Creating USAGE-OCC: A CGE Model of the U.S. With A Disaggregated Occupational Dimension

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Peter B. Dixon
And
Maureen T. Rimmer
Centre of Policy Studies,
Victoria University

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Address: Centre of Policy Studies, Victoria University, PO Box 14428, Melbourne, Victoria, 8001
home page: www.vu.edu.au/CoPS/ email: copsinfo@vu.edu.au Telephone +61 3 9919 1877

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Creating USAGE-OCC: a CGE model of the U.S. with a disaggregated occupational dimension

By

Peter B. Dixon and Maureen T. Rimmer

Centre of Policy Studies, Victoria University

May 23, 2022

Abstract

We created the USAGE-OCC model of the U.S. by adding to USAGE occupation-industry matrices for 2019 that identify numbers of people employed and wagebills in 233 occupations (aggregated from 789 6-digit BLS occupations) and 392 industries (BEA input-output). The aggregation from 789 to 233 occupations was performed in a way that minimized the loss of skill/experience/education detail. In specifying occupational mobility, we took account of: wage differences between occupations; physical requirements of occupations; and education/training/experience requirements. As well as providing detailed occupational projections, USAGE-OCC can generate results for employment by wage band, educational requirements and experience. In an illustrative application, we simulated the effects of a mandated 10 per cent increase in real wage rates in low-wage occupations. The results point to the idea that rectifying inequitable wage disparities without adverse employment effects requires policies such as negative tax rates that raise incomes for low-wage workers without increasing costs to employers.

JEL codes J62; J24; J31; C68

Key words Employment by occupation and industry; Occupational mobility; Labor-market modeling; Wage increases in low-wage occupations

Contents

Summary

Creating occupation-industry employment and wagebill matrices for USAGE

(1) In this project we have created occupation-industry matrices for 2019 that identify numbers of people employed and wagebills in 233 occupations and 392 industries.

(2) The 233 occupations are mainly 6 digit BLS standard occupational categories (SOC) or combinations of a small number of such categories. The 233 occupations were created as aggregations of the 789 occupations available in BLS Economic Projection data. We aggregated from 789 to 233 to reduce computational times for solving models in which the occupation-industry data are used.

(3) The aggregation to 233 occupations was performed in a way that minimized the loss of skill/experience/education detail. That is, we tried to aggregate "like" occupations.

(4) For each of the 233 occupations, BLS data gives three characteristics. These are: median wage rate, typical educational requirements, and required years of experience in associated occupations.

(5) The 392 industries are those used in the most disaggregated versions of the USAGE model. These are mainly industries identified in the BEA benchmark input-output tables for 2012. We also included other industries that have been developed for the USAGE model such as: Domestic tourism, Export tourism and Foreign vacation.

(6) We updated the 392-order database for USAGE to 2019. The database that we created for 2019 is consistent with BEA data for macro variables in 2019 and with wagebill data for most of the 70-order industries used in the BEA annual input-output tables for 2019.

(7) The BLS publishes occupational data for 300 industries. The BLS industry classifications differ in many respects from the BEA input-output classifications used in the USAGE model. In developing our 233 by 392 occupation-industry matrices, we performed a mapping exercise so that we could use the BLS occupational data to indicate the occupational composition of employment in each of the 392 USAGE industries.

(8) We used the BLS median wage rates for the 233 occupations to make a preliminary estimate of the 233 by 392 wagebill matrix. Then we undertook detailed data work on the preliminary BLS-based wagebill matrix and USAGE wagebills for each industry to bring them into line.

(9) Once we had achieved consistency between the 233 by 392 wagebill matrix and the USAGE industry wagebills, we included the wagebill and employment matrices in USAGE to create the model we now refer to as USAGE-OCC.

The labor-market module in USAGE-OCC

(10) USAGE-OCC can be used to make baseline projections for employment in 233 occupations. These projections can be bland, taking account only of macro developments. More ambitiously, they can be informed by scenarios concerning technological developments that affect both the industrial composition of employment and the occupational composition of employment in each industry.

(11) We included in USAGE-OCC the USAGE labor-market perturbation module. In USAGE-OCC, this module can be used to project the effects of policy and other shocks to the economy on employment in 233 occupations.

(12) The labor-market module has 5 key ingredients:

(a) *the division of the workforce into categories at the start of year t reflecting workforce activities in year t-1.* In USAGE-OCC the categories include: employed in occupation o in year t-1 where o is one of the 233 occupations; short-run unemployed in t-1 in occupation o; and long-run unemployed in t-1 in occupation o. We also include new-entrant categories for each of the 233 occupations.

(b) *the determination of labor supply from each category to each activity*. Via category-specific optimization problems, we specify what activities people in each category wish to perform in year t. These category-specific optimization problems capture a variety of ideas from labor economics: people in long-run unemployment become discouraged and offer less effectively to employment activities than do employed and short-run unemployed people; people in occupation o offer strongly to continue in occupation o; and people in occupation o cannot make an effective labor supply to occupation oo if the qualifications required for these two occupations are incompatible.

(c) *the determination of demand for labor in employment activities*. This is part of the core USAGE model. Demand for labor in each occupation is specified for each industry via cost minimizing problems and then aggregated across industries.

(d) *the specification of wage adjustment processes reflecting demand and supply.* We adopt sticky-wage adjustment equations. These equations recognize that when a shock affects either the demand for or supply of workers in occupation o, it takes time for wages to adjust to their market clearing level.

(e) *the determination of everyone's activity: who gets the jobs and what happens to those who don't?* This part of USAGE labor-market modules specifies vacancies in each occupation taking account of demand for workers in that occupation and desires of incumbents to continue in their occupation. The modules then describe competition to fill vacancies in occupation o between new entrants, unemployed workers and workers from other occupations. Employed worker who make unsuccessful offers to change occupation fall back into their original occupation. Unemployed workers who make unsuccessful offers move to or stay in long-run unemployment. Unsuccessful new entrants go to short-run unemployment.

(13) The inclusion in USAGE-OCC of 233 occupations along with their characteristics allows the model to produce baseline and perturbation results for employment classified by wage-band, education and experience requirements. For example USAGE-OCC can be used to answer questions concerning the effects of trade

policies on employment of people in high-wage occupations compared with people in low-wage occupations.

Specifying occupational mobility

(14) Occupational mobility assumptions are important in the category-specific optimization problems that generate supply to each occupation in USAGE-OCC, point 12(b) above. We investigated four specifications of occupational mobility:

(i) no special connections between occupations -- all moves are equally feasible;

(ii) making the feasibility of occupational moves inversely proportional to wage differences;

(iii) same as (ii) plus an allowance for making differences between occupations in physical requirements an inhibiting factor for occupational moves;

(iv) same as (iii) plus the introduction of education/training/experience requirements in the determination of the feasibility of occupational moves.

(15) We see scope for strengthening the empirical basis for the mobility specification in USAGE-OCC by making further use of the 10-year economic projections published by the BLS.

Illustrative application

(16) To show how USAGE-OCC works, we simulated the effects of a mandated 10 per cent increase in real wage rates in low-wage occupation. These are the 14 occupations in the BLS data that had median wage rates in 2019 less than $29,500. They are mainly in food service, personal care and household service industries, and account for 20 per cent of jobs but only 9 per cent of total wagebill.

(17) We introduced the real wage increases in 2021 as sustained 10 per cent deviations above baseline paths over a four year simulation period.

(18) We conducted four simulations, one for each of the occupational mobility specifications listed in (14).

(19) Under mobility specification (iv), our preferred specification, the deviation from the baseline in aggregate employment in the fourth year is -1.142 per cent. Employment in all occupations is adversely affected. For low-wage occupations the average employment deviation is -2.458 per cent and for other occupations it is -0.807 per cent.

(20) Employment in low-wage occupations is damaged relative to other occupations mainly through damage to the industries in which low-wage occupations are concentrated. Our model also encompasses substitution between occupations by employers, but this is a minor effect.

(21) The results point to the idea that rectifying inequitable wage disparities without adverse employment effects requires policies such as negative tax rates that raise incomes for low-wage workers without increasing costs to employers.

1. Introduction

The aim of this project was to equip USAGE models with the ability to project demand for labor in the U.S. at a detailed occupational level. We achieved this objective for a dynamic 392-industry national version of the model, which we refer to as USAGE-OCC. This version of the model has a labor-market module identifying 233 occupations. We also updated the model so that its base-year data refer to 2019.

Section 2 sets out the theory of the labor-market module. This is largely an edited version of the theory for an earlier model that we created for the U.S. Department of Commerce, see Dixon and Rimmer (2018). In that earlier model, the occupational dimension was implemented with 10 broadly defined occupations.

Section 3 describes the Bureau of Labor Statistics (BLS) data that we used to create 233 by 300 occupation-industry employment and wagebill matrices for 2019.

Section 4 describes the modifications and corrections that we made to USAGE industry data for 2015 prior to updating to 2019. Modifications were necessary to bring the USAGE BEA-based conventions into line with BLS conventions.

Section 5 describes the updating of the database of the USAGE model to 2019 and the creation of a bland 2019 to 2024 year-on-year baseline.

Section 6 describes how we specified mobility between occupations. This required judgements concerning the feasibility for people in one occupation to move to another occupation. The specification of inter-occupational mobility is an important part of the labor-market module.

Section 7 sets out illustrative simulations showing the effects of a policy in which real wage rates in low-wage occupations are raised by 10 per cent.

Concluding remarks are in section 8.

During the course of our research we followed several leads that were not ultimately useful for the current project. Nevertheless we think it is worth recording this work in appendices because it may be useful in future research. Appendix 1 describes attempts to inform mobility assumptions by using BLS data on workforce flows at the macro level. Appendix 2 describes attempts to inform mobility assumptions by using BLS projections at the occupational level. Appendix 3 gives locations for programs and research notes that were created during the project. This information may be valuable for future research.

2. Theory of the labor-market module

2.1. Overview

In building the labor-market module for USAGE-OCC we used our previous labor-market modules as a starting point. These modules have been added to the USAGE model in several studies of the effects on the U.S. economy of immigration and trade policies[1].

The five key ingredients in our labor-market modules are:

(1) *the division of the workforce into categories at the start of year t reflecting workforce activities in year t-1.* In previous studies, categories at the beginning of year t have included: “Domestic-born and employed in occupation o in year t-1”; “Illegal

[1] See, for example, Dixon and Rimmer (2009, 2010, 2018 and 2021), Dixon, Johnson and Rimmer (2011), Dixon, Rimmer and Roberts (2014) and Zahnizer *et al.* (2012).

immigrant and employed in occupation o in year t-1"; "Domestic-born and long-run unemployed in year t-1"; "Domestic-born new entrant"; etc.

(2) *the determination of labor supply from each category to each activity*. Apart from new entrants, there is a corresponding activity for each category. Via category-specific optimization problems, we specify what activities people in each category wish to perform in year t. These category-specific optimization problems capture a variety of ideas from labor economics: people in long-run unemployment become discouraged and offer less effectively to employment activities than do employed and short-run unemployed people; people in occupation o offer strongly to continue in occupation o; and people in occupation o cannot make an effective labor supply to occupation oo if the qualifications required for these two occupations are incompatible.

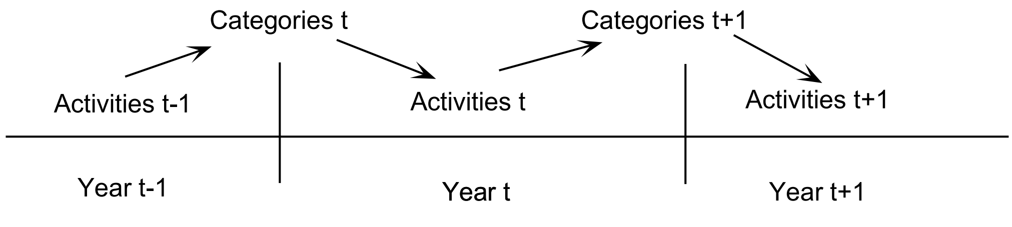
(3) *the determination of demand for labor in employment activities*. This is part of the core USAGE model. Demand for labor in each occupation is specified for each industry via cost minimizing problems and then aggregated across industries.

(4) *the specification of wage adjustment processes reflecting demand and supply.* We adopt sticky-wage adjustment equations. These equations recognize that when a shock affects either the demand for or supply of workers in occupation o, it takes time for wages to adjust to their market clearing level.

(5) *the determination of everyone's activity: who gets the jobs and what happens to those who don't?* This part of USAGE labor-market modules specifies vacancies in each occupation taking account of demand for workers in that occupation and desires of incumbents to continue in their occupation. The modules then describe competition to fill vacancies in occupation o between new entrants, unemployed workers and workers from other occupations. Employed worker who make unsuccessful offers to change occupation fall back into their original occupation. Unemployed workers who make unsuccessful offers move to or stay in long-run unemployment. Unsuccessful new entrants go to short-run unemployment.

Figure 2.2.1 is a useful way of conceptualizing the dynamics in USAGE labor-market modules.

Figure 2.2.1. Labor-market dynamics in USAGE



2.2. Equations and notation for the USAGE-OCC labor-market module

Table 2.2.1 lists the equations that form the USAGE-OCC labor-market module.

Equations (T1) and (T2): numbers in each category at the beginning of year t

We divide the workforce at the start of year t into categories, $CAT_t(o,\ell)$, where o refers to occupation and ℓ refers to status. To see what these categories mean, the easiest place to start is with status. As can be seen from the definition of ST in the notation listing in Table 2.2.1, there are four possibilities for status: empl, S, L and New. In determining categories at the start of year t, people who were employed in year t-1 have the status "empl". People who were unemployed in year t-1 but employed in year t-2 have the status short-run unemployed denoted by "S". People who were unemployed in both years t-1 and t-2 have the status long-run unemployed denoted by "L". People who were not in the workforce in year t-1 but are entering the workforce in year t have the status new entrant denoted by "New". As specified in equation (T1), except when ℓ equals "New", the number of people in category (o,ℓ) at the start of year t is determined by the number of people who undertook activity (o,ℓ) in year t-1, $H_{t-1}(o,\ell)$. Activity in year t-1 refers to what people did during that year. Examples of activities include: working as a Financial manager, (Financial manager, empl); and short-run unemployed but previously working as a Financial manager, (Financial manager, S). Departures from the labor force through retirement and death are handled through the variable $CR(o,\ell)$. This variable is normally exogenous. A value of 0.98 means that 2 per cent of the people who undertook activity (o,ℓ) leave the workforce at the end of year t-1.

Equation (T2) indicates that the number of people in new entrant categories is exogenous. Despite these people not having workforce experience we give them an occupational characteristic. How this is done in the base-year database discussed in section 6.2.

Equations (T3) and (T4): labor supply from each category to each activity

We assume that at the beginning of year t, people in category c [where c is a convenient shorthand notation for an (occupation, status) double] decide their offers to activity a [where a is also a (o,ℓ) double] for the year by solving a problem of the form: choose $L_t(c;a)$, for all activities a

$$\text{to maximize } U_c\left[ATW_t(a)*L_t(c;a)\ \ \forall \text{ activities a}\right] \qquad (2.2.1)$$

$$\text{subject to } \sum_a L_t(c;a) = CAT_t(c) \qquad (2.2.2)$$

where

$L_t(c;a)$ is the labor supply that people in category c make to activity a;

$CAT_t(c)$ is the number of people in category c;

$ATW_t(a)$ is the real after-tax wage rate of labor in activity a (for non-employment activities, that is short-and long-run unemployment, $ATW_t(a)$ can be thought of as a social security payment or other support); and

U_c is a homothetic function with the usual properties of utility functions (positive first derivatives and quasi-concavity).

In (2.2.1) and (2.2.2), people in category c treat dollars earned in different activities as imperfect substitutes. This is a convenient and flexible specification through which we can allow labor supplies to shift between activities in response to changes in after-tax rewards. By specifying a separate utility function for each c, we can ensure that each category makes supplies to activities that are compatible with the category's occupational and status characteristics.

In USAGE-OCC, U_c has the CES form:

Table 2.2.1. Representation of the labor market module for USAGE-OCC

Numbers in each category at the beginning of year t

$$CAT_t(o,\ell) = H_{t-1}(o,\ell) * CR(o,\ell) \qquad \text{for all o, and } \ell \neq \text{New} \tag{T1}$$

$$CAT_t(o,\text{"New"}) = \text{exogenous} \qquad \text{for all o} \tag{T2}$$

Planned labor supply

$$L_t(o,\ell\,;oo,\ell\ell)$$

$$= CAT_t(o,\ell) * \left[\frac{\left(B_t(o,\ell;oo,\ell\ell) * ATW_t(oo,\ell\ell)\right)^{\eta}}{\sum\limits_{m\in OCC} \sum\limits_{k\in NonNew} \left(B_t(o,\ell;m,k) * ATW_t(m,k)\right)^{\eta}} \right]$$

$$\text{for all } o\in OCC,\ \ell \in ST \text{ and all } oo\in OCC,\ \ell\ell \in \text{NonNew} \tag{T3}$$

$$L_t(m) = \sum_{o\in OCC} \sum_{\ell\in ST} L_t(o,\ell;m,\text{"empl"}) \qquad m\in OCC \tag{T4}$$

Demand for labor by industry and occupation

$$D_t^{Ind}(j) = f_j^{Ind}\left(BTW_t^{Ind}(j)\,;K_t(j);A_t(j)\right) \text{ for all } j\in IND \tag{T5}$$

$$BTW_t^{Ind}(j) = g_j^{Ind}\left(BTW_t(o) \text{ for all } o \in OCC\right) \text{ for all } j\in IND \tag{T6}$$

$$D_t(o,j) = D_t^{Ind}(j) * h_{o,j}\left(BTW_t(oo) \text{ for all } oo \in OCC\right)$$

$$\text{for all } o \in OCC \text{ and all } j \in IND \tag{T7}$$

$$H_t(o,\text{"empl"}) = \sum_{j\in Ind} D_t(o,j) \text{ for all } o \in OCC \tag{T8}$$

Relationship between after-tax and before-tax wage rates

$$ATW_t(o,\text{"empl"}) = BTW_t(o) * \left(1 - T_t(o)\right) \quad \text{for all } o \in OCC \tag{T9}$$

$$ATW_t(o,\ell) = BTW_t^{ave} * F_t(\ell) \quad \text{for all } o \in OCC,\ \ell \in \text{Unemp} \tag{T10}$$

$$BTW_t^{ave} = \text{Ave}(BTW(o) \text{ for all } o \in OCC) \tag{T11}$$

Wage adjustment

$$\frac{ATW_t(o,\text{"empl"})}{ATW_t^{base}(o,\text{"empl"})} - \frac{ATW_{t-1}(o,\text{"empl"})}{ATW_{t-1}^{base}(o,\text{"empl"})} = \alpha \left(\frac{H_t(o,\text{"empl"})}{H_t^{base}(o,\text{"empl"})} - \frac{L_t(o)}{L_t^{base}(o)} \right),$$

$$\text{for all } o \in OCC \tag{T12}$$

Vacancies, and movements into employment activities

$$V_t(o) = H_t(o,\text{"empl"}) - H_t\left[o,\text{"empl"};o,\text{"empl"}\right] \quad \text{for all } o \in OCC \tag{T13}$$

$$H_t(m,k\,;o,\text{"empl"}) = V_t(o) * \left[\frac{L_t(m,k\,;o,\text{"empl"})}{L_t(o) - L_t(o,\text{"empl"};o,\text{"empl"})} \right],$$

$$\text{for all } m\in OCC,\ k \in ST,\ o\in OCC \text{ such that } (o,\text{"empl"}) \neq (m,k), \tag{T14}$$

$$\sum_{m\in OCC} H_t(o,\text{"empl"};m,\text{"empl"})$$

$$= CAT_t(o,\text{"empl"}) - L_t(o,\text{"empl"};o,\text{"S"}) - SF_t(o) * CAT_t(o,\text{"empl"})$$

$$\text{for all } o\in OCC \tag{T15}$$

Table A1 continued

Time spent in unemployment

$$H_t(o,"S") = \left[L_t(o,"empl";o,"S") + SF_t(o) * CAT_t(o,"empl")\right] + \left[CAT_t(o,"N") - \sum_{oo \in OCC} H_t(o,"N";oo,"empl")\right] \qquad o \in OCC \qquad (T16)$$

$$H_t(o,"L") = CAT_t(o,"L") + \left[CAT_t(o,"S") - \sum_{m \in OCC} H_t(o,"S";m,"empl")\right] - \sum_{m \in OCC} H_t(o,"L";m,"empl") \qquad o \in OCC, \qquad (T17)$$

Ensuring that vacancies are positive

$$V_t(o) \geq 0.02 * CAT_t(o,"empl") \quad \text{for all } o \in OCC \qquad (T18)$$

$$SF_t(o) \geq 0.05 \quad \text{for all } o \in OCC \qquad (T19)$$

$$\left[V_t(o) - 0.02 * CAT_t(o,"empl")\right] * \left[SF_t(o) - 0.05\right] = 0 \quad \text{for all } o \in OCC \qquad (T20)$$

Notation

Sets:

OCC	Occupations
ST	Workforce status, {empl, S, L, New} where empl means employed, S means short-run unemployed, L means long-run unemployed, and N means new entrant
NonNew	Statuses excluding New, {empl, S, L}
Unemp	Unemployed, {S, L}
IND	Industries

Variables and parameters

$CAT_t(o,\ell)$ for $o \in OCC$, $\ell \in NonNew$. This is the number of people in the extended workforce at the start of year t who had occupational characteristic o and employment status ℓ in year t-1. We refer to this as the number of people in category (o,ℓ) at the start of year t.

$CAT_t(o,New)$ for $o \in OCC$. This is the number of people in the extended workforce at the start of year t who have occupational characteristic o and were not in the extended workforce in year t-1. We refer to this as the number of people in category (o,New) at the start of year t.

$H_{t-1}(o,\ell)$ for $o \in OCC$, $\ell \in NonNew$. This is the number of people in activity (o,ℓ) in year t-1.

$H_t^{base}(o,"empl")$ for $o \in OCC$. This is the base or forecast value of $H_t(o,"empl")$.

$CR(o,\ell)$ for $o \in OCC$, $\ell \in NonNew$. This is the proportion of people in activity (o,ℓ) in year t-1 who continue to be in the extended workforce at the start of year t. These people form category (o,ℓ) at the start of year t.

$L_t(o,\ell;m,\ell\ell)$ for $o \in OCC$, $\ell \in ST$ and $oo \in OCC$, $\ell\ell \in NonNew$. This is the labor supply that people in category (o,ℓ) make to activity $(m,\ell\ell)$.

$L_t(m)$ for $m \in OCC$. This is the total labor supply to employment activity (m).

$L_t^{base}(m)$ is the base or forecast value of $L_t(m)$.

α is a positive parameter. In policy or perturbation runs, α controls the sensitivity of wage movements by occupation to changes in demand relative to supply.

$ATW_t(o,\ell)$ for $o \in OCC$ and $\ell \in NonNew$ is the real after-tax wage rate (or unemployment benefit) for labor in activity (o,ℓ).

$ATW_t^{base}(o,\ell)$ is the base or forecast value of $ATW_t(o,\ell)$.

η is a parameter reflecting the ease with which people feel that they can shift between activities.

$B_t(o,\ell;oo,\ell\ell)$ for $o \in OCC$, $\ell \in ST$ and $oo \in OCC$, $\ell\ell \in NonNew$. This is a variable reflecting the preference of people in category (o,ℓ) for receiving money in activity $(oo,\ell\ell)$ in year t.

$K_t(j)$ for $j \in IND$. This is industry j's capital stock at the start of year t.

$BTW_t^{Ind}(j)$ is the overall real before-tax wage rate to industry j.

$A_t(j)$ is a vector of variables that influence industry j's demand for labor.

$D_t^{Ind}(j)$ is labor input to industry j.

$BTW_t(o)$ is the real before-tax wage rate of employed workers in occupation o.

$D_t(o,j)$ for $o \in OCC$ and $j \in IND$. This is j's input of labor of occupation o.

$T_t(o)$ for $o \in OCC$. This is the payroll and income-tax rate applying to employed workers in occupation o.

BTW_t^{ave} is the average real before-tax wage rate of employed workers.

$F_t(\ell)$ for $\ell \in Unemp$. This is the fraction of BTW_t^{ave} that unemployed people of status ℓ receive in unemployment benefits.

$V_t(o)$ for $o \in OCC$. This is vacancies in employment activity o.

$H_t(o,\ell;m,k)$ for all $o \in OCC$, $\ell \in ST$, $m \in OCC$ and $k \in Nonnew$. This is the flow of people from category (o,ℓ) to activity (m,k).

$SF_t(o)$ for $o \in OCC$. This is the fraction of people of category $(o,"empl")$ who become involuntarily unemployed.

Other notation

f_j^{Ind}, g_j^{Ind}, $h_{o,j}$ Ave are functions.

$$U_c = \left[\sum_a \left(B_t(c;a) * ATW_t(a) * L_t(c;a) \right)^{\frac{\eta}{1+\eta}} \right]^{\frac{1+\eta}{\eta}} . \qquad (2.2.3)$$

where

η is a positive parameter reflecting the ease with which people feel that they can shift between activities; and

$B_t(c;a)$ is a variable reflecting the preference of people in category c for receiving money in activity a in year t.

The $B_t(c;a)$'s play two roles. The first is to ensure that supply behavior in our model is realistic. Realism is achieved through the initial settings of the Bs, that is the values assigned to them in our database year, year 0. For example:

- We set $B_0(o,\ell;oo,\ell\ell)$ close to zero if the qualifications of people in occupation o are incompatible with working in occupation oo. In this way, we ensure for example that people in the occupation Miscellaneous agricultural worker do not make a significant supply of labor to the occupation Dental specialist. On the other hand, if o and oo require similar qualifications/skills, e.g Generalist college degree then we set $B_0(o,\ell;oo,\ell\ell)$ at a higher value to ensure that, for example, short-run unemployed Financial managers can apply to be Business financial advisors.
- We set $B_0(o,"empl";o,"empl")$ at a high value to ensure that most people employed in year t-1 in occupation o offer to continue to work in o in year t.

- We set $B_0(o,\ell;oo,"S")$ at zero for all oo and $\ell \in$Unemp. We do this to ensure that no-one can stay in short-run unemployment in successive years or move from long-run unemployment back to short-run unemployment. Only employed people can offer to be short-run unemployed, and when they do so they retain their o characteristic, that is $B_0(o,"empl";oo,"S")$ is zero if $oo \neq o$.
- We set $B_0(o,"S";o,"L")$ at a moderate value to introduce a mild discouraged-worker effect for people suffering short-run unemployment. We set $B_0(o,"L";o,"L")$ at a larger value to introduce a stronger discouraged-worker effect for people suffering long-run unemployment.

The second role of the $B_t(c;a)$'s is to carry shocks in policy runs. For example, the labor-market effects of tighter qualification requirements for entry into occupation oo might be simulated through decreases in $B_t(o,\ell;oo,"empl")$ for all $o \neq oo$.

Under (2.2.3), problem (2.2.1) - (2.2.2) generates labor-supply functions of the form shown in (T3). The total supply of labor to any employment activity is given by (T4).

In simulations with other labor-market modules we have set η in (T3) at 2. We continue to use this value. For understanding what this means, it is useful to express (T3) in percentage change form as:

$$\ell_t(c\,;a) = cat_t(c) + \eta*\left(atw_t(a) - atw_t^{ave}(c)\right) + \eta*\left(b_t(c;a) - b_t^{ave}(c)\right) \quad . \qquad (2.2.4)$$

In (2.2.4), the lowercase symbols $\ell_t(c\,;a)$, $cat_t(c)$, $atw_t(a)$ and $b_t(c;a)$ are percentage changes in the variables denoted by the corresponding uppercase symbols, and $atw_t^{ave}(c)$ and $b_t^{ave}(c)$ are weighted averages of the $atw_t(q)$s and $b_t(c;q)$s with the weights reflecting the share of activity q in the offers from people in category c. Thus (2.2.4) implies that people in category c will switch their offers towards activity a if the wage rate in activity a rises relative to an average of the wage rates across all the activities in which category-c people could participate. With η set at 2, we assume that the number of people who wish to change jobs is quite sensitive to changes in relative wage rates. However, where a is a work activity, an increase in $ATW_t(a)$ does not have much affect on $L_t(a;a)$. This is because the bulk of offers from people in category a are to activity a, so that $atw_t(a) - atw_t^{ave}(a)$ is always close to zero. The major part of the supply of labor to any work activity a is from incumbents [that is, $L_t(a;a)$ is a very large fraction of $L_t(a)$]. Thus, even with η as high as 2, the elasticity of supply of labor to activity a with respect to the wage rate in a is relatively low.

Equations (T5) to (T8): demand for labor by industry and occupation

The labor input, $D_t^{Ind}(j)$, to industry j in year t is represented by equation (T5). In USAGE-OCC labor demand by j is specified along conventional CGE lines as a function of j's: capital stock, $K_t(j)$; the overall real before-tax wage rate to j, $BTW_t^{Ind}(j)$; and other variables, $A_t(j)$, that influence j's demand for labor, including technology and commodity prices.

The overall real wage rate to j is determined in (T6) as a suitable average of the real wage rates applying to the types of labor that j employs.

Within j's labor input, the demand for labor by occupation is determined by a nested CES cost minimization problem. The resulting demand functions are represented by (T7). We assume that there are low substitution possibilities between occupations such as Food and beverage server, Grounds maintenance worker, etc, a substitution elasticity of 0.05. While it may be possible for a Food and beverage server to change occupation to Grounds maintenance, we assume that there is little possibility for employers to use Food and beverage service activities in place of Ground maintenance activities.

In (T8) we assume that employment of workers in occupation o, $H_t(o,"empl")$, is demand determined. Demand for o workers is demand for o workers aggregated across industries.

Equations (T9) to (T11): relationship between after-tax and before-tax wage rates

After-tax wage rates are important in motivating labor supply [see (T3) and (T4)] while before-tax wage rates motivate demand [see (T5) – (T8)]. Equation (T9) relates after-tax wage rates to before-tax wage rates for employment activities. In (T10) and (T11) we assume that unemployed workers of status ℓ receive the fraction $F_t(\ell)$ of average before-tax wages, BTW_t^{ave}. In applications of the model $F_t(\ell)$ is normally exogenous.

Equation (T12): wage adjustment

In policy runs, we assume that wage rates adjust according to equation (T12). This equation implies that if a policy causes the market for o employment in year t to be tighter than it was in the basecase forecast (i.e., if the policy causes a larger percentage deviation in demand than supply), then there will be an increase between years t-1 and t in the deviation in o's real after-tax wage rate. In other words, in periods in which a policy has elevated demand relative to supply, real after-tax wage rates will grow relative to their basecase values.

Our assumed wage-adjustment process is compatible with a search model [see for example, Bohringer *et al.* (2005)] in which reductions in labor supply or increases in labor demand, with resulting reductions in the unemployment rate, generate decreases in the value of having a job relative to the value of not having a job, thereby emboldening workers to demand higher wage rates. It is also compatible with efficiency-wage theory, see for example, Layard *et al.* (1994, pp. 33-45). Under this theory, employers offer wage rates that optimize worker effort per dollar of wage cost. The theory suggests that the effort-optimizing wage rate rises when there is a decrease in labor supply or an increase in labor demand and a consequent temporary decrease in unemployment.

In the context of USAGE-OCC, we can think of equation (T12) as having the role of determining after-tax wage rates for occupations. Then at given tax rates, equation (T9) determines before-tax wage rates for occupations.

Equations (T13) to (T15): vacancies and movements into employment activities

Under (T12), markets for occupations do not clear. Consequently, we need to specify which offers to employment are accepted and what activities are undertaken by those whose offers to employment are not accepted. In terms of Figure 2.2.1, we need to specify the downward sloping arrows.

In linking categories at the start of year t to activities in year t, we specify an equation for the flow from each category (m,k) to each activity (o,ℓ), $H_t(m,k;o,\ell)$.

We start in (T13) by defining vacancies in employment activity $(o,\text{"empl"})$ in year t as employment, $H_t(o,\text{"empl"})$, less the number of jobs filled in the activity by people in category $(o,\text{"empl"})$, that is vacancies in $(o,\text{"empl"})$ are jobs less those filled by incumbents.

The flow of people from category (m,k) to employment activity $(o,\text{"empl"})$, where this is an off-diagonal flow [$(o,\text{"empl"}) \neq (m,k)$], is modeled in (T14) as being proportional to the vacancies in o and to the share of category (m,k) in the supply of labor to activity $(o,\text{"empl"})$ from people outside category $(o,\text{"empl"})$. Thus, if people in category (m,k) account for 10 per cent of the people outside category $(o,\text{"empl"})$ who want jobs in occupation o, then people in category (m,k) fill 10 per cent of the vacancies in o.

The left hand side of (T15) is total employment in year t of people in category $(o,\text{"empl"})$ calculated as a sum over their employment in all occupations. The right hand side is total employment in year t of people in category $(o,\text{"empl"})$ calculated as the number of people in the category, $CAT_t(o,\text{"empl"})$, less the number that flow to unemployment. The flow to unemployment has two components. The first is voluntary flows from category $(o,\text{"empl"})$ to short-run unemployment (recall that there are no flows from employment directly to long-run unemployment). Voluntary flows, $L_t(o,\text{"empl"};o,\text{"S"})$, are determined in (T3). The second component is involuntary flows calculated as a fraction, $SF_t(o)$, of the number of people in category $(o,\text{"empl"})$. As we will see in the discussion of (T18) to (T20), this fraction is determined endogenously. It rises if employment growth in occupation o is weak. The only variable on either the left or right hand side of (T15) that is not determined elsewhere is the diagonal flow from category $(o,\text{"empl"})$ to activity $(o,\text{"empl"})$, $H_t(o,\text{"empl"};o,\text{"empl"})$. Thus, (T15) determines these diagonal flows.

Equations (T16) to (T17): time spent in unemployment

Equation (T16) specifies short-run unemployment of people with occupational characteristic o as the sum of two flows. The first is the flow from employment category $(o,\text{"empl"})$ to short-run unemployment. This flow, which is the first square-bracketed term on the right hand side of (T16), has already been explained in connection with (T15). The second flow contributing to short-run unemployment of workers in occupation o comes from new entrants who don't find employment. This is calculated in the second square-bracketed term on the right hand side of (T16) as the number of new o entrants less those that find jobs.

In equation (T17) the number of workers in occupation o who are long-run unemployed during year t is the number in category $(o,\text{"L"})$ plus the inflow to long-run o unemployment minus the outflow. The inflow are people who were short-run unemployed in year t-1 and stayed in the workforce, but failed to get a job in year t. The outflow are long-run unemployed people who stayed in the workforce and succeeded to getting a job in year t.

Equations (T18) to (T20): ensuring that vacancies are positive, endogenizing SF_t

(T18) and (T19) place lower bounds on vacancies, $V_t(o)$, in occupation o and on the fraction, $SF_t(o)$, of employed workers in occupation o who lose their jobs involuntarily.

Equation (T20) is a complementary slackness condition: either vacancies are at their lower limit or the involuntary unemployment fraction is at its lower limit. (T20) endogenizes $SF_t(o)$. If o employment is declining then it is possible that there are not sufficient o jobs even for the incumbents. In these circumstances there will be a tendency for o vacancies to fall below their lower bound. This triggers an increase in $SF_t(o)$ to values above its lower bound, generating additional vacancies in o employment.

Via (T18) to (T20), our model captures the idea that there is an underlying rate of dismissals [the lower bound on $SF_t(o)$] that is independent of market conditions. However, if market conditions dictate that employers of o must downsize, then $SF_t(o)$ will increase.

3. Creating occupation by industry matrices

3.1. BLS data

For implementing equations (T5) to (T8) in USAGE-OCC, we require matrices of employment and wagebills by occupation and industry. With these requirements in mind we examined the following three BLS datasets.

(1) The BLS publication occupations.xlsx, sheets Table 1.1 to 1.12 and 5.3 and 5.4 available at https://www.bls.gov/emp . This source shows aggregate employment for 2019 at 162.796 million. This dataset is part of the BLS Occupational Employment Projections (EP) for 2019 to 2029. The data identify about 800 occupations and about 300 industries. Unlike some other BLS datasets, it covers self-employment and workers in agriculture. The self-employment data shows occupations but not industries. All the employment data refer to jobs, not people.
The occupation by industry data are projected to 2029. The projections for occupations show separations and various potentially useful occupational characteristics.

(2) BLS OES data on employment by industry and occupation shows aggregate employment for 2019 at 146.875 million (for 2018, 144.733m). To access the data, we clicked on https://www.bls.gov/oes/2019/may/naics4_212200.htm and then clicked on *downloadable xlsx files* to receive oes9in4.zip. The data are in the file nat4d_M2019_dl.xlsx.

    The data identify about 808 occupations in 250 industries. The data do not cover self-employed or agricultural industries or military. We think the data refer to jobs because they are collected by surveys of employers. The data is from OEWS section.

    Even when we add about 9.5m for self-employment and about 2m for agriculture Dataset (2) seems to be missing about 4 million jobs.

    The occupational dimension is not trivially related to that in (1). Unlike (1) there is no useful indication of occupational characteristics or projections.

(3) The BLS CPS publication at https://www.bls.gov/webapps/legacy/cpsflowstab.htm gives aggregate employment for each month of 2019, averaging 157.531million. This publication doesn't distinguish occupations or industries. It focuses on labor market statuses such as Employed, Unemployed and Not in the labor force, and flows between these statuses. These data refer to numbers of people not jobs. We think they include agriculture and self-employment.

    The data identity about 8 million multi-job holders. So on a jobs basis these data would put employment in 2019 at about 165million. This is reasonably close to the aggregate in dataset (1).

As described in Appendix 1, we tried to use dataset (3) to work out the determinants of transitions. For example, we wanted to show that transitions between unemployment and employment depend on growth in employment. We expected to find that strong growth in employment reduces flows from employment to unemployment and increases flows from unemployment to employment. But the results were disappointing.

To obtain our labor-market matrices we chose dataset (1) in preference to (2) for the following reasons:

(a) it has a better coverage of employment – includes self-employed and agriculture and gives an aggregate employment number that is reasonably compatible with the macro number in (3);

(b) it contains useful occupational characteristics including median wage rates, typical educational requirements and typical training; and

(c) it contains projections, separations etc.

3.2 Developing an industry by occupation employment matrix for 2019 using dataset (1)

The BLS industry/employment data are not presented in a convenient matrix. In Table 1.8 in dataset (1), the data are presented as a list of occupations. Each occupation is linked to a matrix of data showing number of jobs in the occupation that are located in each industry in 2019 and projected for 2029. Self-employment for the occupation is treated as though it is an industry. Table1.9 in dataset (1) presents the data as a list of industries. Each industry is linked to a matrix of data showing number of jobs in the industry that are located in each occupation in 2019 and projected for 2029. Consistent with Table 1.8, the list of industries includes self-employment.

We chose to work with Table 1.9. For each line industry we accessed the occupational data for 2019. For each industry j we formed a 4-column matrix. The first column shows the industry identifier in every row. The second column shows occupational identifiers. These refer to the occupations with non-negligible employment numbers for the industry. The third column shows whether the occupation is a line item or a summary. The fourth gives the employment numbers.

Having created a 4-column matrix for every line industry[2], we stacked them in a super 4-column matrix. As a first guess, we might expect this super matrix to have about 240,000 rows: about 800 occupations by about 300 industries. However, not all occupations are used in each industry, most industries have between 100 and 300 occupations. This suggests that the number of rows in our super matrix should be much less than 240,000. On the other hand, the occupation identifiers include summary occupations, boosting the number of rows in our super matrix. In fact the number of rows turned out to be about 58,000. We sorted these 58,000 rows by whether the occupation was a line item rather than a summary. This produced a 4-column matrix of line item data with about 34,000 rows. In GEMPACK this matrix is easily treated as a rectangular matrix showing employment by 295 line industries (columns) and 789 line occupations (rows). In this matrix about 34,000 entries are non-zero.

[2] By line industry and line occupation we mean classifications at the most detailed available level. Summary items are aggregations of line items.

We could have formed the industry-occupation matrix by using Table 1.8. But this would have been even more cumbersome than using Table 1.9. If we had used Table 1.8 we would have had to access industry data for about 800 occupations. By using Table 1.9 we needed to access occupation data for only about 300 industries.

Total employment

Disappointingly, when we added the items in our initial industry-occupation matrix they indicted total employment of only 142.4 m. There are about 20m jobs missing.

We commenced the search for these 20m jobs by comparing the row sums of our occupation-industry matrix with the all-industry occupation data in BLS table 1.10. The all industry occupation data shows employment at 162.8 m.

Occupations 35-3023 & 37-2011

The two occupation with the most missing jobs in our matrix were 35-3023 (fast food and counter worker) with 3.084m missing jobs and 37-2011 (janitors and cleaners, except maids and housekeeper cleaners) with 1.106m missing jobs.

On inspection of occupation 35-3023 in Table 1.8 we found that the major employing industry at the summary level was 722500 (Restaurants and other eating places) with employment of 3.191m. We found that for all occupations the only line industry within 722500 is 722511 (full-service restaurants). Employment of occupation 35-3023 in 722511 is only 0.167m. Thus by using line items in our initial matrix we missed out on 3.024m jobs in occupation 35-3023 occurring in summary industry 722500. We rectified this situation by replacing line industry 722511 in our occ-ind matrix with summary industry 72250. This not only recovered most of the lost jobs in occ 35-3023 but also recovered about 2m jobs in other occupations, boosting total employment from 142.4m jobs to about 147m.

On inspection of occupation 37-2011 in Table 1.8 we found that the major employing industry at the summary level was 561700 (Services to buildings and dwellings) with employment of 0.886m. We found that for all occupations the only line industry within 561700 is 561710 (exterminating & pest control services). Employment of occupation 37-2011 in 561710 is only 0.0001m. Thus by using line items in our initial matrix we missed out on 0.8859m jobs in occupation 37-2011 occurring in summary industry 561700. We rectified this situation by replacing line industry 561710 in our occ-ind matrix with summary industry 561700. This not only recovered most of the lost jobs in occ 37-2011 but also recovered about 1m jobs in other occupations, boosting total employment from 147m jobs to about 149m.

The two examples alerted us to the general problem that the BLS line data is not complete. Using the line data is the reason for the missing 20m jobs. In the two examples, we recovered about 7m jobs. Unfortunately the remaining 13 million jobs are spread relatively evenly across the occupations. This means that recovering them is a laborious process.

The case of utilities: NAICS industry 221

We noticed from Table 1.9 that employment in this industry is 0.549m. But our matrix showed employment for the line items in this industry of only 0.292m. On inspection of the NAICS codes we found that industry 221120 was missing from the BLS data. However the BLS data includes BLS summary industry 2211 and all other sub industries. We deduced occupational employment for industry 221120 by subtraction. Then we added a column for industry 221120 to our occ-ind matrix.

Occupation 53-7062

We noted that the total for Occupation 53-7062 in BLS Table 1.10 was 2.986m but in our ind x occ matrix the sum over inds for this occupation was 2.536m. We tracked the problem to the BLS classifying Emp("53-7062",492000) =0.32288 as a summary item while at the same time the line item industries under 492000, 492100 and 492200, both have zero employment for occupation 53-7062. The line items in 492100 were 0.347 short of the all occupations total and 492200 was hardly short at all. So we added the entry 0.3228 to the 53-7062 occupation in industry 492100.

The case of Traveler accommodation: NAICS industry 7211

We noticed from Table 1.9 that employment in this summary industry is 1.990m. But our matrix showed employment for only one sub-industry N721120 (Casino hotels) in the line item industries in Table 1.9. This means that the line item industries in Table 1.9 leave out most of the jobs in N7211. We decided to replace N721120 with N721100.

The cases of Health and personal care stores and Sporting goods, hobbies & musical instrument stores: NAICS industry N446100 and N451100

We used these summary items to replace line items N446110 and N451110.

Further minor adjustments

As shown in our GEMPACK code we made further minor adjustments concerning industries N666402 and N666602.

Distributing the self-employed across industries

Table 1.9 treats the self-employed as though they were an industry. Thus we know the occupational characteristics of the self-employed, but not their industries. We distributed the self-employed to industries by assuming that if industry j employs x % of the wage and salary workers in occupation k then it employs x per cent of the self-employed workers in occupation k. This seems reasonably satisfactory. For example, most of the wage and salary farmers are in Agricultural industries. With our approach we put most of the self-employed farmers into agriculture.

Corrections of two errors in data retrieval from Table 1.9 of BLS dataset (1)

We discovered that we had omitted the BLS employment by occupation data for NAICS industries N332720 (Screw, nuts and bolts) and N721120 (Hotels).

After this correction and earlier adjustments to lessen missing jobs our employment matrix had 301 NAICS industries and 789 occupations, and total employment reached 152.5 million.

[We stored the code for the manipulations described in this section at *C:\dixon\consult\Commerce\2021\Employment\BLS data\EP\ReviseGlyn\ BLSBig2e.Tab Run with BLSBig2e.cmf*]

3.3. Aggregating the occupational classification from 789-order to 233-order

We encountered computing difficulties with 789 occupations. To relieve these problems we reduced the occupational dimension to 233. The aggregation to 233 occupations is shown in Table 3.3.1.

Column 2 of the table shows the standard occupational codes (SOC) included in each of the 233 aggregated occupations. For example the third occupation (S3) in our 233-order classification is an aggregation of occupations 11-3010, 11-3111, 11-3121 and 11-3131. As indicated in the table, we describe this aggregated occupation as Administrative and facilities & people-related managers. By referring to the SOC 6-digit codes, we can see that this aggregated occupation consists of:

11-3010 Administrative services and facilities managers

11-3111 Compensation and benefits managers

11-3121 Human resources managers

11-3131 Training and development managers.

The fourth 233-level occupation (S4) consists of a single 6-digit SOC category:

11-3021 Computer and information systems managers.

Similarly, with the fifth 233-level occupation (S5):

11-3031 Financial managers.

At the 789-level, most of the occupations are 6-digit SOC categories. In aggregating to 233 we tried to combine similar occupations. By similar, we mean occupations that require similar skills and similar qualifications and have similar remuneration. For example, we judged that people working in occupations 11-3010, 11-3111, 11-3121 and 11-3131 require similar non-technical people-managing skills. We can imagine people moving easily between these occupations. BLS data (BLS EP Table 1.7, part of dataset 1 described in section 3.1) shows that each of these occupations requires a Bachelor's degree, and 5 or more years' relevant experience. Typical salaries for the four occupations are in the range $99,000 to $125,000.

By contrast, we judged that people in occupation 11-3021 must come to senior management with particular technical skills in computing and information systems. Similarly, people in occupation 11-3031 must come to senior management with particular technical skills in finance. We don't think that people in the aggregated people managing occupation (S3 in our 233-order classification) are easily interchangeable with people in either 11-3021 or 11-3031. Thus, in forming the 233-order aggregation, we kept these two management categories separate from each other and from the people managers.

Glancing through Table 3.3.1 shows many examples where we have tried to avoid loss of skill identification in our aggregation choices. For example, we have retained the distinction between computer specialists as problem solvers and computer support specialists (S20 and S21). We judge that these occupations require quite different skills. This is supported by the wage data shown in column (4) of Table 1: $100,127 for the problem solvers and $55,510 for

Table 3.3.1. 233-order occupations: wage rate; physical or non-physical; and calculated numbers of new entrants

Occs	constituent SOCs	Description	WAGE $	PH or NPH *	NEWE1 '000#	NEWE2 '000#	NEWE3 '000 #
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S1	11-1000	Top executives	106180	0	51.48	121.29	112.47
S2	11-2000	Advertising, marketing, promotions, public relations, and sales managers	134120	0	18.83	46.82	44.84
S3	11-3010, 3111, 3121, 3131	Administrative and facilities & people-related managers	107722	0	10.92	23.77	21.97
S4	11-3021	Computer and information systems managers	151150	0	8.43	25.99	25.06
S5	11-3031	Financial managers	134180	0	16.48	39.82	38.14
S6	11-3051, 3061	Industrial production and purchasing managers	113729	0	1.06	7.90	7.09
S7	11-3071	Transportation, storage, and distribution managers	96390	0	1.55	4.15	3.64
S8	11-9013	Farmers, ranchers, and other agricultural managers	68090	0	23.22	29.61	24.78
S9	11-9021	Construction managers	97180	0	5.44	14.59	12.84
S10	11-9030	Education and childcare administrators	93470	0	5.53	16.15	13.89
S11	11-9041, 9111, 9121	Scientific and technical managers	120712	0	21.51	41.72	39.77
S12	11-9051, 9071, 9081, 9131, 9141, 9151, 9161, 9171, 9198	Non-technical managers NEC, e.g. Food service, postmasters	90944	0	27.39	66.49	58.15
S13	13-1011, 1070, 1151	Busin & finanical ops: people managers	63887	0	40.13	45.19	39.28
S14	13-1020, 1030, 1041, 1051, 1081, 1141	Busin & finanical ops: quantitative tasks	69032	0	30.35	43.08	35.00
S15	13-1111, 1198	Busin & finanical ops: Management analysts & other senior specialists	81429	0	79.10	111.18	101.73
S16	13-1121, 1131, 1161	Busin & finanical ops: market res, fundraising, events	63887	0	50.44	55.00	49.68
S17	13-2011	Accountants and auditors	73560	0	38.39	52.97	46.22
S18	13-2020, 2031, 2041, 2052, 2053, 2061, 2070, 2098	Financial specialists: mainly advisors	73812	0	21.53	36.77	29.78
S19	13-2080	Tax examiners, collectors and preparers, and revenue agents	50580	0	4.51	4.16	3.24
S20	15-1210, 1221, 1240, 1250, 1299	Computer specialsits: problem solvers	100127	0	66.65	152.32	139.82
S21	15-1230	Computer support specialists	55510	0	14.40	14.74	9.48
S22	15-2011	Actuaries	111030	0	0.27	0.95	0.86
S23	15-2021, 2031, 2041, 2098	Mathematical occupations	90170	0	6.80	9.89	9.14
S24	17-1011	Architects, except landscape and naval	82320	0	0.78	2.50	1.94
S25	17-1012	Landscape architects	70630	1	0.05	0.24	0.72
S26	17-1020	Surveyors, cartographers, and photogrammetrists	66250	0	0.86	1.19	0.87
S27	17-2041, 2031, 2131	Chemical, bio aand material engineers	100025	0	-0.10	1.50	1.21

S28	17-2051, 2021, 2081, 2110, 2151, 2171	Civil, agric, environmental, industrial, mining & petroleum engineers	91354	0	6.55	19.38	16.47
S29	17-2161	Nuclear engineers	116140	0	0.56	2.44	2.23
S30	17-2070, 2011, 2061	Electrical, electronics, computer and aeorspace engineers	108030	0	0.16	9.67	8.33
S31	17-2141, 2121	Mechanical and marine engineers	90350	0	-0.33	5.09	3.80
S32	17-2199	Engineers other: optical, corrosion, salvage	103380	0	-0.07	3.52	2.93
S33	17-3011, 3022, 3025, 3026	Civil engineering drafters & technologists	56107	0	6.35	6.46	4.92
S34	17-3013, 3027	Mechanical engineering drafters & technologists	58253	0	2.03	2.16	1.57
S35	17-3023, 3012, 3021, 3024	Electrical engineering drafters and technologists	66205	0	4.37	5.35	4.42
S36	17-3031	Surveying and mapping technicians	46200	0	2.87	2.60	2.21
S37	17-3098, 3019	Calibration technologists and technicians and engineering technologists and technicians	62811	0	2.68	3.05	2.46
S38	19-1010	Agricultural and food scientists	68830	0	1.46	1.71	1.53
S39	19-1020, 1099	Biological scientists and other life scientists NEC	83153	0	2.71	4.46	3.91
S40	19-1030	Conservation scientists and foresters	64010	0	1.15	1.30	1.10
S41	19-1041	Epidemiologists	74560	0	0.15	0.23	0.19
S42	19-1042	Medical scientists, except epidemiologists	91510	0	2.65	4.99	4.45
S43	19-2010, 2021	Astronomers, physiciists, atmospheric & space scientists	119438	0	0.33	1.17	1.09
S44	19-2030	Chemists and materials scientists	80680	0	2.19	3.37	2.96
S45	19-2040, 2099	Environmental scientists, geoscientists & physical scientists NEC	81959	0	4.69	6.71	6.04
S46	19-3011	Economists	108350	0	0.42	0.90	0.83
S47	19-3022	Survey researchers	59870	0	0.32	0.34	0.27
S48	19-3030	Psychologists	82180	0	-0.01	2.55	1.72
S49	19-3041	Sociologists	86110	0	0.11	0.16	0.15
S50	19-3051	Urban and regional planners	75950	0	1.29	1.71	1.53
S51	19-3090	Miscellaneous social scientists and related workers	85890	0	2.02	2.89	2.65
S52	19-4010, 4021, 4031, 4040, 4071, 4090	Life & physical science technicans	48448	0	16.32	15.17	12.94
S53	19-4051	Nuclear technicians	84190	0	0.17	0.26	0.23
S54	19-4061	Social science research assistants	49210	0	2.27	2.14	1.88
S55	19-5000	Occupational health and safety specialists and technicians	72530	0	-0.83	0.27	-0.33
S56	21-1010	Counsellors	50270	0	42.19	40.19	34.65
S57	21-1020, 1090	Social workers & Miscellaneous community and social service specialists	45902	0	74.14	67.78	58.05
S58	21-2000	Religious workers	48430	0	21.79	20.23	17.20
S59	23-1011	Lawyers	126930	0	-9.87	14.98	12.86

S60	23-1021	Administrative law judges, adjudicators, and hearing officers	97520	0	-0.24	0.05	-0.01
S61	23-1012, 1022	Judicial law clerks & Arbitrators, mediators, and conciliators	60068	0	-0.29	-0.24	-0.38
S62	23-1023	Judges, magistrate judges, and magistrates	141080	0	-0.43	0.60	0.53
S63	23-2000	Legal support workers	52960	0	18.59	18.11	15.32
S64	25-1011	Business teachers, postsecondary	88010	0	3.08	4.74	4.31
S65	25-1020	Math and computer science teachers, postsecondary	78090	0	1.55	2.69	2.24
S66	25-1030	Engineering and architecture teachers, postsecondary	101990	0	1.25	2.35	2.16
S67	25-1041	Agricultural sciences teachers, postsecondary	90340	0	0.22	0.41	0.36
S68	25-1042	Biological science teachers, postsecondary	85600	0	1.61	2.57	2.30
S69	25-1043	Forestry and conservation science teachers, postsecondary	87400	0	0.07	0.10	0.10
S70	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondary	94520	0	0.22	0.45	0.40
S71	25-1052	Chemistry teachers, postsecondary	80400	0	0.49	0.82	0.70
S72	25-1053	Environmental science teachers, postsecondary	84740	0	0.16	0.27	0.24
S73	25-1054	Physics teachers, postsecondary	90400	0	0.33	0.61	0.54
S74	25-1061, 1062, 1064, 1065, 1066, 1067, 1069	Social sciences teachers, postsecondary except economics teachers	77547	0	2.50	3.95	3.37
S75	25-1063	Economics teachers, postsecondary	107260	0	0.36	0.74	0.68
S76	25-1070	Health teachers, postsecondary	90890	0	12.86	18.40	17.10
S77	25-1080	Education and library science teachers, postsecondary	65940	0	1.62	2.06	1.62
S78	25-1111, 1113	Criminal justice and law enforcement teachers & social work teachers, postsecondary &	67624	0	0.72	0.93	0.75
S79	25-1112	Law teachers, postsecondary	116430	0	0.44	1.01	0.94
S80	25-1120, 1190	Arts, communications, history, humanities teachers & miscellaneous, postsecondary	66956	0	12.26	16.63	12.93
S81	25-2000	Preschool, elementary, middle, secondary, and special education teachers	59410	0	59.49	72.50	48.41
S82	25-3000, 9000	Other teachers , teaching assistants & other support	32275	0	147.26	109.09	83.55
S83	25-4000	Librarians, curators, and archivists	50860	0	14.08	13.47	11.71
S84	27-1011	Art directors	97270	0	3.18	5.05	4.68
S85	27-1012, 1019, 1023	Craft, floral and other artists NEC	36349	0	0.61	-0.25	-0.82
S86	27-1013	Fine artists, including painters, sculptors, and illustrators	52340	0	1.00	0.96	0.78
S87	27-1014	Special effects artists and animators	77700	0	2.74	3.51	3.20
S88	27-1021	Commercial and industrial designers	71640	0	0.88	1.24	1.03
S89	27-1022	Fashion designers	75810	0	0.55	0.85	0.72

S90	27-1024	Graphic designers	53380	0	5.63	5.38	3.66
S91	27-1025, 1027, 1029	Interior, set & exhibit designers & designers NEC	58072	0	2.12	2.25	1.63
S92	27-1026	Merchandise displayers and window trimmers	30810	0	3.71	1.52	0.10
S93	27-2010, 2090	Actors, producers, and directors & entertainers NEC	60615	0	9.70	10.34	8.84
S94	27-2020	Actors, producers, and directors & entertainers NEC	60615	0	30.42	31.24	29.37
S95	27-2030	Dancers and choreographers	39750	0	1.77	1.61	1.48
S96	27-2040	Musicians, singers, and related workers	39283	0	11.00	8.69	6.94
S97	27-3011	Broadcast announcers and radio disc jockeys	36770	0	1.21	0.75	0.44
S98	27-3023	News analysts, reporters, and journalists	49300	0	1.18	1.03	0.70
S99	27-3031	Public relations specialists	62810	0	10.21	11.20	9.68
S100	27-3040	Writers and editors	67730	0	8.30	10.29	8.71
S101	27-3090	Miscellaneous media and communication workers	53330	0	5.92	5.79	4.99
S102	27-4000	Media and communication equipment workers	50870	0	14.45	13.66	11.33
S103	29-1011	Chiropractors	70720	0	-1.70	-1.29	-1.55
S104	29-1021	Dentists, general	158940	0	-3.92	1.23	0.97
S105	29-1022, 1023, 1024, 1029	Dental specialists	208000	0	-0.57	0.34	0.31
S106	29-1031	Dietitians and nutritionists	63090	0	0.72	0.99	0.58
S107	29-1041	Optometrists	118050	0	-1.23	-0.03	-0.16
S108	29-1051	Pharmacists	128710	0	-8.42	1.41	0.58
S109	29-1071	Physician assistants	115390	0	3.53	6.91	6.52
S110	29-1081	Podiatrists	134300	0	-0.14	0.20	0.17
S111	29-1120	Therapists	79970	0	5.17	15.19	11.64
S112	29-1131	Veterinarians	99250	0	-1.11	0.65	0.32
S113	29-1141, 1151, 1161, 1171	Nurses	79139	0	-2.09	41.00	26.16
S114	29-1181	Audiologists	81030	0	0.03	0.20	0.14
S115	29-1211, 1216, 1218, 1221, 1223, 1228	Physician specialists	208000	0	-18.06	9.56	8.80
S116	29-1215	Family medicine physicians	207380	0	-3.30	2.23	2.07
S117	29-1248	Surgeons, except ophthalmologists	208000	0	-1.40	0.42	0.37
S118	29-1290, 2000, 9000	Health technologists and technicians, Dental hygine, and other technical health care	48414	0	44.69	35.50	14.22
S119	31-1100	Home health and personal care aides; and nursing assistants, orderlies, and psychiatric aides	28270	0	446.85	400.26	361.51
S120	31-2000	Occupational therapy and physical therapist assistants and aides	54250	0	17.05	16.96	15.69
S121	31-9000	Other healthcare support occupations	36780	0	108.70	89.95	76.81
S122	33-1000	Supervisors of protective service workers	72360	0	3.15	6.13	4.51
S123	33-2011	Firefighters	52500	1	3.65	3.18	10.29

S124	33-2020	Fire inspectors	62120	0	0.71	0.77	0.67
S125	33-3010	Bailiffs, correctional officers, and jailers	47440	0	6.71	4.95	1.94
S126	33-3021	Detectives and criminal investigators	86940	0	0.29	2.02	1.56
S127	33-3031, 3041, 3050	Police and other enforcement	65254	1	8.72	12.40	26.91
S128	33-9000	Other protective service workers	31230	1	144.65	125.44	161.87
S129	35-1011	Chefs and head cooks	53380	0	9.42	9.29	8.37
S130	35-1012	First-line supervisors of food preparation and serving workers	34570	0	89.39	77.49	69.51
S131	35-2000	Cooks and food preparation workers	27070	0	307.83	282.02	255.77
S132	35-3000	Food and beverage serving workers	24050	0	1025.54	1072.78	1030.82
S133	35-9000	Dining attendants, dishwashers, hosts & Other food preparation and serving NEC	25010	0	179.44	173.89	162.39
S134	37-1000	Supervisors of building and grounds cleaning and maintenance workers	46280	0	20.82	19.01	16.30
S135	37-2000	Building cleaning and pest control workers	28360	1	265.33	227.98	316.45
S136	37-3000	Grounds maintenance workers	32220	1	94.90	79.66	108.77
S137	39-1000	Supervisors of personal care and service workers	42850	0	18.67	16.05	13.42
S138	39-2000	Animal care and service workers	26370	0	40.63	37.70	34.81
S139	39-3000	Entertainment attendants and related workers	24980	0	100.70	98.02	92.95
S140	39-4011, 4021	Funeral attendants & Embalmers	31037	0	3.25	2.78	2.48
S141	39-4031	Morticians, undertakers, and funeral arrangers	54100	0	1.13	1.11	0.95
S142	39-5000	Personal appearance workers, except theatre makeup artists	28310	0	50.82	40.44	32.63
S143	39-5091	Makeup artists, theatrical and performance	106920	0	0.26	0.37	0.35
S144	39-6000	Baggage porters, bellhops, and concierges	30110	0	6.50	5.52	4.86
S145	39-7000	Tour and travel guides	29460	0	6.09	5.44	4.98
S146	39-9011	Childcare workers	25460	0	90.64	84.46	75.51
S147	39-9030	Recreation and fitness workers	31250	1	88.08	78.57	96.21
S148	39-9041	Residential advisors, e.g. activity organizers for group homes	31190	0	11.35	9.92	9.01
S149	39-9098	Crematory operators & personal care and service workers NEC	28420	0	10.15	8.91	8.00
S150	41-1011	First-line supervisors of retail sales workers	41580	0	42.14	30.57	20.21
S151	41-1012	First-line supervisors of non-retail sales workers	78560	0	4.13	8.94	7.12
S152	41-2000	Retail sales workers	26270	0	714.80	692.37	636.67
S153	41-3011	Advertising sales agents	54940	0	5.96	5.95	5.11
S154	41-3021	Insurance sales agents	52180	0	15.25	14.52	11.40
S155	41-3031, 3091	Securities, commodities, and financial services sales agents & Other services sales except Advertising, Insurance and Travel	60585	0	71.15	75.97	67.45

S156	41-3041	Travel agents	42350	0	0.79	0.19	-0.37
S157	41-4011	Sales representatives, wholesale and manufacturing, technical and scientific products	86650	0	11.06	15.98	14.67
S158	41-4012	Sales representatives, wholesale and manufacturing, except technical and scientific products	62070	0	42.70	47.88	40.23
S159	41-9010	Models, demonstrators, and product promoters	32490	0	10.21	9.12	8.40
S160	41-9020	Real estate brokers and sales agents	51220	0	11.99	11.05	8.05
S161	41-9031	Sales engineers	108830	0	2.75	4.26	4.05
S162	41-9041, 9090	Miscellaneous sales and related workers, e.g. telemarketers, door-to-door	29505	0	17.28	13.34	10.57
S163	43-1011	First-line supervisors of office and administrative support workers	58450	0	44.54	47.55	38.75
S164	43-2000	Communications equipment operators	32060	0	0.83	-0.10	-0.70
S165	43-3000	Financial clerks	39550	0	108.10	80.37	58.24
S166	43-4000	Information and record clerks	35300	0	338.29	280.40	238.52
S167	43-5000	Material recording, scheduling, dispatching, and distributing workers	41160	0	39.24	21.18	5.63
S168	43-6011	Executive secretaries and executive administrative assistants	63110	0	6.89	9.11	5.93
S169	43-6012	Legal secretaries and administrative assistants	48980	0	1.55	1.02	-0.07
S170	43-6013	Medical secretaries and administrative assistants	37350	0	34.23	27.44	22.67
S171	43-6014	Secretaries and administrative assistants, except legal, medical, and executive	38850	0	60.73	39.43	23.15
S172	43-9000	Other office and administrative support workers	35870	0	156.82	114.53	85.03
S173	45-1011, 2011	First-line supervisors of farming, fishing, and forestry workers & Agric inspect	48390	0	5.00	4.76	4.31
S174	45-2021	Animal breeders	40770	0	0.66	0.58	0.52
S175	45-2041, 2090	Miscellaneous agricultural workers & graders, sorter	28500	1	79.79	70.04	90.84
S176	45-3031, 4000	Fishing , Forest, conservation, and logging workers	40000	1	6.61	5.60	7.94
S177	47-1011	First-line supervisors of farming, fishing, and forestry workers	67840	0	23.65	28.29	24.77
S178	47-2011	Agricultural inspectors	65360	0	0.44	0.52	0.43
S179	47-2020, 3011	Brickmasons, blockmasons, and stonemasons & helpers	53000	1	2.81	2.67	5.22
S180	47-2031, 3012	Carpenters & helpers	50000	1	28.79	26.34	48.68
S181	47-2040	Carpet, floor, and tile installers and finishers	43000	1	3.26	2.41	5.09
S182	47-2050	Cement masons, concrete finishers, and terrazzo workers	46000	1	4.61	3.67	7.93
S183	47-2061, 2070, 3019, 4031, 4041, 4051, 4061, 4071, 4090	Construction laborers, equip operators & helpers & other construction related	41250	1	95.15	77.58	126.27

S184	47-2080	Drywall installers, ceiling tile installers, and tapers	48830	1	2.80	2.32	5.44
S185	47-2111, 3013	Electricians & helpers	56900	1	41.47	42.40	59.69
S186	47-2121	Glaziers	46080	1	2.17	1.92	3.05
S187	47-2130	Insulation workers	45820	1	2.23	1.93	3.24
S188	47-2140, 3014	Painters and paperhangers & helpers	42150	1	9.97	6.94	15.55
S189	47-2150, 3015	Plumbers, pipefitters, Pipelayers and steamfitters Helpers	54980	1	25.16	25.21	37.60
S190	47-2161	Plasterers and stucco masons	47020	1	0.51	0.40	0.99
S191	47-2171, 2211, 2221	Construction metal workers	52350	1	9.06	8.72	13.65
S192	47-2181, 3016	Roofers & helpers	43580	1	5.37	4.28	7.97
S193	47-2231	Solar photovoltaic installers	46470	1	1.54	1.48	1.75
S194	47-4011	Construction and building inspectors	62860	0	6.09	6.52	5.85
S195	47-4021	Elevator and escalator installers and repairers	88540	1	1.21	1.67	2.19
S196	47-5000	Extraction workers	46020	1	20.80	19.52	25.44
S197	49-1011	First-line supervisors of mechanics, installers, and repairers	70240	0	11.55	15.53	13.05
S198	49-2011, 2092, 2096, 2097, 2098	Computer installer & repairers	44517	0	8.70	7.42	5.86
S199	49-2020, 2091, 2093, 2094, 2095	Radio and telecommunications equipment installers and repairers & other high skill electronics	63650	0	10.13	11.62	9.64
S200	49-3011	Aircraft mechanics and service technicians	66440	1	2.82	3.60	6.39
S201	49-3020, 3041, 3050, 3090	Automotive, farm machine, small engine, bike & tyre repairs	40000	1	31.49	20.47	46.87
S202	49-3031, 3042, 3043	Bus, truck, train & other heavy mobile vehicle repairs	53000	1	12.20	11.73	21.39
S203	49-9010, 9031, 9060, 9071, 9091, 9094, 9095, 9098, 9099	Intstallation, maintenance & repairs: non-physical low skill	52560	0	65.46	63.99	52.01
S204	49-9060	Precision instrument and equipment repairers	50740	0	2.83	2.64	2.12
S205	49-9021, 9040, 9050, 9081, 9097	Intstallation, maintenance & repairs: physical low skill	50590	1	37.77	35.44	59.94
S206	49-9092	Commercial divers	54800	1	0.17	0.17	0.26
S207	49-9096	Riggers	50850	1	0.67	0.61	1.11
S208	51-1011	First-line supervisors of production and operating workers	62850	0	17.44	19.88	16.32
S209	51-2000	Production: Assemblers and fabricators	34970	1	43.76	22.58	64.25
S210	51-3000	Production: Food processing workers	30960	1	47.42	37.41	55.79
S211	51-4000	Production: Metal workers and plastic workers	40770	1	53.13	37.23	78.31
S212	51-5100	Production: Printing workers	37600	1	5.45	2.74	8.36
S213	51-6000	Production: Textile, apparel, and furnishings workers	28020	0	23.98	17.61	12.67
S214	51-7000	Production: Woodworkers	33800	1	9.85	6.61	12.73
S215	51-8000	Production: Plant and system operators	62540	0	5.87	6.94	5.23
S216	51-9000	Production: Other production occupations	37200	1	111.84	84.27	145.22
S217	53-1000	Supervisors of transportation and material moving workers	54840	0	17.77	17.74	14.93

S218	53-2010	Aircraft pilots and flight engineers	130440	0	4.83	8.81	8.49
S219	53-2021	Air traffic controllers	130420	0	0.53	1.28	1.22
S220	53-2022	Airfield operations specialists	51330	0	0.30	0.28	0.21
S221	53-2031	Flight attendants	59050	0	8.94	9.14	8.43
S222	53-3000	Motor vehicle operators	40600	0	237.10	200.57	168.37
S223	53-4011, 4041	Locomotive engineers & subway and streetcar drivers	71187	1	0.64	0.95	1.70
S224	53-4013, 4022, 4031.4099	Rail workers other	60995	0	0.91	1.04	0.74
S225	53-5011, 5022	Water transport workers: other	45719	1	1.73	1.56	2.29
S226	53-5021, 5031	Ship captains, mates and engineers	76921	0	1.39	1.92	1.70
S227	53-6011, 6021, 6031, 6041, 6061, 6098	Other transportation workers: parking attendants etc	28854	0	26.29	22.50	19.75
S228	53-6051	Transportation inspectors	78400	0	1.02	1.37	1.24
S229	53-7011, 7031, 7051, 7060, 7072, 7081, 7121, 7199	Material moving workers: laborers and others	30860	1	453.97	390.52	546.76
S230	53-7021	Crane and tower operators	59710	1	1.79	1.87	2.83
S231	53-7041	Hoist and winch operators	62610	1	0.18	0.20	0.30
S232	53-7071	Gas compressor and gas pumping station operators	67840	1	0.16	0.19	0.26
S233	53-7073	Wellhead pumpers	60720	1	0.70	0.73	1.02

* The 45 occupations that we judged as physical are shown in this column with a score of 1. The 188 non-physical have a score of 0.

The meaning of the numbers in these columns is explained in Appendix 2.

the support specialists. Similarly, we retain the distinction between post-secondary teachers in different disciplines (S64 to S80): these people require long-periods of training to acquire the particular skills relevant for their occupations. On the other hand, we judged that construction-laborer skills in nine 6-digit occupations are readily interchangeable. Consequently, we aggregated these into a single 233-order occupation: S183, Construction laborers, equip operators & helpers & other construction related.

3.4. Forming a wagebill matrix

Using the occupational wage-rate data in Table 3.3.1 and the 233 by 300 occ-ind employment matrix, we formed 233 by 300 wagebill matrix. In forming this matrix we inflated the wage rates so that the sum of the wagebill matrix was $10.7 trillion, reasonably compatible with macro data.

[see Header "WB" and "W23N" produced by c:\Dixon\consult\Commerce\2021\Employment\BLSdata\EP\REviseGlyn\BLSBig2e.tab run with BLSbig2e.cmf]

4. Adjusting USAGE industries to conform with BLS conventions, and making miscellaneous corrections to the 2015 USAGE database

USAGE identifies 392 industries based on Benchmark BEA input-tables for 2012 updated to 2015. As described in section 5, we made a further update to 2019.

Before we could link our 2019 occupation-industry matrix to USAGE we needed to adjust government and agricultural industries in the 2015 database for USAGE to conform with BLS conventions. We also made various corrections to the 2015 USAGE database.

[*Initial combined revisions were done in c:\rundynam\Can150317\extra DW9.tab run with DW9.cmf to alter the starting Buy America database in c:\rundynam\Can150317\data*]

4.1. Government industries

Electricity generation

Reflecting the BEA input-output tables, our 392-order USAGE model has 3 electricity generation industries: Power generation; Federal electric utility; and S&L electric utility. All 3 industries produce only one product, Power generation. Our BLS industry by occupation data identifies only one electricity industry. We changed the USAGE database so that our revised model effectively has only one electricity generation industry. We did this by moving 99% of all inputs and outputs of Federal electric utility and S&L electric utility into Power generation.

Education

Reflecting the BEA input-output tables, our 392-order USAGE model has 3 education products: Elementary & secondary; College; and Other education services. These commodities are mainly produced by 3 industries: Elementary & secondary; College; and Other education services. There is also significant production by S&L government.

The BLS data shows employment by occupation in Elementary & secondary; College; and Other education services. We decided to allocate the S&L government outputs of the 3 education products to the 3 specialist education industries. This move required us to allocate 0.4% of S&L costs to Elementary and secondary; 4.2% of S&L costs to Colleges; and 0.1%

to Other education.   These percentages seemed far too low and left us with unrealistically low wagebills relative to the BLS employment levels for each of the 3 education industries.

The BEA data implies that S&L produces a large amount of a commodity entitled S&L, about 80% of its output.   This is an amalgam of education products and other products such as Water & sewage, Highways and Hospitals. To bring the labor input numbers in the education industries in our CGE model into reasonable conformity[3] with the BLS numbers we allocated 29.8 per cent of S&L output and inputs to Elementary and secondary; 12.7 per cent to Colleges; and 1.1 per cent to Other education services. We rebalanced by adjusting down the sales of S&L to government and increased the sales of the 3 education commodities to government.

Water & Sewage

Reflecting the BEA input-output tables, our 392-order CGE model has a Water and sewage industry. However in the BEA input-output data, 81 per cent of the Water and sewage commodity is produced by the S&L government enterprises industry. We allocated the production of Water & sewage from Other S&L government enterprises industry to the Water and sewage industry. In the BEA data, Water & sewage is 19.5165 per cent of the output of the Other S&L government enterprises industry. Consequently, we transferred 19.5165 per cent of all the inputs of the Other S&L government enterprises industry into the Water & sewage industry. No rebalancing is then required.

Hospitals

Reflecting the BEA input-output tables, our 392-order CGE model has a Hospitals industry. However in the BEA input-output data, 20 per cent of the Hospitals commodity is produced by the S&L government industry. We allocated this production of Hospitals from S&L government to the Hospitals industry. In the BEA data, Hospitals are 8.8777 per cent of the output of the S&L government industry. Consequently, we transferred 8.8777 per cent of all the inputs of S&L government into the Hospitals industry. No rebalancing is then required.

4.2. Agriculture

Our BEA-based CGE model shows only a small value of labor in agricultural industries relative to the values that are realistic on the basis of BLS employment numbers. The reason is that the BEA considers all of the returns to self-employed farmers and their families as gross operating surplus, not as returns to labor. By contrast, the BLS employment numbers recognize labor input of self-employed farmers. We adjusted the CGE database by allocating part of gross operating surplus in agricultural industries to labor.

Table 4.2.1 shows original 2015 data from our CGE model. These data give returns to labor in crop industries (Inds 1-6) as $15,664m and returns to Animal farms (Inds 7-10) as $14,329m.

Our BLS-based wagebill matrix described in section 3.4 gives returns to labor in crops and animals in 2019 at $85,858m and $48,992m. For our revised 2015 database we adopt returns to labor values that are 2/3rds of the 2019 BLS numbers. Thus, we revise the CGE database so that returns to labor in crops and animals are $57,239m and $32,661m. For crops this requires moving $41,575m into returns to labor and out of returns to capital and land. We

[3] By reasonable conformity we mean that the revised 2015 wagebill numbers are 2/3rd of the wagebill numbers that we estimate for 2019 from the BLS

achieve this be moving 51.57 % of returns to capital and land into labor for all crop farms. For animals we move $18,333m into returns to labor and out of returns to capital and land. We achieve this be moving 30.68 % of returns to capital and land into labor for all animal farms. After these revisions the returns to primary factors are as in Table 4.2.2.

Table 4.2.1. Initial USAGE data: returns to primary factors in Agriculture in 2015 ($m)

Industry	LAB	CAP	LND	Total
1 OilSeedFarm	2949	11442	4759	19150
2 GrainFarm	3181	7414	1218	11814
3 VegMelonFarm	3126	11690	3069	17885
4 FruitNutFarm	2500	9613	9124	21238
5 GreenNursPrd	1292	11067	0	12359
6 OthCropFarm	2616	9550	1667	13832
Total crop farms	15664	60776	19837	96277
7 CattRancFarm	3877	14041	2947	20866
8 DairCattProd	3059	10611	634	14303
9 OtherAnimal	4569	17015	653	22237
10 PoultryEgg	2823	10999	2852	16674
Total animal farms	14329	52665	7086	74080

Table 4.2.2. Revised USAGE data: returns to primary factors in Agriculture in 2015 ($m)

Industry	LAB	CAP	LND	Total
1 OilSeedFarm	11304	5541	2305	19150
2 GrainFarm	7633	3591	590	11814
3 VegMelonFarm	10738	5661	1486	17885
4 FruitNutFarm	12164	4655	4419	21238
5 GreenNursPrd	6999	5359	0	12359
6 OthCropFarm	8400	4625	807	13832
Total crop farms	57239	29431	9607	96277
7 CattRancFarm	9090	9733	2043	20866
8 DairCattProd	6509	7355	439	14303
9 OtherAnimal	9990	11794	452	22237
10 PoultryEgg	7073	7624	1977	16674
Total animal farms	32661	36507	4912	74080

4.3. Miscellaneous 2015 database corrections to the 392-order USAGE model

Initial correction of labor used by government

Initially when we tried to allocate labor out of government to education, sewage etc, we found that our 392-order CGE model had insufficient labor in the government industries to make the reallocations plausible. Consequently we revised the initial CGE data for government industries.

In the original 2015 database for the CGE model we have 9 government industries which pay labor a total of $1,381,402m and capital a total of $996,641m, see Table 4.3.1. The 71-order

BEA input-output table for 2015 shows payments to labor by the Federal government (including enterprises) of $469,030m and by SLG (including enterprises) of $1,377,292m.

We decided to revise our CGE data, preliminary to other revisions, by bringing the payments to labor in government industries into line with the BEA IO numbers for Fed and SLG. We did this by scaling up returns to labor and making compensating reductions in returns to capital.

The revised data are in Table 4.3.2.

Table 4.3.1. Initial USAGE data: payments to labor and capital in government industries in 2015 ($m)

	Labor	Capital
377 FedGovDef	200149	169537
378 FedGovNonDef	173978	101208
379 PostalSvc	33159	13167
380 FedElecUtil	2923	1276
381 OthFedGEnt	2434	4904
Fed total	*412643*	*290092*
382 SLG	931282	589413
383 SLGPassTrans	6922	22226
384 SLGElecUtil	4719	13964
385 OthSLGEnt	25836	80946
SLG total	*968759*	*706549*
Total	**1381402**	**996641**

Table 4.3.2. Revised USAGE data: payments to labor and capital in government industries in 2015 ($m)

	Labor	Capital
377 FedGovDef	227499	142187
378 FedGovNonDef	197752	77434
379 PostalSvc	37690	8636
380 FedElecUtil	3322	877
381 OthFedGEnt	2767	4571
Fed total	*469030*	*233705*
382 SLG	1324011	196684
383 SLGPassTrans	9841	19307
384 SLGElecUtil	6709	11974
385 OthSLGEnt	36731	70051
SLG total	*1377292*	*298016*
Total	**1846322**	**531721**

Using the BEA input-output data at the approximately 70-order level to correct the USAGE database for 2015

Preliminary to updating to 2019, we decided to revise some of the 392-order wagebills in our 2015 USAGE data to achieve more conformity with the BEA 2015 IO data.

Oil and gas extraction

We moved $28,275m from LAND into LABIND_J to match the BEA 2015 number for LABIND_J

Funds Trusts and SecurInvest

We moved $16,183 from LABIND_J(FundsTrust) to LABIND_J(SecurInvest). We rebalanced by adjusting MAKE and consumption.

Rental lease

The 70-order sector Rental lease covers four 392-order industries: AutoRental, GenrlRentl, MachEquRentl and AssetLessors. In combination these four industries had a lot less labor than implied in the input-output data for Rental lease. We moved a total of $40,000m out of returns to capital in the four industries and added it to labor, inflating the original labor inputs by a common factor.

Adjustments to depreciation rates and values of capital stocks

As will be described in section 5.1, we updated the 2015 USAGE database to 2019 by simulation. In our initial 2015-19 simulation we found that many industries in the 2019 database had implausible values for capital growth (K_GR) and rates of return (ROR) where these were calculated from the simulated 2019 data according to the formulas:

$$\mathrm{K\_GR}(j) = \frac{\mathrm{VINVEST}(j)}{\mathrm{VCAP}(j)} - \mathrm{DEP}(j) \quad \text{for all } j \in \mathrm{IND} \tag{4.3.1}$$

and

$$\mathrm{ROR}(j) = \frac{\mathrm{RENTAL}(j)}{\mathrm{VCAP}(j)} - \mathrm{DEP}(j) \quad \text{for all } j \in \mathrm{IND} \tag{4.3.2}$$

where

VINVEST(j) is the value of investment (capital creation) in industry j;
VCAP(j) is the value of industry j's capital stock at the start of the year;
RENTAL(j) is the returns to the owners of capital in industry j during the year; and
DEP(j) is the rate of capital depreciation.

We traced the problem back to implausible values in the 2015 database. Some of this implausibility was probably caused by elimination of large phantom taxes through adjustments in returns to primary factors without changes in VCAP.

The data on both DEP(j) and VCAP(j) are weak. For high-growth industries, we adjusted DEP(j) to bring K_GR(j) in 2015 into an acceptable range (<0.08). This was satisfactory for many industries, achieved with reasonable values for DEP and implying plausible values for ROR. However for some industries we also had to make adjustments in VCAP and possibly further adjustments in DEP. Having revised the 2015 VCAPs and DEPs we reran the 2015-19 simulation and obtained reasonable 2019 values for the K_GRs and RORs.

5. Updating the USAGE database from 2015 to 2019 by simulation and revising the 2019 database

5.1. Update simulation: 2015 to 2019

Having completed the revisions described in section 4 to the 2015 database for the 392-order USAGE model, we conducted an update simulation to 2019. In the update simulation we introduced BEA macro data for the 2019 values of C, I, G, X, M, inventory accumulation, CPI and aggregate employment. We also introduced 2019 data for industry wagebills obtained for 69 sectors from BEA input-output tables for 2019. In the update simulations we imposed shocks to hit these wagebill values for most sectors. Excluded sectors were those in Government, Education, Hospital and Agriculture. To hit the wagebill values, we endogenized a common wage shift variable for the 392-order industries in each of the 69-order sectors.

5.2. Revising the simulated USAGE database for 2019 to increase compatibility with BLS data

As described in section 3.4, we used BLS data to create an occupation-industry wagebill matrix for 2019. By aggregating across occupations we obtained wagebills for about 300 BLS industries. The update simulation in section 5.1 produced wagebills at the 392 level for industries defined mainly according to BEA input-output conventions. To facilitate comparison of these wagebill vectors, we aggregated both vectors to 153 compatible industries. The aggregation went both ways. For example, BEA-based agricultural industries are more detailed than the BLS agricultural industries. Thus, for wagebill comparison we needed to aggregate the BEA-based wagebill data for agricultural industries. By contrast, BLS wholesale and retail industries are much more disaggregated than BEA wholesale and retail industries. Thus, for wagebill comparison we needed to aggregate the BLS wagebill data for wholesale and retail industries.

We revised both sets of estimates at the 153-order level to make them consistent. This required changes to our BLS-based occupation-industry data and to our BEA-based CGE input-output data.

5.3 Moving the targets and adjusting the simulated 2019 CGE database

[*see c:\rundynam\Can150317\extra\Work161221Revised190122.xlsx, sheet answer210122*]

We have a 153-order vector of wagebills that we derived from BLS jobs and wage data. We refer to this vector as the target (T) vector.

We also have an updated 153-order vector of wagebills that we obtained for 2019 by update simulation. We refer to this vector as the simulation (S) vector.

We aimed to revise the 2019 post simulation USAGE database to achieve as much compatibility as possible with a revised T vector.

Our method was to bring the S and T vectors together by altering both of them by moving dollars out of T and into S and vice versa. What is moved out of S must be rebalanced by changes in returns to capital and land in the USAGE database. The maximum move for each industry j was set according to:

$$\mathrm{MoveMax}(j) = \min\left\{\mathrm{abs}(T - S), 0.25 * (\mathrm{CAP}(j) + \mathrm{LND}(j))\right\} \tag{5.3.1}$$

The actual move is given by:

$$\mathrm{Move}(j) = \min\left\{\mathrm{MoveMax}(j), \frac{\mathrm{abs}(T(j) - S(j))}{2}\right\} \tag{5.3.2}$$

The revised targets, RT(j), are then

$$RT(j) = \begin{cases} T(j) + Move(j) \text{ if } T(j) < S(j) \\ T(j) - Move(j) \text{ if } T(j) >= S(j) \end{cases} \tag{5.3.3}$$

The revised values of the industry wagebills in the 2019 data are:

$$RS(j) = \begin{cases} S(j) - Move(j) \text{ if } T(j) < S(j) \\ S(j) + Move(j) \text{ if } T(j) >= S(j) \end{cases} \tag{5.3.4}$$

Fixing the large gaps

[C:\Rundynam/Can150317/extra/D19h.tab with D19h.cmf. This produces the Wagebill and Jobs matrices WBMT and JMAT that are incorporated into the FID file of year-on-year forecasts]

The percentage differences between RT(j) and RS(j) for each of the 153 industries are given by

$$\%Diff(j) = 100 * \frac{RT(j) - RS(j)}{\left[RT(j) + RS(j)\right]/2} \tag{5.3.5}$$

Despite the revisions implemented by (5.3.1) – (5.3.4), large gaps remained between our two sets of wagebill vectors. For 15 industries, %Diff(j) was less than -25 and for 8 industries it was greater than +25.

[see answer210122 sheet in C:\Rundynam\Can150317\extra\Work161221revised190122.xlsx]

From here, we make no further adjustments to the RS vector and as will be seen shortly, we impose the RS values in the USAGE database for 2019 [*generated in the2015 to 2019 simulation F49b in C:\Rundynam\Can150317*]. However, for industries in which there were large values for %Diff we did further data work leading to revisions in our BLS-based occupation-industry wagebill and employment matrices.

(i) N339900 (shown as 339910 in our spreadsheets) All other manufacturing (%Diff = -131)

Of our 153 industries, the one that gives the largest absolute value for %Diff is N339900. The BEA-based estimate after the revisions in (5.3.1) to (5.3.4) is 4.8374 times bigger than our revised BLS-based estimate. On inspection we found that the BLS data gave us only one 6-digit subindustry of N3399. This was Jewelry and silverware manufacturing (N339910), which is only a small percentage of the BEA 392-order industry N3399. We decided to inflate the occupational entries for N339910 in our revised BLS wagebill and jobs matrices by the factor of 4.8374 to bring the industry wagebill in the revised BLS data into line with our revised simulated wagebill for 2019 in USAGE.

(ii) Other non-hospital non-residential health services (excluding physicians and dentists)

At the 153 level, this category comprises five industries: Ag6213, N621420, N621500, N621600, Ag6219. In total the wagebills for these industries in the RS(j) and RT(j) correspond well, but there are large %Diffs of different signs for 4 of the 5 industries. We took the decision to aggregate the 5 industries, reducing the industry dimension of our occupational matrices from 153 to 149.

(iii) N334600 and N334300, Manufacturing & reproducing magnetic optical media and Audio & video equipment manufacture

The percent diff is large and negative for both industries. -63 and -49. We did not find any satisfactory way to fix this. Fortunately both industries are very small. We decided to scale the BLS jobs and wagebill matrices for these industries to match the 2019 revised simulated wagebills. This will happen when we do the final scaling for all industries.

(iv) N623220 and Ag623R, Residential mental health& substance abuse facilities and All other residential care facilities

At the 153 level, the wagebills for these industries in the RS(j) and RT(j) correspond reasonably well, but there are large %Diffs of different signs for the two industries. We took the decision to aggregate the 2 industries, reducing the industry dimension of our occupational matrices from 149 to 148.

(v) N712000, Museums, zoos and nature parks (%Diff = 46)

We suspect that there might be a lot of low-paid or volunteer workers in this sector. This would cause us to overestimate BLS target wagebill. We decided to scale down the BLS wagebill but leave the jobs unaltered.

(vii) N813200, N813300 and Ag813R, Grants & giving services, Social advocacy services, and Civic, social and labor organizations

The percent diffs for these three industries are -37, -3 and -47. We contemplated aggregation but decided it wasn't worthwhile.

Final steps

As can be seen from our GEMPACK code [*C:\Rundynam\Can150317\extra\D19h.tab run with D19h.cmf*], we implemented the decisions described above in a series of steps. In step (1) we amended the USAGE database and in steps (2) to (6) we amended the BLS-based wagebill and employment matrices. In Step (7) we expanded the industry dimension of the wagebill and employment matrices to 392. The steps were as follows.

(1) We amended the returns to capital, labor and land in the 392-order post-sim USAGE database for 2019 so that it remains balanced and is consistent at the 153-level with the wagebills in the RS vector.

(2) We amended the 153 by 233 wagebill matrix to reflect the wagebill targets after the application of (5.3.1) to (5.3.4). At this stage we did not change the jobs matrix.

(3) We aggregated the 153 industry dimension to 148 in the wagebill and jobs matrices to reflect the decisions we made under (ii) and (iv).

(4) We performed the changes to the wagebill and job matrices described in (i) for Other manufacturing.

(5) We performed the changes to the wagebill matrix (but not the jobs matrix) described in (v).

(6) We scaled the revised BLS Wagebill matrix at the 148 level so that it is consistent with the revised CGE wagebill data at the 148 level and we did corresponding scaling to the revised BLS jobs matrix.

(7) For each of the 392 USAGE industries we selected an industry at the 148 level to represent its occupational structure. That is we assumed that each 392-order industry in the same 148 sector has the occupational structure of that 148-order sector. This enabled us to create occupation-industry employment and wagebill matrices at the 233-occupation and 392-industry level, with the wagebill data being consistent with the 2019 revised USAGE database.

At this stage we had a balanced 2019 database for USAGE incorporating BEA values for macro variables. The database was also informed by 2019 data for sectoral wagebills at the 69-order level. In addition we had 233 by 392 occupation-industry employment and wagebill matrices. The wagebill matrix was consistent at the 392-industry level with the USAGE data. The occupational structure of employment in each industry was informed by the BLS data.

The amendments to returns to capital at the 392 level in step (1) caused implied rates of return in the 2019 database for some industries to move out of an acceptable range. We modified both depreciation rates and the start-of-2019 values of capital stocks to get the rates of return into acceptable ranges while not allowing the capital growth rates to move out of acceptable ranges.

[*The postsim values for VCAP_AT_T, DEP, and VINVEST from the historical sim (F49b) are in the M, T and E columns (shaded yellow) in the FixForc sheet of C:\Rundynam\Can150317/INVEST_CAPITAL.xlsx {see ext-F49b-2020.har and par_rev4v.har and the F49b solution}. Capital values in column F (shaded pink) are from Dout19h.har. . Given the VINVEST and Capital values we adjust new VCAP_AT_T and DEP values in columns D and G (shaded blue to achieve satisfactory ROR and K_GR values shown in columns I and J.]*

As a check on the wagebill and employment matrices, we computed the 233 implied occupational wage rates. These were highly correlated with the occupational wage rates shown in Table 3.3.1 from the original BLS data. However, they were considerably higher reflecting the higher aggregate wagebill given by the BEA relative to the aggregate wagebill that can be calculated using the wage rate data in Table 3.3.1 together with our BLS-based employment matrix ($10.7t compared with $7.9t). The wage rates in Table 3.3.1 are median wage rates. They also seem to be capped at a maximum of $208,000. We suspect that median occupational wage rates are generally lower than mean occupational wage rates and that there are some occupations for which even the median wage rate is greater than $208,000. Consequently, it is not surprising that considerable inflation of the BLS-based wage rates was necessary to generate realistic wagebills.

6. Specifying the labor supply matrix and the occupational mobility coefficients

A key data requirement for the USAGE-OCC labor-market module is the 4-dimension labor-supply matrix for the initial year. In the notation of section 2, the typical component of this matrix is $L_0(o,\ell;oo,\ell\ell)$, which denotes labor-supply from people in category (o, ℓ) to activity (oo, $\ell\ell$) in year 0 (the initial year). This section describes how we create the L_0 matrix. Rather than using the notation from section 2, we now adopt GEMPACK notation: L_0 becomes LFC_OFFER. Using this admittedly cumbersome notation facilitates the link between this document and the GEMPACK code.

6.1. Filling in the components in the initial LFC_OFFER matrix: Mathematical specification

We start by thinking about people employed in occupation o [those in the category (o, "empl")]. One option for these people is to offer to leave employment by going to short-run unemployment. We denote the proportion who take this option as $P_{emp,S}(o)$. In applications of our model including those in section 7 we typically set $P_{emp,S}(o)$ at 0.005. That leaves the proportion of (o, "empl") people who want to continue in employment as 1 - $P_{emp,S}(o)$. These people can offer to move to another occupation or stay in o. We denote the proportion who want to move by P1OCC(o), implying that the proportion who want to stay in their current occupation is 1 - P1OCC(o). Typically we set P1OCC(o) at 0.07. Thus, we normally assume for the initial year that the proportions of (o, "empl") people who want to go to short-run unemployment, go to employment in a different occupation, or go to employment in their current occupation, are 0.005, 0.06965 [=0.995*0.07] and 0.92535 [=0.995*(1-0.07)].

We will define similar concepts for unemployed people in occupation o [those in the categories (o, "S") and (o, "L")] and new entrants in occupation o [those in the categories (o, "N")], but we can delay this until they are needed.

(a) Offers from employment categories to employment activities (E2E components of the LFC_OFFER matrix)

To calculate the E2E components we start with the equation

LFC_OFFER(o, "empl", oo, "empl") =

DUM_OFFER(o,"empl", oo,"empl")*OFFER_FROM(o, "empl")

for all o and oo (6.1.1)

where

OFFER_FROM(o, "empl") is the number of people in category (o, "empl"); and

DUM_OFFER(o, "empl", oo, "empl") is the proportion of these people that offer to the (oo, "empl") activity.

In the database for the initial year we set

DUM_OFFER(o, "empl", oo, "empl")

$$=(1-P_{emp,S}(o))*P1(o,oo)*Z(o, oo) * \text{for all o and oo} \qquad (6.1.2)$$

where P1(o,oo) is given by

$$P1(o,oo) = P1OCC(o) \text{ if } oo\neq o \text{ and} \qquad (6.1.3)$$

$$P1(o,oo) =(1- P1OCC(o) \text{ if } oo =o \qquad (6.1.4)$$

and Z(o,oo) is given by

$$Z(o,oo) = \frac{HM(o;oo)}{\sum_{k\neq o} HM(o;k)} \qquad \text{for } oo\neq o \qquad (6.1.5)$$

$$Z(o,oo) = 1 \qquad \text{for } oo=o \qquad (6.1.6)$$

where

$$HM(o;oo) = MF(o,oo) * H(oo) \;, \qquad \text{for } oo \neq o \qquad (6.1.7)$$

In (6.1.2) to (6.1.7), H(oo) is employment in occupation oo. MF(o,oo) is a factor that measures the closeness of occupation oo to occupation o. By closeness we mean the feasibility of moves from o to oo, where oo ≠ o. We will explain MF shortly. We will also explain HM(o; oo).

For understanding (6.1.2) to (6.1.7), a good strategy is to assume initially that no pair of occupations are closer to each other than any other pair. In this case we can assume that MF(o; oo) = 1 implying that $HM(o;oo)$ is the same as H(oo).

With no closeness, (6.1.5) implies that Z(o,oo) for oo≠o is the share of (oo) employment in total non-o employment.

If oo=o then (6.1.6), (6.1.2) and (6.1.4) imply that the proportion of o workers who would like to remain employed in o is simply (1-$P_{emp,S}$(o))*P1(o,oo), typically 0.92535.

What about the MF factor?

By setting MF(o, a) at twice MF(o, b), for a, b ≠ o, we introduce a judgement that for any size of employment of workers in occupations a and b, o workers will offer twice as strongly to *a* jobs as to *b* jobs. That is, if H(a) and H(b) happen to have the same values, then:

$$LFC\_OFFER\left(o,\ \text{“empl”},\ a,\ \text{“empl”}\right) = 2 * LFC\_OFFER\left(o,\ \text{“empl”},\ b,\ \text{“empl”}\right)$$

In this way, we allow for the idea that occupation a is more compatible than b with the skills of occupation o. In section 6.2 we explain how we set the MF factors.

(b) Offers from unemployment categories to employment activities (U2E components of the LFC_OFFER matrix)

To calculate the U2E components we start with the equation

LFC_OFFER(o, k, oo, “empl”)

= DUM_OFFER(o, k, oo,“empl”)*OFFER_FROM(o, k) for k∈{S, L}

and for all o and oo (6.1.8)

In this equation

OFFER_FROM(o, k) is the number of people in category (o, k) where k belongs to UNEMP, that is k is short-run or long-run unemployment; and

DUM_OFFER(o, k, oo, “empl”) gives the proportion of (o, k) people that offer to the (oo, “empl”) activity.

Similar to (6.1.2), we set

DUM_OFFER(o, k, oo, “empl”) = (1-$P_{k,unemp}$(o))* P2(o,oo)*Z(o, oo)

k∈{S, L} (6.1.9)

where

P2(o,oo) = P2OCC(o) if oo≠o and (6.1.10)

P2(o,oo) =(1- P2OCC(o) if oo =o (6.1.11)

In equations (6.1.9) to (6.1.11),

$P_{k,unemp}(o)$ is the proportion people of type-k unemployment (S or L) in occupation o who want to stay unemployed[4];

P2OCC(o) is the proportion of job-seeking unemployed people in occupation o who wish to change occupation;

P2(o,oo) is defined by (6.1.10) and (6.1.11); and

Z(o,oo) is as defined earlier in (6.1.5).

Whereas $P_{emp,S}(o)$ typically has a low value (0.005), we set $P_{S.unemp}(o)$ and $P_{L,unemp}(o)$ at 0.25 and 0.50. This introduces an increasingly large discouraged worker effect with increased longevity of unemployment. With regard to P2OCC(o), we assume that unemployed job-seekers are more willing to change occupation than employed people.

We introduce this assumption by specifying

$$P2OCC(o)= F2(o)*P1OCC(o) \qquad (6.1.12)$$

where F2(o)>1. In the illustrative applications in section 7, we set F2(o) at 2 for all o.

(c) Offers from new-entrant categories to employment activities (N2E components of the LFC_OFFER matrix)

To calculate the N2E components we use the equation

LFC_OFFER(o, "N", oo, "empl")

= DUM_OFFER(o, "N", oo,"empl")*OFFER_FROM(o, "N") (6.1.13)

where

OFFER_FROM(o, "N") is the number of people in category (o, "N"); and

DUM_OFFER(o, "N", oo, "empl") gives the proportion of (o, "N") people that offer to the (oo, "empl") activity. This proportion is determined by

DUM_OFFER(o, "N", oo, "empl") = P3(o,oo)*Z(o, oo) (6.1.14)

P3(o,oo) = P3OCC(o) if oo≠o and (6.1.15)

P3(o,oo) =(1- P3OCC(o) if oo =o (6.1.16)

In equations (6.1.14) to (6.1.16),

P3OCC(o) is the proportion of new entrants in occupation o who wish to change occupation[5];

P3(o,oo) is defined by (6.1.15) and (6.1.16); and

Z(o,oo) is as defined earlier in (6.1.2).

By contrast with (6.1.2) and (6.1.9), there is no allowance on the right-hand side of (6.1.14) for voluntary unemployment. We assume that all new entrants are seeking employment.

It is realistic to assume that new entrants are as prepared to change their occupation as unemployed people. Typically we assume

[4] The occupation of unemployed people is either the last occupation in which they worked or if they have never worked then it is the occupation that they were deemed to have as a new entrant to the workforce.

[5] The determination of the occupation of new entrants is discussed in section 6.2.

$$P3OCC(o) = P2OCC(o) \tag{6.1.17}$$

(d) Offers from employment categories to unemployment activities (E2U components of the LFC_OFFER matrix)

These components of the LFC_OFFER *matrix* are filled in according to

$$LFC\_OFFER(o, \text{“empl”}, o, \text{“S”}) = P_{emp,S}(o)*OFFER\_FROM(o, \text{“empl”}) \tag{6.1.18}$$

$$LFC\_OFFER(o, \text{“empl”}, oo, \text{“S”}) = 0 \quad \text{for } oo \neq o \tag{6.1.19}$$

$$LFC\_OFFER(o, \text{“empl”}, oo, \text{“L”}) = 0 \quad \text{for all } oo \tag{6.1.20}$$

Equations (6.1.18) to (6.1.20) imply that all offers from employed people to unemployment are to the activity short-run unemployment in their own occupation.

(e) Offers from unemployment categories to unemployment activities (U2U components of the LFC_OFFER matrix)

These components of the LFC_OFFER matrix are filled in according to

$$LFC\_OFFER(o, \text{“S”}, o, \text{“L”}) = P_{S,unemp}(o)*OFFER\_FROM(o, \text{“S”}) \tag{6.1.21}$$

$$LFC\_OFFER(o, \text{“L”}, o, \text{“L”}) = P_{L,unemp}(o)*OFFER\_FROM(o, \text{“L”}) \tag{6.1.22}$$

$$LFC\_OFFER(o, \text{“L”}, oo, \text{“L”}) = 0 \quad \text{for all } oo \neq o \tag{6.1.23}$$

$$LFC\_OFFER(o, \text{“S”}, oo, \text{“S”}) = 0 \quad \text{for all } oo \tag{6.1.24}$$

Equations (6.1.21) to (6.1.24) imply that all offers from unemployed people to unemployment are to the activity long-run unemployment in their own occupation.

6.2. Determining the occupational closeness factors, MF(o,m) for m ≠ o

We experimented with four specifications of the MF coefficients. The effects on results as we move between specifications is discussed in section 7.

Specification 1: No special connections between occupations

Under specification 1, we set MF(o, m) according to:

$$MF1(o, m) = 1 * N1(o) \quad \text{for all o, and all } m \neq o \tag{6.2.1}$$

where N1(o) is a normalizing factor set so that

$$\sum_{m \neq o} MF1(o, m) = 1 \quad \text{for all o .} \tag{6.2.2}$$

With 233 occupations, N1(o) is simply 1/232. We do not need a value for MF(o, o): it does not appear in our equations.

Specification 2: Closeness determined by wage differences

Under this specification we assume that a transfer from occupation o to occupation m is more likely if wage rates in o and m are similar than if there is a large difference. To implement this specification, we start by defining an indicator of occupational wage differences:

$$WDiff(o, m) = \frac{ABS\left[W(o) - W(m)\right]}{\left(W(o) + W(m)\right)/2} \tag{6.2.3}$$

where W(o) and W(m) are median wages in occupations o and m, appearing in column (4) of Table 3.3.1. Then we set our second specification of closeness according to

$$\mathrm{MF2(o,m)} = \frac{1}{\mathrm{EXP}(\alpha * \mathrm{WDiff(o,m)})} * \mathrm{N2(o)} \quad \text{for all o, and all m} \neq \text{o} \qquad (6.2.4)$$

where

α is a positive parameter; and

N2(o) is a normalizing factor set so that

$$\sum_{m \neq o} \mathrm{MF2(o,m)} = 1 \quad \text{for all o .} \qquad (6.2.5)$$

Initially we set α = 1, but we judged that this gave insufficient impact on the off-diagonal flows. Subsequently we reset α at 2.

Specification 3: Closeness determined by wage differences and physical characteristics of jobs

We now introduce Physical/Non-physical in the measurement of occupational closeness. As shown in column (5) of Table 3.3.1, we specify 188 occupations as non-physical and the remaining 45 as physical. We assume that movements from non-physical occupations to physical occupations are relatively unlikely. This effect is achieved by setting MF3 as:

$$\mathrm{MF3(o,m)} = \frac{\mathrm{MF2(o,m)}}{\mathrm{NPHtoPH(o,m)}} * \mathrm{N3(o)} \quad \text{for all o, and all m} \neq \text{o} \qquad (6.2.6)$$

where

$$\mathrm{NPHtoPH(o,m)} = \begin{cases} 2 & \text{if o is non-physical and m is physical} \\ 1 & \text{otherwise} \end{cases} \quad \text{for all o, m} \qquad (6.2.7)$$

and

N3(o) is a normalizing factor set so that

$$\sum_{m \neq o} \mathrm{MF3(o,m)} = 1 \quad \text{for all i .} \qquad (6.2.8)$$

Specification 4: Closeness determined by wage differences, physical characteristics of jobs, and specific occupational compatibilities

In specification 4, we introduce specific occupational compatibilities into the measurement of occupational closeness. For each occupation o, we form a set of occupations which we judge are those to which o is most likely to make offers. These judgements are shown in Table 6.2.1.

For example we assume that Motor vehicle operators (Occupation 222) and Locomotive engineers (occ 223) are most likely when changing occupations to offer to be Transport supervisors (occ 217). Transport supervisors on the move are most likely to offer to be Transport inspectors (occ 228) or to move further up the occupational ladder to positions such as Manager transport (occ 7), Manager construction (occ 9) and Top executive (occ 1).

Looking at the problem the other way around, we assume that an occupation requiring long technical education is likely to receive offers from the limited number of other occupations, those with similar training. For example, we assume that specialist health occupations such as Surgeon (occ 117) receive compatibility-enhanced offers only from tertiary academics in the health field (occ 76). This can be seen by searching column (3) of Table 6.2.1: the row for occ 76 is the only one showing an entry for occ 117.

We introduce the specific compatibility effect by resetting the MF matrix according to:

$$\mathrm{MF4(o,m)} = \frac{\mathrm{MF3(o,m)}}{\mathrm{COMP(o,m)}} * \mathrm{N4(o)} \quad \text{for all o, and all } \mathrm{m} \neq \mathrm{o} \tag{6.2.9}$$

where

$$\mathrm{COMP(o,m)} = \begin{cases} 1 & \text{if m is compatible with o (o readily offers to m)} \\ 2 & \text{otherwise} \end{cases}$$

$$\text{for all o and m} \neq \text{o} \tag{6.2.10}$$

and

N4(o) is a normalizing factor set so that

$$\sum_{\mathrm{m} \neq \mathrm{o}} \mathrm{MF4(o,m)} = 1 \quad \text{for all o .} \tag{6.2.11}$$

Modifying the occupational characteristics of new entrants

In previous applications of USAGE with a labor-market module we assumed that the occupational characteristics of new entrants mirror those of the employed labor force. We continue this treatment in the first illustrative simulation in section 7 in which we adopt specifications 1 for the MF coefficients. In this simulations we assume that:

$$\mathrm{OFFER\_FROM(o,"N")} = 0.02 * \mathrm{H(o)} \quad \text{for all o} \tag{6.2.12}$$

where

OFFER_FROM(o, “N”) is the number of new entrants at the start of the year classified as occupation o; and

H(o) is employment in occupation o.

The coefficient 0.02 allows for approximately 1 per cent growth in the labor force on the assumption that the retirement coefficients CR in (T1) in Table 2.2.1 are set at 0.99.

Relative to specification 1 for the MF coefficients, specifications 2, 3 and 4 sharply reduce offers to very-high wage and technical occupations, such as Surgeon, from employed and unemployed people from outside the occupation. These technical occupations rely to a greater extent than other occupations on new entrants.

Table 6.2.1. Compatible occupations

Occs	GEMPACK name	Compatible occupations	Description
(1)	(2)	(3)	(4)
1	ManTopExec	2,3,4,5,6,7,9,1,11,12,62,	Top executives
2	ManAdvert	1,3,5,	Advertising, marketing, promotions, public relations, and sales managers
3	ManAdmini	1,2,12,	Administrative and facilities & people-related managers
4	ManComput	1,24,	Computer and information systems managers
5	ManFinanc	1,2,3,24,	Financial managers
6	ManIndust	1,7,9,	Industrial production and purchasing managers
7	ManTrnsprt	1,6,9,	Transportation, storage, and distribution managers
8	ManFarmer	,	Farmers, ranchers, and other agricultural managers
9	ManConstrct	1,6,7,122,	Construction managers
10	ManEducat	1,	Education and childcare administrators
11	ManScient	1,4,5,6,24,	Scientific and technical managers
12	ManNonTech	1,	Non-technical managers NEC, e.g. Food service, postmasters
13	BusPeopMan	5,14,15,16,18,64,	Busin & finanical ops: people managers
14	BusQuantMan	5,13,15,16,18,64,	Busin & finanical ops: quantitative tasks
15	BusAnalst	5,7,13,14,16,18,64,153,	Busin & finanical ops: Management analysts & other senior specialists
16	BusResFndEve	5,13,14,15,18,64,	Busin & finanical ops: market res, fundraising, events
17	BusAccount	5,13,14,15,16,18,19,64,	Accountants and auditors
18	BusFinAdvc	2,5,13,14,15,16,64,154,155,	Financial specialists: mainly advisors
19	BusTaxExam	5,13,14,15,16,17,18,64,	Tax examiners, collectors and preparers, and revenue agents
20	CmpPrbSolv	2,4,5,6,7,9,1,1,1,2,1,22,23,65,	Computer specialsits: problem solvers
21	CmpSupprt	2,22,23,65,	Computer support specialists
22	CmpActuary	2,4,5,6,7,9,1,1,1,2,2,1,23,65,	Actuaries
23	CmpMath	2,4,5,6,7,9,1,1,1,2,2,1,22,65,	Mathematical occupations
24	Arcitects	4,5,6,9,1,1,66,	Architects, except landscape and naval
25	ArcLandscpe	4,5,6,9,1,1,2,2,1,22,23,4,66,	Landscape architects
26	ArcSurvey	4,5,6,9,1,1,2,2,1,22,23,66,	Surveyors, cartographers, and photogrammetrists
27	ArcEngCBM	4,5,6,9,1,1,2,2,1,22,23,66,	Chemical, bio aand material engineers
28	ArcEngCivInd	4,5,6,9,1,1,2,2,1,22,23,66,	Civil, agric, environmental, industrial, mining & petroleum engineers
29	ArcEngNuc	4,5,6,9,1,1,2,2,1,22,23,66,	Nuclear engineers
30	ArcEngElectr	4,5,6,9,1,1,2,2,1,22,23,66,	Electrical, electronics, computer and aeorspace engineers
31	ArcEngMecMar	4,5,6,9,1,1,2,2,1,22,23,66,	Mechanical and marine engineers
32	ArcEngOptSal	4,5,6,9,1,1,2,2,1,22,23,66,	Engineers other: optical, corrosion, salvage
33	ArcCivDraft	4,5,6,9,1,1,2,2,1,22,23,66,	Civil engineering drafters & technologists

34	ArcMecDraft	4,5,6,9,1,1,2,2,1,22,23,66,	Mechanical engineering drafters & technologists
35	ArcEleDraft	4,5,6,9,1,1,2,2,1,22,23,66,	Electrical engineering drafters and technologists
36	ArcSurveyTec	4,5,6,9,1,1,2,2,1,22,23,66,	Surveying and mapping technicians
37	ArcCalTech	4,5,6,9,1,1,2,2,1,22,23,66,	Calibration technologists and technicians and engineering technologists and technicians
38	LfSAgrFod	4,5,1,1,2,2,1,22,23,67,	Agricultural and food scientists
39	LfSBioOthLif	4,5,1,1,2,2,1,22,23,68,	Biological scientists and other life scientists NEC
40	LfSConser	4,5,1,1,2,2,1,22,23,69,	Conservation scientists and foresters
41	LfSEpidem	4,5,1,1,2,2,1,22,23,76,	Epidemiologists
42	LfSMedica	4,5,1,1,2,2,1,22,23,76,	Medical scientists, except epidemiologists
43	LfSAstron	4,5,1,1,2,2,1,22,23,7,73,	Astronomers, physiciists, atmospheric & space scientists
44	LfSChemis	4,5,1,1,2,2,1,22,23,7,1,	Chemists and materials scientists
45	LfSEnvGeoPhy	4,5,1,1,2,2,1,22,23,7,72,73,	Environmental scientists, geoscientists & physical scientists NEC
46	LfSEconom	2,3,4,5,1,1,2,2,1,22,23,75,	Economists
47	LfSSurveyRes	4,5,1,1,2,2,1,22,23,74,	Survey researchers
48	LfSPsychol	2,3,4,5,1,1,2,2,1,22,23,74,	Psychologists
49	LfSScociol	2,3,4,5,1,1,12,2,2,1,22,23,74,	Sociologists
50	LfSUrbRegPln	4,5,1,1,12,2,2,1,22,23,74,	Urban and regional planners
51	LfSMiscSocS	2,3,4,5,1,1,12,2,2,1,22,23,74,	Miscellaneous social scientists and related workers
52	LfSLifPhyTec	4,5,1,1,12,2,2,1,22,23,74,	Life & physical science technicans
53	LfSNucTech	4,5,1,1,12,2,2,1,22,23,74,	Nuclear technicians
54	LfSSocialTec	4,5,1,1,12,2,2,1,22,23,74,	Social science research assistants
55	LfSOHStech	74,	Occupational health and safety specialists and technicians
56	SSvCounsel	12,74,	Counsellors
57	SSvSocWrk	12,74,	Social workers & Miscellaneous community and social service specialists
58	SSvReligious	74,	Religious workers
59	LegLawyer	6,62,78,79,	Lawyers
60	LegAdmLawJud	59,62,78,79,	Administrative law judges, adjudicators, and hearing officers
61	LegClkArbMed	78,79,	Judicial law clerks & Arbitrators, mediators, and conciliators
62	LegJudgMagis	6,	Judges, magistrate judges, and magistrates
63	LegSupprtWrk	6,1,78,79,	Legal support workers
64	EduBusTeaTrt	7,1,1,1,13,14,15,16,17,18,19,2,2,1,22,23,65,	Business teachers, postsecondary
65	EduMthTeaTrt	7,1,1,1,13,14,15,16,17,18,19,2,2,1,22,23,4,1,46,64,75,	Math and computer science teachers, postsecondary
66	EduEnATeaTrt	7,1,1,1,2,2,1,22,23,24,46,47,157,	Engineering and architecture teachers, postsecondary
67	EduAgrTeaTrt	8,1,1,1,2,2,1,22,23,38,45,	Agricultural sciences teachers, postsecondary
68	EduBioTeaTrt	,1,1,1,2,2,1,22,23,39,45,157,	Biological science teachers, postsecondary

69	EduForTeaTrt	,1,1,1,2,2,1,22,23,25,4,45,	Forestry and conservation science teachers, postsecondary
70	EduAESTeaTrt	,1,1,1,2,2,1,22,23,43,45,	Atmospheric, earth, marine, and space sciences teachers, postsecondary
71	EduChmTeaTrt	,1,1,1,2,2,1,22,23,44,45,	Chemistry teachers, postsecondary
72	EduEnvTeaTrt	,1,1,1,2,2,1,22,23,4,45,	Environmental science teachers, postsecondary
73	EduPhyTeaTrt	,1,1,1,2,2,1,22,23,43,45,46,157,	Physics teachers, postsecondary
74	EduSoSTeaTrt	,1,1,1,2,2,1,22,23,47,48,49,5,5,1,52,53,54,55,56,57,58,	Social sciences teachers, postsecondary except economics teachers
75	EduEcoTeaTrt	,1,1,1,2,2,1,22,23,46,	Economics teachers, postsecondary
76	EduHeaTeaTrt	,1,4,1,42,13,14,15,16,17,18,19,1,1,11,1,112,113,114,115, 116,117,118	Health teachers, postsecondary
77	EduEduTeaTrt	,1,12,8,1,83,	Education and library science teachers, postsecondary
78	EduJudTeaTrt	,1,59,6,6,1,62,	Criminal justice and law enforcement teachers & social work teachers, postsecondary &
79	EduLawTeaTrt	,1,59,6,6,1,62,	Law teachers, postsecondary
80	EduHumTeaTrt	,1,12,56,57,58,63,	Arts, communications, history, humanities teachers & miscellaneous, postsecondary
81	EduTeachPS	12,33,34,35,36,37,47,52,53,54,55,56,57,58,63,77,82,83,	Preschool, elementary, middle, secondary, and special education teachers
82	EduTeaSupp	33,34,35,36,37,47,52,53,54,55,56,57,58,63,83,	Other teachers , teaching assistants & other support
83	EduLibrary	63,77,8,1,82,	Librarians, curators, and archivists
84	ArtArtDirect	86,87,88,89,9,9,1,92,94,95,	Art directors
85	ArtCraftFlor	84,	Craft, floral and other artists NEC
86	ArtFineArts	84,87,88,89,9,9,1,92,94,	Fine artists, including painters, sculptors, and illustrators
87	ArtSpecEffec	84,86,88,89,9,9,1,92,94,	Special effects artists and animators
88	ArtCmIndDsgn	84,86,87,89,9,9,1,92,94,	Commercial and industrial designers
89	ArtFashDsgn	84,86,87,88,9,9,1,92,94,	Fashion designers
90	ArtGraphDsgn	84,86,87,88,89,9,1,92,94,	Graphic designers
91	ArtInterDsgn	84,86,87,88,89,9,92,94,	Interior, set & exhibit designers & designers NEC
92	ArtDisplyWin	84,	Merchandise displayers and window trimmers
93	ArtActDirNEC	84,86,87,88,89,9,9,1,92,	Actors, producers, and directors & entertainers NEC
94	ArtAthletWrk	84,	Actors, producers, and directors & entertainers NEC
95	ArtDancerCho	84,	Dancers and choreographers
96	ArtMusicSing	84,	Musicians, singers, and related workers
97	ArtBroadcRad	84,98,99,1,1,1,12,	Broadcast announcers and radio disc jockeys
98	ArtNewsRpJou	84,97,99,1,1,1,12,	News analysts, reporters, and journalists
99	ArtPublicRel	84,97,98,1,1,1,12,	Public relations specialists
100	ArtWriterEdi	84,97,98,99,1,1,12,	Writers and editors
101	ArtMisMedCom	84,97,98,99,1,12,	Miscellaneous media and communication workers
102	ArtMedComEqp	84,97,98,99,1,1,1,	Media and communication equipment workers

103	HePChiroprac	,	Chiropractors
104	HePDentist	,	Dentists, general
105	HePDentalsp	,	Dental specialists
106	HePDietNutri	,	Dietitians and nutritionists
107	HePOptometr	,	Optometrists
108	HePPharmacst	,	Pharmacists
109	HePPhysAssis	,	Physician assistants
110	HePPodiatrst	,	Podiatrists
111	HePTherapist	,	Therapists
112	HePVet	,	Veterinarians
113	HePNurse	,	Nurses
114	HePAudiolog	,	Audiologists
115	HePPhysSpec	42,76,	Physician specialists
116	HePPhysician	42,76,	Family medicine physicians
117	HePSurgeon	42,76,	Surgeons, except ophthalmologists
118	HePTechnic	,	Health technologists and technicians, Dental hygine, and other technical health care
119	HeSPerCarAid	,	Home health and personal care aides; and nursing assistants, orderlies, and psychiatric aides
120	HeSOcTherAss	,	Occupational therapy and physical therapist assistants and aides
121	HeSSupprtNEC	,	Other healthcare support occupations
122	ProSupervise	7,9,12,	Supervisors of protective service workers
123	ProFireFight	122,124,	Firefighters
124	ProFireInsp	122,123,	Fire inspectors
125	ProCorrctOff	122,	Bailiffs, correctional officers, and jailers
126	ProDetective	122,127,	Detectives and criminal investigators
127	ProPolice	122,126,	Police and other enforcement
128	ProServicNEC	122,	Other protective service workers
129	FodChefs	,	Chefs and head cooks
130	Fodsupervise	12,	First-line supervisors of food preparation and serving workers
131	FodCookPrep	13,132,	Cooks and food preparation workers
132	FodFdBevServ	13,13,1,	Food and beverage serving workers
133	FodPrpSrvNEC	13,13,1,132,	Dining attendants, dishwashers, hosts & Other food preparation and serving NEC
134	BldSuprvBGCM	,	Supervisors of building and grounds cleaning and maintenance workers
135	BldCleaners	134,	Building cleaning and pest control workers
136	BldGrndMaint	134,	Grounds maintenance workers

137	PerSupervise	12,	Supervisors of personal care and service workers
138	PerAnimCare	137,	Animal care and service workers
139	PerEntertAtt	137,	Entertainment attendants and related workers
140	PerFunerlAtt	137,	Funeral attendants & Embalmers
141	PerMortician	137,	Morticians, undertakers, and funeral arrangers
142	PerAppearWrk	137,	Personal appearance workers, except theatre makeup artists
143	PerMakupArt	137,	Makeup artists, theatrical and performance
144	PerBagPorter	137,	Baggage porters, bellhops, and concierges
145	PerTravGuide	137,	Tour and travel guides
146	PerChildcare	137,	Childcare workers
147	PerRecFitwrk	137,	Recreation and fitness workers
148	PerResidAdvs	137,	Residential advisors, e.g. activity organizers for group homes
149	PerCarWrkNEC	137,	Crematory operators & personal care and service workers NEC
150	SalSuprvsRt	,	First-line supervisors of retail sales workers
151	SalSupvsNrt	2,12,157,158,159,16,16,1,	First-line supervisors of non-retail sales workers
152	SalRetail	15,	Retail sales workers
153	SalAdvrtAgnt	12,15,1,156,	Advertising sales agents
154	SalInsurance	15,1,	Insurance sales agents
155	SalFinSrvNEC	15,1,	Securities, commodities, and financial services sales agents & Other services sales except Advertising, Insurance and Travel
156	SalTravlAgnt	15,1,153,	Travel agents
157	SalTecSciPrd	15,1,16,1,	Sales representatives, wholesale and manufacturing, technical and scientific products
158	SalNonTScPrd	15,1,	Sales representatives, wholesale and manufacturing, except technical and scientific products
159	SalPrdPromot	15,1,	Models, demonstrators, and product promoters
160	SalRealEstat	2,15,1,	Real estate brokers and sales agents
161	SalEngineer	15,1,157,	Sales engineers
162	SalMiscNEC	15,	Miscellaneous sales and related workers, e.g. telemarketers, door-to-door
163	Offsupervise	1,6,12,168,	First-line supervisors of office and administrative support workers
164	OffCmEquipOp	163,165,166,167,168,169,17,17,1,172,	Communications equipment operators
165	OffFinanClrk	163,164,166,167,168,169,17,17,1,172,	Financial clerks
166	OffInfoClrk	163,164,165,167,168,169,17,17,1,172,	Information and record clerks
167	OffSchdulWrk	163,164,165,166,168,169,17,17,1,172,	Material recording, scheduling, dispatching, and distributing workers
168	OffExecSec	163,	Executive secretaries and executive administrative assistants
169	OffLegalSec	163,164,165,166,167,168,17,17,1,172,	Legal secretaries and administrative assistants
170	OffMediclSec	163,164,165,166,167,168,169,17,1,172,	Medical secretaries and administrative assistants

171	OffSecretNEC	163,164,165,166,167,168,169,17,172,	Secretaries and administrative assistants, except legal, medical, and executive
172	OffSupWrkNEC	163,164,165,166,167,168,169,17,17,1,	Other office and administrative support workers
173	Frmsupervise	8,17,17,1,	First-line supervisors of farming, fishing, and forestry workers & Agric inspect
174	FrmAnimBreed	8,173,175,176,	Animal breeders
175	FrmMiscAgWrk	173,174,176,	Miscellaneous agricultural workers & graders, sorter
176	FrmFisForWrk	173,174,175,178,	Fishing , Forest, conservation, and logging workers
177	Consupervise	1,7,9,194,	First-line supervisors of farming, fishing, and forestry workers
178	ConBoilMaker	177,194,	Agricultural inspectors
179	ConBrickMasn	177,194,	Brickmasons, blockmasons, and stonemasons & helpers
180	ConCarpenter	177,194,	Carpenters & helpers
181	ConFloorInst	177,179,182,183,184,187,188,19,192,193,194,196,	Carpet, floor, and tile installers and finishers
182	ConCemntMasn	177,179,18,1,183,184,187,188,19,192,193,194,196,	Cement masons, concrete finishers, and terrazzo workers
183	ConLaborNEC	177,179,18,1,182,184,187,188,19,192,193,194,196,	Construction laborers, equip operators & helpers & other construction related
184	ConDryWalIns	177,179,18,1,182,183,187,188,19,192,193,194,196,	Drywall installers, ceiling tile installers, and tapers
185	ConElectricn	177,194,	Electricians & helpers
186	ConLaazier	177,194,	Glaziers
187	ConInsulate	177,179,18,1,182,183,184,188,19,192,193,194,196,	Insulation workers
188	ConPainter	177,179,18,1,182,183,184,187,19,192,193,194,196,	Painters and paperhangers & helpers
189	ConPlumber	177,194,	Plumbers, pipefitters, Pipelayers and steamfitters Helpers
190	ConPlaster	177,179,18,1,182,183,184,187,188,192,193,194,196,	Plasterers and stucco masons
191	ConMetalWrk	177,194,	Construction metal workers
192	ConRoofers	177,179,18,1,182,183,184,187,188,19,193,194,196,	Roofers & helpers
193	ConSolarInst	177,179,18,1,182,183,184,187,188,19,192,194,196,	Solar photovoltaic installers
194	ConBldInspct	177,	Construction and building inspectors
195	ConElevatIns	177,194,	Elevator and escalator installers and repairers
196	ConExtrcTWrk	177,179,18,1,182,183,184,187,188,19,192,193,194,	Extraction workers
197	IMRsupervise	1,6,7,	First-line supervisors of mechanics, installers, and repairers
198	IMRComputer	197,2,1,22,23,24,25,26,27,	Computer installer & repairers
199	IMRRadioTelc	197,	Radio and telecommunications equipment installers and repairers & other high skill electronics
200	IMRAircrftMc	197,	Aircraft mechanics and service technicians
201	IMRAutoSEngn	197,198,22,23,24,25,26,27,	Automotive, farm machine, small engine, bike & tyre repairs
202	IMRHeavyVeh	197,198,2,1,23,24,25,26,27,	Bus, truck, train & other heavy mobile vehicle repairs
203	IMRLowSklNP	197,198,2,1,22,24,25,26,27,	Intstallation, maintenance & repairs: non-physical low skill
204	IMRPrecisIns	197,	Precision instrument and equipment repairers
205	IMRLowSklPh	197,198,2,1,22,23,24,26,27,	Intstallation, maintenance & repairs: physical low skill
206	IMRComDiver	197,198,2,1,22,23,24,25,27,	Commercial divers

207	IMRRigger	197,198,2,1,22,23,24,25,26,	Riggers
208	Prdsupervise	1,6,7,215,	First-line supervisors of production and operating workers
209	PrdAssemFabr	2,1,21,1,212,213,214,216,	Production: Assemblers and fabricators
210	PrdFoodProc	29,21,1,212,213,214,216,	Production: Food processing workers
211	PrdMetlPlast	29,2,1,212,213,214,216,	Production: Metal workers and plastic workers
212	PrdPrinting	29,2,1,21,1,213,214,216,	Production: Printing workers
213	PrdAppTexFur	29,2,1,21,1,212,214,216,	Production: Textile, apparel, and furnishings workers
214	PrdWoodWork	29,2,1,21,1,212,213,216,	Production: Woodworkers
215	PrdPlntSysOp	28,	Production: Plant and system operators
216	PrdNEC	29,2,1,21,1,212,213,214,	Production: Other production occupations
217	TrnSupervise	1,7,9,228,	Supervisors of transportation and material moving workers
218	TrnPilotFltE	,	Aircraft pilots and flight engineers
219	TrnAirTrfCnt	7,	Air traffic controllers
220	TrnAirfldSpe	7,217,	Airfield operations specialists
221	TrnFlightAtt	,	Flight attendants
222	TrnMotVehOp	217,	Motor vehicle operators
223	TrnTrainDriv	217,	Locomotive engineers & subway and streetcar drivers
224	TrnRailOther	223,	Rail workers other
225	TrnWaterOthr	226,	Water transport workers: other
226	TrnShipCapME	217,	Ship captains, mates and engineers
227	TrnWorkNEC	222,224,225,	Other transportation workers: parking attendants etc
228	TrnInspector	,	Transportation inspectors
229	TrnMatMovWrk	222,224,225,	Material moving workers: laborers and others
230	TrnCrane	,	Crane and tower operators
231	TrnHoist	,	Hoist and winch operators
232	TrnGasPmpCmp	,	Gas compressor and gas pumping station operators
233	TrnWellhdPmp	,	Wellhead pumpers

To recognize this effect and to ensure that supply into technical occupations grows broadly in line with demand, we recalculated the year zero new entrant numbers under specifications 2, 3 and 4 as:

$$\text{OFFER\_FROM}(o,\text{"N"}) = 0.02 * H(o) - \text{DIFF1j}(o) \quad \text{for all o} \qquad (6.2.13)$$

where DIFF1j(o) is the increase in offers to occupation o from employed and unemployed workers as we go from occupation mobility specification 1 to specification j where j = 2, 3, or 4.

To clarify, we consider the example of Surgeon (occ 117). The move from specification 1 to specification 4, reduces the offers to the occupation from employed and unemployed workers in other occupations by 2.105 thousand:

DIFF14(Surgeon) = -2.105.

This causes the adjustments shown in Table 6.2.2. Under specification 1, new entrants accounted for only 14 per cent of non-incumbent offers to occupation 117 (0.70 out of 5.1). Under specification 4 the New entrant share rises to 54 per cent (2.73 out of 5.02).

Table 6.2.2. Non-incumbent offers to Surgeon (occ 117): 2019 database, thousands

Non-incumbent offers from:	Specification 1	Specification 4
New entrants	0.70	2.73
Existing non-Surgeons excl. new entrants	4.40	2.29
Total	5.10	5.02

Note: We expected the column sum under specification 4 to be 5.10, the same as in specification 1. However we now realize that (6.2.13) does not quite implement our intended adjustment of offers from new entrants to occupation o to compensate for the change in non-incumbent non-new offers to occupation o. This is a second order error which can be fixed in future applications of USAGE-OCC.

7. Illustrative application: the effects of increasing wage rates in low-wage occupations

7.1. Setting up the simulations

To illustrate how USAGE-OCC works, we simulate the effects of a 10 per cent increase in the real wage rates of low-wage occupations. Low wage occupations are those shown in column (4) of Table 3.3.1 with median wage rates less than $29,500. As listed in Table 7.1.1, there are 14 low-wage occupations. They account for 20.47 per cent of employment and 9.44 per cent of the economy-wide wagebill.

We performed four simulations, one for each of the mobility specifications described in section 6. Each of the simulations is year-on-year dynamic and requires two runs of the model: a baseline showing the path of the economy without the shock and a perturbation run which shows the path of the economy with the shock.

In creating the baseline, we incorporated a smoothed version of macro forecasts published by the Energy Information Administration.[6] In the perturbation runs, we assumed that the shock (10% real wage increases for the low-wage occupations) is imposed in 2021 and maintained

[6] The EIA forecasts were taken from Table 20 available at https://www.eia.gov/outlooks/aeo/data/browser/#/?id=18-AEO2021&region=0-0&cases=ref2021&start=2019&end=2050&f=A&linechart=&sourcekey=0
Our processing of the forecasts is stored in d:\Rundynam\Can150317\data\EIA_pubFeb2021.xlsx.

Table 7.1.1. Low-wage occupations

Occs	GEMPACK name	Description
119	HeSPerCarAid	Home health and personal care aides; nursing assistants, orderlies, psychiatric aides
131	FodCookPrep	Cooks and food preparation workers
132	FodFdBevServ	Food and beverage serving workers
133	FodPrpSrvNEC	Dining attendants, dishwashers, hosts & Other food preparation and serving NEC
135	BldCleaners	Building cleaning and pest control workers
138	PerAnimCare	Animal care and service workers
139	PerEntertAtt	Entertainment attendants and related workers
142	PerAppearWrk	Personal appearance workers, except theatre makeup artists
145	PerTravGuide	Tour and travel guides
146	PerChildcare	Childcare workers
149	PerCarWrkNEC	Crematory operators & personal care and service workers NEC
152	SalRetail	Retail sales workers
175	FrmMiscAgWrk	Miscellaneous agricultural workers & graders, sorter
227	TrnWorkNEC	Other transportation workers: parking attendants etc

through the simulation period to 2024. This means that in the years 2021 to 2024, real wage rates in low-wage occupations are 10 per cent higher in the perturbation run than in the baseline. In imposing the wage shocks, it was necessary to turn off the model's wage-adjustment equation for the 14 low-wage occupations. In terms of Table 2.2.1, we endogenized a shift variable in equation (T12) for these occupations.

7.2. Macro effects after 4 years

Table 7.2.1 shows effects of the wage policy on macro variables as percentage deviations from their baseline values in 2024 (that is, four years after the imposition of the shock).

Mobility specification 1, column 1 in Table 7.2.1

With mobility specification 1 (described at the foot of Table 7.2.1), the 10 per cent wage increase for low-wage occupations causes the average real wage rate over all workers to be 0.618 per cent above baseline (row 1). A higher average real wage rate requires workers to achieve a higher value for their marginal product to remain employed. With no change in technology, this requires a higher input ratio of capital to labor (K/L).[7] Higher wages reduce rates of return on capital, inhibiting investment (row 10) and reducing K. Since K/L must rise L must fall, by a greater percentage than K. In column 1 of Table 7.2.1, the reduction in capital is 0.309 per cent (row7) compared with the reduction in labor input of 1.255 per cent (row 5).

Employment falls in all occupations. Measured in terms of jobs, the reduction in aggregate employment is 1.462 per cent (row 2). This is greater than the percentage reduction in labor input (row 5) because employment reductions are more severe for low-wage occupations than for other occupations.

Employment in low-wage occupations falls 2.715 per cent below baseline, while employment for other occupations falls by 1.143 per cent (rows 3 & 4). Employment in low-wage

[7] The percentage change in the input of labor is measured by a weighted average of the percentage changes in jobs in each occupation, where the weights are occupational shares in the aggregate wagebill. The percentage change in the input of capital is measured by a weighted average of the percentage changes in the capital stock in each industry, where the weights are industry shares in the aggregate rental value of capital.

occupations falls relative to that in other occupations for two reasons. First, industries that intensively employ workers in low-wage occupations suffer cost increases and consequent reductions in activity relative to other industries. These industries include restaurants and a variety of industries providing personal care and household services. Second, our model allows for substitution in employment against occupations for which there is an increase in the wage rate relative to that of other occupations. However, as explained in section 2.2, in the discussion of equations (T5) to (T8), this substitution effect is weak.

The reduction in real GDP is 0.844 per cent (row 8). This can be explained approximately as a weighted average of the reductions in labor and capital input, with weights 0.57 and 0.43 representing the labor and capital shares in GDP:

$$-0.844 \approx 0.57*(-1.255)+0.43*(-0.309) \;.$$

In percentage deviations, real private and public consumption (rows 9 and 11) are locked together in the perturbation runs by assumption. In column 1 of Table 7.2.1 they decline by 0.941 per cent relative to baseline. The percentage decline in consumption is a slightly greater than that in GDP. This reflects a reduction in the terms of trade associated with the increase in exports (row 12). Expansion in exports above baseline pushes foreign-currency export prices below baseline generating a terms-of-trade reduction. [We assume no effect on foreign-currency import prices.] A terms-of-trade reduction lowers the ability of any given level of GDP to support consumption.

Table 7.2.1. Effects after four years of a sustained 10 per cent increase in real wage rates in low-wage occupations under different occupational mobility specifications (percentage deviations from baseline)

	Mobility specification[(a)]	1	2	3	4
1	Average real wage rate, wagebill weights	0.618	0.400	0.405	0.398
2	Aggregate employment, jobs	-1.462	-1.154	-1.152	-1.142
3	Employment, low-wage occupations	-2.715	-2.455	-2.463	-2.458
4	Employment, other occupations	-1.143	-0.823	-0.817	-0.807
5	Aggregate labor input, wagebill weights	-1.255	-0.913	-0.915	-0.906
6	Labor supply	-0.488	-0.360	-0.364	-0.359
7	Capital input, rental weights	-0.309	-0.210	-0.207	-0.204
8	Real GDP	-0.844	-0.610	-0.610	-0.603
9	Real private consumption	-0.941	-0.711	-0.717	-0.710
10	Real aggregate investment	-1.565	-0.988	-0.954	-0.937
11	Real public consumption	-0.941	-0.711	-0.717	-0.710
12	Real exports	0.654	0.518	0.505	0.500
13	Real imports	-1.191	-0.785	-0.774	-0.763

[(a)] The mobility specifications are those described in section 6.
In specification 1, there are no special connections between occupations: all moves are equally feasible.
In specification 2, large wage differences inhibit occupational moves.
In specification 3, wage differences and physical characteristics are taken into account.
In specification 4, wage differences, physical characteristics and education/training/experience requirements are taken into account.

With the percentage reduction in investment exceeding the percentage reduction in GDP, 1.565 per cent compared with 0.844 per cent, and with the reductions in private and public consumption being relatively close to that in GDP, the real trade balance (X-M) must move towards surplus. This is achieved by an increase in exports and a reduction in imports (rows 12 and 13) facilitated by real devaluation (a reduction in the U.S. price level relative to that of trading partners expressed in a common currency).

Despite the increase in wage rates, there is a reduction in labor supply, 0.488 per cent (row 6). Labor supply is initially stimulated in response to wage increases. However, after four years, the build-up of unemployment reduces labor supply below baseline: recall the discouraged worker effect discussed in section 6.1 in connection with the coefficients $P_{S.unemp}(o)$ and $P_{L,unemp}(o)$. The discouraged-worker effect means that employment cannot return to the baseline path for a very long time, if at all.

Mobility specifications 2 to 4, columns 2 to 4 in Table 7.2.1

Comparing the results in column 2 of Table 7.2.1with those in column 1 shows the effects of introducing occupational closeness based on wage differences. At the macro level, these effects are favorable in the experiment in which low-wage occupations get a 10 per cent real wage increase. The explanation is as follows. The economy-wide real wage increase in simulation 2 is less than in simulation 1 (0.400 compared with 0.618, row 1). Thus, in simulation 2 the economy-wide damage to employment is smaller than in simulation 1 (a reduction in labor input of 0.913 per cent compared with 1.255 per cent). Less damage to labor input translates into less damage to consumption, investment, capital and GDP.

The critical question is: why is the real wage increase damped in simulation 2 compared with simulation 1?

With the recognition of occupational closeness based on wage differences, there is less tendency for people in occupations (employed, unemployed or new entrant) outside the low-wage group to increase their offers to the low-wage group in response to the 10 per cent wage increase. This reduces supply to the low-wage occupations and increases supply to the other occupations. The first of these two supply effects does not affect wage rates in the low-wage occupations because these wage rates are set exogenously. The second of the two supply effects reduces wages in the occupations outside the low-wage group. Thus, the effect on the economy-wide wage rate of introducing wage-related occupational closeness is negative.

Next we compare the results in column 3 of Table 7.2.1 with those in column 2. This comparison shows that macro outcomes from increasing the wage rates of low-wage occupations are very little affected by including physical characteristics of occupations along with wage differences in the specification of occupational closeness.

Comparison of the results in column 4 of Table 7.2.1with those in column 3 shows the effects of adding judgements concerning education/training/experience compatibilities to the measure of occupational closeness. Again, adding these characteristics has little effect on the macro results.

Overall, the results in Table 7.3.1 point to the idea that rectifying inequitable wage disparities without adverse employment effects requires policies such as negative tax rates that raise incomes for low-wage workers without increasing costs to employers

7.3. Dynamic effects

Charts 7.3.1 to 7.3.3 show the deviation paths for key variables in simulation 4.

Chart 7.3.1. Real GDP, factor inputs and the average real wage: the effects of a 10% increase in real wage rates for low-wage occupations under mobility specification 4 (Percentage deviations from baseline)

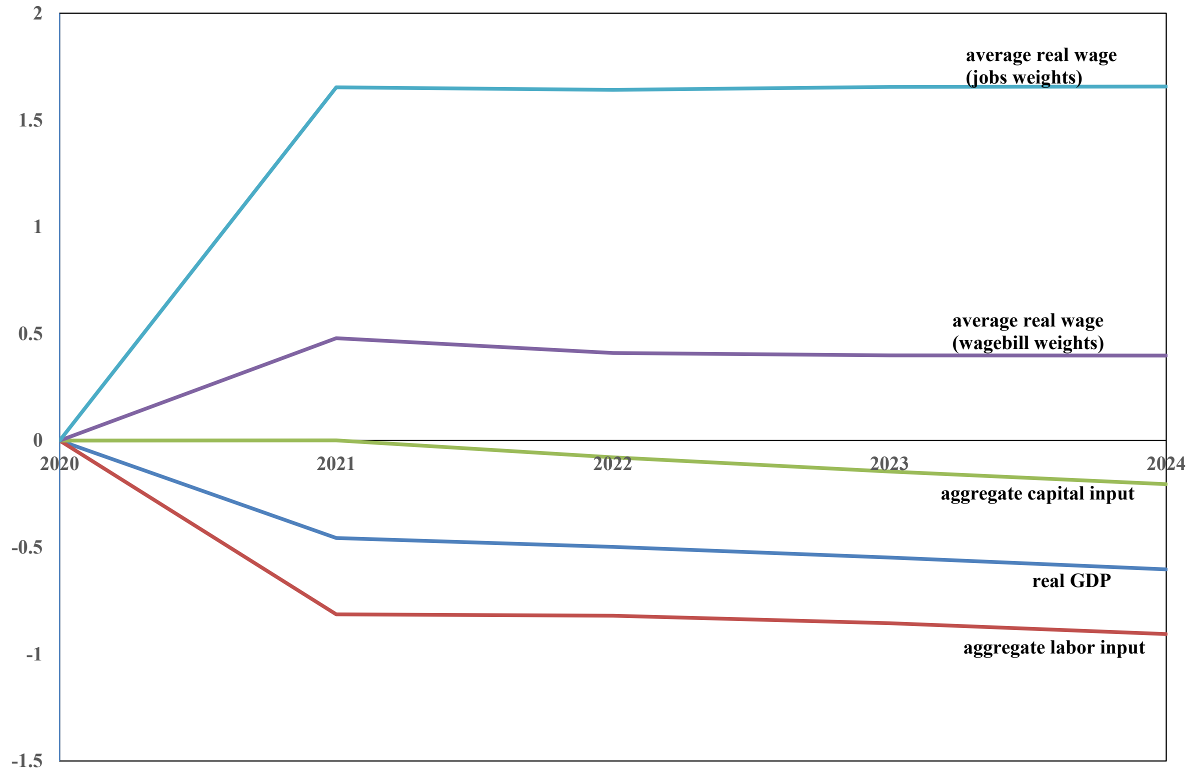


Chart 7.3.1 gives results for the average real wage rate measured in two ways: as averages of occupational real wage deviations with wagebill weights and with jobs weights. With jobs weights, the average wage increase is much higher than with wagebill weights because, as mentioned earlier, low-wage occupations account for a much greater share of total jobs than of the total wagebill.

The three charts show large negative deviations in the first year (2021) for: aggregate labor input and real GDP (Chart 7.3.1); employment in low-wage occupations (Chart 7.3.2); and employment and labor supply in other occupations (Chart 7.3.3). Beyond the first year there is gradual further deterioration in these variables.

With a higher average wage cost per unit of effective labor (the wagebill measure), lower rates of return and less investment, the capital stock must eventually adjust to a lower level. But this takes time, making capital stock a slow-adjusting variable (Chart 7.3.1). The continuing decline in the capital stock puts downward pressure on employment. Thus, beyond the first year, we see gradual further declines in employment for both low wage and other occupations (Charts 7.3.2 and 7.3.3).

Chart 7.3.2. Labor supply, employment & average real wage for low-wage occs: the effects of a 10% increase in real wage rates for low-wage occupations under mobility specification 4 (Percentage deviations from baseline)

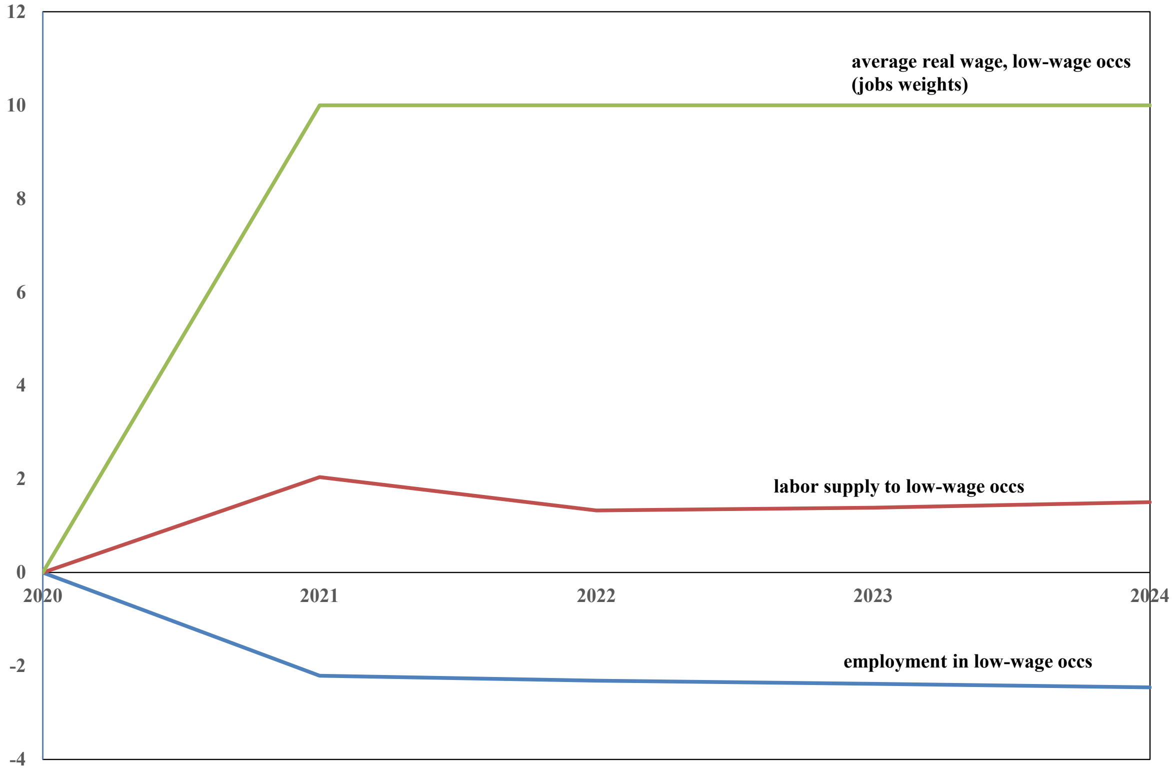
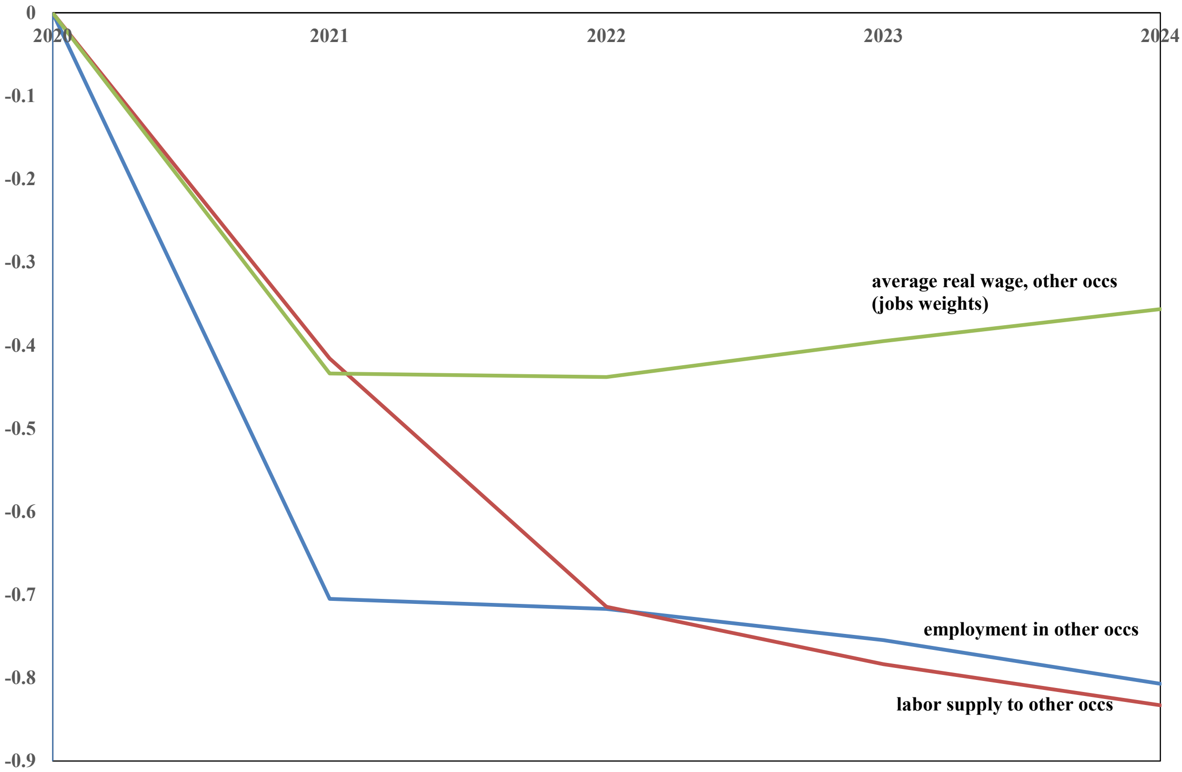


Chart 7.3.3. Labor supply, employment & average real wage for other occs: the effects of a 10% increase in real wage rates for low-wage occupations under mobility specification 4 (Percentage deviations from baseline)



The usual mechanism in CGE models for bringing employment back to baseline after a negative shock is reduction in real wages. This mechanism doesn't work in the current simulation for two reasons. First, the wage increase for low-wage occupations is sustained: it doesn't respond to the forces of demand and supply. As illustrated in Chart 7.3.2, employment in these occupations is permanently reduced and supply to them is permanently increased, but real wage rates are stuck at 10 per cent above baseline. Second, with the labor module in place, our model recognizes the connection between unemployment and labor supply. The initial increase in unemployment caused by the wage increases for low-wage occupations reduces labor supply, implying that even if demand and supply for labor are brought back to equality this will occur at employment levels below the baseline path.

Finally, one aspect of the results that seems strange is the flatness of the average wage paths in Chart 7.3.1 beyond 2022. In Chart 7.3.2, the deviation path for the average real wage rate in low-wage occupations is flat (the sustained 10 per cent increase). In Chart 7.3.3 the deviation path for the average real wage rate in other occupations turns upwards beyond 2022. So we expected the aggregate average wage paths in Chart 7.3.1 to also turn upwards. We found that changes in the employment and wagebill shares of low-wage workers in total employment and total wagebill explain the rather curious flatness result.

Perhaps more important than this quirky behavior of the paths of the aggregate average real wage measures is the upward turn of the average real wage path for other occupations in Chart 7.3.3. This reflects a tightening of the labor market as supply is reduced by discouraged worker effects and drops below demand. This is a temporary effect. If we were to continue the simulation over a longer period, we would expect supply and demand to converge but at a level below baseline.

8. Concluding remarks

The creation of detailed occupation-industry employment and wagebill matrices for the U.S. compatible with BEA input-output data has been a major task. But now that the work has been completed there should be considerable benefits. With these matrices embedded in USAGE-OCC we anticipate a wide range of applications including:

- baseline projections of employment identified by occupation and training requirements. The projections could complement those prepared by the BLS. Generating projections from USAGE-OCC would allow testing of the effects on occupational employment of different scenarios for demographic, technology and trade variables.
- analyses of the effects of policies on employment by occupation. The range of policies could include the whole suite of those subject to CGE applications in the areas of trade, environment, public finance, industry regulation and micro-economic reform. Generating results at the detailed occupational level would be a major step towards working out the income-distribution implications of policies.

While USAGE-OCC is an operational model ready for application, several improvements could be made. As set out in Appendices 1 and 2, we see considerable potential for making further use of BLS data to inform the specifications in USAGE-OCC of occupational mobility. We also think that the regional dimension is important in labor-markets. We have prepared a regional version of USAGE-OCC but further work on the data and solution algorithm will be necessary to bring this preliminary version to an operational standard.

Another area for future work is documentation. This report is a comprehensive description of the data sources, data manipulations, and the theoretical structure of USAGE-OCC. However, we have not created a user friendly code for the model. The current code is an early beta version. It includes non-transparent segments designed largely for computing efficiency but not for explaining the model. It also includes some dead ends reflecting research paths that were eventually dropped. Cleaning up the code and producing teaching material to facilitate its transfer will be necessary for USAGE-OCC to reach its full potential as a policy tool.

References

Böhringer, C., S. Boeters and M. Fiel (2005), "Taxation and unemployment: an applied general equilibrium approach for Germany", *Economic Modelling*, 22, pp. 81-108.

Dixon, P.B. and Maureen T. Rimmer (2009), "Restriction or Legalization? Measuring the economic benefits of immigration reform", Trade Policy Analysis paper no. 40, Cato Institute, Washington DC, August, pp. 22.

Dixon, P.B. and Maureen T. Rimmer (2010), "U.S. imports of low-skilled labor: restrict or liberalize?", chapter 5, pp. 103-51 in John Gilbert (editor) *New Developments in Computable General Equilibrium Analysis of Trade Policy*, Volume 7 of H. Beladi and K. Choi (series editors) *Frontiers of Economics and Globalization*, Emerald Publishing, UK.

Dixon, P.B. and M.T. Rimmer (2018) "Creating a labor-market module for USAGE-TERM: illustrative application, theory and data", June, CoPS working paper G-283 available at https://www.copsmodels.com/elecpapr/g-283.htm

Dixon, P.B. and M.T. Rimmer (2021), "Immigration reform scenarios for U.S. agriculture", chapter 16, pp. 517-57 in *Policy Analysis and Modeling of the Global Economy: A Festschrift Celebrating Thomas Hertel*, World Scientific, pp. xvii +576.

Dixon, P.B., Martin Johnson and Maureen T. Rimmer (2011), "Economy-wide effects of reducing illegal immigrants in U.S. employment" *Contemporary Economic Policy*, Vol. 29(1), January, pp. 14-30.

Dixon, P.B., M.T. Rimmer and B.W. Roberts (2014), "Restricting employment of low-paid immigrants: a general equilibrium assessment of the social welfare implications for legal U.S. wage-earners" *Contemporary Economic Policy*, Vol. 32(3), pp. 639-52.

Layard, R., S. Nickell and R. Jackman (1994), *Employment crisis*, Oxford University Press, Oxford UK.

Zahniser, S. T. Hertz, P.B. Dixon and M.T. Rimmer (2012), "Immigration policy and its possible effects on U.S. agriculture and the market for hired farm labor: a simulation analysis", *American Journal of Agricultural Economics*, Vol. 94(2), January, pp. 477-82.

Appendix 1. An attempt to use BLS transition data

A1.1. Calculation of transition matrices

The BLS provides data [CPS publication at https://www.bls.gov/webapps/legacy/cpsflowstab.htm] that show transitions from month to month in labor-force categories identified as Employed, Unemployed, Not in the labor force and Marginal. This last category refers to people who come into working age (turned 16) during the month or arrive as migrants and to people who die or leave the U.S.

We examined BLS data for the period January 2011 (denoted byY2011M01) to May 2021 (denoted byY2021M05). For each month we manipulated the data into flow matrices of the form given in Table A1.1.1. The table shows that in February 2019, there were 156.166 million people employed in the U.S. The first row shows what these 156.166m people did in March 2019: 150.434m stayed employed; 1.406m became unemployed; 4.301m left the labor force; and 0.025m died or left the U.S.

The second row shows that 6.625m were unemployed in February 2019. Of these people, 1.770m were employed in March, 3.284m remained unemployed, 1.569m left the labor force, and 0.002m had died or left the U.S.

The third row shows transitions for people who were not in the labor force in February 2019.

The fourth row shows that 0.374m people came into the working-age population (16+) between February and March. Of these, 0.098m were employed in March, 0.012m were unemployed and 0.264m were not in the labor force.

We are interested in using data such as that in Table A1.1.1 to parameterize annual employment transitions in USAGE.

The first difficulty we had was with the category Not in the labor force (NLF). This category combines genuinely retired people who have low probability of taking a job with people who have dropped out the labor force temporarily for reasons such as pregnancy, child rearing and education. It also includes people who are not actively looking for work but who will take a job if it becomes available.

We separated NLF into Retired and Want work. For the Retired group we assume that there is no flow back to the labor force. In making the separation we initially referred to BLS data that splits NLF into “Persons who currently want a job” and those who don’t. This suggested an approximate 95:5 split of NLF people into Retired and Want work. However, our concept of Want work is broader than the BLS category for “Persons who currently want a job”. It includes people who will return to the workforce after a temporary absence for pregnancy, child rearing, education, etc. In any case the observed flows of NLF to labor force categories for some months are too high to make 95:5 split legitimate. To deal with this problem we changed the split to approximately 88:12. We did this by setting

$$R(Y2011M01) = NLF(Y2011M01) * 0.88 \qquad (A1.1.1)$$

$$R(t) = R(t-1) * 1.00130 \quad \text{for } t = Y2011M02 \text{ to } Y2021M05 \qquad (A1.1.2)$$

and

$$W(t) = NLF(t) - R(t) \quad \text{for } t = Y2011M01 \text{ to } Y2021M05 \qquad (A1.1.3)$$

Equation (A1.1.2) imposes smooth growth on the number of retired people at the rate of 0.00130 per month. This is the average rate of growth in the BLS data for NLF net of their category “Persons who currently want a job” over the period Y2011M01 to Y2021M05. By imposing smooth growth for R, we assume that the month-to-month fluctuations in the growth of NLF are fluctuations in the growth of W.

Table A1.1.2 shows the February-March flow matrix for 2019 after the separation of NLF into R and W.

For each month, we calculated the transition matrix, T(t). The i,jth component is the share of the people who were in category j (excludes Marginal) in month t-1 who were in category i (excludes Marginal) in month t. The T matrix for March 2019 is given in Table A1.1.3. It shows that: 26.7 per cent of the people who were unemployed in February 2019 were employed in March 2019; 43.2 per cent of people who wanted a job in February 2019 were employed in March 2019 while 17.5 per cent of these people were reclassified as unemployed in March 2019.

Using the T matrix, we can reproduce the E, U, W and R values for month t by using the equation

$$X(t) = T(t) * X(t-1) + MI(t) \quad \text{for t = Y2011M02 to Y2021M05} \qquad (A1.1.4)$$

where

X(t) is the column vector formed from E(t), U(t), W(t) and R(t); and

MI(t) is the vector of inflows (Marginal flows) into E, U, W and R in month t.

Transition matrices for multiple-month periods

From (A1.1.4), we obtain

$$X(t) = T(t) * T(t-1) * X(t-2) + T(t) * MI(t-1) + MI(t) \qquad (A1.1.5)$$

In general

$$X(t) = \left[\prod_{j=0}^{\tau-1} T(t-j) \right] * X(t-\tau) + \sum_{s=0}^{\tau-1} \left[\prod_{j=0}^{s-1} T(t-j) \right] * MI(t-s) \qquad (A1.1.6)$$

where $\prod_{j=0}^{-1} z(j)$ is defined as being 1.

We interpret $\prod_{j=0}^{\tau-1} T(t-j)$ as a τ-month transition matrix. Table A1.1.4 shows the transition matrix for the 12 month period December 2018 to December 2019. This matrix tells us that 89.3 per cent of the people who were employed in December 2018 were employed in December 2019. 89.0 per cent of the people who were unemployed in December 2018 were employed in December 2019.

The 89.0 number seems very high. Is it realistic? The key assumption underlying this number is that once a person moves into unemployment their chances of coming out of unemployment and moving to any other category are exactly the same as those for any other person in unemployment. There is no recognition of people getting stuck in unemployment.

Table A1.1.1. Labor-force transitions, Feb-March 2019 ('000s)

	Emp	Unemp	NLF	Marginal	Total Feb 2019
Emp	150434	1406	4301	25	156166
Unemp	1770	3284	1569	2	6625
NLF	4139	1680	89580	201	95600
Marginal	98	12	264	0	374
Total March 2019	156441	6382	95714	228	

Table A1.1.2. Labor-force transitions with disaggregated NLF, Feb-March 2019 ('000s)

	Emp	Unemp	Want work	Retired	Marginal	Total Feb 2019
Emp	150434	1406	4019	282	25	156166
Unemp	1770	3284	1557	12	2	6625
Want work	4139	1680	3751	17	2	9588
Retired	0	0	0	85812	199	86012
Marginal	98	12	264	0	0	374
Total March 2019	156441	6382	9591	86123	228	

Table A1.1.3. Transition Matrix, March 2019

	Emp E	Unemp U	Want work W	Retired R
E	$\frac{150434}{156166}$	$\frac{1770}{6625}$	$\frac{4139}{9588}$	0
U	$\frac{1406}{156166}$	$\frac{3284}{6625}$	$\frac{1680}{9588}$	0
W	$\frac{4019}{156166}$	$\frac{1557}{6625}$	$\frac{3751}{9588}$	0
R	$\frac{282}{156166}$	$\frac{12}{6625}$	$\frac{17}{9588}$	$\frac{85812}{86012}$

=

E	U	W	R
0.963	0.267	0.432	0.000
0.009	0.496	0.175	0.000
0.026	0.235	0.391	0.000
0.002	0.002	0.002	0.998

Table A1.1.4. 12-month Transition Matrix, Dec 2018 to Dec 2019

		E	U	W	R
E		0.893	0.890	0.891	0.000
U		0.030	0.031	0.031	0.000
W		0.048	0.049	0.049	0.000
R		0.023	0.023	0.023	0.969

How long do people in state j in December 2018 spend in state i during 2019?

Table A1.1.5 shows 12 transition matrices: Dec 2018 to Jan 2019; Dec 2018 to Feb 2019; …, Dec 2018 to Dec 2019. Table A1.1.6 is an average of the 12 matrices in Table A1.1.5.

We interpret Table A1.1. 6 as showing what people in various states in December 2018 do during 2019. The first entry (E,E) in Table A1.1.6 tells us that people who were employed in December 2018 had a 91.1 per cent employment rate in 2019. This could mean that 91.1 per cent of these people were employed throughout the year and 8.9 per cent were not employed at any time during the year. Alternatively it could mean that all the people who were employed in December 2018 were in employment for 91.1 per cent in the months in 2019. More generally, it means that 91.1 per cent of the potential labor from the group of people employed in Dec 2018 is used in employment during 2019.

Going down the first column of Table A1.1.6 tells us that people who were employed in December 2018: had an unemployment rate of 2.7 per cent in 2019; were not in the labor force but were wanting work for 4.4 per cent of 2019; and were retired for 1.3 per cent of 2019. The sum of the entries in the first column of Table A1.1.6 is 0.995, implying that 0.5 per cent of the potential labor from the people who were employed in December 2018 was lost in 2019 through death or departure from the U.S.

The second column of Table A1.1.6 says that people who were unemployed in December 2018 were employed for 75.6 per cent of the months in 2019. This seems a high number to us. Again we should emphasize that our calculations do not recognize the possibility of people becoming progressively less effective suppliers of labor as their length of unemployment increases.

[Calculations above are in C:/dixon /consult/Commerce/2021/Employment/BLS data/Bls3.tab run with BLS3.cmf]

A1.2. Calculation of vacancies and attempt to relate labor-market flows to vacancies

We calculate vacancies [V(t)] in month t as employment less employment of incumbents:

$$V(t) = E(t) - \left[E(t-1) - E2U(t) - E2W(t) - E3R(t) - E2M(t)\right] \quad . \tag{A1.2.1}$$

Next we specify offers from non-employment categories to employment according to

$$OU2E(t) = \alpha_{U2E}(t) * U(t-1) \tag{A1.2.2}$$

$$OW2E(t) = \alpha_{W2E}(t) * W(t-1) \tag{A1.2.3}$$

$$OM2E(t) = \alpha_{M2E}(t) * MI(t) \tag{A1.2.4}$$

Finally, we specify actual flows from each of the categories of U, W and M according to the category's share in offers:

Table A.1.5. Transition matrices starting Dec 2018 for 1-month, 2-months, etc

Dec 2018 to Jan 2019

	E	U	W	R
E	0.953	0.238	0.414	0.000
U	0.013	0.540	0.180	0.000
W	0.028	0.215	0.400	0.000
R	0.003	0.003	0.003	0.995

Dec 2018 to Feb 2019

	E	U	W	R
E	0.934	0.490	0.644	0.000
U	0.020	0.287	0.157	0.000
W	0.037	0.214	0.191	0.000
R	0.005	0.005	0.005	0.992

Dec 2018 to Mar 2019

	E	U	W	R
E	0.921	0.641	0.745	0.000
U	0.025	0.184	0.117	0.000
W	0.043	0.164	0.128	0.000
R	0.007	0.007	0.007	0.990

Dec 2018 to Apr 2019

	E	U	W	R
E	0.914	0.734	0.801	0.000
U	0.024	0.116	0.079	0.000
W	0.050	0.138	0.107	0.000
R	0.009	0.009	0.009	0.988

Dec 2018 to May 2019

	E	U	W	R
E	0.909	0.802	0.842	0.000
U	0.027	0.082	0.061	0.000
W	0.050	0.102	0.083	0.000
R	0.010	0.010	0.010	0.985

Dec 2018 to Jun 2019

	E	U	W	R
E	0.907	0.847	0.870	0.000
U	0.032	0.068	0.055	0.000
W	0.044	0.068	0.059	0.000
R	0.012	0.012	0.012	0.983

Dec 2018 to Jul 2019

	E	U	W	R
E	0.906	0.873	0.885	0.000
U	0.035	0.058	0.049	0.000
W	0.040	0.050	0.046	0.000
R	0.014	0.014	0.014	0.980

Dec 2018 to Aug 2019

	E	U	W	R
E	0.899	0.880	0.887	0.000
U	0.033	0.045	0.041	0.000
W	0.047	0.053	0.051	0.000
R	0.016	0.016	0.016	0.978

Dec 2018 to S 2019

	E	U	W	R
E	0.900	0.889	0.893	0.000
U	0.030	0.036	0.034	0.000
W	0.048	0.052	0.050	0.000
R	0.018	0.018	0.018	0.976

Dec 2018 to Oct 2019

	E	U	W	R
E	0.901	0.894	0.897	0.000
U	0.030	0.034	0.032	0.000
W	0.044	0.047	0.046	0.000
R	0.019	0.019	0.019	0.974

Dec 2018 to Nov 2019

	E	U	W	R
E	0.897	0.893	0.895	0.000
U	0.030	0.032	0.031	0.000
W	0.046	0.047	0.047	0.000
R	0.021	0.021	0.021	0.971

Dec 2018 to Dec 2019

	E	U	W	R
E	0.893	0.890	0.891	0.000
U	0.030	0.031	0.031	0.000
W	0.048	0.049	0.049	0.000
R	0.023	0.023	0.023	0.969

Table A1.1.6. State in Dec 2018 (column), proportion spent by state 2019 (row)

	E	U	W	R
E	0.911	0.756	0.805	0.000
U	0.027	0.126	0.072	0.000
W	0.044	0.100	0.105	0.000
R	0.013	0.013	0.013	0.982

$$U2E(t) = \frac{OU2E(t)}{\sum_{k=U,W,M} Ok2E(t)} * V(t) \tag{A1.2.5}$$

$$W2E(t) = \frac{OW2E(t)}{\sum_{k=U,W,M} Ok2E(t)} * V(t) \tag{A1.2.6}$$

and

$$M2E(t) = \frac{OM2E(t)}{\sum_{k=U,W,M} Ok2E(t)} * V(t) \quad . \tag{A1.2.7}$$

We were hoping to estimate the α's by assuming that they are 50 per cent greater, for example, than the observed maximum values for U2E(t)/U(t), W2E(t)/W(t) and M2E/MI(t)

We were hoping to specify E2U(t) and E2W(t) as functions of employment growth.

However, we couldn't find any sensible relationship between monthly employment growth and flows into and out of U and W. We are now out of time and will have to move on.

[These calculations are on the end of Bls3.tab run with BLS3.cmf mentioned above]

Appendix 2. Developing transition matrices using BLS occupational and industry projections

We put considerable research time into investigating the possibility of using BLS projections for occupations and industries to inform our base-year setting for the 4-dimension labor-supply matrix, $L_0(o,\ell;oo,\ell\ell)$. [8] We didn't bring this research to a successful conclusion and eventually we adopted the approach described in section 6. Nevertheless, we think using the BLS projections is potentially a better approach. Consequently we are recording in this appendix for use in future research the progress we made.

A2.1. Preliminary calculations at the 22-occupation level

We illustrate our planned approach at the 22-occupation level.

Table A2.1.1 shows the projection data at the 22-order level for transitions in 2019-20 derived as though there was smooth growth in the period 2019-2029.

The shaded cells in Table A2.1.1 were deduced directly from the BLS projections (in Table 1.10 of the employment projections data).

The last column of Table A2.1.1 shows employment by occupation in 2019. Looking across an occupational row we see what happened to these worker in 2020. For example, in 2019 there were 10.6972 million workers in Management occupations (first row, last column). Of these, 9.9047m were projected to stay in Management occupations in 2020 (the diagonal entry), and 0.2878m where projected to leave the workforce (second last column). Thus, 0.504m workers (=10.6972 – 0.2878 – 9.9047) were projected to change occupations. The table shows our initial calculation (to be explained below) of what occupations these 0.504m workers took up: 0.0300 to Business & finance, 0.0162m to Computing & mathematics occupations, etc.

In Table A2.1.1 we calculated the off-diagonal entries by assuming that workers who change occupations between 2019 and 2020 are distributed across other occupations in 2020 according to the size of employment in these occupations in 2020. For example, 5.9% of workers in 2020 outside management are employed in Business & finance [0.059 = 9.0639/(163.3995 – 10.7477), see second last row]. Thus we assume that of the 0.504m Management workers who change occupations, 0.0300m go to Business & finance [0.0300 = 0.059* 0.504].

The second last row in Table A2.1.1 shows employment by occupation in 2020. New entrants for each occupation were calculated as the difference between 2020 employment for the occupation and the sum of the entries for transition into the occupation from employment in 2019. For example, new entries to Management is 0.1886m (third last row), calculated as 10.7477m minus (9.9047m + 0.0355m + … + 0.0635m). Notice that the new entrants to Health practitioners is negative, -0.0062m. This indicates a problem with our calculation of the off-diagonals: too many people are moving into the occupation Health practitioners from other occupations.

[8] BLS detailed employment projections data are available at https://www.bls.gov/emp/tables.htm
[click on the link *All occupational tables in a single file (XLSX)*]

Table A2.1.1. Transitions 2019-2020 assuming smooth growth from 2019-2029 (‘000s of people): simple calculation of off-diagonals

	1 Manage	2 BusFin	3 CompMath	4 ArchEng	5 LifePhysSocS	6 CommSocServ	7 Legal	8 Education	9 ArtEntSprtMd	10 HealthPrac	11 HealthSupp	12 ProtectServ	13 FoodPrepServ	14 BuildMaint	15 PersonalCare	16 Sales	17 OfficeAdmin	18 FarmFishFor	19 Construct	20 InstalRepair	21 Production	22 Transport	Totals	Exit	Emp 2019
1 Manage	9904.7	30.0	16.2	9.0	4.9	9.4	4.4	32.4	9.7	30.5	23.7	12.0	45.8	18.8	15.7	51.2	67.9	3.7	24.4	20.3	31.1	43.6	10409.4	287.8	10697.2
2 BusFin	35.5	8250.9	16.2	9.0	4.8	9.4	4.4	32.3	9.7	30.5	23.7	12.0	45.8	18.8	15.7	51.2	67.9	3.7	24.4	20.3	31.1	43.6	8760.9	255.4	9016.3
3 CompMath	16.2	13.6	4521.0	4.1	2.2	4.3	2.0	14.7	4.4	13.9	10.8	5.5	20.9	8.6	7.2	23.3	30.9	1.7	11.1	9.2	14.1	19.8	4759.4	85.7	4845.1
4 ArchEng	8.0	6.8	3.7	2542.8	1.1	2.1	1.0	7.3	2.2	6.9	5.3	2.7	10.3	4.2	3.5	11.6	15.3	0.8	5.5	4.6	7.0	9.8	2662.6	66.3	2728.9
5 LifePhysSocS	6.1	5.1	2.8	1.6	1340.2	1.6	0.8	5.5	1.7	5.2	4.1	2.1	7.9	3.2	2.7	8.8	11.6	0.6	4.2	3.5	5.3	7.5	1432.0	28.3	1460.3
6 CommSocServ	11.6	9.8	5.3	2.9	1.6	2522.7	1.4	10.5	3.2	9.9	7.7	3.9	14.9	6.1	5.1	16.7	22.1	1.2	7.9	6.6	10.1	14.2	2695.6	102.1	2797.7
7 Legal	3.2	2.7	1.4	0.8	0.4	0.8	1252.8	2.9	0.9	2.7	2.1	1.1	4.1	1.7	1.4	4.6	6.1	0.3	2.2	1.8	2.8	3.9	1300.6	35.0	1335.6
8 Education	27.7	23.4	12.7	7.1	3.8	7.3	3.5	8938.8	7.6	23.8	18.5	9.4	35.8	14.7	12.3	40.0	53.0	2.9	19.1	15.9	24.3	34.0	9335.4	409.3	9744.7
9 ArtEntSprtMd	11.6	9.8	5.3	3.0	1.6	3.1	1.4	10.6	2637.6	10.0	7.7	3.9	15.0	6.1	5.1	16.7	22.2	1.2	8.0	6.6	10.2	14.2	2810.9	112.7	2923.6
10 HealthPrac	17.2	14.5	7.8	4.4	2.3	4.5	2.1	15.6	4.7	8646.3	11.4	5.8	22.1	9.1	7.6	24.7	32.8	1.8	11.8	9.8	15.0	21.0	8892.4	241.3	9133.7
11 HealthSupp	28.4	23.9	12.9	7.2	3.9	7.5	3.5	25.8	7.7	24.3	6171.9	9.6	36.6	15.0	12.6	40.9	54.2	2.9	19.5	16.2	24.8	34.8	6584.1	429.3	7013.4
12 ProtectServ	13.8	11.6	6.3	3.5	1.9	3.6	1.7	12.5	3.8	11.8	9.2	3237.5	17.8	7.3	6.1	19.9	26.3	1.4	9.5	7.9	12.1	16.9	3442.3	173.6	3615.9
13 FoodPrepServ	91.9	77.5	41.9	23.4	12.5	24.2	11.5	83.7	25.1	78.8	61.3	31.0	11449.4	48.7	40.7	132.5	175.6	9.5	63.1	52.5	80.4	112.7	12727.7	1033.6	13761.3
14 BuildMaint	24.9	21.0	11.4	6.3	3.4	6.6	3.1	22.7	6.8	21.4	16.6	8.4	32.1	4970.0	11.0	35.9	47.6	2.6	17.1	14.2	21.8	30.5	5335.5	328.5	5664.0
15 PersonalCare	23.7	20.0	10.8	6.0	3.2	6.3	3.0	21.6	6.5	20.4	15.8	8.0	30.6	12.6	4043.2	34.2	45.3	2.5	16.3	13.6	20.8	29.1	4393.5	330.6	4724.1
16 Sales	79.5	67.1	36.3	20.2	10.9	21.0	9.9	72.4	21.7	68.2	53.1	26.8	102.6	42.1	35.2	13638.9	151.9	8.3	54.6	45.5	69.6	97.5	14733.2	792.1	15525.3
17 OfficeAdmin	86.5	72.9	39.4	22.0	11.8	22.8	10.8	78.7	23.6	74.1	57.7	29.2	111.5	45.8	38.3	124.6	18519.6	9.0	59.4	49.4	75.7	106.0	19668.8	964.2	20633.0
18 FarmFishFor	7.6	6.4	3.5	1.9	1.0	2.0	0.9	6.9	2.1	6.5	5.1	2.6	9.8	4.0	3.4	11.0	14.5	956.8	5.2	4.3	6.7	9.3	1071.6	45.0	1116.6
19 Construct	33.3	28.1	15.2	8.5	4.5	8.8	4.2	30.4	9.1	28.6	22.2	11.2	43.0	17.6	14.8	48.0	63.7	3.5	6644.8	19.1	29.2	40.9	7128.6	220.5	7349.1
20 InstalRepair	23.6	19.9	10.8	6.0	3.2	6.2	3.0	21.5	6.4	20.3	15.8	8.0	30.5	12.5	10.5	34.1	45.1	2.5	16.2	5588.6	20.7	29.0	5934.3	193.7	6128.0
21 Production	40.7	34.3	18.6	10.4	5.6	10.7	5.1	37.1	11.1	34.9	27.2	13.7	52.5	21.6	18.0	58.7	77.8	4.2	27.9	23.3	8518.4	49.9	9101.6	345.4	9447.0
22 Transport	63.5	53.5	29.0	16.2	8.7	16.7	7.9	57.8	17.3	54.4	42.4	21.4	81.9	33.6	28.1	91.5	121.3	6.6	43.6	36.3	55.6	11648.5	12535.9	598.9	13134.8
New entrants	188.6	261.1	75.4	20.0	33.6	131.1	3.8	246.9	108.4	-6.2	558.5	159.8	1641.4	369.7	422.2	976.0	864.2	88.8	283.1	175.7	318.2	763.0	7683.2		
Emp 2020	10747.7	9063.9	4903.8	2736.4	1467.1	2832.6	1342.4	9788.8	2931.0	9217.1	7171.9	3625.4	13862.1	5692.0	4760.5	15495.0	20537.0	1116.5	7378.7	6145.3	9404.7	13179.7	163399.5		
Totals																								7079.3	162795.6

The calculation of the off-diagonal terms in Table A2.1.1 doesn't take account of the relative closeness or similarity between occupations. We use BLS data to introduce closeness.

Wage differences

In Table A2.1.2 we modify the calculation of off-diagonal flows by assuming that these flows are a diminishing function of wage differences. That is, we assume that it relatively unlikely that a person can move between two occupations with sharply different wage rates. To introduce this idea we start by forming an indicator of occupational wage differences:

$$\mathrm{WDiff}(i,j) = \frac{\mathrm{ABS}\left[W(i) - W(j)\right]}{\left(W(i) + W(j)\right)/2} \qquad \text{(A2.1.1)}$$

where W(i) and W(j) are median wages in occupations i and j. Then, we revise the off-diagonals from Table A2.1.1

$$\mathrm{ODFLOW2}(i,j) = \frac{\mathrm{ODFLOW1}(i,j)}{\mathrm{EXP}(\alpha * \mathrm{WDiff}(i,j))} * N(i) \quad \text{for all i, and all } j \neq i \qquad \text{(A2.1.2)}$$

where

ODFLOW1(i,j) and ODFLOW2(i,j) are the off-diagonal i to j flows in Tables A2.1.1 and A2.1.2;

α is a positive parameter; and

N(i) is a normalizing factor set so that

$$\sum_{j \neq i} \mathrm{ODFLOW2}(i,j) = \sum_{j \neq i} \mathrm{ODFLOW1}(i,j) \quad \text{for all i,} \qquad \text{(A2.1.3)}$$

Initially we set $\alpha = 1$, but we judged that this gave insufficient impact on the off-diagonal flows. In generating Table A2.1.2 we set $\alpha = 2$.

Perhaps fortuitously, all of the entries in Table A2.1.2 for new entrants are positive. However, new entrants in Table A2.1.2 for Management are quite high, about 5.3 per cent of Management employment. One possibility is to wind this flow back close to zero and rebalance the table via RAS.

An urgent problem now is to work out how the BLS are handling involuntary unemployment. Is this part of Labor force exit? We don't think so. We think that some of the 0.504m Managers who stop being Managers but stayed in the workforce should be allocated to unemployment rather than being entirely allocated to other occupations.

A2.2. Calculations at the 233-occupation level

We applied the two methods from section A2.1 to our 233-order occupation data. The wage rates required for the second method are shown in column (4) of Table 3.3.1.

Table A2.1.2. Transitions 2019-2020 assuming smooth growth from 2019-2029 ('000s of people): taking account of wage differences for off-diagonals

	1 Manage	2 BusFin	3 CompMath	4 ArchEng	5 LifePhysSocS	6 CommSocServ	7 Legal	8 Education	9 ArtEntSprtMd	10 HealthPrac	11 HealthSupp	12 ProtectServ	13 FoodPrepServ	14 BuildMaint	15 PersonalCare	16 Sales	17 OfficeAdmin	18 FarmFishFor	19 Construct	20 InstalRepair	21 Production	22 Transport	Totals	Exit	Emp 2019
1 Manage	9904.7	62.6	53.6	24.8	9.5	9.2	12.7	37.4	11.5	59.7	11.5	10.2	18.1	9.1	7.0	26.6	47.7	1.8	24.8	20.8	20.8	25.3	10409.4	287.8	10697.2
2 BusFin	42.1	8250.9	27.5	18.5	12.2	11.1	8.7	46.3	14.3	77.1	12.3	12.1	18.3	9.7	7.3	28.8	54.8	1.9	30.2	25.3	23.6	28.0	8760.9	255.4	9016.3
3 CompMath	37.9	28.9	4521.0	11.5	4.4	4.1	5.9	16.8	5.2	27.5	4.8	4.5	7.4	3.8	2.9	11.2	20.7	0.7	11.1	9.3	9.0	10.8	4759.4	85.7	4845.1
4 ArchEng	13.7	15.1	9.0	2542.8	2.3	2.1	2.9	8.7	2.7	14.4	2.4	2.3	3.7	1.9	1.5	5.7	10.6	0.4	5.7	4.8	4.6	5.5	2662.6	66.3	2728.9
5 LifePhysSocS	6.1	11.7	4.0	2.7	1340.2	1.8	1.3	7.7	2.4	12.7	2.0	2.0	3.0	1.6	1.2	4.7	9.0	0.3	5.0	4.2	3.9	4.6	1432.0	28.3	1460.3
6 CommSocServ	4.5	8.1	2.8	1.9	1.4	2522.7	0.9	16.4	4.8	8.8	5.9	6.2	8.4	4.7	3.5	14.0	27.8	0.9	14.4	11.9	11.9	13.9	2695.6	102.1	2797.7
7 Legal	5.7	5.8	3.7	2.3	0.9	0.8	1252.8	3.3	1.0	5.5	0.9	0.9	1.4	0.7	0.6	2.2	4.1	0.1	2.2	1.8	1.8	2.1	1300.6	35.0	1335.6
8 Education	14.1	26.0	9.0	6.0	4.5	12.6	2.8	8938.8	15.4	28.2	13.1	13.7	18.9	10.4	7.7	31.0	61.1	2.0	34.4	28.9	26.2	30.6	9335.4	409.3	9744.7
9 ArtEntSprtMd	5.9	10.8	3.7	2.5	1.9	5.0	1.2	20.9	2637.6	11.8	5.2	5.4	7.5	4.1	3.1	12.3	24.1	0.8	13.6	11.4	10.3	12.1	2810.9	112.7	2923.6
10 HealthPrac	18.6	35.6	12.1	8.1	6.1	5.6	3.8	23.2	7.2	8646.3	6.1	6.1	9.1	4.8	3.6	14.3	27.4	0.9	15.1	12.7	11.8	14.0	8892.4	241.3	9133.7
11 HealthSupp	5.5	8.7	3.3	2.1	1.5	5.7	1.0	16.5	4.8	9.3	6171.9	8.6	50.4	28.5	21.0	70.3	61.9	5.5	14.3	11.9	30.3	51.1	6584.1	429.3	7013.4
12 ProtectServ	4.5	8.0	2.8	1.9	1.4	5.7	0.9	16.1	4.7	8.7	8.0	3237.5	11.4	6.4	4.7	19.1	38.1	1.2	14.1	11.7	16.3	19.0	3442.3	173.6	3615.9
13 FoodPrepServ	19.2	28.9	11.1	7.1	5.0	18.3	3.4	53.2	15.5	31.0	112.4	27.4	11449.4	89.3	84.7	219.9	194.9	17.8	45.8	38.0	95.2	160.2	12727.7	1033.6	13761.3
14 BuildMaint	4.8	7.6	2.8	1.8	1.3	5.0	0.9	14.4	4.2	8.1	31.3	7.5	44.0	4970.0	18.4	61.2	53.8	4.8	12.5	10.3	26.3	44.5	5335.5	328.5	5664.0
15 PersonalCare	4.5	7.0	2.7	1.7	1.2	4.6	0.8	13.2	3.8	7.5	28.4	6.8	51.3	22.6	4043.2	55.5	49.0	4.5	11.4	9.4	23.9	40.4	4393.5	330.6	4724.1
16 Sales	16.6	26.6	9.9	6.4	4.6	17.8	3.0	51.1	14.9	28.7	91.8	26.8	128.7	72.7	53.7	13638.9	192.5	14.0	44.4	36.8	94.2	159.2	14733.2	792.1	15525.3
17 OfficeAdmin	23.9	40.9	14.7	9.6	7.1	28.4	4.6	81.2	23.6	44.2	65.0	43.0	91.9	51.5	38.1	155.1	18519.6	9.9	70.8	58.7	132.8	154.2	19668.8	964.2	20633.0
18 FarmFishFor	1.4	2.2	0.8	0.5	0.4	1.5	0.3	4.3	1.2	2.4	9.3	2.2	13.5	7.4	5.6	18.1	15.9	956.8	3.7	3.1	7.8	13.2	1071.6	45.0	1116.6
19 Construct	13.9	25.1	8.8	5.8	4.4	16.4	2.7	51.0	14.8	27.2	16.8	17.8	24.1	13.3	9.9	39.9	79.0	2.6	6644.8	37.0	33.9	39.5	7128.6	220.5	7349.1
20 InstalRepair	9.8	17.8	6.2	4.1	3.1	11.5	1.9	36.2	10.5	19.3	11.8	12.4	16.9	9.3	6.9	28.0	55.4	1.8	31.3	5588.6	23.7	27.7	5934.3	193.7	6128.0
21 Production	10.1	17.0	6.2	4.0	2.9	11.8	1.9	33.7	9.8	18.4	30.8	17.8	43.4	24.4	18.0	73.4	128.4	4.7	29.4	24.3	8518.4	73.0	9101.6	345.4	9447.0
22 Transport	14.1	23.3	8.5	5.5	4.0	15.8	2.6	45.3	13.2	25.1	59.8	23.8	84.1	47.4	35.0	142.8	171.7	9.1	39.4	32.7	84.1	11648.5	12535.9	598.9	13134.8
New entrants	566.0	395.3	179.7	64.8	47.0	115.2	25.6	253.1	107.9	95.2	470.5	130.4	1757.4	298.3	382.9	821.9	689.6	73.9	260.4	152.1	193.9	602.3	7683.2		
Emp 2020	10747.7	9063.9	4903.8	2736.4	1467.1	2832.6	1342.4	9788.8	2931.0	9217.1	7171.9	3625.4	13862.1	5692.0	4760.5	15495.0	20537.0	1116.5	7378.7	6145.3	9404.7	13179.7	163399.5		
Totals																								7079.3	162795.6

We also implemented a third method in which we assume that a transfer from i to j is unlikely if i is a non-physical occupation and j is a physical occupation. For example, we assume that transfers from clerical occupations to laboring occupations are relatively unlikely. Occupations that we judge to be physical are shown in column (5) of Table 3.3.1 with a one, non-physicals with a zero.

To implement the third method, we started by defining a physical/non-physical non-compatibility coefficient by

$$\mathrm{PH\_NPH}(i,j) = \begin{cases} 2 & \text{if i is non-physical and j is physical} \\ 1 & \text{otherwise} \end{cases} \qquad \text{for all i,j} \qquad \text{(A2.2.1)}$$

Then, we revise the flows calculated under the second method according to

$$\mathrm{ODFLOW3}(i,j) = \frac{\mathrm{ODFLOW2}(i,j)}{\mathrm{PH\_NPH}(i,j)} * \mathrm{N3}(i) \quad \text{for all i, and all } j \neq i \qquad \text{(A2.2.2)}$$

where

N3(i) is a normalizing factor set so that

$$\sum_{j \neq i} \mathrm{ODFLOW3}(i,j) = \sum_{j \neq i} \mathrm{ODFLOW2}(i,j) \quad \text{for all i.} \qquad \text{(A2.2.3)}$$

Under each method (m = 1, 2, 3) we calculate new entrants according the equation

$$\mathrm{NEWEm}(i) = \mathrm{EMP20}(i) - \left[\mathrm{EMP19}(i) - \mathrm{EXIT}(i) - \mathrm{TRANSOUT}(i)\right] - \sum_{k \neq i} \mathrm{ODFLOWm}(k,i)$$

$$\text{for method m and for all i,} \qquad \text{(A2.2.4)}$$

where

NEWEm(i) is new entrants (entrants from outside the workforce) to occupation i in 2020 calculated under method m;

EMP19(i) is employment in occupation i in 2019; and

EXIT(i) is departures from the workforce by people who were in occupation i in 2019.

Results for these new entrant calculations are given in columns (6) to (8) of Table 3.3.1.

Equation (2.2.4) provides no safeguard against the occurrence of negatives. For example, new entrants to occupation S115 (Physicians specialists) calculated under method 1 is -18,060. This indicates that method 1 generates too many flows into occupation S115 from other occupations, that is, $\sum_{k \neq i} \mathrm{ODFLOW1}(k, \mathrm{S115})$ is too high. When we move to method 2, the problem for S115 disappears: NEWE2(S115) = 9,560. Taking account of the very high wage applicable to S115 reduces calculated flows to this occupation from other occupations. The high wage makes flows to S115 unrealistic for most occupations. However, 5 of the 233 NEWE2 values are negative, down from 19 for NEWE1.

The largest NEWE2 negative is -1,290 for S103 (Chiropractors). This occupation has a mid-level wage rate ($70,720). Consequently the introduction of the wage-difference factor has little impact on the calculation of new entrants. At the same time, this occupation has a low percentage for its separation rate, that is, the percentage of workers who leave the occupation either to join other occupations (TRANSOUT) or to exit the workforce (EXIT). With few departures from the occupation there is relatively little space for new entrants. As outlined in section A2.3, we hope to rectify this problem for S103 and other occupations requiring special skills by limiting the ability of people in other occupations to transfer into these occupations.

Adoption of method 3 doesn't help to reduce the number of negatives for new entrants. NEWE3 has 9 negatives, up from 5 for NEWE2. In NEWE3, S103 (Chiropractors) remains the occupation with the largest negative entry, -1,550. In common with all other non-physical occupations, the NEWE3 value for S103 is less than the NEWE2 value. In the move from method 2 to method 3, we reduce calculated transfers from non-physical occupations to physical occupations, thereby increasing the transfers from non-physical to non-physical. This reduces the space for new entrants in all non-physical occupations. Correspondingly the move from method 2 to method 3 increases the calculated number of new entrants in all physical occupations.

A2.3. Next steps

We continued work on the 233-by-233 occupation transition matrix. However, as can be seen from section 6, we did not continue to use the BLS projection data. We were particularly worried about the treatment of unemployment. Nevertheless, the work reported in this appendix pointed to various ideas most of which we have implemented in section 6.

(a) Natural career progression. 12 of our 233 occupation have the word supervisor in their description. Under these occupations are associated occupations that are supervised. It would be reasonable to assume that there is enhanced transfer from supervised occupations to the relevant supervisory occupation. For example, we could assume enhanced transfer opportunities into the occupation Supervisors of protective service workers (S122) from the occupations: Firefighters; Fire inspectors; Bailiffs, correctional officers, and jailers; Detectives and criminal investigators; Police and other enforcement; and Other protective service workers (occupations S123 to S128). In other words, we could assume that the supervised occupations are the prime recruitment source for the supervisory occupations.

Other examples of natural progressions that we could take into account can be found in the professions. For example, we could assume that vacancies for:

- Judges, magistrate judges and magistrates (S62) are filled mainly from legal occupations (S59 to S61);
- Top executives (S1) are filled mainly from senior management occupations (S2 to S12, excluding S8);
- Senior managers are filled mainly by professionals from the relevant areas. For example, we could assume that Computer Specialists (S20 and S21) can graduate to Computer and information system managers (S4).

(b) Specialist skills. Some occupations require long-training and/or education programs. For these occupations we could configure the occupation transition matrix so that there are limited possibilities for entry from other occupations. Examples include many of the occupations from S22 to S80 and from S103 to S117. We would expect new entrants to provide the bulk of recruits for these occupations.

Appendix 3. Archiving useful research material

1. Program for developing the occupation-industry matrices described in section 3.

C:\dixon\consult\Commerce\2021\Employment\BLS data\EP\ReviseGlyn\ BLSBig2e.Tab Run with BLSBig2e.cmf]

2. Programs contributing to the creation and illustrative application of USAGE-OCC

We start from the 2015 database used in the Buy American project.

The modifications described in section 4 to this database are carried out in:

C:\Rundynam\Can150317\extra\Dw9.tab run with DW9.cmf.

Next we conduct the 2015 - 2019 update simulation described in section 5.1. This is run in:

C:\Rundynam\Can150317\F49b (baseline)

We make initial adjustments to the post-simulation results. These are described in section 5.3 and carried out in:

c:\rundynam\Can150317\extra\Work161221Revised190122.xlsx, sheet answer210122]

and

C:\Rundynam\Can150317\extra\D19h.tab run with D19h.cmf.

We form the 2019 database for the baseline and policy simulations. This requires adding the 233 by 392 wagebill and Jobs matrices [given the output file (Dout19h.har) of D19h.cmf].

As described at the end of section 5 we made final adjustments to VCAP_AT_T and DEP in

sheet FIXFORC of *C:\Rundynam\Can150317/ INVEST_CAPITAL.xlsx*

The four simulations described in section 7 are stored in

C:\Dixon\Consult\Commerce\2021\Employment\FinalReport020322\FinalSims

(See Readme.docx in this directory.)

3. Research notes and programs that did not contribute to the current project but may be useful in future projects

[*stored in*

c:\Dixon\consult\commerce\2011\Employment\FinalReport020322\NotesPossibleFuture]

3.1. Note entitled "Labor offers from occupation-by-region categories: keeping the dimensions manageable" by Peter B. Dixon and Maureen T. Rimmer, September 25, 2021. This note sets out the theory of the labor offers for a regional model such as USAGE-TERM

3.2. Operational version of USAGE-TERM. We created a version of USAGE-TERM with 40 industries, 6 regions and 233 occupations. We zipped up runs that simulated the collapse of exports of U.S, machinery equipment (as in our report to Commerce in March 2018). We were not happy with the national data, and decided to go with an occupational version of USAGE instead. The zips of the USAGE-TERM runs are:

UT80-A42B-A29R-A29P.zip

UT82-A50B-A50R-A50P.zip

This version of USAGE-TERM contains Florian's tricks for reducing the burden of storing large data arrays.

3.3. Note entitled "The relationship between the employment and wage deviations in an occupation with sticky-wage-rate adjustment" By Peter B. Dixon and Maureen T. Rimmer, February 26, 2022

This note explains why the first year employment and wage deviations are close to equal in the illustrative simulations in section 7 (see chart 7.3.3).

3.4. Here is a scrappy note explaining why we went from 789 occupations to 233. The times quoted were before we introduced Florian's tricks.

Coping with large dimensions

Eventually, by carefully arranging equations, eliminating high-dimension coefficients and substituting out high-dimension variables we managed to compute with the 789 occupations, 10 regions and 40 industries. However, the computational times were not practical. On our mid-strength PC a solution for a single year took about 15 minutes. Thus, in a 10 year simulation with baseline, rerun and policy we anticipate a solution time of about 7.5 hours (=0.25*10*3, memory constraints meant that simultaneous solutions were of limited value).

We experimented with the occupational dimension reduced to 260 but with made-up data. This gave acceptable computation times, 12 minutes for 3 years (baselines, rerun and policy), 40 industries and 10 regions. This implies that a 10-year simulation could be achieved in about 40 minutes.

In light of this encouraging result, we decided to aggregate the 789 occupations in our jobs matrix. The aggregation to 233 occupations is shown in Table 2.4.1.