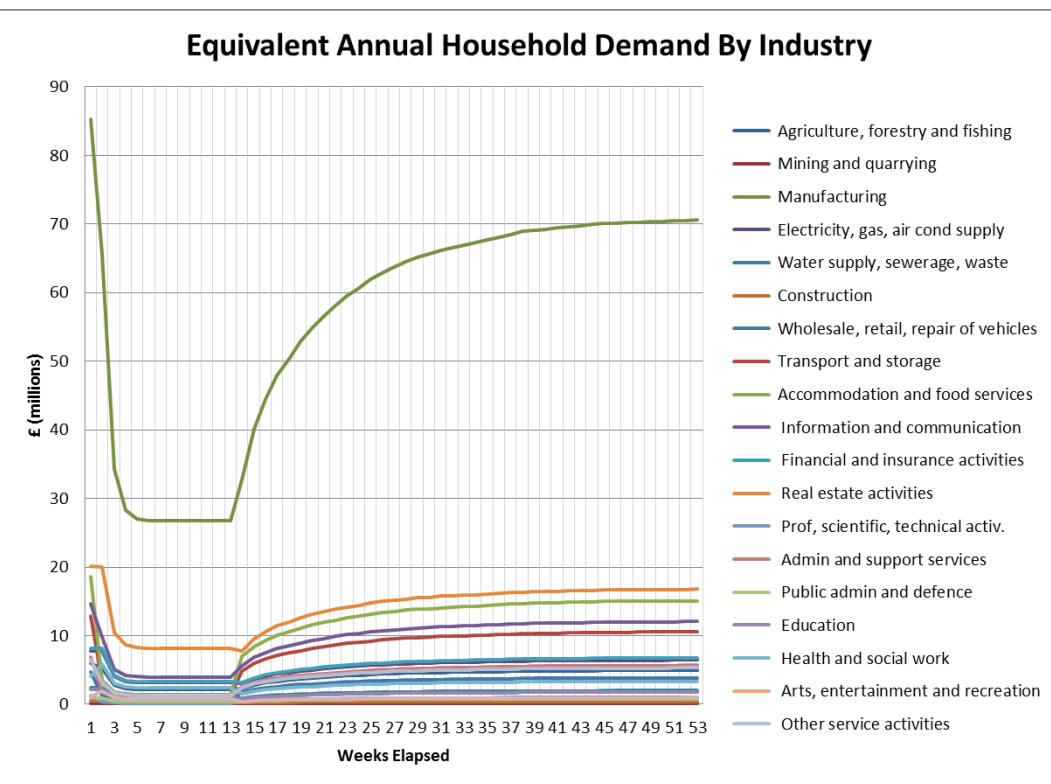
Scenario 11



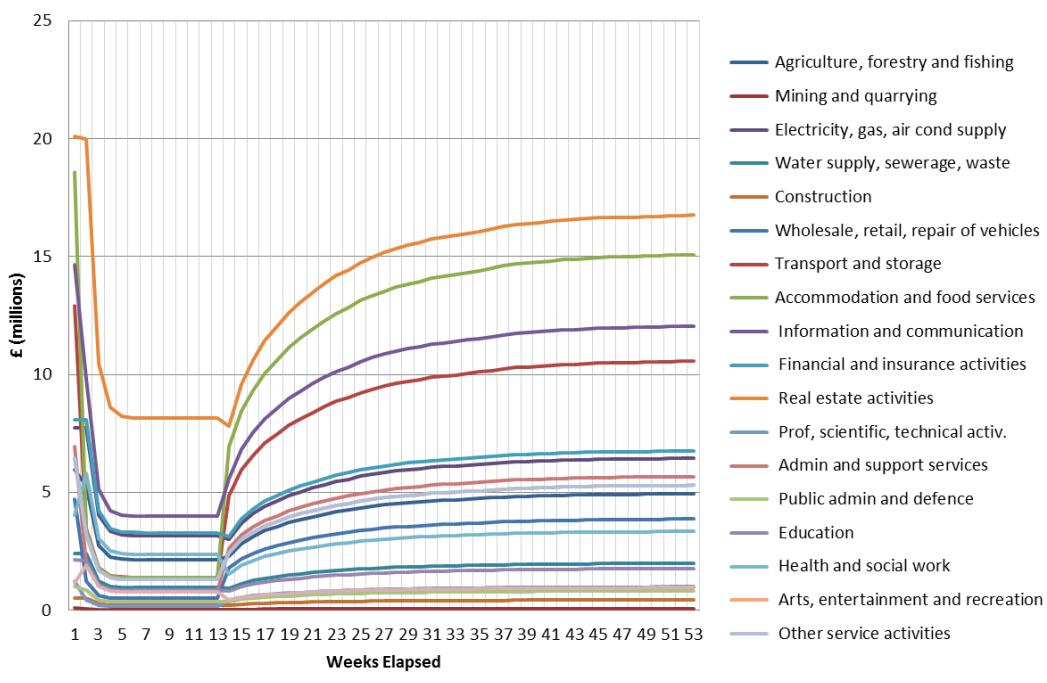




Scenario 13



Equivalent Annual Household Demand By Industry excluding Manufacturing



Size of Industry Workforce

