DISTRIBUTIONAL EFFECTS OF UNEMPLOYMENT AND DISINFLATION IN CANADA: 1981-1987

by

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ABSTRACT

In this thesis a microsimulation model is developed in order to analyse the distributional effects of changing macroeconomic conditions in Canada in the 1981-1987 period. This period was characterized by higher rates of unemployment and declining inflation rates.

Chapter 2 analyses the distributional effects of higher unemployment on the human wealth of individuals and households. In Chapter 3, the distributional effects of disinflation on the non-human wealth of households are analysed. Chapter 4 combines the effects of unemployment and disinflation on household total wealth. Conclusions are included in Chapter 5.

There are two methodological novelties in this study. First, the simulation model is a behavioral model in a dynamic macroeconomic environment. The model also allows for new possibilities of empirical verification by integrating the hypothetical steady state path and the actual performance of the Canadian economy. The second novelty is the analysis of simultaneous effects of unemployment and disinflation on the human and non-human wealth of households.

The major results of the study indicate that the losses in total wealth are \$55.8 billion in 1981 dollars. The losses in total human wealth and non-human wealth are about \$38.7 billion, and 17.1 billion respectively. In the 1981-1987 period there is also an increase in inequality in the distribution of household total wealth. The wealth is redistributed from the less wealthy to the more wealthy, from the young to the old, from females to males, from singles to the married. Therefore, a disinflationary macroeconomic shock unambiguously increases economic inequality.

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CHAPTER 1: INTRODUCTION

This study develops a microsimulation model in order to analyse the distributional effects of changing macroeconomic conditions in the Canadian economy during the 1981-1987 period. This period was characterized by higher rates of unemployment accompanied by declining inflation rates due to introduction of a restrictive macroeconomic policy in the last quarter of 1981 in order to bring the inflation rate down.

For the past two decades or so, inflation has been regarded by policy makers as one of the major economic evils that has to be avoided.[1] Some often cited costs of inflation include: (1) adverse effects on the stability of an economic system, which is based upon the principle of nominal contracts, due to an increase in reluctance of people to enter money contracts during serious inflation, (2) the resource costs of frequent price changes (also known as "menu costs"), (3) unfair distributional consequences (since inflation does not effect all income earners or asset holders equally).

Implementation of restrictive macroeconomic policies to achieve price stability, however, also has strong distributional effects and powerful real effects in

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[1] A recent evaluation of these policies can be found in Smithin (1990).

the form of unemployment and lost output.[2]

Several studies in the past have investigated the distributional effects of inflation and/or unemployment separately by using a variety of methods, such as simple trend analysis, regression analysis, and microsimulation. Some early studies analysed the redistribution of income and wealth among the household, business, and government due to inflation[3]. Others have investigated the effects of inflation and/or unemployment on various demographic groups.[4] The general consensus that emerges from these studies is that both inflation and unemployment have strong distributional effects on income and wealth in society. These studies, however, consider the effects of inflation and unemployment on income-demographic groups separately.

For the last two decades or so there has been also considerable empirical work on the distributional impacts of cyclical fluctuations in the macroeconomy.[5] There is, however, no general consensus on the distributional effects of cyclical fluctuations in the literature. Shultz (1969), for example, finds no significant impact of the cyclical variations in the macroeconomy. Beach (1976, 1977), however, suggests that bottom deciles primarily lose in a recession. Blinder and

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[2] For a recent discussion of the costs and benefits associated with restrictive policies in Canada see Lipsey(ed)(1990), and York(ed)(1990).

[3] See, e.g., Bach and Stephenson (1974), Budd and Seiders (1971).

[4] See, e.g., Nordhaus (1973), Gramlich (1974), Palmer and Barth (1977), Wolff (1979), Minarik (1979), Dunson and Jackson (1986).

[5] A useful survey of the literature is provided in Livada (1992).

Esaki (1978) also show that the impact of unemployment is stronger than inflation and bottom deciles are the major losers in a recession. Weil (1984), on the other hand, concludes that unemployment adversely affects the rich but the poor benefit from inflation.

The objective of this study is to simulate simultaneously the effects of disinflation and higher unemployment on Canadian households within the 1981-1987 period. In this period the unemployment rate in Canada rose from 7.5 percent to 11 percent in 1982, and reached a peak at 11.8 percent in 1983. In the following years it started to decline and finally reached 8.8 percent in 1987. Meanwhile the inflation rate steadily declined from about 12 percent in 1981 to 4.4 percent in 1987.

This study consists of three major parts. In Chapter 2, the distributional effects of higher unemployment on the human wealth of Canadian households is examined. The objective is to simulate the effects of higher unemployment on the distribution and value of household human wealth in Canada. The analysis is first conducted for individuals and then aggregated into households. In Chapter 3, the distributional effects of disinflation on household non-human wealth is simulated. Chapter 4 combines the simulation results of the effects of disinflation and higher unemployment on Canadian households.

CHAPTER 2: SIMULATION MODEL OF HUMAN WEALTH

In this part of the study the objective is to simulate the effects of disinflation on the distribution and value of human wealth in Canada.[6] Using an expectations-augmented Phillips curve framework, the maintained hypothesis of the simulation model is that the economy starts from an initial steady state equilibrium corresponding to an equilibrium level of aggregate unemployment[7] and constant fully anticipated price inflation, where the expected inflation rate has fully adjusted to the actual rate. A macroeconomic shock is introduced by the authorities in order to achieve a lower rate of inflation. In the absence of hysteresis effects[8], the economy is expected to converge over (n) periods to a new equilibrium with a lower inflation rate and the initial equilibrium rate of unemployment. However, because of slow adjustment of expectations the economy suffers from a period of higher unemployment. In the simulation model changes in the demographic characteristic of the population, such as mortality,

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[6] The Labour Market Activities Survey (1986,1987) and the Assets and Debts Survey (1984) of Statistics Canada are used in the simulation. The Labour Market Activities Survey is used to obtain the parameters in the simulation model and the simulation is performed by using the Assets and Debts Survey. The reason for this procedure will be explained in more detail in Section 2.2. As mentioned earlier non-human wealth effects are included in Chapters 3 and 4.

[7] Also known as the "non-accelerating inflation rate of unemployment" (NAIRU).

[8] Hysteresis effect refers to the automatic adjustment of the equilibrium level of unemployment to the path of the actual unemployment rate. See, e.g., Gordon (1989) or Setterfield (1992).

retirement, intergenerational transfer of wealth are not accounted for.

As an illustration of this process the inflation and aggregate unemployment rates are given by the experience of the Canadian economy during the 1981-1987 period. The inflation rate in the fourth quarter of 1981 (12.3%) and the unemployment rate in December 1981 (8.5%) are chosen as the initial steady state values. The reason for this choice is that the unemployment rate, following an initial rise, fell back to a level which approximates a convergence to the chosen initial level. The unemployment rate rose to 11.0 percent in 1982, and reached a peak of 11.8 percent in 1983 and in the following years steadily declined and reached 8.8 percent in 1987. The inflation rate began to decline in 1982 and reached 4.4 percent in 1987.[9] The details of the simulation model will be presented in the following sections. Sections 2.1 to 2.4 describe the details of the simulation model. In Section 2.5 the econometric specification and estimation results of individual probabilities of becoming unemployed are included. Sections 2.6 to 2.8 develop an accelerated failure time model for the estimation of expected duration of unemployment. Section 2.9 presents the specification checks and estimation results of the accelerated failure time model. In Section 2.10 the simulation results are discussed. Finally, in Section 2.11 summary conclusions are included.

2.1 Definition of Human Wealth

In this study human wealth of an individual (HW_t) is defined as the present

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[9] See Appendix A.

value of expected employment earnings including unemployment insurance benefits (UIB):[10]

(1)
$$HW_i = \int_{t=1}^{T} E_{it} e^{-rt} dt + \int_{t=1}^{T} B_{it} e^{-rt} dt$$

where

E_{it} = (wage/week)•(52-weeks unemployed-weeks out of labour force),

B_{it} = (UIB/week)•(weeks unemployed - 2).

The second term in the benefit equation includes two weeks of waiting period. Furthermore, B_{it} is not automatically assigned. An individual must also meet the requirement of minimum weeks of employment in his/her region in order to qualify for unemployment insurance benefits. The basic entrance requirement, i.e., weeks of insurable employment, varies depending on the regional unemployment rate.[11]

Human wealth of an individual, therefore, may change as the individual makes transitions from employment to unemployment and vice versa. For example, a decrease in human wealth is expected to occur if the individual becomes unemployed since the unemployment insurance benefits are 60% of

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[10] In this study human wealth is measured in dollar incomes only. Values of utility of leisure or disutility of unemployment are not accounted for.

[11] See Appendix A for basic UI entrance requirement.

insurable employment earnings in Canada.[12]

There are two types of events and three types of losses that are simulated. The events consist of (1) the baseline simulation in which incidence and duration of unemployment are distributed under the assumption of constant inflation and aggregate unemployment rates (i.e., 12.3 percent inflation rate and 8.5 percent unemployment rate), and (2) the shock simulation in which incidence and duration of unemployment are distributed as in the actual inflation and unemployment rates in the 1981-1987 period. Losses may occur in the shock simulation due to (1) increases in the incidence of unemployment, (2) increases in the average duration of unemployment, and (3) changes in the real earnings of employed individuals. The details of the calculations are given in the following sections.

The calculation of the distributional effects of an increase in aggregate unemployment on human wealth consists of comparing the baseline value and distribution of human wealth with the distribution and value of human wealth in the shock case, i.e., after a simulated change in the present value of employment earnings and unemployment insurance benefits.

The human wealth effects of the shock scenario are analysed both at the individual and household levels. Calculations of these effects on households as a whole is especially important since total human wealth effects are later calculated

[12] Weekly earnings above $99 and below an insurable ceiling of $495 are covered by unemployment insurance.

on the basis of total household financial wealth and human wealth. When calculations are done for households, spouses' work patterns and hence employment earnings are taken into account. Therefore, household human wealth is calculated as the sum of household head's human wealth and spouse's human wealth. This procedure is explained in more detail in Section 2.4.

2.1.1 Labour Force Status of Individuals in the Simulation

In each simulation period individuals may be employed, unemployed, or out of the labour force. Individuals may also experience any combination of these states. For analytical convenience the possibility of multiple spells of unemployment in a given period is ignored and total number of weeks of unemployment for each individual is aggregated into a single spell. Weeks out of the labour force per year are calculated for each individual in the initial steady state equilibrium and assumed to be constant in all simulation periods.

2.1.2 Accounting Period As a Calender Year

As mentioned above, the working hypothesis of this study is that aggregate unemployment is determined within the expectations augmented Phillips curve framework and that the shock scenario rate of inflation and unemployment for each period as well as the number of simulation periods are given by the experience of the Canadian economy during the 1981-1987 period. Therefore, each simulation period is a calender year and a year is considered as the accounting period.

2.2 Aggregate Unemployment in Simulation Data

The Assets and Debts Survey (1984) of Statistics Canada is used in the simulation.[13] The survey provides the following relevant information on unemployment in the initial period:

(1) Unemployment status of individuals in the reference week of the survey,

(2) Unemployment weeks of individuals in the previous year,

(3) Number of individuals who experience some unemployment in the previous year.

Individuals are male household heads, female household heads, and wives.

Therefore, unemployment (U) can be decomposed into two elements: (1) incidence of unemployment, I_u, i.e., the number of individuals who enter the state of unemployment, and (2) the average duration of unemployment, D_u:

(2) $$U = I_u \cdot D_u .$$

[13] This survey contains information on net-worth of individuals which is required for simulating the effects of disinflation on nonhuman (financial) wealth of individuals. Labour Market Activities Survey (1986,1987) is also used in the stage of estimating the parameters of the model, since it covers two periods and hence enables us to obtain year-to-year correlation between unemployment durations in the simulation, as well as unemployment incidence over time. For details see section 2.4.

Dividing both sides by the labour force (L), we obtain:

$$(3) \qquad U/L = (I_u/L) \bullet D_u \,,$$

where U/L is the unemployment rate, and I_u/L is the inflow into the unemployment state, expressed in terms of a proportion of the labour force.[14]

The strategy in both baseline and shock scenarios is to determine the total number of unemployment weeks in each period that corresponds to the aggregate unemployment rates, and then distribute them among the individuals. Recall that the aggregate unemployment rates in the baseline scenario is a constant 8.5 percent per period over seven simulation periods. In the shock scenario, unemployment rates follow the actual rates in the Canadian economy during the 1981-1987 period. Therefore, the total number of weeks of unemployment which corresponds to these rates must first be determined. The technical aspects of distributing the total weeks of unemployment among the individuals, given their unemployment probabilities and expected unemployment durations, will be discussed in Sections 2.2.1 and 2.2.2. What follows explains the general framework of distributing total unemployment weeks.

In the simulation the incidence and expected duration of unemployment are distributed among individuals, given the
aggregate unemployment rate (U) in each period as implied by baseline and

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[14]see, e.g., Hasan and de Broucker (1985, pp.8-9).

shock scenarios, as follows:

$$U = \frac{\sum_{i=1}^{N} u_i \cdot E(D_i)}{LFW}$$

where, u_i is a variable which takes on the value 1 if the ith individual is unemployed (0 otherwise), $E(D_i)$ is the expected duration of unemployment for the same individual, LFW is the total labour force weeks in the sample, in a given period.

The first step is to calculate the total number of labour force weeks so that total unemployment weeks can be obtained given the aggregate unemployment rate. The procedure is as follows.

There is information about the individual weeks of unemployment in the data for 1983. Observations on weeks of unemployment are first aligned with 1981 values by using the proportionate changes in annual average interrupted weeks of unemployment in Canada as an adjustment factor.[15] In Canada, average interrupted weeks of unemployment was 23.2 for males and 16.4 for females in 1983. They were 13.7 weeks for males and 14.7 weeks for females in

[15] For details see section 2.4.

1981. The adjustment factor for males, therefore, is 0.59 (= 13.7/23.2). All weeks of unemployment for males in the original data set are multiplied by this factor in order to align unemployment durations in the data to 1981 levels. The same procedure is used for females. As mentioned earlier, for analytical simplicity out of labour force weeks per year (NLFW) are calculated from the 1983 data and assumed to be constant in the simulation. Therefore, each individual's employment weeks are given by (52 -NLFW - unemployment weeks). The sum total of all individual labour force participation weeks gives the total labour force weeks (TLFW) in the above equation. And the calculated value of total labour force weeks for each simulation period is about 480 million weeks when a population weight is used for each observation.

In the baseline scenario total weeks of unemployment is, therefore, about 40.8 million (= 480 x 0.085). This value of total weeks of unemployment is used as the total steady state weeks of unemployment in each period of the simulation. In other words, it is used as the cut-off value in distributing incidence and duration of unemployment in the baseline scenario, which will be explained in detail below.

In the shock scenario, weeks of unemployment durations are also calculated from the above equation by using the unemployment rates in the 1982-1987 period. For instance, in 1982 the unemployment rate was 11.0 percent. Given the total labour force weeks of about 480 million, the rise in the unemployment rate to 11 percent corresponds to the increase in total weeks of unemployment to 52.8 million (= 480 x 0.11). The total number of unemployment weeks are, 56.6 million weeks in 1983, 53.7 million weeks in 1984, 50.3 million weeks in 1985, 45.5 million weeks in 1986, and 42.2 million weeks in 1987. Therefore, given the aggregate unemployment rates in the shock simulation, total number of unemployment weeks first rises with the rise in the aggregate unemployment rate, and then gradually declines and settles around 42.2 million weeks when the aggregate unemployment rate falls back to 8.8 percent.[16]

The next step is to distribute the incidence and duration of unemployment in the sample, given the values of total weeks of unemployment for each simulation period. Clearly, it is important to distribute both incidence and duration of unemployment in the sample because having information on the unemployment status of an individual (incidence) is not sufficient to determine the changes in human wealth since human wealth of an individual is also related to the time spent unemployed (duration), as indicated in equation (1). The following subsections explain these procedures.

2.2.1 Distributing Incidence of Unemployment

Our objective in each scenario is to calculate human wealth of individuals based on their work experiences and their employment earnings. Therefore, we must first determine those individuals who experience unemployment in each simulation period. This amounts to distributing incidence of unemployment in the

[16] See Appendix A, Table A1.

labour force in each period. In order to distribute the incidence of unemployment in each period, individual probabilities of becoming unemployed (conditional on demographic characteristics and previous unemployment experience) are calculated using the estimated parameters of a logistic regression model. The details of econometric specification and estimation results of the model are included in Section 3. The following paragraphs help explain the procedure of determining individual unemployment probabilities in each period.

It is important to note that for a given individual the expected probability of becoming unemployed is likely to be different under the steady-state and policy shock scenarios. Unemployment weeks of individuals may differ from period to period in a given scenario but they may also differ for the same period in the alternative scenarios. For instance, an individual may have zero weeks of unemployment in the baseline scenario but may experience some weeks of unemployment in the shock case. If the number of previous year's unemployment weeks differs in the baseline and the shock scenarios then the probability of becoming unemployed in subsequent periods will also differ in these scenarios, since previous unemployment weeks variable is one of the determinants of the unemployment probability. Therefore, for each period baseline and shock probabilities are calculated separately by using corresponding baseline and shock previous weeks of unemployment for each individual as follows:

$$E(P_{ibt}) = f(U_{bt-1}, X), \text{ (Base)}$$

$$E(P_{ist}) = f(U_{st-1}, X), \text{ (Shock)}$$

where X denotes control variables.

In the real world, apart from the expected probability of becoming unemployed, individuals also face a purely stochastic element. That is, it is quite possible that out of two people with identical characteristics only one may experience unemployment in a year while the other remains employed. Put another way, one individual may be luckier than the other and hence may avoid unemployment in that year. This fact is accounted for in the present simulation by including random numbers, generated from the error distribution of the estimated logit regression, in the calculation of the individual predicted probabilities as follows.

A stream of random numbers is generated as a random draw from the error distribution of the estimated logistic model and assigned to each individual at the outset of the simulation. Each random number in the stream corresponds to a specific simulation period. That is, for each period the individual has a luck element represented by the random number. In each period, the random number of that period is added to the calculation of the predicted probability of becoming unemployed. As mentioned above, the predicted probability is also determined by the previous weeks of unemployment, and previous weeks of unemployment may differ in the baseline and shock scenarios. Thus baseline and shock probabilities are calculated separately. However, the same random number is used in the baseline and shock probabilities. Including the same random number in the two different probability calculations, therefore, helps control the stochastic variation due to luck in individual unemployment probabilities in the alternative scenarios. Put another way, an individual's relative luck for that period, represented by his/her random number, remains the same regardless of any changes in the aggregate unemployment rate in that period:

$$P_{ibt} = E(P_{ibt}) + \epsilon_{it},$$

$$P_{ist} = E(P_{ist}) + \epsilon_{it},$$

where ϵ_{it} is the random number of the individual (i) at (t).[17]

Once the unemployment probabilities are calculated individuals are ordered in a descending order according to their probabilities. This ordering method is performed twice in each period: once for the baseline scenario and once for the shock scenario. Therefore, those with relatively higher probabilities go to the top of the list As will be shown below, the relative position of the individuals in the ordered data set and the number of total unemployment weeks in a given scenario determine those individuals who experience unemployment in any given period.

2.2.2 Assigning Unemployment Durations

In order to be able to assign unemployment durations in each period, expected duration of unemployment, conditional on his/her demographic

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[17] In the probability equation random number is generated as $z_{it} \cdot \sigma$, where z_{it} is the random number generated from the error distribution of the logistic model, and σ is the standard error of the model. In the LMAS data the unemployment incidence correlation between 1986 and 1987 is about 0.40. In the simulation, after experimenting with the data, approximately the same correlation in the initial two simulation periods is obtained by scaling down the original value, $\sigma = 1.83$, to unity.

characteristics and work history, must be estimated for each individual. Then the expected duration of unemployment can be assigned in that period conditional on his/her position in the ordered data set. The calculated expected unemployment durations are constrained to a maximum of 52 weeks in each period. The details of econometric specification and estimation results are given in Sections 4 and 5. The assignment procedure is illustrated in Section 2.3.

It is important to note that two different expected durations are calculated for each individual in each period. This procedure is the outcome of the same concern mentioned above for calculating unemployment probabilities for individuals. That is, expected unemployment durations are likely to be different in the baseline and shock scenarios due to differences in previous unemployment experiences since the previous year's unemployment weeks is one of the determinants of expected duration in a given period. Therefore, in the baseline scenario expected durations are calculated using the baseline unemployment experiences, and in the shock scenario using the shock unemployment experiences:

$$E(D_{ibt}) = f(U_{bt-1}, X), \qquad \text{(Baseline)}$$

$$E(D_{ist}) = f(U_{st-1}, X). \qquad \text{(Shock)}$$

At this point it is also worth mentioning another important aspect of unemployment duration. Unemployment duration is continuous in time. However, in survey data one normally observes unemployment durations in discrete time periods. For example, information on unemployment durations in the Labour Market Activities Survey (1986,1987) is only for two consecutive years, and in the Assets and Debts Survey (1983) for only a single year. Typical of such surveys is that in the beginning and at the end of the survey periods unemployment durations of the unemployed are observed incompletely - a problem known as censoring. If the censoring problem is not handled carefully the resulting expected duration estimates become biased and hence unreliable. The censoring problem is explained below in some detail, and the technical aspects of overcoming this difficulty are further explained in Section 4.

Suppose that we have survey data on 4 individuals with some unemployment experience in period (t). We have information on the unemployment status of individuals at the reference week of the survey which is, say, the last week in (t). It is clear that an individual who is already unemployed in the first week of this period has been unemployed for some time in the previous period but the origin of his/her spell is unknown. In other words, we do not know their unemployment weeks in period (t-1) since we survey unemployment experiences in period (t). As shown in Figure 1, individuals (a_1) and (a_2) have started their unemployment spells some time during period (t-1). This means that the length of their unemployment spells is observed in period (t) but unobserved in (t-1). In terms of the data at hand, which cover only one period, the length of the unemployment spell is left-censored in period (t). On the other hand, someone who is unemployed at the reference week of the survey has not completed his/her spell either. Even if we knew the origin of the spell in period (t) we would not have information on the complete length of the spell. We would only have information on the number of unemployment weeks in period (t). This problem is known as right-censoring and represented by individual b2 in Figure 1. Consider now the following example.

Assume that individual a_1 has 25 weeks of observed unemployment in period (t) and 5 weeks of unobserved unemployment in period (t-1). Similarly, individual a_2 has 5 weeks of observed unemployment in period (t) and 15 weeks of unobserved unemployment in period (t-1). On the other hand, individuals b_1 and b_2 both make transitions to unemployment in period (t). Individual b_1, however, makes a transition back to employment in period (t) and hence has an unemployment spell of 3 weeks, which is completely observed. Individual b_2 has a spell length of 7 weeks in period (t) which is stretching into the future period (t+1). That is, his/her actual spell length of 11 weeks of unemployment is right-censored and not recorded completely in the data. Therefore, the calculation of average duration of unemployment, based on the observed durations, will clearly indicate a downward bias in the estimated average duration.[18] However, if the

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[18] Suppose that the objective is to calculate the average duration of unemployment from the data. If we could observe all of the individual spells completely we would have a simple unbiased average duration of unemployment of 16 weeks, i.e., (30 + 20 + 3 + 11)/4 = 16. However, our data consist of information on the unemployment spells in period (t) only. Therefore, if we calculate observed unemployment spells in period (t) we obtain 10 weeks of average duration, i.e., (25 + 5 + 3 + 7)/4 = 10. This means that the average duration of completed spells of unemployment from the survey data is biased downward.

origin of spell lengths are known the problem of bias due to right-censoring can be eliminated by using special techniques. These techniques are described in detail in Section 4.[19]

An accelerated failure time model, which is one of the techniques that can be used in estimating expected durations of unemployment under right censoring, is used in calculating expected unemployment durations in each period. The chance factor for individuals is again accounted for by including random numbers, generated from the distribution of the error term of the duration regressions, in the calculation of individual expected durations of unemployment. The same procedure is used for both scenarios. This is important because regression coefficients give point estimates for unemployment durations, and unless the real world variation (due to luck and unobservable variables) is accounted for by this technique, individuals with the same set of characteristics will always be assigned

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[19] In the initial specification of the simulation model an attempt was made to account for both left- and right-censoring. This was an attempt to account for the continuous nature of unemployment duration over time. First, two separate expected unemployment durations were estimated using the LMAS (1986,1987) data: (1) for those with unknown time origin of unemployment spells (left-censored), (2) for those with known time origins but may also be right censored. Second, in each period of the simulation right-censoring probabilities were calculated for those who were predicted to be unemployed. Given these probabilities, individuals were assigned right-censoring flags, using a Monte Carlo method. If an individual's expected duration of unemployment is determined to be right-censored (i.e., stretching to the next period) then in the next period unemployment was automatically assigned using the expected duration of unemployment calculated from the first specification above. However, after numerous experimentations with the model, the distributional results are found to be insensitive to this specification. Therefore, a more simple approach, which is based on calculation of complete but unbiased expected unemployment durations for each period, was adopted.

identical unemployment durations from one period to another which, of course, is not desirable.

At the outset of the simulation a stream of random numbers is generated for each individual from the error distribution of estimated duration equations. Therefore, each individual has a random number specific to each simulation period. This random number represents the individual's luck for that period which, in turn, determines the length of his/her unemployment spell in that period. For example, as will be explained in detail in Section 4, unemployment spell durations are assumed to be Weibull distributed. The natural log of spell durations, as in the accelerated failure time models, of a Weibull distribution has an extreme value distribution. Therefore, a random number can be included in the calculations for each individual as follows:

$$D_{ibt} = E(D_{ibt}) + v_{it}, \qquad \text{(Baseline)}$$

$$D_{ist} = E(D_{ist}) + v_{it}, \qquad \text{(Shock)}$$

where v_{it} is the random number of the individual (i) at (t).[20] Therefore, in each simulation period the individual's corresponding random number is included in the calculation of his/her expected unemployment duration, and as in the probability calculations, a single random number is used in calculating both

[20] In the duration equations the random number is included as $\ln(-\ln(\epsilon_{it}))\cdot\sigma$, where ϵ_{it} is a random number generated from a uniform distribution on the interval [0,1], and σ is the scale coefficient. See, e.g., Nelson (1990).

baseline and shock unemployment durations in a given period.

2.3 Baseline and Shock Scenarios

The simulation consists of seven periods, following two periods of "warming up". In the warm-up periods incidence and duration of unemployment are distributed using the baseline value of total unemployment weeks. Including warm-up periods is considered necessary because the statistical information which is accumulated during the simulation must be based upon steady state behaviour of the model which, in turn, should be independent of the initial conditions. However, since there is no criterion for determining the number of warm-up periods, the choice for two periods was arbitrary.[21]

In each period the model generates and assigns individuals employment and/or unemployment weeks as well as employment earnings under alternative scenarios. In any given period simulation data are organized in four steps as shown in Figure 2. The first step is to sort individuals in descending order given their calculated baseline unemployment probabilities, P_{ibt}. This is represented by the first column. The second step involves assigning unemployment durations, D_{ibt}, starting with the individual with the highest unemployment probability. As individuals are assigned unemployment their weeks of unemployment are summed up. This procedure continues until the cumulative weeks of unemployment reaches the value of total weeks of unemployment in the base scenario. Once the

[21] See, e.g., Gottfried (1984: 179-180).

cut-off value is reached the unemployment experience in the shock case is then assigned. The third step, therefore, consists of reordering the data set given the individual unemployment probabilities in the shock scenario. In the fourth step unemployment weeks are assigned by summing the expected unemployment durations in the shock scenario. This time the cut-off value in the period is given by the total weeks of unemployment in the shock scenario. The following subsections elaborate on this procedure with the aid of a hypothetical case.

2.3.1 Baseline Simulation

The baseline simulation is performed under the steady-state assumptions. That is, the aggregate unemployment which corresponds to the December 1981 level (8.5%) in Canada is kept constant in each period. As mentioned above, individuals are ordered using the baseline probabilities and are assigned unemployment given their baseline expected unemployment durations.

For each individual expected duration of unemployment is calculated and constrained to a maximum value of 52 weeks in another variable. Starting from the observation with the highest probability of unemployment, a cumulative variable for constrained expected unemployment durations is created. The first element in this array is the expected unemployment duration of the individual with the highest probability of becoming unemployed. For the second individual the corresponding value in the array is his/her expected unemployment weeks plus the first element in the array, and so on. The cut-off value for assigning unemployment durations is then determined by the value of the total weeks of unemployment in that period. For the baseline scenario this value corresponds to the total weeks of unemployment of about 40 million weeks. Therefore, given the cut-off value, if the individual's position in the ordered data set is below the value of the cumulative unemployment weeks, zero weeks of unemployment is assigned. If an individual is assigned unemployment a baseline unemployment flag is turned on.

The above mentioned process is illustrated in Table 1a for a single period by using simple hypothetical values. There are five individuals and five variables in this simple system. The first column in the table identifies the individual; the second column gives the probability of becoming unemployed in the baseline scenario; the third column gives the calculated expected duration of unemployment in the baseline; the fourth column gives the array of cumulative unemployment durations, and the last column gives the assigned employment/unemployment status of the individual.

It can be seen from the second column that the individuals are sorted in descending order according to their baseline probabilities of becoming unemployed. As mentioned above the calculated cut-off value gives the total weeks of baseline unemployment in the economy in that period. Here total weeks of unemployment is assumed to be 15 weeks. Therefore, individuals A and B are assigned unemployment since their combined weeks of unemployment is 15 weeks and they are the ones with the highest unemployment probabilities. Accordingly, individuals C, D, and E experience no unemployment in that period and zero weeks of unemployment will be assigned in calculating their income, which is the number or weeks of employment times the weekly employment earnings. Baseline flag assumes the value of one for individuals A and B, and zero for the rest.

2.3.2 Shock Scenario

The policy shock scenario reflects the actual experience of the Canadian economy in the 1981-1987. When the policy shock is simulated, individuals are reordered in the same period according to their unemployment probabilities for the shock scenario. Their expected unemployment durations are also calculated using the shock duration equations. As before a cumulative unemployment variable is generated in order to determine the cut-off value for unemployment assignment. In the shock case the total weeks of unemployment traces the historical values in the 1981-1987 period. As mentioned in Section 2.2, total weeks of unemployment increases from 40.8 to 52.7 million weeks when the shock is introduced. It continues to rise to 56.6 million weeks and thereafter begins to fall and finally settles around 42 million weeks in the last period.

Whenever an individual is assigned unemployment a shock unemployment flag is also turned on. In any given period, some of those who experience no unemployment at all in the baseline simulation may become unemployed due to the increase in aggregate unemployment. However, those who already experience unemployment in the baseline simulation may also remain unemployed in the shock case. However, it is clear that the former group of individuals are losers when there is an increase in aggregate unemployment. This process too is illustrated in Table 1b.

The simple system of Table 1a is replicated in Table 1b. This time individuals are reordered in the same simulation period given their probabilities of becoming unemployed in the shock scenario. Recall that baseline and shock probabilities may differ due to differences in the previous year's weeks of unemployment. This variable may assume different values under the baseline and shock cases thereby changing the probability of becoming unemployed under these two different scenarios.

In the shock scenario the total number of unemployment weeks in the economy is different from that of the baseline scenario in which the total number of weeks of unemployment is assumed to remain constant in each period of the baseline simulation. In this example it is assumed to be 28 weeks. Therefore, individuals who have the highest probabilities and whose cumulative number of weeks of unemployment is less than or equal to this value are assigned unemployment. Here individuals A and B are again assigned unemployment. However, individual C becomes unemployed due to the increase in total weeks of unemployment.

2.3.3 Identification of Incidence Losers in Each Period

The objective in this Chapter is to analyse the distributional effects of higher unemployment on Canadian households. Therefore within the context of the present model it is important to identify those who become victims of changing economic circumstances. That is, it is important to identify those who lose their jobs and hence their employment earnings strictly due to the changes in aggregate unemployment.

The example given above clarifies loser identification. Those unemployed individuals in the shock scenario who would not have experienced unemployment had the aggregate unemployment remained the same are defined as losers. These individuals are simply identified by comparing their baseline and shock scenario unemployment flags, as shown in Table 1b. If an individual in a given period is assigned unemployment in the shock case but not in the base case then he/she is identified as a loser in that period. Therefore, individual C is clearly an incidence loser in the shock scenario. Had the total weeks of unemployment remained the same he/she would not have experienced unemployment at all.

2.3.4 Employment Earnings and Human Wealth

Once the number of unemployed and their expected durations of unemployment are assigned in each period, the human wealth for all individuals is calculated using the equation (1) above. That is, the calculations of employment earnings are repeated over (n) periods for both the baseline and the policy shock scenarios in order to generate earnings path for each individual over (n) periods.

When assigning unemployment insurance benefits, regional eligibility requirements are also taken into account by using the actual regional unemployment rates during the 1981-1987 period.[22] For example, if the unemployment rate in the region where the individual resides is less than or equal to 6 percent then the individual must have at least 14 weeks of insurable employment in order to enter the UI program. For higher regional unemployment rates, required weeks of employment declines and becomes 10 weeks if the regional unemployment rate is over 9 percent. For the shock scenario actual regional unemployment rates in the 1981-1987 period, and for the baseline scenario regional unemployment rates in 1981 are used in the simulation periods.

If the individual experiences unemployment and qualifies for the UI program then a maximum of 50 weeks of benefit period is assigned. If the individual has also experienced some unemployment and qualified for UI benefits in the previous period then in the next period only the remaining benefit weeks are assigned.

Once the individual earning paths are determined, the change in the flow of income from employment earnings is discounted at 5.5 percent real interest rate to the initial period in order to compare the distribution and value of human wealth in the baseline scenario with that of the policy shock scenario.[23]

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[22] Regional unemployment rates in the simulation are from Statistics Canada. See Tables A3 and A4 in the Appendix.

[23] The actual rather than the expected inflation rate is used in calculating the real interest rate. Therefore, it is a rough approximation given by the difference between

2.4 Data and Adjustments

2.4.1 Data

The Labour Market Activities Survey (1986, 1987) and the Assets and Debts Survey (1984) of Statistics Canada are used for the purposes of the simulation.

As mentioned above, in order to simulate the policy shock individual work histories must also be included in the estimation of probability and duration of unemployment. Unfortunately, a single data set which includes all the necessary variables is not available. However, the Labour Market Activities Survey (1986, 1987) provides information on individuals for two consecutive years and hence it is possible to obtain information on the previous and current unemployment experience of individuals. In fact, as will be shown below the simulation results show some degree of sensitivity to using probabilities with and without the coefficients of year-to-year correlations in unemployment durations. On the other hand, LMAS does not contain information on the net-worth of households which is also required for building the simulation model within the complete framework.

The strategy adopted here is to determine the common variables available in both data sets first, and then to estimate the coefficients of the logit model and the model of unemployment duration using the Labour Market Activities Survey. These estimated coefficients are then used in building the simulation model in

five year nominal mortgage rate and the actual inflation rate in 1981.

order to determine the predicted individual probabilities and expected durations using the Assets and Debts Survey.

The simulation output is analysed both at the individual and household levels. In calculating household human wealth a major trade-off has to be made. In the Assets and Debts Survey (1983) it is possible to obtain correlations between husband and wife earnings, and unemployment experiences, since information on spouses is available. This information could be valuable in determining work patterns and employment earnings in a household. However, there is only single period information in this survey. Therefore, this necessitates the following trade-off: either the within family work pattern correlations is to be obtained in a single period and the resulting estimated parameters to be used throughout the simulation, or year to year correlation between unemployment durations of individuals is to be obtained from the LMAS without any information on the correlation between husband and wife work patterns. As mentioned above the latter method is preferred over the former one because, as will be shown below, this choice proves to be an important one in calculating the amount, distribution, and sources of the losses in total human wealth. That is, the sensitivity results show that if unemployment correlations over time are omitted from the model there is a considerable change in the magnitude and sources of total loss in human wealth.[24]

[24] Note that the sensitivity of excluding within family work correlations is not tested. It could also show important effects on the simulation results, as well.

In the Assets and Debts Survey each household is also identified by a special sequence number. This makes it possible to include wives as separate points of observations in the simulation data. This is accomplished by first creating a data set containing information on wives. The records of this data set are first identified by using a special flag and then added to the data set containing records of household heads. The new data set is then used in the simulation. Once human wealth calculations are completed for each individual, the records of wives are again identified with the aid of the special flag and separated from the household heads. Subsequently, the records on wives are merged with the records of household heads using household identification numbers.

2.4.2 Adjustments

The initial data base is only representative of Canadian households in 1983. The simulation, however, covers the periods of 1981 to 1987. Therefore, at first the data set must be made representative of 1981 by reweighing the data records on unemployment durations and employment earnings. However, since the adjustment period is relatively short, no adjustment of demographic characteristics is considered necessary.

As mentioned earlier unemployment duration records in the Assets and Debts Survey (1983) are adjusted by using the ratio of actual average interrupted duration weeks of unemployment in 1981 to the actual average interrupted duration weeks in 1983 as the adjustment factor.[25] Recall that for each individual out of labour force weeks per period are kept constant. Therefore, given the out of labour force weeks and adjusted unemployment weeks, the labour force weeks for each individual per year is given by:

$$TLFit = (52 - u - nlfw),$$

where, u is the adjusted unemployment weeks, nlfw is the out of labour force weeks. The sum total of individual labour force weeks then gives the total labour force weeks in the simulation.

Therefore, for the baseline simulation total unemployment weeks in the economy in each period is 8.5 percent of the total labour force weeks (TLF). For the shock scenario historical changes in the unemployment rates in the 1982-1987 period give the total amount of unemployment weeks as 11.0 percent of TLF in 1982, 11.8 percent of TLF in 1983, 11.2 percent of TLF in 1984, 10.5 percent of TLF in 1985, 9.5 percent of TLF in 1986, and 8.8 percent of TLF in 1987.

Another important aspect of the simulation data is related to the fact that weekly wages are not available in the Assets and Debts survey. Therefore, a weekly employment earnings variable is created by dividing the total employment earnings of the individual by his/her employment weeks. This variable, however, can only be calculated for those who have positive employment weeks.

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[25] Reweighing a sample drawn from a population at time t to make it representative of that population at time t + n by exogenously given multipliers is also known as "aging" procedure. See, e.g., Merz, J (1986), McClung (1986) or Lietmeyer (1986). For actual average weeks of unemployment in Canada, see Appendix A.

Employment weeks include self-employment, as well as jobs. Therefore, those who do not have positive employment weeks are excluded from the sample. This means that the simulation is performed for labour market participants with at least one week of employment. Household heads with at least one week of work are about 75 percent of the total household sample. On the other hand, only 58 percent of the wives have at least one week of work. Overall, 85 percent of total household heads and wives in the Asset and Debts Survey are represented in the simulation data.

The weekly employment earnings variable is adjusted to the initial period by using an adjustment factor. The adjustment factor is 0.84 which is the ratio of total nominal employment earnings in 1981 to total nominal employment earnings in the simulation data. In the simulation weekly employment earnings in the initial period is assumed to be the base value.

The base value of individual employment earnings is allowed to grow in real terms in each period. This adjustment, however, is a uniform adjustment across individuals and does not take into account the differences in the growth of real earnings across individuals. In the baseline scenario, for example, the base value is allowed to grow in real terms at the rate of productivity growth for all individuals. This reflects the steady state assumption that inflationary expectations are fully adjusted to actual inflation. The rate of growth of productivity is assumed to be 0.56 percent. This value is given by the average of the productivity growth rates in the 1977-1981 period. In the shock case, on the other hand, the change in real weekly employment earnings in each period is given by the difference between actual inflation rates and the nominal growth rate of average weekly earnings during the 1981-1987 period. For instance, the rate of growth of nominal average weekly earnings in 1982 was 10 percent and the inflation rate was 10.8 percent. Therefore, in the shock scenario the rate of growth of real weekly earnings is assumed to be -0.8 percent for that period. In fact, with the exception of 1983, in all periods the real growth rates of average weekly earnings were negative.[26] As will be shown later negative growth of real earnings accounts for a considerable portion of total human wealth losses in the simulation.

2.5 Econometric Specification and Estimation Results of Probability of Becoming Unemployed

As mentioned above individual probabilities of becoming unemployed must be calculated in order to distribute the incidence of unemployment in each simulation period. This section provides the details of econometric specification and estimation results of a logistic regression model that is used in calculating individual probabilities.

Consider the individual response variable, u_i, which takes on two possible values: $u_i = 1$ if the individual experiences any unemployment at time period t, $u_i = 0$ otherwise. The following logit specification is used to investigate the relationship between the response probability and the explanatory variables.

[26] See Appendix A, Table A5.

(4) $$\log[\frac{p_i}{1-p_i}] = \alpha + \beta' X_i + u_i$$

where $p_i = P(u_i = 1)$, X_i is a set of explanatory variables related to the probability of experiencing unemployment, during the time period t, α is the intercept parameter, and β is the vector of slope parameters, and u is the stochastic disturbance.

Once the parameter values are estimated using the weighted least-squares procedure, predicted probabilities are calculated as:

(5) $$\hat{P}_i = \frac{1}{1 + e^{-X_i b + z_i}}.$$

where z_i is the random number generated from the error distribution of the logit model.

The estimated parameters of the determinants of the unemployment probability are presented in Table 2. Variable means are reported in Appendix C. The reference category is: Ontario resident, 25-44 years of age, married, blue-collar worker with high school education. For males, all the coefficients, except for the coefficient of Quebec, is highly significant. Again for females all the coefficients are highly significant. Being from Ontario appears to lower unemployment probabilities for both females and males. Only being from Prairies increases the probability of being unemployed for females. For males, those with higher levels of education have lower probability of becoming unemployed. For females, those who have university degree or a certificate or diploma are less likely to become unemployed than those with high school degree. This is the same for those with little or no education. However, some post-secondary education appears to increase the unemployment probability for females. For males, those with blue-collar occupations have higher probability of unemployment compared to all other occupations. However, for females only those who are classified as professionals appear to have lower probability compared to those with blue-collar occupations. While the very young males (16-24) appear to have higher unemployment probability compared to the prime age group, the older males (55-69) have lower unemployment probability relative to the same group. The same pattern is also observed for the females. For both males and females being single also appears to increase the unemployment probability.

For the purposes of the simulation one of the most important variables is the duration of the previous unemployment since it is the only time variant variable in the simulation. The significant and positive sign of the coefficients for both males and females indicate that previous unemployment durations increase the unemployment probability.[27]

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[27] In an earlier specification potential UI benefit variable was also included in the probability model. However, the estimated parameters had unexpected negative sign for both males and females which is inconsistent with "search theory" of

2.6 Duration of Unemployment Spells

This section develops econometric specification of unemployment durations. There is an extensive literature on the methods and problems related to duration analysis (also known as survival analysis).[28] These methods rely on hazard functions in order to overcome the difficulties related to the estimation of unemployment durations due to censoring encountered in duration data.

Survival analysis puts the focus on the group of individuals who exit from unemployment after a length of time called the survival time. In order to determine the survival time, (1) an unambiguous time origin, (2) a scale for measuring the passage of time, (3) a clear meaning for the exit from unemployment must be established.

Different individuals often have different time origins for their unemployment durations. These unemployment spells can begin at any date, and the spell lengths are typically the dependent variable in the analysis. As mentioned above, some unemployment spells of individuals may not be observed for the full time period until they exit unemployment. Such incomplete observation of the spells is called censoring. Censoring, like exit from unemployment, is an event occurring at some time, and unemployment spells for

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unemployment entry which states that the probability of unemployment increases with expected unemployment benefits. Similar results were reported elsewhere, e.g., in Stern (1984).

[28] see, e.g., Kalbfleisch and Prentice(1979), Cox and Oaks(1984), Miller(1981), Nickell(1979), Lancaster(1979), Heckman and Borjas(1980), etc. Kiefer(1988) provides a useful survey.

censored durations must also be included in the data set. Therefore, the duration data consist of measured spell lengths and the related information whether or not they are censored.

In this study spell lengths are measured as the number of weeks of unemployment. Furthermore, multiple spells in each period are aggregated into a single spell. This is convenient since the objective is to evaluate the changes in human wealth for each individual given the total weeks of unemployment in a given period. Individuals may end their unemployment spells with employment or may exit the labour force. The weeks out of the labour force per year is calculated for each individual in the initial period and assumed to remain constant over the (n) simulation periods. Therefore, if the individual's unemployment duration is less than 52 weeks the remaining weeks in that period is partitioned between employment weeks and weeks out of the labour force. Human wealth of the individual is then calculated given the total amount of weeks of employment and unemployment.

Let T, a random variable, be a spell length for an individual in the absence of censoring. Let C_i be independently, identically distributed with distribution function G and $i=1,\ldots,n$. C_i is the censoring time associated with T_i. Suppose that we only observe (Y_i,d_i) where

$$Y_i = \min\,(T_i,C_i)\ ,$$

$$d_i = 1 \text{ if } T_i \leq C_i\ ;\ \text{uncensored},$$

$$d_i = 0 \text{ if } C_i > T_i\ ;\ \text{censored}.$$

This is known as right censoring.[29] Given the time origin, the censoring times are usually known constants, such as the end of a year. Left censoring may also be present in the data if the time origin of unemployment spells are unknown at the beginning of the survey. A common practice in estimating unemployment durations, however, is to include only those spells whose origin is known in order to avoid problems related to left-censoring. This method is applied in this study. Right censored spells, on the other hand, can be handled by special techniques as will be shown below. The following sub-sections develop the model of unemployment duration when right-censoring is present in the data.

2.6.1 Survival Functions and Hazard Functions

Let $T \geq 0$ be a random variable representing the duration of unemployment of an individual from a homogeneous population with distribution function

(6) $F(t) = P(T < t)$,

where t represents a typical spell length in its range.[30] F(t) specifies the probability that the random variable T is less than some value t. When t is

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[29] see Miller(1981, pp.3-9).

[30]For analytical convenience the convention $F(t) = p(T < t)$ rather than $F(t) = P(T \leq t)$ is often adopted.

continuous the probability density function is given by

$$(7) \qquad f(t) = dF(t)/dt.$$

The probability that the random variable T will equal or exceed the value t is given by the survival function S(t)

$$(8) \qquad S(t) = 1 - F(t) = P(T \geq t), \quad 0 < t < \infty .$$

The hazard rate or hazard function represents the conditional probability of exiting unemployment in a small interval dt given survival to time t and can be expressed as

$$(9) \qquad \lambda(t) = \lim_{dt \to \infty} [\ P(t \leq T \langle\ t+dt \mid T \geq t)\ ] / dt$$

or equivalently,

$$(10) \quad \lambda(t) = f(t) / [\ 1 - F(t)] = f(t) / S(t).$$

The hazard function $\lambda(t)$ specifies the distribution of T since

$$(11) \quad \lambda(t) = f(t) / S(t) = [\ dF(t)/dt\ ] / S(t) = -\ln dS(t)/dt.$$

Therefore, integrating $\lambda(t)$, we obtain an important expression,

(12)
$$S(t)=\exp[-\int_0^t \lambda(u)du].$$

Notice that $F(\infty) = 1$ (i.e., $S(\infty)=0$) iff

(13)
$$\int_0^\infty \lambda(u)du=\infty.$$

Then the p.d.f of T can be written as

(14)
$$f(t)=\lambda(t)\exp[-\int_0^t \lambda(u)du].$$

2.7 Nonparametric Estimation of Unemployment Durations and Specification Checks[31]

Nonparametric techniques do not require specification of the functional form of the duration distributions and are useful in graphical or other assessment of goodness of fit for parametric models in a preliminary analysis. The results of this procedure are included in Section 2.9.

In the nonparametric survival analysis it is convenient to summarize duration of unemployment spells in terms of the sample survival function. The

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[31] For the nonparametric methods see, e.g., Miller(1981,pp. 39-80), Kalbfleisch and Prentice(1980,pp.10-20), Cox and Oaks(1984,pp.48-59)

sample survival function for a sample of n observations from a homogeneous population with no censoring is a step function decreasing by n^{-1} following each observed spell duration. This is given by

$$\hat{S}(t) = n^{-1}(\textit{number of sample points} \geq t). \tag{15}$$

However, since duration data often involves right censoring a modification becomes necessary to allow for censoring.

Let $t_1 < \ldots, < t_k$ represent the completed durations in a sample of size n from a homogeneous population with survival function S(t). The number of completed durations, k, is less than n because some observations are censored. Suppose that h_j is the number of completed duration spells of duration $t_{j.}$ for $j=1,\ldots,k$. Let m_j be the observations censored between t_j and t_{j+1}, and hence m_k is the number of observations with durations greater than t_j. Let n_j be the number of spells that are at risk just prior to $t_{j.}$:

$$n_j = \sum_{i \geq j}^{k} (m_i + h_i) \tag{16}$$

The hazard $\lambda(t)$ is the probability of completing a spell duration at t_j provided that the spell lasts until duration t_j. Then an estimator for $\lambda(t_j)$ is given by

$$\hat{\lambda}(t_j) = \frac{h_j}{n_j}, \tag{17}$$

i.e., the number of "failures" at t_j divided by the number "at risk" at t_j. The estimator of the corresponding survival function S(t) is given by

(18)
$$\hat{S}(t) = \prod_{i=1}^{J} \frac{(n_i - h_i)}{n_i} = \prod_{i=1}^{J} (1 - \hat{\lambda}_i)$$

which is the Kaplan-Meier (or product-limit) estimator.

The Kaplan-Meier estimator is related to the actuarial estimator of the life-table method. In the life-table method duration data grouped into intervals and then a survival rate is calculated for each interval. Let λ_i be the probability of completing a spell in the interval I_i, given survival to I_j

Then we may write,

(19)
$$\hat{\lambda}_i = 1 \qquad \text{if } n_i = 0 \, ,$$
$$\hat{\lambda}_i = \frac{d_i}{n_i - m_i/2} \qquad \text{otherwise.}$$

In the denominator an adjustment for censoring is made by subtracting one-half of the number of censored observations in the ith interval from the number entering the interval. Then the corresponding life-table estimator of the survival function is given by

(20) $$\hat{S}_i = \prod_{j=1}^{i} (1-\lambda_j)$$

Plots of the hazard, integrated hazard, and log-integrated hazard are useful in preliminary specification checks for hazard function models. For the exponential distribution the hazard is constant and the integrated hazard is linear in duration. The integrated hazard can be estimated by

(21) $$\begin{aligned}\hat{\Lambda}(t) &= \sum_{i \le j} \hat{\lambda}(t_i) \\ &= -\ln \hat{S}(t)\end{aligned}$$

which is the minus natural logarithm of the estimated survivor function. A convex Λ implies that the hazard is increasing (i.e., positive duration dependence). A concave integrated

hazard implies a decreasing hazard (i.e., negative duration dependence). Apart from visual inspections least-squares regressions can also be helpful. As an example consider the Weibull model:

$$S(t) = \exp[-(\lambda t)^{\alpha}] = \exp[-\gamma t^{\alpha}]$$

(22) $$\ln[-\ln S(t)] = \ln\gamma + \alpha \ln t,$$

which should yield a perfect fit when the Weibull specification is correct. The results of this method in the preliminary analysis suggested the appropriateness of the Weibull model in this study (see Section 2.9).

2.8 Parametric Estimation With Covariates: Accelerated Life Time Model

Our main interest concerns the relationship between the duration of unemployment and explanatory variables. However, at this point it is useful to consider some continuous distributions for homogeneous populations.

2.8.1 The exponential Distribution

Consider $\lambda(t) = \lambda > 0$. Then the integrated hazard is,

$$\int_0^t \lambda(u)du = \lambda t, \tag{23}$$

the survival function is

$$S(t) = \exp[-\int_0^t \lambda(u)du] = \exp(-\lambda t), \tag{24}$$

the p.d.f is,

(25) $f(t) = -dS(t)/dt = \lambda \exp(-\lambda t)$,

and the expected duration is given by

$$E(T) = \int_0^\infty \exp[-\int_0^t \lambda(u)du]dt, \tag{26}$$
$$= \int_0^\infty \exp(-\lambda t)dt,$$
$$= \frac{1}{\lambda}.$$

Because the hazard function is constant, $\lambda(t) = \lambda$, the exponential distribution is termed "memoryless" so that it reflects no duration dependence. Put another way, the instantaneous hazard rate is independent of t so that the conditional probability of failure (exit from unemployment) in a time interval of specified length is the same regardless of the length of the unemployment spell.

2.8.2 Weibull Distribution

The Weibull distribution is a two parameter generalization of the exponential distribution and it allows a power dependence of the hazard on time,

(27) $\lambda(t) = \lambda p(\lambda t)^{p-1}$.

This hazard is monotone decreasing for $p < 1$, increasing for $p > 1$, and reduces to exponential hazard if $p = 1$. The survival function is,

(28) $S(t) = \exp[-(\lambda t)^p]$.

Therefore,

(29) $$\int_0^t \lambda(u)du = (\lambda t)^p,$$

and,

(30) $$f(t) = \lambda(t)S(t) = p\lambda(pt)^{p-1}\exp[-(\lambda t)^p].$$

2.8.3 Log Logistic Distribution

The log-logistic distribution with parameters $\lambda > 0$ and $p > 0$, has a nonmonotonic hazard.

(31) $$\lambda(t) = \frac{\lambda p t^{p-1}}{1+\lambda t^p}$$

For $p > 1$ the hazard first increases from zero to a maximum at $t = (p-1)^{1/p}/\lambda$, then decreases toward zero. If $p < 1$ then the hazard function is monotone decreasing from ∞, and if $p=1$ then it is decreasing from λ.

The survival function is,

(32) $$S(t) = \frac{1}{1+\lambda t^p}$$

and the density is given by

(33)
$$f(t)=\lambda(t)S(t)=\frac{\lambda p t^{p-1}}{(1+(\lambda t)^{p})^{2}}$$

This model, like the Weibull and exponential models, has simple algebraic expressions for the survival and hazard functions. It provides a good approximation to the log-normal distribution and it is also more convenient in handling censored data compared to the latter.

2.8.4 Accelerated Failure Time Model

The above mentioned survival distributions can model the survival experience of a homogeneous population. Failure times (i.e., duration of unemployment spells in the present context), however, usually depend on explanatory variables (or covariates), Z. This heterogeneity in the duration data can be accounted for by modelling the relationship between survival time t and Z.

In the accelerated failure time models it is assumed that covariates act multiplicatively on failure time, or linearly on log failure time.

The survival function for an individual with a vector of individual characteristics is assumed to take the following form:

(34)
$$S(t,Z_i,\beta)=S_0(\phi(Z;\beta)),$$

where S_0 is the baseline survival function, β is the vector of parameters, and the covariates Z_i accelerate or decelerate the failure time through the function $\phi(Z_i,\beta)$. The hazard function associated with S(.) is given by

(35) $$\lambda(t,Z_i,\beta)=\lambda_0(t\phi(Z_i,\beta))\phi(Z_i,\beta),$$

where $\lambda_0(.) = -dS_0(.)/dt$ is the hazard function for the baseline survival distribution, and the density is the product of (34) and (35).

In the important special case $\phi(Z,\beta) = \exp(Z\beta)$ these models admit log-linear transformations.[32]

Assume that the hazard function is given by

(36) $$\lambda(t,Z)=\exp(-Z'\beta).$$

Equivalently one may write the survival probability as

(37) $P(T \geq t) = \exp(-t \cdot \exp(-Z\beta)).$

Suppose that the random variable $Y = \ln T$. Then,[33]

(38)
$$\begin{aligned} P(Y \geq t) &= P(\ln T \geq t) \\ &= P(T \geq \exp(t)) \\ &= \exp[-\exp(t - Z\beta)] \\ &= \exp\{ -\exp[(t - \mu)/\sigma] \} \end{aligned}$$

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[32] see, e.g., Gertsbakh (1989).

[33] see Gertsbakh (1989, p.197).

where $\mu = \mathbf{Z}\boldsymbol{\beta}$, and $\sigma = 1$. This means that the random variable Y has extreme value distribution with location parameter μ and scale parameter σ, i.e.,

$$Y \sim \mathrm{Extr}(\mathbf{Z}\boldsymbol{\beta},1),$$

or

$$Y - \mathbf{Z}\boldsymbol{\beta} = W \sim \mathrm{Extr}(0,1).$$

Therefore, one may write,

$$Y = lnT = Z\beta + \sigma W \tag{39}$$

where W is the baseline survival distribution playing the role of the error term with known parameters, and σ represents an unknown scale parameter. One can see that covariates, **Z**, have additive effect on the random variable Y and hence multiplicative effect on the survival time T. Clearly, the distribution of the error term in the accelerated failure time model is not restricted to a single distribution and may assume, e.g., log-normal, log-logistic, exponential or Weibull distribution. For instance, if Weibull distribution is assumed, it can be shown that the model takes the form

$$Y = \alpha + Z'\beta^{*} + \sigma W, \tag{40}$$

where $\alpha = -\ln\lambda$, $\sigma = 1/p$, and $\beta^{*} = \beta/p$.

2.8.5 Estimation

The presence of right censoring in the recording of unemployment durations necessitates the use of specialized statistical techniques in the estimation of the model.[34] The log failure time Y in the model presented in equation (27) has density

$\sigma^{-1}f(W_i)$,

where $W_i = (Y_i - \mathbf{Z}\boldsymbol{\beta})/\sigma$, and σ is a scale constant which provides information about the shape of the baseline hazard function, and if $Z_1 = 1$ identically, the first component of $\boldsymbol{\beta}$ represents the general location of Y.

Assuming that the censoring mechanism is independent of the failure mechanism, and letting $d_i = 1$ for a completed spell and $d_i = 0$ for a censored spell, the log likelihood function for log spell durations has the following form

(41)
$$L = \sum_{i=1}^{n} d_i \ln[\frac{f(W_i)}{\sigma}] + (1-d_i)\ln S(W_i)$$

where f(.) is the density and S(.) is the survival function. It is clear that, through the survival function, a censored value lnt contributes only the information that lnT exceeds lnt.

The score statistics are given by

[34] See, e.g., Kalbfleisch and Prentice (1980, pp.54-56).

$$(42)\qquad \begin{aligned} U_j(.) &= \frac{\partial lnL}{\partial \beta_j} = \sigma^{-1}\sum Z_{ji}a_i \quad j=1,\ldots,s. \\ U_{s+1}(.) &= \frac{\partial lnL}{\sigma} = \sigma^{-1}\sum (W_i a_i - d_i), \end{aligned}$$

where,

$$\begin{aligned} a_i &= -(d_i\frac{d\ lnf(W_i)}{dW_i} + (1-d_i)\frac{d\ lnS(W_i)}{dW_i}) \\ &= -d_i\frac{d\ lnf(W_i)}{dW_i} + (1-d_i)\lambda(W_i) \end{aligned}$$

where $\lambda(.)$ denotes the hazard function. The observed information matrix $\mathbf{I}(\boldsymbol{\beta},\sigma)$ is obtained by taking second order derivatives with respect to β and σ,

$$\begin{aligned} \frac{-\partial^2 lnL}{\partial\beta_j\beta_k} &= \sigma^{-2}\sum Z_{ji}Z_{ki}A_i,\ j=1,\ldots,s \quad k=1,\ldots,s \\ \frac{-\partial^2 lnL}{\partial\sigma^2} &= \sigma^{-2}\sum Z_{ji}W_iA_i + \sigma^{-1}U_j(\beta,\sigma),\quad j=1,\ldots,s \\ \frac{-\partial^2 lnL}{\partial\sigma^2} &= \sigma^{-2}\sum (W^2{}_iA_i + D_i) = 2\sigma^{-1}U_{s+1}(\beta,\sigma), \end{aligned}$$

where,

$$A_i = \frac{da_i}{dW_i}$$
$$= -d_i \frac{d^2 lnf(W_i)}{dW^2_i} + (1-d_i)[\lambda(W_i)\frac{dlnf(W-i)}{dW_i} + \lambda^2(W_i)].$$

Fitting these models require an iterative solution. Maximization of the likelihood is performed by the Newton-Raphson technique available in S.A.S lifereg procedure.

2.9 Preliminary Analysis and Estimation Results

Nonparametric methods are useful for the preliminary analysis of the data which may provide information on the distributional form of the unemployment durations. Empirical hazard rates are derived separately for female and male unemployment durations by using the life-table method with intervals defined by one week intervals. The sample contains information on those who start the estimation period as unemployed. The Weibull specification is chosen on the basis of preliminary data analysis. As indicated above, the appropriateness of a Weibull specification can be checked by running a least squares regression of the log-log transformation of the survival function:

$$\ln(-\ln S(t)) = \ln\gamma + \alpha \ln t,$$

which should yield a perfect fit. The coefficient on lnt indicates the shape of the distribution. The results from the regressions testing the appropriateness of the Weibull specification for both male and female data sets are presented in Table 3.

The R^2 in the regressions is very close to the perfect fit, indicating the appropriateness of the Weibull specification. The shape parameter α is less than 1, indicating negative duration dependence for the hazard function (i.e., decreasing hazard rate). These parameters, however, do not indicate the actual estimates of the parameters in question due to the heterogeneous nature of the data.

The results of the maximum likelihood estimation of the accelerated life time models for males and females are given in Table 4. The reference category is : Ontario resident, 25-44 years of age, married, blue-collar worker with high school education. Other variables are the previous weeks of unemployment and potential unemployment insurance benefits.[35]

Except for the coefficient of one education category for males and one occupation coefficient for females, all other coefficients are highly significant. Furthermore, the scale coefficient is above 1, indicating negative duration dependence (decreasing exit probabilities or hazard rates). That is, the longer the duration of unemployment the less likely it is to exit from unemployment.

For males, residing in Atlantic Canada or Quebec appears to increase

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[35] Industry of occupation could not be included since this information is not available in the Assets and Debts Survey of Statistics Canada.

unemployment durations, and for females residing in British Columbia appears to lower duration of unemployment compared to all other regions. Having clerical jobs appear to increase unemployment durations for males relative to blue-collar jobs. Although an opposite effect is observed for females in this category, the coefficient is not significantly different from zero. All other occupation categories reduce unemployment durations for males relative to blue-collar jobs. Managerial and administrative occupations appear to have the highest coefficient, indicating a strong negative impact on unemployment durations. For females, however, being in the managerial or professional category appears to have a strong positive impact on unemployment durations. Again for females, all other white-collar jobs appear to increase unemployment durations. While rural jobs appear to reduce the duration of unemployment for females, they increase unemployment durations for males. This may be due to the end of resource boom in the early 1980s. Younger male workers appear to have longer durations compared to the 25-44 age group. However, the coefficient for the very young is relatively small. For females the very young and the very old have shorter durations compared to other age groups. More education for both males and females appear to increase the unemployment durations. Being single, however, indicates shorter unemployment spells for females, and longer spells for males. The coefficient of the potential weekly UI benefit variable has a positive sign and also significant for both males and females. However, the magnitude of the coefficient is again very small for both males and females.

The coefficient of the most important variable for the simulation, previous unemployment weeks, is statistically significant and appears to increase the unemployment durations for both males and females. This variable is the only time variant variable in the duration equations and captures the correlation between unemployment durations from one period to the next. The positive correlation implies that those who experience unemployment in one period will experience longer durations in the next period. However, the magnitude of the coefficient is rather small for both categories, being slightly higher for males.

2.10 Simulation Results

Simulation is performed over seven periods following two periods of initial "warming-up" in order to eliminate the effects of initial conditions in the simulation. In the warm-up periods both incidence and duration of unemployment are distributed among individuals while keeping the aggregate unemployment rate constant. Subsequently a shock is introduced to the steady state system in the form of an increase in aggregate unemployment. The magnitude of the shock reflects the increase in the aggregate unemployment rate in Canada in 1982. Thereafter the historical values of unemployment rates up to 1987 are used to carry out the simulation over the remaining periods. In each period baseline unemployed individuals and those who become unemployed due to changes in aggregate unemployment are identified. The latter group of individuals are called incidence losers. The employment earnings of all individuals, including unemployment insurance benefits, are calculated for the baseline and shock scenarios and are discounted at 5.5 percent real interest rate to the initial period in order to obtain the values of their human wealth in 1981 dollars. This choice of a relatively higher discount rate on behalf of household labour earnings reflects a compensation for human risk factors in discounting future stream of incomes, such as injury, sickness, etc.

In the following paragraphs the simulation results will be first analysed at the individual level. Subsequently, the analysis will be conducted at the household level.

The impact on individuals

Table 5 reports the distribution of incidence of unemployment among individuals in the loser category by their ranking in human wealth deciles. Recall that losers are those who would not have experienced any unemployment had there been no increase in aggregate unemployment. There was an initial increase in the aggregate unemployment rate from 8.5 percent in 1981 (December) to 11 percent in 1882, and also a further increase to 11.8 percent in 1983. Thereafter the aggregate unemployment rate began to decline. It was 11.2 percent in 1984, 10.5 percent in 1985, 9.5 percent in 1986, and finally 8.8 percent in 1987 which was very close to the 1981 level. As mentioned earlier this amounts to an initial rise in total weeks of unemployment from 40.8 to 52.8 million. Thereafter, the total number of unemployment weeks was calculated as 56.6 million in 1983, 53.7 million in 1984, 50.3 million in 1985, 45.5 million in 1986, and finally 42.2 million in 1987. The average change in incidence of unemployment over the simulation periods, which is strictly due to the increase in the aggregate unemployment rate, is therefore 1.9 percent as shown in the first row of the table. The average incidence of losers in the top two human wealth deciles are 1.8 percent and 1.9 percent while in the lower deciles it ranges between 1.3 percent and 2.3 percent. The lowest average incidences are in the first two deciles. This may indicate that they are already disadvantaged in the baseline scenario with higher unemployment experiences, and additional burden created by increases in unemployment do not affect their situation much and hence do not qualify them as incidence losers. There is, however, relatively heavy concentration of incidence losers in the middle human wealth deciles, i.e., fourth, fifth, and sixth deciles. The average incidence losers over the simulation periods in this group ranges between 2 and 2.3 percent. The overall picture is such that loser individuals are concentrated more heavily in the relatively lower and especially in the middle human wealth deciles.

Inequality statistics for human wealth of the individuals in the baseline and shock scenarios are reported in Table 6. There is a slight decline in the average human wealth from $100910 to $96943 in the shock scenario, which is about 4 percent. The coefficient of variation, Gini index, Theil's entropy measure, and Atkinson's index for different degrees of inequality aversion show a slight increase in inequality.[36] Higher levels of ϵ in the Atkinson's measure indicates greater inequality aversion. These inequality measures, except for the coefficient of

[36] See Appendix B for the formulae.

variation, fall between zero and one. A value of zero indicates perfect equality and a value of one indicates perfect inequality. Therefore, as the indices move closer to 1 inequality is said to increase.

As shown in the last column of the table, all these measures indicate some increase in inequality. However, the magnitude of changes are in the second or third digit level and do not seem to be striking. For example, the Gini index rises from 0.375 to 0.380, and Theil's index increases from 0.238 to 0.244. Relatively small changes in these measures are expected since the increase in the number of unemployed individuals is only a small percentage of total population. Put another way even if the unemployment rate rises from 10 to 13 percent employment will decline from 90 percent to 87 percent, a rather small change. Furthermore, as mentioned in Section 2.4.2, a uniform distribution of real wage effects is also assumed in the simulation. Therefore, it is reasonable to expect that such aggregate inequality measures can only be small indicators of a direction in the change of distribution of human wealth under the baseline and shock scenarios. This also implies that a disaggregated analysis of the distributional impacts of increases in aggregate unemployment is required.

Table 7 reports the baseline and shock distribution of average human wealth by deciles, decile shares of total human wealth, and percentage losses in each decile. The values of human wealth are obtained by discounting employment earnings at 5.5 percent real interest rate which is assumed to be prevailing in the initial period. The real interest rate here is a rough approximation since the actual rather than the expected inflation rate is used in the calculation. It is simply the difference between the five year nominal mortgage rate and the actual inflation rate in 1981. Average human wealth in the baseline scenario ranges from $10555 in the bottom decile to $251614 in the top decile. In the shock scenario average human wealth ranges between $10173 in the bottom decile and $243345 in the top decile. This clearly shows that there is a decline in average human wealth in each decile in the shock scenario. The magnitude of this decline is expressed in percentage terms in the last column of the table. The percentage loss in average human wealth in the bottom decile is 3.6 percent. Percentage losses in average human wealth are higher in the middle human wealth deciles. For example, the losses range between 4.9 percent in the third decile and 4.5 percent in the sixth decile. Thereafter it steadily declines and reaches 3.3 percent in the top decile. There is also a slight change in the decile shares in the shock scenario. On the one hand, a small decline in decile shares of the second, third, fifth, and eighth deciles is observed. On the other hand, shares of total human wealth in the top two deciles shows a small increase. All these changes, however, are in the third digit level.

Relatively small variation in losses seems to be related to the magnitude of changes in real earnings during the shock scenario, as well as increased incidence and duration of unemployment. Table 8a reports the total simulated losses in human wealth. The first column of the table decomposes the total human wealth loss into 3 sources: (1) losses due to changes in the real earnings of the employed individuals in both scenarios, (2) losses due to changes in the real earnings of those who experience some unemployment in both scenarios, (3) losses due to changes in the real earnings of those who become unemployed in the shock scenario, i.e., incidence losers.

As shown in the last row of the second column, the total loss in human wealth is $38.7 billion. The changes in the real earnings of the employed accounts for 20 percent of total loss in human wealth. Changes in the real earnings of those with some experience of unemployment during the baseline scenario accounts for 77 percent, and the losses of losers due to higher unemployment accounts for 3 percent. What this indicates is that the total labour force is affected by the shock scenario. Those who do not experience any unemployment due to an increase in the aggregate unemployment rate also appear to lose because of a decline in their real earnings. The decline in real earnings, of course, generates additional losses for those who lose employment earnings due to unemployment. Therefore, those who experience unemployment in both cases and also the loser unemployed account for 80 percent of total losses in the simulation and the remainder of the losses are accounted for by the losses of those who are employed in both scenarios.

The total magnitude, source, and distribution of human wealth losses proves to be sensitive to initial specification of the probability and duration equations. A sensitivity test was performed by assigning zero value to the coefficient of previous unemployment variable in the calculation of unemployment probabilities and expected durations. That is, year-to-year correlation between unemployment durations and the effect of previous unemployment duration on the current unemployment probability are simply omitted from the simulation. The results, as shown in Table 8b, indicate important differences. First, the total amount of losses decline by about \$3 billion to \$35.8 billion. It is plausible that more of unemployment is experienced by low wage workers since total unemployment is fixed. Second, 11 percent of the losses become attributable to the changes in real earnings of those who are employed in both scenarios. This is about one half of the amount compared to the original specification and hence indicates much lower real wage effects. It is plausible that this may be due to the increased stochastic variation in assigning unemployment probabilities and expected durations when the effects of previous unemployment on current level of these variables are not accounted for. Furthermore, the loss attributable to the changes in the real earnings of losers is 5 percent of the total loss compared to 3 percent in the original specification. Therefore, the inclusion of year-to-year unemployment correlations in determining the probabilities and expected duration of unemployment proves to be important.

The total amount of loss in human wealth, however, is an underestimate of the actual total losses that may have occurred during the 1981-87 period. The simulation starts with the assumption of 8.5 percent aggregate unemployment, which is the level in December 1981. The aggregate unemployment first increases to 11 percent in 1982, and then to 11.8 percent in 1983. Thereafter it begins to decline gradually to the level of 8.8 percent in 1987. Assuming that each percentage point increase in the annual unemployment rate costs society an equivalent of 2 percent of GDP (Okun's Law), the present value of this cost for the initial period can be calculated by using the following formula:[37]

$$\frac{C_t}{GDP_t} = 2 \cdot \sum_{i=0}^{6} \left(\frac{1.025}{1.0545}\right)^i (u_{t+i} - 0.085)$$

where, C is the cost, t = 1981, and u is the unemployment rate. Furthermore, the real economic growth and the real interest rate are assumed to be 2.5 percent and 5.45 percent, respectively. The result of the calculation is 21.6% of the GDP. Since GDP in 1981 was \$355.9 billion in nominal terms, the cost to 1981 GDP is \$76.9 billion. Therefore, the estimated \$38.7 billion in the simulation is rather an underestimate of the total loss since it accounts for only 50.3 percent of the total loss in the economy.

The total loss in human wealth itself may also be somewhat underestimated. As mentioned above weekly employment earnings for individuals are calculated for those who have positive weeks of employment in the original sample as the ratio of total earnings to weeks of employment. Therefore, those who do not have positive employment weeks are excluded from the sample.

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[37] Howitt (1990) uses the same formula for the 1981-1988 period and estimates the cost to 1982 GDP as 36 percent. In his calculation the initial unemployment rate is 7.5 percent which is the 1981 average.

Moreover, those who are under the category of "special units" for the protection of their identity, although a ve·ⁿ small percentage of the sample, are also excluded since no regional information is available about them. Therefore, it is plausible that because of some sample attrition the simulation model may also be generating an underestimate of the total amount of loss in human wealth. Although the total amount of human wealth loss may be somewhat underestimated the distribution of this loss is still of interest.

A more detailed analysis of loser individuals is performed by ranking them relative to their human wealth losses. Table 9 reports the baseline and shock average human wealth, and also percentage average losses in each decile when individuals are ranked relative to their human wealth losses in absolute terms. Let us define the first decile as the small losers and the 10th decile as the big ones. Average loss among the small losers is 1.9 percent and among the big losers 33.5 percent. In Table 10 distribution of individuals by their human wealth ranks among the big and small losers are reported. Among the big losers there is a heavy concentration of individuals who are ranked in the upper human wealth deciles. The biggest share goes to the top human wealth decile as 29.7 percent. The bottom three deciles are nonexistent among the big losers. By contrast, individuals from the lowest human wealth decile has the major share (39,5 percent) among the small losers, and the top human wealth decile is nonexistent. Since individuals are ranked by their absolute amount of losses these results seem plausible. Those who are in the upper human wealth deciles are likely to lose in absolute terms much more than those in the lower human wealth deciles because they had more to lose, and vice versa.

Alternatively, one may analyse the same distribution in terms of percentage losses. In Table 11 loser individuals are ranked by their percentage losses in human wealth. The small losers are again in the first decile and their average loss is 1.2 percent. On the other hand, the big losers are in the 10th decile and they lose 44.7 percent on average. It is also clear that one half of the population of losers experiences losses ranging between 1.2 percent and 7.4 percent, and the other half experiences losses between 10.1 percent and 44.7 percent. What this indicates is that there is a heavy concentration of losses in the population. Therefore, it is important to have a close examination of those who lose considerable amounts due to changing unemployment rates. In the following paragraphs we will examine the losers by their human wealth ranks, and also by their income-demographic characteristics. Income-demographic characteristics will be first examined by their distribution in the population and later by regression analysis. Comparisons will also be made between loser individuals and nonlosers.

As shown earlier, those who come from upper human wealth deciles concentrate among the big losers when losses are measured in absolute terms. However, the share of the top human wealth decile becomes only 6.9 percent among the big losers when losses are measured in percentage terms, as shown in Table 11. Instead, there appears to be a heavy concentration of those who are in the middle or lower human wealth decile groups among the big losers. The obvious implication is that individuals who are ranked highly in human wealth deciles may lose substantially in absolute terms, yet what they lose is rather small when compared to what they keep in the baseline scenario. The opposite is also true for those who are ranked low in human wealth deciles. They lose small amounts in absolute terms; but whatever they lose is rather a significant portion of what they keep.

Tables 13 and 14 report the distribution of nonloser and loser individuals, respectively, as a proportion of their total sample frequencies by their demographic characteristics. The second column in these tables reports the total sample frequencies for each category. Therefore, a value close to or equal to 1 indicates equal representation of the given demographic category in the sample in question. A value greater or less than 1 indicates over-representation or under-representation, respectively. In Table 13 the distribution of top and bottom human wealth deciles are included. In Table 14, losers are grouped into three categories: total losers, big losers, and small losers. The losses are in relative terms, i.e., proportionate to their baseline human wealth.

Among the nonloser individuals in Table 13, males, married individuals, those who have managerial and administrative jobs and also professionals, older individuals, those with university education, and those who reside in Ontario, Prairies, and British Columbia are all over represented in the top decile. All other categories are under represented. Furthermore, the very young individuals are basically excluded from the top decile. In the bottom decile females, single individuals, those in sales and services, the very young and the very old, those with little education, and also those who are residing in Atlantic provinces or in Prairies are clearly over represented.

Among the loser individuals in Table 14, males, married individuals, those with blue-collar occupations or with rural jobs, younger individuals, those with little education, and those who reside in Atlantic provinces, Prairies are either over represented or keep their population share. When losses are measured as a percentage change in human wealth, males, married individuals, those who have rural, clerical, or blue-collar occupations, younger individuals, those with little education, and those who reside in Atlantic provinces, or Quebec, appear to be over represented among the big losers. Among the small losers over represented categories are: females, married individuals, those with clerical jobs, younger individuals, those with little education, and also those who reside in Ontario, or British Columbia.

An alternative way of analysing the distribution and magnitude of losses in human wealth is to regress the ratio of shock human wealth to baseline human wealth on the income-demographic characteristics of the household heads. The dependent variable is therefore a proportionate measure of human wealth in the shock scenario relative to baseline scenario. Table 15 reports the results of regressions for three different samples: (1) total sample, including all household heads, (2) sample of individuals who experience some unemployment in both the baseline and shock scenarios, (3) sample of losers, i.e., unemployed only in the shock scenario. The reference category is a married, blue-collar male worker with high school education in the 25-44 age group, residing in Ontario. The employment incomes in the first year of the baseline scenario are also included as an explanatory variable. Columns with the heading P > t gives the significance level of parameter estimates, based on absolute value of the calculated t-statistics.

The parameter estimates of the total sample regression are highly significant with the exception of two regional and three education variables, i.e., Quebec, Prairies, elementary, some post secondary, and university education. The adjusted R^2 is 0.087. The constant term indicates that the mean value of human wealth in the shock scenario is about 90 percent of the baseline human wealth for the reference category. Therefore, there is 10 percent loss in human wealth for the reference category. The losses in percentage terms appear to increase for those who reside in Atlantic Canada by 13 percent. Although the coefficients of Quebec and Prairies indicate the same direction, they are rather small and statistically insignificant. Residing in British Columbia appears to reduce the loss by about 0.7 percent.

The losses are also greater for the younger people: 3.3 percent for teenagers, and 5.8 percent for the 20-24 age group. For older individuals losses are reduced by 0.9 percent for the 45-54 age group, and by 2.2 percent for those

55 and above.[38] Having little education appears to increase human wealth losses. However, with the exception of certificate/diploma category, the coefficients are statistically insignificant. All white-collar occupations appear to incur smaller losses compared to blue-collar occupations and all of the coefficients are significant. Those with managerial-administrative occupations, or in sales/services appear to lose the least: their losses reduced by about 1.8 percent and 1.9 percent, respectively. They are followed by those who are professionals, or with clerical, rural occupations. The biggest losers, therefore, appear to be those with the blue-collar jobs. Being single also decreases the loss by 0.4 percent. Furthermore, being a male reduces the loss by about 1.7 percent. Over and above demographic characteristics incomes matter. Higher income levels also appear to decrease losses. An individual with a $30000 income experiences about 1.5 percent less, with a $60000 income 3.0 percent less, and so on. Therefore, the higher the income level the less is the human wealth loss.

For the sample of those who experience some unemployment either in the baseline or in the shock scenarios, the coefficients point to similar percentage losses in human wealth for all categories. For the reference category the mean shock human wealth in this specification is 89 percent of the baseline human wealth and the adjusted R^2 is 0.089. Therefore, for those with some unemployment in the reference category, average loss in human wealth is 11

[38] This implies that the main impact is on entry cohorts in labour markets, which is consistent with the findings of Picot, et al. (1990) which suggest declining real wages for the young in the 1980s.

percent, which is about 1 percent greater than the average loss of the same category in the total sample. Those who reside in Atlantic provinces appear to experience bigger human wealth losses. And again the coefficients of Quebec and Prairies are not statistically significant. Younger individuals who have some unemployment also experience bigger human wealth losses. As before, in the education category those who have little education have human losses greater than those with more years of formal education. However, the coefficients of the education categories, with the exception of certificate/diploma, are not statistically significant. All white-collar occupations and rural jobs have significant positive coefficients which imply less human wealth losses compared to blue-collar occupations. Being single, and also being male appear to reduce losses when some unemployment is experienced. In higher income groups human wealth losses appear to be less when individuals experience unemployment. For instance, for someone with $30000, losses in human wealth will be 1.8 percent less compared to the average loss. This amount rises to 3.6 percent when income level is doubled.

Those who experience unemployment only in the shock scenario are classified in the loser category. A separate regression results for those who fall into this category are also reported in Table 15. For the reference category, the mean human wealth in the shock scenario is about 74 percent of the baseline human wealth and the adjusted R^2 is 0.123. Therefore, the average loss of the reference group in the shock scenario is about 25 percent. The estimated coefficients have quite similar signs compared to those reported in the previous samples. They are, however, slightly larger indicating stronger effects on the percentage losses in human wealth. Those who reside in Atlantic provinces, or Quebec appear to lose more in percentage terms. The coefficient of Quebec, however, is not statistically significant. Among the losers residing in Atlantic Canada increases the loss by about 2.4 percent. The coefficients in the age categories also indicate higher losses for younger individuals; but the coefficient of the 16-19 age group is not significantly different from zero. Higher levels of education are associated with smaller losses, and this time, with the exception of elementary and some post secondary education, the estimated coefficients are statistically significant. Among the losers those with white-collar occupations again appear to lose less compared to blue-collar occupations but the estimated coefficients, with the exception of rural occupations, are all statistically insignificant. The rural jobs indicate bigger losses. Males appear to lose less by 5.3 percent and their coefficient is also highly significant. Single individuals again lose less by about 3.7 percent. Income variable again has a positive sign and it is also statistically significant. Higher income levels appear to be associated with smaller percentage losses in human wealth.

The impact on household wealth

A final step in analysing the distributional effects of higher aggregate unemployment involves the assessment of this impact on household human wealth. This is especially important within the context of this study because the ultimate objective is to analyse simultaneous effects of higher unemployment and disinflation on the human and nonhuman (financial) wealth of Canadian households. Financial effects of disinflation on household net-worth is of special interest, and the total effects are basically the combined effects on household human wealth and household net-worth. Total wealth effects are included in later sections.

As mentioned earlier when calculating household human wealth work patterns and employment earnings of wives are calculated as separate points of observation. The regression coefficients for females in the probability and duration equations are also applied to this group in the simulation. This means that they are treated independent of their spouses' work patterns or earnings. This procedure is an outcome of data limitations. That is, there is a necessary trade-off between unemployment duration correlations over time and husband and wife correlations within households in determining household human wealth in the simulation, since both pieces of information are not available in a single data set. Therefore, in each household the total human wealth is given by the sum total of the separate calculations on husband and wife.

Table 16 reports the summary statistics for households. The mean household wealth shows a slight change from $144,618 to $138,933, which is about 4 percent decline. The percentage decline in mean human wealth is necessarily the same when compared to that of the individuals. As before, all inequality statistics show slight increases. The magnitude and percentage changes in the inequality measures, however, appear to be somewhat different compared to those for the individuals as shown in Table 6. As shown above, the size of the inequality measures indicates a higher degree of inequality among the individuals. However, the percentage changes in inequality measures appear to be greater for households. For instance, in Table 16 the Gini index for the households shows 1.7 percent increase from 0.345 to 0.351, or about 30 percent greater increase compared to that of individuals. Theil' entropy measure rises from 0.200 to 0.207, a change in the third digit level or about 3.5 percent. The increase in this index is only 2.5 percent for the individuals. Atkinson's measures with different degrees of inequality also indicate slight increases in the inequality, ranging between 1 percent and 3.7 percent, and the changes are again greater in magnitude compared to the case of individuals.

Nevertheless, the changes in inequality measures for the households can also be considered rather small. Relatively small changes reflected in these measures can be explained by the same reasoning that applies to previous analysis on individuals. That is, increases in aggregate unemployment within the simulation periods affect relatively small proportion of total population. Furthermore, real wage effects are assumed to be uniformly distributed across individuals.

Table 17 reports the baseline and shock distribution of average household human wealth by deciles. These results are also comparable with that of household heads. The magnitude of percentage losses shows basically the same trend. As one moves from the bottom deciles toward the middle and upper deciles, percentage losses appear to first increase and then decrease. The variation in percentage losses in average human wealth is, however, slightly higher. While the biggest decline in average human wealth, the bottom second decile, is 6.5 percent, the top decile loses only 3.2 percent. Furthermore, when compared to the case of individuals the upper household human wealth deciles appear to have smaller percentage losses, and the middle and lower deciles experience similar losses, if not bigger. Higher losses in the middle and lower deciles may be due to the additional losses incurred by working spouses in these households.

Table 18 ranks the loser households by their percentage losses in human wealth. When either the husband or the wife (or both) experiences unemployment strictly due to higher aggregate unemployment in a given period, that household is classified as a loser. The percentage losses of these households range between 2.4 percent in the first decile and 36.6 percent in the top decile and are called small losers and big losers, respectively. Table 19 reveals the distribution of households in the small and big loser categories by their human wealth deciles. Among the big losers there is a considerable concentration of households who come from middle or lower human wealth deciles. More than 60 percent of households come from somewhere between the bottom and fifth human wealth deciles. The share of the top human wealth decile is only 6.7 percent among the big loser households. This picture is almost completely reversed when we look at the small loser households. Most of the small losers come from middle and upper human wealth deciles. The share of top 5 human wealth deciles is more than 70 percent among the small loser households.

2.11 Summary and Conclusions.

In this chapter the effects of higher unemployment rates in Canada during the disinflationary period of 1981-1987 on the individual and household human wealth have been simulated. The simulation has been performed with and without changes in the aggregate unemployment rates in order to compare the value and distribution of present value of employment earnings, including UI benefits. The simulation results clearly indicate that individuals and households as a whole incurred losses in human wealth due to changes in real earnings, as well as higher unemployment.

The total amount of simulated human wealth losses is about $40 billion for the Canadian households which is, if anything, an under estimate of the actual losses incurred by the economy during this period. The major source of this loss is the changes in real earnings of households who experience some unemployment in both baseline and shock scenarios. This result, however, is found to be sensitive to the specification of unemployment probability equations. When the effects of previous year's unemployment duration on the current expected duration and probability of unemployment are omitted in the simulation, there is about $3 billion or about 8 percent reduction in the amount of total human wealth losses. Moreover, the losses attributable to the changes in the real earnings of employed individuals in both scenarios also decline considerably.

There is also a considerable variation in the distribution of losses by income-demographic categories. Those who reside in the Atlantic provinces, those who have little education, those with blue-collar jobs, those with relatively small incomes, and younger individuals are by far the biggest losers. Those with white-collar occupations, and especially those who hold managerial positions or professionals, appear to lose considerably less. Males, and also single individuals appear to lose considerably less, as well. Human wealth losses are also smaller for those individuals with higher incomes.

The results also indicate that there is a somewhat greater variation in losses of human wealth at the household level. Middle and lower household deciles appear to lose more relative to upper household deciles compared to the human wealth deciles for individuals. In the distribution of human wealth a slightly higher degree of inequality is observed for the individuals when compared to households. However, households appear to be much more affected by the changes in aggregate unemployment, as indicated by greater percentage increases in inequality measures. The loser households also appear to be concentrated in the middle and lower human wealth deciles.

Therefore, based on these results, one may conclude that those who are already socially or economically disadvantaged are the hardest hit by disappearance of jobs, and by declining real employment earnings. And the losses appear to be more dramatic when Canadian households rather than individuals are considered.

CHAPTER 3: SIMULATION MODEL OF NON-HUMAN WEALTH

3.1 Introduction

This chapter develops a simulation model in order to analyse the distributional effects of 1981-1987 disinflation on non-human wealth (net worth) of Canadian households. As before the simulation is performed for the baseline (constant inflation) and shock (disinflationary adjustment) scenarios for purpose of comparisons.

Household non-human wealth is defined as the real value of assets owned less debt owed by households. This relationship can be expressed in the balance sheet identity as:

Non-human wealth = Assets - Liabilities,

which could be positive or negative, and in the former case the household is called a net creditor and in the latter case a net debtor. As will be explained below the effect of disinflation on non-human wealth of a household, however, is dependent on the composition of the household's assets and liabilities.

In Table 20 the family wealth components in the Assets and Debts Survey (1984) of Statistics Canada are included. In the present model household non-human wealth is aggregated into (1) liquid assets, (2) bonds, (3) stocks, (4) houses, (5) mortgage outstanding, and (6) other debt. Liquid assets include cash on hand, deposits, and Canada Saving Bonds, which is consistent with this category given in the table. Other debt is the sum total of personal debt and consumer debt. Items such as vehicles are assumed to depreciate within the period 1981-1987 and finally be replaced. Therefore, there is no need to include them in the model. They represent 5.5 percent of the total assets in the Assets and Debts Survey (1984). Equity in business, farm or profession are also excluded since reported values are not usually reliable in sample surveys. They represent 21.3 percent of the total assets in the survey. Other debt is treated as negative cash holdings in the model. Furthermore, it is also assumed that households are not engaged in trading of their assets or debts in the simulation periods.

The change in household net worth in non-human wealth is dependent on the composition of assets held and debts outstanding in the initial period of the simulation and the extent to which the value of the net worth components are affected by disinflation.

There are two types of price changes which affect the real net worth position of the households in the model. (1) Changes in the *specific* prices of the net worth components, (2) changes in the purchasing power of the monetary unit due to changes in the consumer price index (CPI). Changes in the former, which consist of changes in interest rates or price indexes of the asset in question, result in nominal capital gains or losses.[39] The calculation of capital gains/losses by asset type will be explained in the following sub-sections. Changes in the latter reflect the real value changes in the net worth components and applies to all net

[39] Several studies in the past have incorporated capital gains or losses in analysing the distribution of non-human wealth. See, e.g., Budd and Seiders (1971), Babeau (1978), Wolff (1979), Praet (1980, 1983), Sunga (1987).

worth components. More specifically, the specific price changes include:

(1) changes in average nominal interest rates on bonds,

(2) changes in average nominal mortgage interest rates,

(3) changes in average stock price indexes,

(4) changes in average house price indexes.

Note that relative price changes *within* asset types are not taken into consideration. This amounts to assuming that relative price changes within each asset type ultimately net out. In other words, changes in the prices of some assets within each category, which are less than the average change for the asset type, are assumed to be offset by changes in the prices of some other assets which are more than the average change.[40] Also note that while the value of all holdings of bonds, stocks, mortgages, and houses are affected by changes in their specific prices and CPI, real value of liquid assets and other debt are affected by changes in CPI only. The following section provides a more detailed explanation of non-human wealth calculations.

3.2 The Model of Non-human Wealth

Under the efficient financial markets hypothesis the market value of

[40] Consider, for example, stock prices. In the simulation, Toronto composite (300) stock price indexes are included in calculating capital gains or losses on stock holdings. However, relative to the composite index the prices of individual stocks may perform differently depending on their volatility. Discrepancies in the relative performance of individual stock prices are assumed to be randomly distributed across individuals and to cancel out at the aggregate level. Hence the market value of each stock holding in the data is assumed to behave as the composite index.

financial assets must equal the discounted present value of their future income payments. In the baseline scenario the economy is assumed to be operating in a steady state with equilibrium rates of unemployment and inflation, where expected inflation is fully adjusted to the actual inflation. Capital markets are assumed to be efficient in the baseline. The implication of this assumption for the simulation is that with the exception of liquid asset and other debt categories, there is no need for adjustments for the initial market values of the financial assets or debts in the baseline scenario since these values should reflect the present discounted value of expected returns.

In the shock scenario, however, the expected returns are no longer the actual returns. As will be explained below the specific prices of net worth components such as bond and mortgage interest rates, housing prices, and stock prices do change unexpectedly due to unexpected changes in inflation, generating capital gains or losses in household non-human wealth.

A general adjustment for *all* net worth components in order to account for the changes in the purchasing power of the monetary unit is also made by using the consumer price indexes. For the baseline scenario consumer price indexes are created at the assumed 12.8 percent inflation rate in order to calculate the deflated values of liquid assets and other debt components of household net worth. In the shock scenario actual consumer price indexes are used for the remaining periods.

The initial period in both cases assumes the index value of 100. The consumer price indexes in the shock simulation are used to deflate the nominal returns on assets/debts in order to obtain the real values of returns in each period. These real returns are then discounted to the initial period using the real discount rate 0.0545 which is the difference between the nominal interest rates on long term mortgage rate and the inflation rate in 1981 Recall that in Chapter 2 the same rate is used for human wealth calculations. This choice of a relatively high real discount rate on behalf of household labour earnings reflects a compensation for human risk factors in discounting future streams of incomes, which may be stochastic events such as injury, sickness, etc., in a household's future horizon.[41] This real interest rate is also assumed to reflect foregone real consumption for individual households, since households are assumed to make inter-temporal choices between consuming now and the future, e.g., between paying down their mortgage principal or consuming. When they hold interest bearing assets they do so in order to obtain real future consumption. Therefore, it is assumed that their choices are based upon the difference between the actual nominal interest rate and the actual inflation in the initial period, i.e., at the time when the choices are made.

Adjustment coefficients for each asset type are calculated in order to simulate the disinflationary gains or losses for each asset type in the baseline and shock scenarios. The coefficients represent the present discounted value of per

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[41] Sensitivity of the results to different real discount rates will be included in future studies.

dollar holding of an asset or debt type in the baseline and shock scenarios. For the liquid assets and other debt components they are the deflated values of one dollar, payable at the end of the simulation periods.

Once the coefficients are calculated, the value of household total wealth is obtained by simply multiplying each net worth component by its coefficient. The following paragraphs explain the numerical calculation of coefficients for individual net worth components. The adjustment coefficients are also reported in Table 22. All relevant data are obtained from various issues of Bank of Canada Review and Canadian Housing Statistics and are included in Appendix A, Table A6.

1. Fixed-income instruments: bonds and mortgages.

As mentioned above, financial markets in the baseline simulation are assumed to operate efficiently. That is, market values of bonds in the initial period reflect the discounted present value of expected returns, assuming constant continued inflation. In the shock simulation, however, actual nominal interest rates change due to disinflation in the 1981-1987 period. The following general equation is used in calculating the real values of bonds in the shock simulation:

$$Bond = \sum_{j=1}^{4} \frac{c1/CPI_j}{(1+r)^j} + \sum_{j=5}^{6} \frac{c2/CPI_j}{(1+r)^j} + \frac{1/CPI_6}{(1+r)^6}.$$

where r is the discount rate at 0.0545, reflecting the real interest rate used in non-human wealth calculations in the previous chapter. This equation gives the real value of bond holdings per $ of investment in the shock simulation. It is assumed that principal amount is invested in the initial period and the bond is held initially for 4 years (1982-1985), which approximates average duration of bonds during the 1981-1987 period. After four years the principal ($1) is reinvested on 2-year bonds and at the end of the second term the bond is cashed. Therefore, the coupon payment c1 is the annual dollar amount received on four-year bonds invested, and c2 is the annual dollar payment received on two-year bonds. Therefore, the numerical calculation is as follows:

$$
\begin{aligned}
Bonds &= \frac{(0.1517/110.8)\cdot 100}{1.0545} + \frac{(0.1517/117.2)\cdot 100}{(1.0545)^2} \\
&+ \frac{(0.1517/122.3)\cdot 100}{(1.0545)^3} + \frac{(0.1517/127.2)\cdot 100}{(1.0545)^4} \\
&+ \frac{(0.0988/132.4)\cdot 100}{(1.0545)^5} + \frac{(1.0988/138.2)\cdot 100}{(1.0545)^6}. \\
&= 1.084
\end{aligned}
$$

A similar formula is used in order to calculate mortgage values in the shock simulation by replacing coupon payment by mortgage payments and by changing holding period. The mortgages are assumed to be held initially for two years (1982-1983), and then for 3 years (1984-1986), and finally for one year (1987). During the 1981-1987 period the weighted average of term structure of mortgages was approximately three years. Therefore, three different interest payments, based on the mortgage rates in 1981, 1984, and 1987, are included in the calculation as follows:

$$
\begin{aligned}
mortgage &= \frac{(0.1779/110.8)\cdot 100}{1.0545} + \frac{(0.1779/117.2)\cdot 100}{(1.0545)^2} \\
&+ \frac{(0.1247/122.3)\cdot 100}{(1.0545)^3} + \frac{(0.1247/127.2)\cdot 100}{(1.0545)^4} \\
&+ \frac{(0.1247/132.4)\cdot 100}{(1.0545)^5} + \frac{(1.0879/138.2)\cdot 100}{(1.0545)^6} \\
&= 1.10
\end{aligned}
$$

2. Stocks (equities).

Fundamentally, stocks are valued in the same way as fixed-income instruments, i.e., on the basis of the discounted present value of expected returns. As before in the baseline scenario the market value of stocks are assumed to represent the present discounted value of future stream of incomes on stocks, under the efficient capital markets assumption. Therefore, the adjustment coefficient for the stocks in the baseline scenario is unity.

Common stocks represent residual claims to the value of assets of businesses after claims of creditors have been satisfied. Although the formula for the value of a stock can be written as PV = y/i, the yield (y) is generally not fixed. Therefore, changes in market values of common stocks may result from either changes in yields (dividends or dividends plus capital gains) or changes in interest (discount) rates. The former is usually more important in determining market values. One may simply assume that stock prices would rise by about as much as the general prices rise because earning (profits) would rise by about as much as the general price level. This was the widely accepted belief until the

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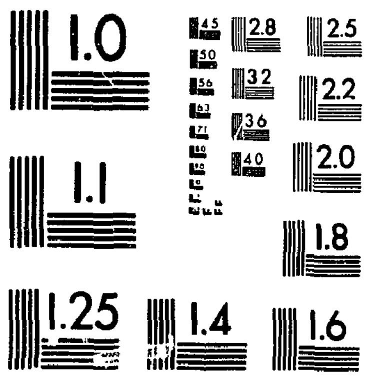

PRECISION[SM] RESOLUTION TARGETS

poor performance of the stock markets in the high inflationary periods of 1970s and early 1980s. However, the evidence from these inflationary periods suggests that inflation per se tends to adversely affect stock prices due to a possible error in valuation of stock prices by investors.[42] These difficulties of valuation of stocks do not pose special problems for the shock simulation since the data on stock price indexes and average yields are readily available.

In the shock scenario, the changes in the stock price indexes and also average yields on equity in the 1981-1987 period are used in calculating the adjustment coefficients as follows:

$$Stock = \sum_{j=1}^{6} \frac{k_j/CPI_j}{(1+r)^j} + \frac{1/CPI_6}{(1+r)^6},$$

where k is the sum total of capital gain/loss due to the changes in stock price indexes and the average yield in period j, and r is the usual discount rate. Note that the stock is assumed to be cashed at the end of the simulation period. Theoretically, stock prices in 1987 capitalize expected future profits, hence should capture any productivity gains due to disinflation, as in Howitt (1991).

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[42] See, e.g., Pesando (1977). Modigliani and Cohn (1979) suggest a possibility of an error in valuation of stock prices by investors in that nominal interest rates are used in discounting expected earnings. Nominal interest rates, however, are improperly high because if earnings are expected to rise the need for a higher discount rate is offset by the expected rise in earnings. This also suggests that stock prices should rise if inflation is reduced because nominal interest rates will also be lower. In fact this is the general consensus that emerges from most studies. See Henning (1988: 373).

Furthermore, in the last period the stock market composite index value is taken as the average of low and close values in December. The reason behind this approximation is the need to exercise caution in calculating capital gains on shares given the stock market crash in October, 1987.[43] The numerical calculation is as follows:

$$
\begin{aligned}
stock &= \frac{((0.0002+0.0403)/110.8)\cdot 100}{1.0545} + \frac{((0.2330+0.0322)/117.2)\cdot 100}{(1.0545)^2} \\
&+ \frac{((-0.060+0.0370)/122.3)\cdot 100}{(1.0545)^3} + \frac{((0.1730+0.0313)/127.2)\cdot 100}{(1.0545)^4} \\
&+ \frac{((0.0540+0.0299)/132.4)\cdot 100}{(1.0545)^5} + \frac{((1-0.0127+0.0308)/138.2)\cdot 100}{(1.0545)^6} \\
&=0.97
\end{aligned}
$$

3. Real Assets: houses.

In the baseline simulation nominal market value of houses are assumed to increase at the assumed inflation rate. The real market values remain the same in each period. Therefore, there are no real capital gains/losses associated with the real assets.

In the shock simulation changes in the new housing price indexes and the CPI in the 1981-1987 period are used in order to approximate the capital gains/losses on houses. The new housing price index for 1987 is 126.1 and the

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[43] The year end indexes for high, low, and close are 3211.8, 2895.5, 3160.1, respectively.

CPI is 138.2. The ratio 126.1/138.2 (= 0.91) is used as the adjustment coefficient in order to account for the real decline in housing prices in the shock scenario.

4. Liquid Assets and Other Debt

The nominal values of these asset types are simply deflated by the last period's CPI in the baseline and shock scenarios in order to obtain their real value changes. Given the initial period value of 100 for both cases, the CPI in the last period of the baseline scenario is 200.7, and in the shock scenario 138.2.

3.3 Non-human Wealth Data and Adjustments

As is well-known the estimation of any model is no better than the available data. This study is by no means an exception. In fact, the data base of the simulation, the Assets and Debts Survey (1984) of Statistics Canada, has important deficiencies. As shown in Davies (1991), wealth surveys are generally less than perfect because of (1) sampling errors due to heavily skewed distribution of wealth, (2) non-sampling errors, such as differential response rates to wealth surveys among different wealth groups, and also misreporting which often takes the form of under-reporting. In Table 21, the discrepancies in the reported values by asset type of the simulation data and of the national balance sheet are reported. The simulation data are from the Assets and Debts Survey (1984) of Statistics Canada and the balance sheet entries are reproduced from Davies (1991) and reflect year end values in 1983. Note that the simulation data used in this study includes only labour market participants and hence consists of the same records used in the human wealth calculations.

The second and third columns of Table 21 indicate the nominal total values for the assets and debt types in the simulation data and the balance sheet, respectively. The last column gives the degree of under-reporting as a ratio of the simulation data to balance sheet values. It is clear that financial assets such as bonds and stocks are severely under-reported in the simulation data: their values are about 8 percent of the balance sheet values for both asset types. Liquid assets such as cash and deposits follow by the under-reporting ratio of 24 percent. The under-reporting ratios for mortgages, other debt, and houses are 57 percent, 75 percent, and 66 percent respectively.

One way of dealing with existing deficiencies is to align the data set with independent estimates of the balance sheet of the household sector. In this study all values of the net worth components are aligned with the reported year end values in the independent balance sheet. The alignment is based on the assumption that the severity of under-reporting increases as the true holding increases. The alignment is done by using the following formula suggested in Davies (1979):

$$ra_{ik} = \gamma_0 \, a_{ik}^{\gamma_1} \; ; \quad 0 < \gamma_1 < 1$$

where ra_{ik} and a_{ik} are the reported and true holdings of asset k by household i, respectively. Here the elasticity of the reporting rate and also that of reported holding are assumed constant with respect to the true holding. Following Davies

(1979), a value of $\gamma 1 = 0.95$ is assumed as a "best-guess" correction for the effect of under-reporting.[44]

Since the data set is representative of 1984, after under-reporting correction is done all values are adjusted to 1981 levels using the actual specific prices of the net worth components, as well as the consumer price index. First the difference in the rates of return on assets and debts are used to adjust the market values of the assets. For example, if the nominal value of a bond holding is, say, \$100 in the 1984 data at 10 percent interest rate, then the adjusted value becomes \$62.5 at 16 percent interest rate corresponding to 1981. That is, \$62.5 gives the same coupon yield of \$10 at 16 percent. In order to express the value in 1981 dollars, \$62.5 is further adjusted by deflating this value using the CPI for 1984. Since the CPI in 1984 is 122.3 the adjusted real value becomes \$51.1 (= 62.5/122.3 x 100) in 1981 dollars. Similar adjustment for stocks and houses are done by using their respective price indexes and the CPI. The values of liquid assets and other debt are simply deflated to 1981 dollars. Therefore, the adjusted values provide the initial real values in both the baseline and shock scenarios.

3.4 Adjustment Coefficients and an Average Household

Table 22 reports the adjustment coefficients obtained using the procedures

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[44] Note that choosing a different "best-guess" correction has little effect on the nature of results in Davies (1979).

mentioned above. These coefficients are used to obtain the real values of the net worth components in the shock simulation by simply multiplying each component of household non-human wealth by its respective coefficient. Except for the coefficients of the liquid assets and other debt (i.e., negative cash), all coefficients have the assumed value of unity under the efficient capital markets assumption in the baseline scenario. Housing prices also have a coefficient of unity since it is also assumed that house prices will increase at the rate of inflation leaving real values of housing unaffected. Adjustment coefficient for the liquid assets and other debt is 0.50 which is considerably lower compared to 0.72 in the shock case. This is because of constant higher rate of inflation (12.3 %) in the baseline scenario. In the shock scenario the coefficient for houses is 0.91, indicating a loss in real market value of houses due to declining housing prices in most of the recessionary period. The coefficients of bonds, stocks, and mortgages are 1.08, 0.97, and 1.10 respectively. While the present discounted values of bonds and mortgages increase, the present discounted value of stocks declines slightly.

Table 23 reports the results of the shock simulation for a household with average holdings in the model. This household in the baseline scenario holds about \$28,000 in cash, owns a house worth about \$105,000, holds about \$4,000 in bonds and about \$27,000 in stocks, and also owes about \$19,000 mortgage and about \$7,000 personal debt, all in 1981 dollars. Therefore, its net worth is about \$137,000. In the shock scenario, its real value of cash holdings increases to about \$41,000, the real value of house declines to about \$95,000, the real value of bond holdings rises to about $4,600 . The real value of stock holdings decline to about $26,000, and the real value of the mortgage outstanding increases to about 21,000, while other debt increases to about $11,000. Overall its net worth decreases to about $135,000. This implies a net loss of about $2,000 for this household in the shock simulation. However, in the real world no household has average holdings. Some households may find themselves much above the average so that this household may become nothing more than a dwarf compared to them. On the other hand, for some others this household may look like a giant for they may find themselves in a much lower position. In fact, we know that the distribution of wealth is highly skewed and most people find themselves with holdings below the average. Furthermore, the distributional effects of disinflation are basically driven by the composition of asset and debt types in household portfolios. Therefore, a more detailed analysis of the distributional consequences of disinflation is in order. The distributional results are examined in the following section.

3.5 Simulation Results

Table 24 reports the inequality statistics for non-human wealth of households in the baseline and shock scenarios. The average non-human wealth is 1.8 percent lower in the shock scenario. This amounts to about $17.1 billion loss in total non-human wealth. This result is, of course, reflects certain assumptions made for certain assets types. For example, if the mortgage contracts are assumed to be held for three-year terms and hence to be renewed only once during the 1981-1987 period, the adjustment coefficient of mortgages rises from 1.10 to 1.15 and the total non-human wealth losses increase by about $6 billion.

The summary inequality measures indicate inconclusive results. The coefficient of variation increases by about 0.5 percent from 2.30 to about 2.35, and the Gini index also rises from 0.701 to 0.730, which is about 4 percent increase. On the other hand, the Atkinson's measures with degrees of inequality aversion factors greater than 1 indicate a decline in inequality in the distribution of non-human wealth. With the exception of coefficient of variation, these indicators of changes in non-human wealth distribution, however, are not strictly valid and should be considered as quasi measures due to the existence of negative net worth values in the distributions.[45]

The baseline and shock distributions of average non-human wealth, and also decile shares are reported in Table 25. Households are ranked by their net worth position in the baseline scenario. It is clear from the table that bigger non-human wealth losses are concentrated in the bottom two deciles and also in the fifth and sixth deciles, while the second and third deciles and the top decile experience gains. The biggest loser households are in fact in the first and second deciles with 57.5 percent and 75.4 percent average losses in non-human wealth, respectively. The biggest winner is the third decile with an average of 30 percent gain in non-human wealth. The top decile, however, also gains on average by 2.1

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[45] See, e.g., Lambert (1989).

percent. The decile shares of the third, ninth and the top deciles also increase by 50 percent, 1.7 percent and 5.7 percent, respectively. However, the change in the decile share of the third decile is merely from 0.002 to 0.003 while that of the top decile is from 0.475 to 0.496. All other typically experience a decline in their shares. The fifth decile, for instance, experiences 11.4 percent decline in its share from 0.035 to 0.031.

In Table 26 households are ranked by the proportionate losses or gains in non-human wealth relative to their baseline human wealth.[46] In the 10th decile there are those with the highest losses as a proportion of their baseline human wealth. In the shock scenario they lose, on average, 84 percent in non-human wealth. By contrast, those who are in the first decile gain, on average, 150 percent in non-human wealth.

In Table 27 the percentage distribution of households among the two extreme cases by their position in the baseline non-human wealth distribution are reported. The big losers in non-human wealth are those who are located in the tenth decile of Table 26, i.e., those with big non-human wealth losses relative to their human wealth. The big winners in non-human wealth are those who are in the first decile of the same table with the biggest gains in non-human wealth relative to their human wealth. Table 27, therefore, reports the distribution of households in these two extreme cases in terms of their non-human wealth

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[46] Due to the existence of negative and zero non-human wealth values in the data it is not possible to sort the observations correctly in terms of percentage losses in non-human wealth.

position in the baseline scenario. Among the big loser households there appears to be a heavy concentration of those who come from the very bottom and upper middle baseline non-human wealth deciles. More than 80 percent of big losers come from the top five non-human wealth deciles. On the other hand, about 60 percent of the big winners come from the top three deciles. In fact, almost one third of the big winners (30.7 %) come from the top non-human wealth decile. The relative significance of changes in non-human wealth for this group is the highest and also they enjoy the biggest gains. Therefore, one may conclude that in these extreme cases of winners and losers there is a heavy concentration of middle and upper baseline non-human wealth deciles.

Table 28 reports the distribution of big non-human wealth losers and big non-human wealth winners, as a proportion of their total sample frequencies and by the demographic characteristics of the household heads. The second column in the table reports the total sample frequencies for each category. In the third and fourth columns, distributions of household heads relative to their total sample frequencies are reported. The third column includes the big losers and the fourth column the big winners. A value close to or equal to 1 in these last two columns, therefore, indicates an equal representation of the given demographic category. A value greater or less than 1 indicates an over-representation or under-representation, respectively. Among the big loser households, those who reside in Ontario, Prairies or British Columbia, those with older household heads, those who have sales/services or rural jobs, and those with little or some post secondary education are all over-represented. All other categories are either underrepresented or keep their population shares.

Among the big non-human wealth winners, those with female, single household heads, those who reside in Quebec or Prairies, those with sales/services or rural occupations, those with older household heads, those with little education are over-represented. All other categories are under-represented.

The analysis in the preceding paragraphs are based on simple cross tabulations and hence caution must be exercised in drawing conclusions. Therefore, in Chapter 4 a regression analysis of distributional consequences of changes in total wealth will be included.

3.6 Summary and Conclusions

In this chapter the effects of 1981-1987 disinflation on the non-human wealth of Canadian households have been simulated. The simulation consists of baseline and shock scenarios. In the former case, capital markets are assumed to operate efficiently. Therefore, except for the real value of liquid assets and personal debt, all net worth components are assumed to retain their real values in this scenario. In the latter case the actual consumer price indexes and specific asset prices are used in order to simulate real value changes in net worth components.

One of the major findings of this chapter is that disinflation has strong distributional consequences. This is due to the variation in the composition of worth components are affected by disinflation. The total amount of simulated non-human wealth losses are found to be about $17.1 billion. The coefficient of variation in the distributions indicate an increase in inequality. Other summary inequality statistics, however, are not strictly valid due to the existence of negative net worth values in the distributions. Therefore, a further analysis is conducted by looking at the decile shares in the baseline and shock scenarios.

It is clear that the gains and losses in non-human wealth are not evenly distributed among the non-human wealth deciles. While the top non-human wealth decile and the third and fourth deciles appear to gain in the shock scenario, other deciles appear to lose. Substantial losses in non-human wealth are especially incurred in the bottom two deciles.

There is also a substantial variation among the big losers and winners in terms of the demographic characteristics of the household heads.

CHAPTER 4: SIMULTANEOUS EFFECTS OF UNEMPLOYMENT AND DISINFLATION ON THE DISTRIBUTION OF CANADIAN HOUSEHOLD WEALTH

4.1 Introduction

So far we have examined the effects of higher unemployment on individual and household human wealth in Chapter 2, and the effects of disinflation on non-human wealth in Chapter 3. Each of these two separate analyses can be considered informative. However, the methodological novelty developed in the previous two chapters adds a further dimension to this study. In this chapter we are able to analyse the simultaneous effects of unemployment and disinflation on Canadian households with labour force participation, by comparing the total wealth of Canadian households in the baseline and shock simulation scenarios. For each household the human wealth component of total wealth is generated by the simulation model of Chapter 2. Again for each household the non-human wealth component is generated by the simulation model of Chapter 3. Therefore, for each household we have total wealth values as the sum total of human and non-human wealth in the baseline and shock scenarios. The following section presents the major results within the same analytical framework used in the previous chapters.

4.2 Simulation Results

Table 29 reports the summary statistics for the distribution of household total wealth in the baseline and shock scenarios. The mean household total wealth declines from \$283,109 to \$274,910 in the shock scenario. This is about a 3 percent decline and amounts to about \$55.8 billion of total loss. The coefficient of variation, the Gini index, and the Theil's entropy measure all indicate higher inequality in the shock scenario. The Gini index, for example, increases by about 3 percent from 0.459 to 0.474. The Theil's measure rises from 0.402 to 0.427, an increase of about 6 percent. The Atkinson's indexes, with the exception of the highest inequality aversion, indicate increases in inequality. Note also that the values of total wealth inequality measures fall between the values of non-human wealth and human wealth inequality measures.

Table 30 reports the baseline and shock distribution of average household total wealth by decile shares. Except for the top decile all deciles appear to lose in the shock scenario. The gain of the top decile, however, is very small and therefore negligible. The top 5 percent also slightly gains but the top 1 percent slightly loses. The loss of the biggest losers in the bottom decile is about 18 percent. Apart from these two extreme cases the percentage losses in mean wealth among deciles range between 2.4 percent in the 9th decile and 7.2 percent in the 2nd decile. As one moves toward upper deciles there is also a decline in percentage losses in average total wealth. The share of the top decile increases by about 3 percent in the shock scenario. By contrast the share of the bottom decile declines dramatically by about 11 percent. All other deciles also experience a decline in their shares of total wealth. Again as one moves toward upper deciles, percentage losses in decile shares become smaller, ranging between 3.9 percent and 1 percent. The top 1 percent and the top 5 percent of the distribution enjoy an increase in their shares by about 3 percent.

In Table 31 households are ranked by their percentage gains/losses in their total wealth in the shock simulation. In the first decile the biggest winners gain 15.8 percent, while in the 10th decile the biggest losers lose 24.8 percent on average. Therefore, there is a considerable variation in terms of percentage gains and losses in household total wealth between the biggest winners and biggest losers.

The percentage distribution of the biggest winners and the biggest losers by their decile ranks in the baseline household total wealth distribution is shown in Table 32. It is clear that the majority of the biggest losers, with an mean loss of 24.8 percent in their wealth, come from the middle and lower baseline total wealth deciles. The share of the top three baseline total wealth deciles is only 7.4 percent and the share of the top decile is only 1.1 percent. On the other hand, more than 50 percent of big losers come from the bottom three deciles. Among the big winners, however, the share of the top total wealth decile is 15.9 percent. It is also interesting to see that the bottom decile appears to have relatively a large share among the big winners (15.8 %), as well as among the big losers (24.1 %). In fact, they are the largest group among the big losers, and the second largest among the big winners.

Table 33 reports the frequency distribution of big losers and big winners in household total wealth by the demographic characteristics of the household heads, as a proportion of their total sample frequencies. Therefore, a value greater than one implies over-representation and a value less than one under-representation of the demographic category in question. Total sample frequencies are given in the second column. Clearly, households with younger and male household heads (16-44 years old) who are single, residing in Atlantic provinces, Prairies, or British Columbia, with high school or post secondary education, and with blue-collar jobs or with rural occupations appear to be concentrated among the big losers. On the other hand, households with older (45+) or very young (16-19) female household heads who are single, who have little education, with white-collar jobs or with rural occupations appear to be overrepresented among the big winners when compared to their total sample frequencies.

In Table 34 the regression results of the distribution and magnitude of losses in total wealth are reported. The dependent variable is a proportionate measure of shock total wealth relative to baseline total wealth. The reference category is a married, blue-collar male worker with high school education in the 25-44 age group, residing in Ontario. The second column reports the estimation results of the first specification. Here the explanatory variables include the demographic characteristics of household heads and the baseline total wealth of households. In the fourth column the only explanatory variable is the baseline household total wealth. The third and fifth columns in the table with the heading P > t indicate the significance level of parameter estimates, based on absolute value of calculated t-statistics.

In the first specification, the adjusted R^2 is 0.016, and the F value is 9.289. The constant term indicates that the mean value of household total wealth in the shock scenario is about 82 percent of the baseline household total wealth for the reference category. The most striking result is that all age coefficients are highly significant. What they indicate is that the relative losses in household total wealth decrease for older people; by about 5 percent for the household heads in the 45-54 age category, and by 8 percent for those in the 55+ age category. Furthermore, being a male household head also significantly reduces household total wealth losses. Being single, however, appear to increase household total wealth losses. The coefficients of Prairies, and clerical jobs are also positive and statistically significant, indicating smaller losses in the shock scenario for these categories. The coefficient of some post secondary education is negative and also statistically significant. Although the coefficient of baseline total wealth is positive, it is not statistically significant. All other coefficients are also statistically insignificant.

In the fourth column, the only explanatory variable is the baseline household total wealth, and its coefficient is positive and highly significant. What this implies is that the wealthy do well in the shock scenario. However, as the results of the first specification indicate, it is not an important factor over and above other variables such as age or gender, which also tends to correlate with wealth.

Therefore, the major results of the regression analysis indicate that in the shock simulation there is a significant inter-generational transfer of wealth. The wealth is transferred from the young, less wealthy households, to more wealthy households with older, male, and married household heads.

4.3 Summary and Conclusions

In this chapter the simultaneous effects of unemployment and inflation on the distribution of household total wealth have been analysed. The results presented in this chapter are based on the simulation model developed in the previous two chapters and reflect an improvement upon the separate analyses presented earlier. With the data generated by the model it is possible to analyse the simultaneous effects of higher unemployment and disinflation in the 1981-1987 period on the household total wealth, defined as the sum total of human and non-human household wealth. As before, the analyses is based on the comparisons between the baseline and shock scenarios.

The amount of total loss in the shock scenario in both human and non-human wealth is about $55.8 billion. There is also a considerable variation in the distribution of total loss in the shock scenario, resulting in higher inequality statistics. When the households are ranked by their baseline total wealth, it appears that the most wealthy (10th decile) enjoys a slight increase in their average wealth compared to the baseline scenario, while the rest loses. The biggest loss in average total wealth is incurred in the bottom decile of the baseline total wealth distribution. Furthermore, the losses in average total wealth show a steady decline as one climbs further up the total wealth deciles.

When losses are considered in percentage terms for each household, majority of the biggest losers come from the lower baseline total wealth deciles. By contrast, the upper and top baseline total wealth deciles form the majority among the biggest winners.

The major results of the regression analysis indicate a significant transfer of total wealth from the less wealthy to more wealthy households, from those with younger heads to the ones with older heads, from the ones with female heads, to those with male household heads.

CHAPTER 5: SUMMARY AND CONCLUSIONS

In this thesis the distributional effects of unemployment and disinflation on Canadian households in the 1981-1987 period have been simultaneously simulated. Chapter 2 analysed the distributional effects of higher unemployment on the human wealth of individuals and households separately. In Chapter 3, the distributional effects of disinflation on Canadian household non-human wealth were analysed. Chapter 4 combined and analysed the effects of unemployment and disinflation on household total wealth.

There are two major methodological novelties in this thesis. The first one is related to the workings of the simulation model. Static and dynamic microsimulation models have been extensively used in the past decades. However, one of the major short comings of static models is that the reaction of economic agents to changing circumstances over time are neglected.

In the so-called dynamic models, on the other hand, the simulation is generally carried out over several years under steady-state assumptions. In other words, the general macroeconomic environment is assumed to remain the same for all simulation periods. Therefore, the reactions of economic agents to changing economic circumstances are necessarily neglected. Furthermore, empirical verification of such models causes difficulties, since business cycles are part of the real world. The present model, however, allows for new possibilities for empirical verification of the model since the hypothetical steady-state and the actual performance of the Canadian economy have been integrated by the baseline and shock scenarios. The second methodological novelty is the integration of unemployment effects with the effects of disinflation over the 1981-1987 period. Although the distributional effects of inflation and unemployment during cyclical fluctuations have been analysed separately in the past, this thesis brings forward the simultaneous impacts of inflation and unemployment on the human and non-human wealth of Canadian households.

The major results of the study indicate that total human wealth and non-human wealth losses are about $38.7 billion, and 17.1 billion respectively in 1981 dollars. In 1990 dollars the simulated total wealth losses of $55.8 billion would be about $89 billion. In this period there is also an increase in inequality in the distribution of household total wealth, as indicated by the summary inequality measures. The biggest losses are incurred in the lower wealth deciles. The losses are smaller in the upper middle deciles and the top decile gains slightly in this period. Furthermore, the wealth is redistributed from the less wealthy to the more wealthy households, from the households with younger, single heads to the ones with older, married heads, from the ones with female heads to those with male household heads. Therefore, a disinflationary macroeconomic shock unambiguously increases economic inequality.

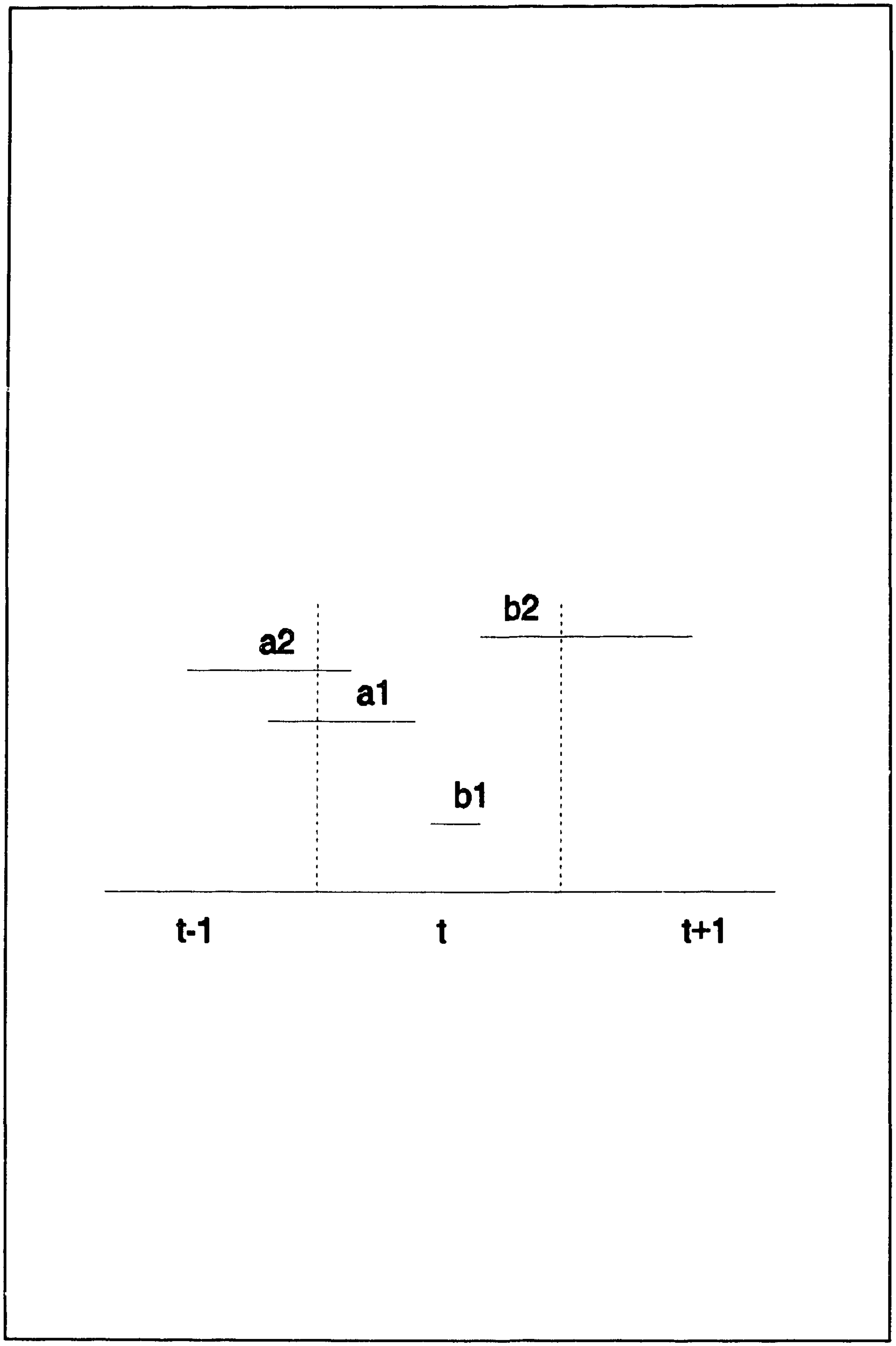

Figure 1. Unemployment spells.

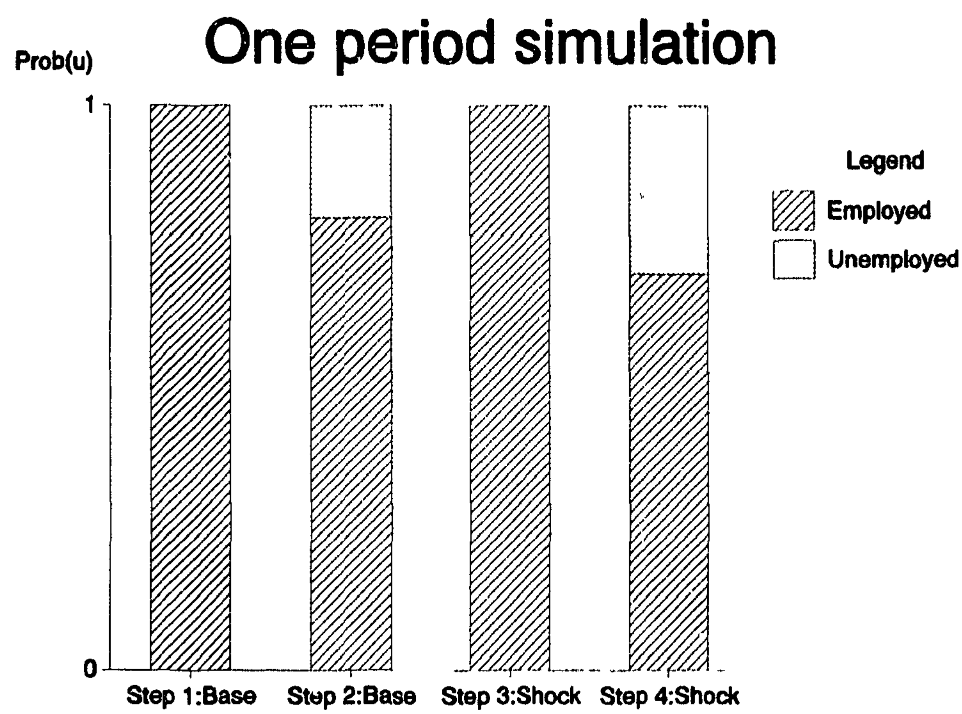

Figure 2. One-period simulation.

Table 1a. An illustration: one-period baseline simulation. Total unemployment weeks = 15.

Assigning unemployment weeks in the baseline simulation					
	P(u)	E(u)	Cumulative Duration	Status	Baseline Flag
A	0.90	5	5	U	1
B	0.80	10	15*	U	1
C	0.70	25	40	E	0
D	0.60	8	48	E	0
E	0.50	6	54	E	0

* The cut-off value = assumed total weeks of unemployment in the baseline scenario.

Table 1b. An illustration: one-period shock simulation. Total unemployment weeks = 28.

Assigning unemployment durations in the shock simulation						
	P(u)	E(u)	Cumulative Duration	Status	Baseline Flag	Loser Flag
A	0.95	11	11	U	1	0
C	0.82	7	18	U	0	1
B	0.77	10	28*	U	1	0
D	0.61	26	54	E	0	0
E	0.45	5	59	E	0	0

* The cut-off value = assumed total weeks of unemployment in the shock scenario.

Table 2. Determinants of the probability of being unemployed. Canada, 1987.

Dependent variable = 1 if weeks unemployed in 1987 > 0.		
	Males N = 30692	Females N = 32257
Intercept	-2.206* (0.003)	-2.362* (0.003)
Atlantic (dummy = 1)	0.215* (0.003)	0.136* (0.003)
Quebec (dummy = 1)	0.002 (0.003)	0.080* (0.003)
Prairies (dummy = 1)	0.133* (0.003)	-0.097* (0.003)
British Columbia (dummy = 1)	0.109* (0.004)	0.069* (0.004)
Manag./Admin. (dummy = 1)	-0.617* (0.005)	0.310* (0.005)
Professional (dummy = 1)	-0.402* (0.005)	-0.113* (0.004)
Sales/Services (dummy = 1)	-0.251* (0.003)	0.512* (0.003)
Clerical (dummy = 1)	-0.217* (0.005)	0.267* (0.003)
Rural (dummy = 1)	-0.363* (0.005)	0.251* (0.008)
Age:16-19 (dummy = 1)	0.793* (0.004)	0.738* (0.004)
Age:20-24 (dummy = 1)	0.698* (0.004)	0.497* (0.003)
Age:45-54 (dummy = 1)	-0.346* (0.004)	-0.467* (0.004)
Age:55-69 (dummy = 1)	-0.968* (0.004)	-1.202* (0.005)
None/Elementary (dummy = 1)	0.156* (0.004)	-0.171* (0.004)

None/Elementary (dummy=1)	0.156* (0.004)	-0.171* (0.004)
Some post-secondary (dummy=1)	-0.143* (0.004)	0.099* (0.003)
Certificate/Diploma (dummy=1)	-0.181* (0.004)	-0.068* (0.003)
University (dummy=1)	-0.458* (0.005)	-0.109* (0.004)
Single (dummy=1)	0.274* (0.003)	0.028* (0.003)
Previous Unemployment weeks	0.090* (0.0001)	0.074* (0.0001)
Chi-Square for Covariates	1721986.8	2169650.2

Note: (.) indicates the standard error.
* indicates p > Wald Chi-Square = 0.0001.

Table 3. Least-Squares Test for Weibull Specification.

Dependent variable = ln(-ln(survival function))		
	Males	Females
$\ln\gamma$	-3.059 (-56.96)	-3.117 (-49.67)
α	0.873 (50.88)	0.853 (42.74)
R^2	0.982	0.974

Note: (.) indicates t-statistics.

Table 4. Determinants of duration of unemployment: Weibull Distribution.

Dependent variable = ln(duration weeks)		
	Males N=1926 Right censored=1094	Females N=1792 Right Censored=1035
Intercept	3.229* (0.034)	2.286* (0.047)
Atlantic (dummy=1)	0.150* (0.007)	0.140* (0.007)
Quebec (dummy=1)	0.075* (0.008)	0.118* (0.008)
Prairies (dummy=1)	-0.014* (0.007)	0.166* (0.007)
British Columbia (dummy=1)	-0.340* (0.008)	-0.149* (0.009)
Manag./Admin. (dummy=1)	-0.336* (0.010)	0.245* (0.011)
Professional (dummy=1)	-0.172* (0.008)	0.504* (0.010)
Clerical (dummy=1)	0.057* (0.009)	-0.009 (0.008)
Sales/Services (dummy=1)	-0.243* (0.006)	0.082* (0.008)
Rural (dummy=1)	0.092* (0.014)	-0.339* (0.031)
Age:16-19 (dummy=1)	0.070* (0.009)	-0.409* (0.008)
Age:20-24 (dummy=1)	0.219* (0.007)	0.219* (0.006)
Age:45-54 (dummy=1)	-0.157* (0.008)	0.346* (0.009)
Age:55-69 (dummy=1)	-0.202* (0.010)	-0.036[a] (0.013)

None/Elementary (dummy=1)	-0.004* (0.008)	-0.466* (0.012)
Some post-secondary (dummy=1)	0.190* (0.007)	0.225* (0.007)
Certificate/Diploma (dummy=1)	0.004 (0.007)	0.079* (0.007)
University (dummy=1)	0.283* (0.008)	0.145* (0.009)
Single (dummy=1)	0.029* (0.006)	-0.320* (0.006)
Previous Unemployment weeks	0.013* (0.002)	0.005* (0.0002)
Potential UI Benefits ($)	0.0003* (0.00003)	0.002* (0.00003)
Scale	1.064 (0.002)	1.061 (0.002)
Log Likelihood for Weibull	-611148.6273	-550917.2911

Note: (.) indicates the standard error.
* indicates p > Chi-Square = 0.0001.

Table 5. Distribution of loser individuals over the simulation periods:total sample and human wealth deciles, (%).

	t+1	t+2	t+3	t+4	t+5	t+6	Average
Total Sample	3.3	1.6	1.7	1.6	1.5	1.5	1.9
1st Decile	3.3	1.3	1.1	0.9	0.6	0.4	1.3
2nd Decile	3.0	1.0	1.0	1.2	1.0	1.2	1.2
3rd Decile	3.5	1.7	1.5	1.5	1.1	1.1	1.7
4th Decile	3.4	1.8	1.4	1.1	2.6	1.9	2.0
5th Decile	4.2	1.4	1.5	1.6	2.3	2.3	2.2
6th Decile	4.1	2.3	2.2	2.0	1.9	1.5	2.3
7th Decile	2.7	1.5	2.0	1.7	1.4	1.6	1.8
8th Decile	3.0	1.7	2.3	2.4	2.0	2.4	2.3
9th Decile	3.1	1.4	1.6	1.7	1.8	1.4	1.8
10th Decile	2.4	1.9	2.7	2.8	1.0	0.8	1.9

Table 6. Summary Statistics: Individuals. Weighted N=9760034.

	Baseline	Shock	Change
Mean ($)	100,910	96,943	-3.9 %
Standard Deviation	71,527	69,665	-2.6 %
Coefficient of Variation	0.71	0.72	1.2 %
Gini Index	0.375	0.380	1.3 %
Theil's Entropy Measure	0.238	0.244	2.5 %
Atkinson's Measure			
$\epsilon=0.5$	0.127	0.130	2.4 %
$\epsilon=1.0$	0.281	0.286	1.8 %
$\epsilon=1.5$	0.491	0.497	1.2 %
$\epsilon=2.0$	0.754	0.761	1.0 %

Table 7. Baseline and shock distribution of average human wealth by deciles: Individuals.

	Base		Shock		
DECILES	Average Human Wealth ($)	Decile Share	Average Human Wealth ($)	Decile Share	Change in Average Human Wealth (%)
1st Decile	10,555	0.011	10,173	0.011	-3.6
2nd Decile	31,841	0.032	30,403	0.031	-4.5
3rd Decile	50,108	0.050	47,665	0.049	-4.9
4th Decile	65,713	0.065	62,560	0.065	-4.8
5th Decile	81,480	0.081	77,897	0.080	-4.4
6th Decile	97,417	0.096	93,055	0.096	-4.5
7th Decile	116,052	0.115	111,170	0.115	-4.2
8th Decile	137,086	0.136	131,643	0.135	-4.0
9th Decile	167,151	0.165	161,440	0.166	-3.4
10th Decile	251,614	0.249	243,345	0.250	-3.3

Table 8a. Sources of simulated losses in total human wealth.

	Loss ($ billion)	Loss (%)
Changes in the real earnings of the employed	7.8	20.0
Changes in the real earnings of nonloser unemployed	29.9	77.0
Changes in the real earnings of losers	1.0	3.0
Total	38.7	100

Table 8b. Sensitivity test results: correlation between individual unemployment durations over time is omitted.

	Loss ($ billion)	Loss (%)
Changes in the real earnings of the employed	3.9	11.0
Changes in the real earnings of the nonloser unemployed	30.2	84.0
Changes in the real earnings of losers	1.7	5.0
Total	35.8	100.0

Table 9. Loser individuals: Ranked by their absolute losses in human wealth. Weighted N=715057.

	Base Average Human Wealth	Shock Average Human Wealth	Average Loss (%)
1st Decile	$43,377	$44,192	1.9
2nd Decile	53,052	51,209	3.5
3rd Decile	81,925	78,847	3.8
4th Decile	95,109	90,565	4.8
5th Decile	105,159	98,413	6.4
6th Decile	120,916	111,454	7.8
7th Decile	108,112	94,448	12.6
8th Decile	136,799	117,657	13.9
9th Decile	117,295	87,994	25.0
10th Decile	173,807	115,559	33.5

Table 10. Percentage distribution of big and small loser individuals by their ranks in human wealth.

	Big Losers (Average Loss=33.5%)	Small Losers (Average Loss=1.9%)
1st Decile	0.0	39.5
2nd Decile	0.0	16.9
3rd Decile	0.0	17.4
4th Decile	3.9	3.2
5th Decile	4.5	10.0
6th Decile	9.0	3.8
7th Decile	15.9	5.4
8th Decile	13.3	2.7
9th Decile	23.7	1.1
10th Decile	29.7	0.0

Table 11. Loser individuals: ranked by their percentage losses in human wealth.

	Base Average Human Wealth	Shock Average Human Wealth	Average Loss (%)
1st Decile	$94,120	$94,008	1.2
2nd Decile	89,518	86,783	3.1
3rd Decile	100,198	96,169	4.0
4th Decile	122,178	115,567	5.4
5th Decile	107,710	99,713	7.4
6th Decile	105,025	94,403	10.1
7th Decile	109,826	92,947	15.4
8th Decile	103,534	81,111	21.7
9th Decile	111,236	78,922	29.1
10th Decile	93,027	51,423	44.7

Table 12. Frequency distribution of loser household heads by their ranks in human wealth deciles.

	Big losers (Loss= 44.7%)	Small Losers (Loss= 1.2%)
1st Decile	8.9	8.7
2nd decile	8.8	8.3
3rd Decile	7.8	15.2
4th Decile	14.9	8.2
5th Decile	12.7	12.6
6th Decile	16.0	9.6
7th Decile	11.0	11.9
8th Decile	9.9	9.9
9th Decile	3.0	9.6
10 Decile	6.9	6.4

Table 13. Distribution of nonloser individuals as a proportion of their total sample frequencies.

	Total Sample	Top Decile	Bottom Decile
Male	58.3	1.59	0.42
Female	41.7	0.17	1.81
Single	21.1	0.56	1.48
Married	78.9	1.12	0.87
Atlantic	7.5	0.56	1.09
Quebec	24.8	0.75	0.86
Ontario	37.0	1.07	1.00
Prairies	18.6	1.08	1.17
B.C.	12.0	1.46	1.00
Manag.Admin.	13.6	2.35	0.65
Professional	16.0	1.73	0.73
Clerical	9.0	0.21	0.92
Sales/Services	18.4	0.64	1.48
Farm	5.4	0.48	1.91
Blue-collar	37.4	0.64	0.89
Age:16-19	0.6	0.00	6.17
Age:20-24	7.6	0.04	1.71
Age:25-44	57.1	0.97	0.81
Age:45-54	18.8	1.47	0.82
Age:55+	15.8	1.08	1.37
None/Element.	15.7	0.42	1.31
High School	45.2	0.64	0.97
Some post-sec	9.4	0.87	1.25
Cert./Diploma	13.6	1.02	0.85
University	16.1	2.64	0.76

Table 14. Distribution of loser individuals as a proportion of their total sample frequencies.

	Total Sample	Total Losers	Big Losers	Small Losers
Male	58.3	1.28	1.62	0.94
Female	41.7	0.62	0.14	1.08
Single	21.1	0.86	0.58	0.74
Married	78.9	1.04	1.11	1.07
Atlantic	7.5	1.19	1.77	0.85
Quebec	24.8	1.05	1.06	1.07
Ontario	37.0	0.95	0.97	0.99
Prairies	18.6	1.05	1.00	0.98
B.C.	12.0	0.84	0.50	1.02
Manag.Admin.	13.6	0.57	0.24	0.57
Professional	16.0	0.79	0.63	0.75
Clerical	9.0	0.91	1.14	1.06
Sales/Services	18.4	0.90	0.58	0.84
Farm	5.4	1.13	1.85	1.26
Blue-collar	37.4	1.30	1.49	1.28
Age:16-19	0.6	0.17	0.00	0.00
Age:20-24	7.6	1.34	2.68	1.01
Age:25-44	57.1	1.18	1.21	1.21
Age:45-54	18.8	0.84	0.47	0.93
Age:55+	15.8	0.42	0.12	0.35
None/Element.	15.7	1.12	1.22	1.43
High School	45.2	1.12	1.04	1.03
Some Post Sec.	9.4	0.97	1.22	0.70
Cert./Diploma	13.6	0.86	0.85	1.00
University	16.1	0.67	0.67	0.67

Table 15. Regression Results: relative human wealth.

Dependent Variable=Shock human wealth/Base human wealth						
	Total Sample N=14730		Sample of Unemployed N=10250		Sample of Losers N=1082	
	Par.Est.	P > t	Par.Est.	P > t	Par.Est.	P > t
Constant	0.907	0.0001	0.886	0.0001	0.739	0.0001
Atlantic	-0.132	0.0001	-0.015	0.0001	-0.024	0.0753
Quebec	-0.001	0.7453	-0.001	0.6969	-0.003	0.7854
Prairies	-0.001	0.7212	0.0002	0.9464	0.004	0.7247
B.C.	0.007	0.0058	0.010	0.0032	0.045	0.0068
A:16-19	-0.033	0.0004	-0.030	0.0057	0.004	0.9794
A:20-24	-0.058	0.0001	-0.045	0.0001	-0.058	0.0001
A:45-54	0.009	0.0001	0.009	0.0009	0.022	0.0701
A:55+	0.022	0.0001	0.002	0.0001	0.035	0.0514
No/Elem.	0.001	0.5643	0.002	0.4965	0.007	0.2742
Some post-sec.	0.002	0.4766	0.001	0.7408	-0.016	0.0879
Cert/Dip	0.007	0.0009	0.007	0.0139	-0.021	0.5922
Univ.	0.003	0.2335	-0.003	0.4554	-0.043	0.0003
Man.Admin	0.018	0.0001	0.016	0.0001	0.200	0.3301
Profes.	0.016	0.0001	0.015	0.0001	0.029	0.5874
Cleric	0.016	0.0001	0.017	0.0001	0.009	0.3169
Sale.Serv.	0.019	0.0001	0.021	0.0001	0.046	0.1639
Farm	0.008	0.0065	0.004	0.4058	-0.017	0.0177
Single	0.004	0.0391	0.010	0.0001	0.037	0.0027
Male	0.017	0.0001	0.025	0.0001	0.053	0.0001
Income	0.47E-6	0.0001	0.64E-6	0.0001	1.42E-6	0.0009
Adj. R^2	0.087		0.089		0.123	
F Value	71.19		50.97		8.55	
P > F	0.0001		0.0001		0.0001	

Table 16 . Human wealth summary Statistics: Households. Weighted N=6810255.

	Baseline	Shock	Change
Mean ($)	144,618	138,933	-3.9 %
Standard Deviation	92,111	89,935	-2.4 %
Coefficient of Variation	0.64	0.65	1.6 %
Gini Index	0.345	0.351	1.7 %
Theil's Entropy Measure	0.200	0.207	3.5 %
Atkinson's Measure			
$\epsilon=0.5$	0.107	0.111	3.7 %
$\epsilon=1.0$	0.240	0.247	2.9 %
$\epsilon=1.5$	0.429	0.438	2.1 %
$\epsilon=2.0$	0.723	0.730	1.0 %

Table 17. Baseline and shock distribution of average human wealth by deciles: households.

	Baseline		Shock		
Deciles	Average Human Wealth ($)	Decile Share	Average Human Wealth ($)	Decile Share	Change in Average Human Wealth (%)
1st Decile	19,731	0.014	18,749	0.014	-5.0
2nd Decile	53,683	0.037	50,174	0.036	-6.5
3rd Decile	78,817	0.055	75,099	0.054	-4.7
4th Decile	100,245	0.069	95,402	0.069	-4.8
5th Decile	120,532	0.083	115,337	0.083	-4.3
6th Decile	141,662	0.098	135,000	0.097	-4.7
7th Decile	165,812	0.115	159,509	0.115	-3.8
8th Decile	194,972	0.134	188,201	0.135	-3.5
9th Decile	233,206	0.161	225,274	0.162	-3.4
10th Decile	337,322	0.233	326,393	0.234	-3.2

Table 18. Loser households: ranked by their percentage losses in human wealth. Weighted N=696830.

	Baseline Average Human Wealth	Shock Average Human Wealth	Average Loss (%)
1st Decile	$166,126	$165,723	2.4
2nd Decile	176,195	171,451	2.7
3rd Decile	152,963	147,502	3.6
4th Decile	156,905	149,549	4.7
5th Decile	146,162	136,904	6.3
6th Decile	147,410	135,037	8.4
7th Decile	153,569	137,844	10.2
8th Decile	138,940	114,420	17.7
9th Decile	137,680	103,749	24.7
10th Decile	125,347	79,504	36.6

Table 19. Frequency distribution of loser households by their ranks in human wealth deciles.

	Big Losers (Average Loss=36.6%)	Small Losers (Average Loss=2.4%)
1st Decile	11.1	2.3
2nd Decile	19.6	5.0
3rd Decile	11.0	10.5
4th Decile	14.9	9.1
5th Decile	7.8	10.9
6th Decile	9.0	6.4
7th Decile	6.2	11.6
8th Decile	5.4	19.2
9th Decile	8.3	17.2
10 Decile	6.7	7.8

Table 20. Assets and Debts Survey (1984): Percentage Composition of Wealth Components.

TOTAL DEPOSITS	**10.0**
Total Canada Savings Bonds	0.2
Cash On Hand	2.6
All other bonds	0.5
TOTAL LIQUID ASSETS	**13.3**
Total Stock Holdings	2.2
Registered Savings Plan	4.0
Miscellaneous	2.4
TOTAL FINANCIAL ASSETS	**22.0**
Equity in Other Real Estate	5.8
Market Value of Vacation Home	2.4
Market Value of Home	42.9
Market Value of Cars, Trucks	4.6
Market Value of Other Vehicles	0.9
Equity in Business	21.3
TOTAL ASSETS	**100.0**
Total Consumer Debt	2.9
Other Personal Debt	0.9
Total Mortgage Debt	8.7
TOTAL DEBT	**12.5**
WEALTH	**87.5**

Source: **The Distribution of Wealth In Canada**, Statistics Canada, Catalogue 13-580, Occasional.

Table 21. Simulation Data and National Balance Sheet (year end, 1983).

	(A) Simulation Data ($ million)	(B) National Balance Sheet ($ million)	(A/B)
Houses	302,050	457,069*	0.66
Cash and Deposits	52,858	224,007	0.24
Canada Savings Bonds	13,947	39,727	0.35
Bonds	2,173	28,453	0.08
Shares	11,087	139,312	0.08
Mortgage Debt	72,902	127,326	0.57
Other Debt	53,675	71,649	0.75

* Includes residential, non-residential structures, and land.

Sources: (1) Assets and Debts Survey (1984), Statistics Canada.
(2) Davies (1991).

Table 22. Price adjustment coefficients for the non-human wealth model.

	Baseline	Shock
Cash and Personal Debt	0.50	0.72
Houses	1.000	0.91
Bonds	1.000	1.08
Stocks	1.000	0.97
Mortgages	1.000	1.10

Table 23. Average wealth holdings in the simulation.

	Baseline ($)	Shock ($)	% Change
Cash	28,503	41,044	44.0
House	105,204	95,736	-9.0
Bonds	4,340	4,687	8.0
Stocks	27,304	26,485	-3.0
Mortgage Debt	19,369	21,306	10.0
Other Debt	7,491	10,788	44.0

Table 24. Non-human wealth summary statistics.

	Baseline	Shock	Change
Mean ($)	138,491	135,977	-1.8 %
Standard Deviation	318,864	320,155	4.05 %
Coefficient of Variation	2.30	2.35	0.5 %
Gini index *	0.701	0.731	4.3 %
Atkinson's * Measure			
$\epsilon = 0.5$	0.453	0.461	1.8 %
$\epsilon = 1.0$	0.573	0.553	-3.5 %
$\epsilon = 1.5$	0.933	0.910	-2.5 %
$\epsilon = 2.0$	0.996	0.995	-0.001 %

* These indexes should be considered as quasi-measures due to the existence of negative values in the household non-human wealth data.

Table 25. Baseline and shock distribution of average non-human wealth by deciles: households.

	Baseline		Shock			
Deciles	Mean ($)	Share	Mean ($)	Share	Mean Loss/ Gain (%)	Mean Loss/ Gain ($)
1st	-16,087	-0.012	-25,330	-0.019	-57.5	-9,243
2nd	-623	-0.001	-1,093	-0.001	-75.4	-470
3rd	3,111	0.002	4,012	0.003	30.0	901
4th	18,586	0.013	18,882	0.014	1.6	296
5th	50,408	0.035	43,174	0.031	-14.3	-7,234
6th	83,700	0.058	74,893	0.053	-10.5	-8,807
7th	122,453	0.085	114,347	0.081	-6.6	-8,106
8th	171,508	0.118	165,659	0.116	-3.4	-5,849
9th	251,467	0.172	249,956	0.175	-0.6	1,511
10th	699,955	0.476	714,828	0.496	2.1	14,873

* Because of the existence of negative net worth values, the percentage changes are calculated by using the absolute value of the mean net worth in the denominator in order to determine non-human wealth losses/gains with conventional (-) and (+) signs.

Table 26. Households: ranked by their non-human wealth gains/losses relative to their human wealth.

	Baseline Mean ($)	Shock Mean ($)	Average Loss/Gain* (%)
1st Decile	298,148	354,726	150.0
2nd Decile	133,356	146,510	9.0
3rd Decile	63,997	67,389	2.0
4th Decile	22,450	22,876	0.3
5th Decile	52,156	50,461	-1.1
6th Decile	82,518	76,664	-3.5
7th Decile	120,615	108,804	-6.6
8th Decile	148,083	130,243	-10.0
9th Decile	164,516	140,783	-14.8
10th Decile	298,691	261,017	-84.0

* Average of percentage losses in each decile.

Table 27. Percentage distribution of big gainers and big losers by their ranks in the baseline non-human wealth (NHW).

	Big Losers (Ave.= 84 %)	Big Gainers (Ave.= 150 %)
1st NHW Decile	11.1	0.0
2nd NHW Decile	1.2	0.2
3rd NHW Decile	0.4	3.5
4th NHW Decile	4.0	7.1
5th NHW Decile	12.9	9.8
6th NHW Decile	12.0	9.8
7th NHW Decile	11.4	9.4
8th NHW Decile	12.1	11.7
9th NHW Decile	14.5	17.7
10th NHW Decile	20.5	30.7

Table 28. Distribution of big loser and big gainer households by the characteristics of household heads: non-human wealth.

	Total Sample Frequencies	Big Losers(Ave=84%)	Big Gainers (Ave=150 %)
Male	83.6	1.01	0.92
Female	16.4	0.95	1.41
Single	30.2	0.92	1.24
Married	69.8	1.03	0.90
Atlantic	7.5	0.92	0.71
Quebec	25.2	0.52	1.24
Ontario	36.7	1.12	0.93
Prairies	18.4	1.17	1.20
British Columbia	12.2	1.43	0.62
Man./Admin.	13.2	0.99	0.86
Professional	16.3	0.83	0.95
Clerical	10.2	0.74	1.02
Sales/Services	18 8	1.26	1.13
Blue-collar	35.8	0.88	0.79
Rural	5.5	1.93	2.40
Age:16-19	0.8	0.75	1.25
Age:20-24	8.7	0.59	0.46
Age:25-44	55.1	1.04	0.43
Age:45-54	18.4	1.01	1.27
Age:55+	17.0	1.08	2.89
None/Elementary	16.4	1.13	1.12
High School	44.6	0.94	0.87
Some Post Sec.	9.5	1.23	0.83
Certificate/Dip.	13.5	0.91	0.74
University	16.0	0.99	0.94

Table 29. Total wealth summary statistics: all households,
Weighted N = 6810255.

	Baseline	Shock	Change
Mean ($)	283,109	274,910	-3.1 %
Standard Deviation ($)	353,092	352,613	-0.1 %
Coefficient of Variation	1.25	1.28	2.4 %
Gini index	0.459	0.474	3.3 %
Theil's Entropy Measure	0.402	0.427	6.2 %
Atkinson's Measure			
$\epsilon = 0.5$	0.182	0.192	5.5 %
$\epsilon = 1.0$	0.343	0.354	3.4 %
$\epsilon = 1.5$	0.536	0.542	1.1 %
$\epsilon = 2.0$	0.850	0.751	-11.6 %

Table 30. Baseline and shock distribution of average total wealth by deciles: households.

	Baseline		Shock				
	Mean Wealth ($)	Share	Mean Wealth ($)	Share	Change in mean wealth (%)	Change in decile share (%)	Change in mean wealth ($)
1	25,696	0.009	20,940	0.008	-18.5	-11.1	-4,756
2	73,837	0.026	68,505	0.025	-7.2	-3.9	-5,332
3	110,587	0.039	105,293	0.038	-4.8	-2.6	-5,294
4	147,641	0.052	139,692	0.050	-5.4	-3.9	-7,949
5	190,108	0.066	179,684	0.065	-5.5	-1.5	-10,424
6	236,620	0.082	224,830	0.081	-5.0	-1.2	-11,790
7	289,747	0.100	276,569	0.099	-4.6	-1.0	-13,178
8	356,294	0.123	344,163	0.122	-3.3	-1.0	-12,131
9	461,079	0.158	449,895	0.159	-2.4	-1.0	-11,184
10	939,188	0.322	939,241	0.332	1.0E-3	3.1	53
5%	1,260,606	0.223	1,262,212	0.230	1.3E-3	3.1	1,606
1%	2,572,729	0.090	2,560,427	0.093	-1E-4	3.3	-12,302

Table 31. Households: ranked by percentage changes in their total wealth.

	Baseline Average Wealth	Shock Average Wealth	Average Change (%)
1st Decile	301,891	349,578	15.8
2nd Decile	332,060	346,308	4.3
3rd Decile	286,926	287,213	0.3
4th Decile	286,521	281,104	-1.9
5th Decile	357,620	345,270	-3.5
6th Decile	322,554	306,354	-5.0
7th Decile	295,639	275,251	-6.9
8th Decile	277,844	252,551	-9.1
9th Decile	226,582	197,651	-12.8
10th Decile	143,489	107,878	-24.8

Table 32. Percentage distribution of big losers and big winners by their ranks in the baseline total household wealth.

	Big Losers (Ave. = 24.8 %)	Big Winners (Ave. = 15.8 %)
1st Decile	24.1	15.8
2nd Decile	17.6	6.5
3rd Decile	12.7	8.9
4th Decile	12.8	8.5
5th Decile	10.7	8.8
6th Decile	8.7	8.7
7th Decile	6.1	7.8
8th Decile	4.0	9.4
9th Decile	2.3	9.7
10th Decile	1.1	15.9

Table 33. Distribution of big losers and big winners proportional to their population frequencies, by household heads's characteristics.

	Total Sample Frequencies	Big losers (Ave= 24.8 %)	Big Winners (Ave= 15.8 %)
Male	83.6	1.11	0.88
Female	16.4	0.42	1.60
Single	30.2	1.17	1.47
Married	69.8	0.93	0.78
Atlantic	7.5	1.43	0.75
Quebec	25.2	0.75	1.25
Ontario	36.7	0.88	0.87
Prairies	18.4	1.32	1.29
British Columbia	12.2	1.13	0.58
Man./Admin.	13.2	0.45	0.74
Professional	16.3	0.66	1.03
Clerical	10.2	0.84	1.20
Sales/Services	18.8	0.83	1.08
Blue-collar	35.8	1.42	0.76
Farm	5.5	1.51	2.49
Age:16-19	0.8	1.63	1.25
Age:20-24	8.7	2.83	0.67
Age:25-44	55.1	1.10	0.57
Age:45-54	18.4	0.53	1.15
Age.55+	17.0	0.22	2.39
None/Elementary	16.4	0.87	1.63
High School	44.6	1.19	0.86
Some Post Sec.	9.5	1.23	0.93
Certificate/Dip.	13.5	0.83	0.76
University	16.0	0.61	0.98

Table 34. Regression Results: relative total wealth.

Dependent variable=Shock total wealth/Base total wealth				
	Parameter Estimate	P > t	Parameter Estimate	P > t
Constant	0.821	0.0001	0.933	0.0001
Base total wealth	2.61E-8	0.1320	5.26E-8	0.0010
Atlantic	-0.017	0.3672		
Quebec	0.002	0.9202		
Prairies	0.026	0.1066		
British Columbia	-0.014	0.4974		
Age: 16-19	-0.620	0.0001		
Age: 20-24	-0.041	0.0597		
Age: 45-54	0.049	0.0017		
Age: 55+	0.080	0.0001		
None/Elementary	0.008	0.6356		
Some post secondary	-0.050	0.0176		
Certificate/Dip.	0.002	0.9267		
University	0.002	0.9268		
Managerial/Admin.	0.010	0.5858		
Professional	0.023	0.2611		
Clerical	0.037	0.0909		
Sales/Services	0.022	0.1834		
Farm	-0.006	0.8117		
Single	-0.030	0.0915		
Male	0.086	0.0001		
Adjusted R2	0.016		0.0010	
F Value	9.289		10.831	
P > F	0.0001		0.0010	

APPENDIX A

Table A1. Inflation and Unemployment Rates, and unemployment duration weeks in the simulation: Canada.

	Inflation (%)	Unemployment (%)	Duration weeks (million)
1981	12.3*	8.5**	40.8
1982	10.8	11.0	52.8
1983	5.8	11.8	56.6
1984	4.4	11.2	53.7
1985	4.0	10.5	50.3
1986	4.1	9.5	45.5
1987	4.4	8.8	42.2

Note: total unemployment durations are calculated by the author for the simulation model. See the text for details.
* Fourth quarter.
** December.
Source: *Bank of Canada Review.* February 1989. Ottawa.

Table A2. Average weeks of interrupted unemployment durations: Canada.

	Males	Females
1981	13.7	14.7
1982	18.0	16.4
1983	23.2	19.9
1984	22.9	19.8
1985	23.2	19.7
1986	21.5	18.8
1987	22.2	18.6

Source: *Labour Force Annual Averages: 1981-1987.* Statistics Canada, Catalogue 71-529, occasional

Table A3. Regional Unemployment Rates.

	Atlantic[1]	Quebec	Ontario	Prairies[2]	B.C.
1981	11.7	10.3	6.6	4.8	6.7
1982	14.2	13.8	9.7	7.4	12.1
1983	14.7	13.9	10.3	9.1	13.8
1984	15.2	12.8	9.0	9.2	14.7
1985	15.7	11.8	8.0	8.8	14.1
1986	15.0	11.0	7.0	8.4	12.5
1987	14.1	10.3	6.1	8.1	11.9

1. Average of the unemployment rates in Newfoundland, Prince Edward Island, Nova Scotia, and New Brunswick.
2. Average of the unemployment rates in Manitoba, Alberta, and Saskachewan.

Source: *Labour Force Annual Averages:1981-1987*. Statistics Canada, Catalogue 71-529, occasional.

Table A4. Unemployment Insurance Entrance Requirement

Regional Unemployment Rate (%)	Weeks of Insurable Employment Required
6 and under	14
6.1 - 7	13
7.1 - 8	12
8.1 - 9	11
over 9	10

Source: *Commission of Inquiry on Unemployment Insurance: Report*, November 1986, Canadian Government Publishing Centre: Ottawa.

Table A5. Changes in average nominal weekly earnings and labour productivity.

	Nominal Change (%)	Simulation: Shock (%)	Simulation: Baseline
1982	10.0	-0.8	0.56
1983	7.0	1.2	0.56
1984	4.3	-0.1	0.56
1985	3.5	-0.5	0.56
1986	2.8	-1.3	0.56
1987	2.7	-1.7	0.56
Labour Productivity Growth*	0.56		

* Average of labour productivity growth rates in the 1976-1981 period.

Sources:

(1) *Quarterly Economic Summary, Statistical Supplement*. April,1987. Statistics Canada. Cat. 13.007E.

(2) *Canadian Economic Observer*, Statistics Canada. Cat. 11-010.

(3) *Aggregate Productivity Measures*, Statistics Canada. Cat. 15-204.

Table A6. Interest Rates and Prices : Canada.

	Gov't. bond yields* (%)	Equity yields (%)	Mortgage rates (3yr) (%)	New Housing price indexes	Stock price indexes (year end) 1975=1000
1981	15.17	4.49	17.79	100.0	1954.1
1982	10.64	4.03	14.13	99.3	1958.1
1983	10.84	3.22	11.80	96.9	2552.1
1984	10.76	3.70	12.47	97.5	2400.4
1985	9.33	3.13	11.15	98.8	2900.3
1986	9.88**	2.99	10.75	108.8	3066.2
1987	7.85**	3.08	11.07	126.1	3027.8***

Note: one year mortgage rate in 1987 is 0.879.
* 3-5 years.
** 1-3 years.
***Average of low and close value.
Sources: *Bank of Canada Review*, various issues.
Canadian Housing Statistics, 1985,1988. Canadian Mortgage and Housing Corporation:Ottawa.

APPENDIX B

INEQUALITY MEASURES[47]

(1) Coefficient of Variation (CV).

Given the variance, V:

$$V = (1/n) \sum_{i=1}^{n} (y_i - \mu)^2$$

$$CV = \frac{\sqrt{V}}{\mu}$$

where y_i is the income of the ith individual, μ is the mean income.

(2) Gini Coefficient (G).

$$G = 1 + (1/n) - [\, 2/(n^2\mu] \sum_{i=1}^{n} (n-i+1)y_i \,.$$

Note: Individuals are ranked by income in ascending order and y_1 is the lowest.

(3) Theil's Entropy Index (T).

$$T = (1/n\mu)\sum_{i=1}^{n} y_i \log(y_i \,/\, \mu) \,.$$

(4) Atkinson's Index (A).

$$A = 1 -[\, \sum_{i=1}^{n} (y_i/\mu)^{1-\epsilon} \cdot 1/n \,]^{\frac{1}{1-\epsilon}} \;;\;\; \epsilon \neq 1, \;\; \epsilon \geq 0 \,.$$

---

[47] See Jenkins (1991).

APPENDIX C

Table C1. Variable means:logistic regression equation.

	Males	Females
Atlantic	0.211	0.183
Quebec	0.188	0.205
Prairies	0.262	0.246
British Columbia	0.102	0.102
Manag.Admin.	0.117	0.061
Professional	0.119	0.140
Sales/Services	0.181	0.212
Clerical	0.053	0.217
Rural	0.054	0.018
Age:16-19	0.088	0.082
Age:20-24	0.121	0.118
Age:45-54	0.148	0.143
Age:55-69	0.178	0.193
None/Elementary	0.149	0.144
Some post secondary	0.105	0.104
Certificate/Diploma	0.124	0.141
University	0.141	0.105
Single	0.277	0.218
Previous unemployment weeks	3.461	2.905

APPENDIX D

SIMULATION CODE (S.A.S)

```
options ls=80 stimer;
libname user 'dal_tempdisk:[erksoy.sasdata]';

        /* HUMAN WEALTH SIMULATION: HEADS AND WIVES */

/* DATASET CREATION */

data ad1;
     set ad83;

     if region=1 then atl=1;
     else atl=0;
     if region=2 then que=1;
     else que=0;
     if region=3 then ont=1;
     else ont=0;
     if region=4 or region=5 then pra=1;
     else pra=0;
     if region=6 then bc=1;
     else bc=0;
     if region=0 then special=1;
     else special=0;

     if hoc=1 then manadm=1;
     else manadm=0;

     if woc=1 then manadmw=1;
     else manadmw=0;

     if hoc=2 then profes=1;
     else profes=0;
     if woc=2 then profesw=1;
     else profesw=0;

     if hoc=3 then cleric=1;
     else cleric=0;
     if woc=3 then clericw=1;
     else clericw=0;

     if hoc=4 or hoc=5  then salserv=1;
```

```
else salserv=0;
if woc=4 or woc=5 then salservw=1;
else salservw=0;

if hoc=6 then farm=1;
else farm=0;
if woc=6 then farmw=1;
else farmw=0;

if hoc=7 or hoc=8 or hoc=9 or hoc=10 then other=1;
else other=0;
if woc=7 or woc=8 or woc=9 or woc=10 then otherw=1;
else otherw=0;

if hage <= 19 then a1=1;
else a1=0;
if wfage <=19 then aw1=1;
else aw1=0;

if 20 <= hage <=24 then a2=1;
else a2=0;
if 20 <= wfage <=24 then aw2=1;
else aw2=0;

if 25 <= hage <=44 then a3=1;
else a3=0;
if 25 <= wfage <=44 then aw3=1;
else aw3=0;

if 45 <= hage <=54 then a4=1;
else a4=0;
if 45 <= wfage <=54 then aw4=1;
else aw4=0;

if hage>=55 then a5=1;
else a5=0;
if wfage >= 55 then aw5=1;
else aw5=0;

if heduc=1 then noel=1;
else noel=0;
if weduc=1 then noelw=1;
else noelw=0;
```

```
if heduc=2 or heduc=3 then high=1;
else high=0;
if weduc=2 or weduc=3 then highw=1;
else highw=0;

if heduc=4 then spsec=1;
else spsec=0;
if weduc=4 then spsecw=1;
else spsecw=0;

if heduc=5 then certdip=1;
else certdip=0;
if weduc=5 then certdipw=1;
else certdipw=1;

if heduc=6 then univ=1;
else univ=0;
if weduc=6 then univw=1;
else univw=1;

if hmars=1 or hmars=3 then single=1;
else single=0;

if hlfs=3 then un=1;
else un=0;
if wlfs=3 then unw=1;
else unw=0;

if hwem > 0 then wage1=(178318100000/212018359155)*htear/hwem;
else wage1=0;
if wemw > 0 then wagew1=(178318100000/212018359155)*wtear/wemw;
else wagew1=0;


if 99 <= wage1 <= 495 then ui=0.6*wage1;
else if wage1 > 495 then ui=0.6*495;
else ui=0;
if 99 <= wagew1 <=495 then uiw=0.6*wagew1;
else if wagew1 > 495 then uiw=0.6*495;
else uiw=0;

if hwun > 0 then su=1;
else su=0;
if wun > 0 then suw=1;
```

```
        else suw=0;

        if hwem > 0 then em=1;
        else em=0;
        if wemw > 0 then emw=1;
        else emw=0;
run;
data ad2;
        set ad1;
        if special=0;
run;
data ad2;
        set ad2;
        if wage1 > 0;
run;
data subad1;
        set ad2(keep=famsno atl que ont pra bc manadm manadmw profes
        profesw cleric clericw salserv salservw farm farmw other otherw a1  a2 a3
        a4  a5  aw1 aw2 aw3 aw4 aw5 noel high spsec certdip univ noelw highw
        spsecw certdipw univw single hwun wun hwem wemw wage1 wagew1 nlfw
        nlfww un unw hsex ui uiw uniwgt su suw special single hmars);

        if hsex=1 then hwun=0.59*hwun;
        else hwun=0.74*hwun;

        wun=0.74*hwun;
run;
data wife;
        set subad1;
        if hmars=2;
run;
data wife;
        set wife;
        hwem=wemw;
        hwun=wun;
        un=unw;
        nlfw=nlfww;
        hsex=3;
        wage1=wagew1;
run;
data wife;
        set wife;
        if wagew1 > 0;
run;
```

```
data subad1;
        set subad1 wife;
run;
data subad1;
        set subad1;

        /* Historical changes in weekly real employment earnings */

        wage2=wage1 - (wage1*0.008);
        wage3=wage2 + (wage2*0.012);
        wage4=wage3 - (wage3*0.001);
        wage5=wage4 - (wage4*0.005);
        wage6=wage5 - (wage5*0.013);
        wage7=wage6 - (wage6*0.017);

        /* Changes in weekly employment earnings at NAIRU

         q=0.0056 Labour productivity growth rate
          p=0.1230 Inflation rate 1981(IV)
          w=p + q = 0.129
          Note: Labour productivity growth is the average of
               1977-1981 rates */

        wnar1=wage1;
        wnar2=wnar1 + (wnar1*0.0056);
        wnar3=wnar2 + (wnar2*0.0056);
        wnar4=wnar3 + (wnar3*0.0056);
        wnar5=wnar4 + (wnar4*0.0056);
        wnar6=wnar5 + (wnar5*0.0056);
        wnar7=wnar6 + (wnar6*0.0056);


        /* RANDOM VARIABLE STREAMS FOR THE PROBABILITY
EQUATIONS */

        rv00=normal(0);
        rv0=normal(0);
        rv1=normal(0);
        rv2=normal(0);
        rv3=normal(0);
        rv4=normal(0);
        rv5=normal(0);
        rv6=normal(0);
        rv7=normal(0);
```

```
        /* RANDOM VARIABLE STREAMS FOR THE DURATION
(UNEMP) EQUATIONS */

                /* FEMALES */

        fz00=1.061*(log(-log(ranuni(0))));
        fz0=1.061*(log(-log(ranuni(0))));
        fz1=1.061*(log(-log(ranuni(0))));
        fz2=1.061*(log(-log(ranuni(0))));
        fz3=1.061*(log(-log(ranuni(0))));
        fz4=1.061*(log(-log(ranuni(0))));
        fz5=1.061*(log(-log(ranuni(0))));
        fz6=1.061*(log(-log(ranuni(0))));
        fz7=1.061*(log(-log(ranuni(0))));

                /* MALES */

        mz00=1.064*(log(-log(ranuni(0))));
        mz0=1.064*(log(-log(ranuni(0))));
        mz1=1.064*(log(-log(ranuni(0))));
        mz2=1.064*(log(-log(ranuni(0))));
        mz3=1.064*(log(-log(ranuni(0))));
        mz4=1.064*(log(-log(ranuni(0))));
        mz5=1.064*(log(-log(ranuni(0))));
        mz6=1.064*(log(-log(ranuni(0))));
        mz7=1.064*(log(-log(ranuni(0))));
run;


/* ADJUSTMENT PERIODS */

%macro adj1(j,buw,pminub);

data subad1;
        set subad1;

        if hsex=1 then
        llm= -2.206 + 0.215*atl +0.002*que + 0.133*pra + 0.109*bc
                -0.617*manadm - 0.402*profes -0.251*salserv -0.217*cleric
                -0.363*farm + 0.793*a1 + 0.698*a2 - 0.346*a4 - 0.968*a5
                +0.156*noel - 0.143*spsec -0.181*certdip -0.458*univ+ 0.274*single
                +0.09*&pminub;
        else if hsex=2 then
        llm= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
```

```
        +0.310*manadm -0.113*profes +0.512*salserv +0.267*cleric
        +0.251*farm +0.738*a1 +0.497*a2 -0.467*a4 -1.202*a5
        -0.171*noel +0.099*spsec -0.068*certdip -0.109*univ
        +0.028*single +0.074*&pminub;

else if hsex=3 then
llm= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
        +0.310*manadmw -0.113*profesw +0.512*salservw
        +0.267*clericw+0.251*farmw +0.738*aw1 +0.497*aw2 -0.467*aw4
        -1.202*aw5-0.171*noelw +0.099*spsecw -0.068*certdipw
        -0.109*univw+0.074*&pminub;


rllm=llm + rv&j;
prob&j= 1 /(1 + exp(-rllm));


if hsex=1  then
do;
durb=2.592 +0.150*atl +0.075*que -0.014*pra -0.34*bc
        -0.336*manadm-0.172*profes +0.057*cleric -0.243*salserv
        +0.092*farm+0.07*a1 + 0.219*a2 -0.157*a4 -0.202*a5
        -0.004*noel+0.190*spsec +0.004*certdip +0.283*univ
        +0.029*single+0.0003*ui+0.013*&pminub;

                    /* Adjustment factors (Males): */

        /* (NAIRU)     1981. log(13.7/23.2)+3.119=2.592 */
            /*         1982. log(18.0/13.7)+2.592=2.865 */
            /*         1983. log(23.2/18.0)+2.865=3.119 */
            /*         1984. log(22.9/23.2)+3.119=3.106 */
            /*         1985. log(23.2/22.9)+3.106=3.119 */
            /*         1986. log(21.5/23.2)+3.119=3.043 */
            /*         1987. log(22.2/21.5)+3.043=3.075 */

/* Initially the intercept is aligned with the asset & debt survey (a.d.) as
3.229+log(25.31/28.26)=3.119 */

ub=exp(mz&j+durb);
end;


else if hsex=2 then
do;
```

```
        durb=1.768 +0.140*atl +0.118*que +0.166*pra -0.149*bc
              +0.245*manadm+0.504*profes -0.009*cleric +0.082*salserv
              -0.339*farm-0.409*a1 +0.219*a2 +0.346*a4 -0.036*a5
              -0.466*noel+0.225*spsec +0.079*certdip +0.145*univ
              -0.320*single+0.002*ui +0.005*&pminub;


                   /* Adjustment Factors (Females & Wives) */

               /* (NAIRU)     1981. log(14.7/19.9)+2.071=1.768 */
                   /*         1982. log(16.4/14.7)+1.768=1.877 */
                   /*         1983. log(19.9/16.4)+1.877=2.07 */
                   /*         1984. log(19.8/19.9)+2.07=2.065 */
                   /*         1985. log(19.7/19.8)+2.065=2.06 */
                   /*         1986. log(18.8/19.7)+2.06=2.013 */
                   /*         1987. log(18.6/18.8)+2.013=2.002 */

/* Initially the intercept is aligned with a.d as 2.286+log(23.96/29.71)=2.071 */

        ub=exp(fz&j + durb);
        end;

        else
        do;

        durb=1.768 +0.140*atl +0.118*que +0.166*pra -0.149*bc
              +0.245*manadmw+0.504*profesw -0.009*clericw +0.082*salservw
              -0.339*farmw-0.409*aw1 +0.219*aw2 +0.346*aw4 -0.036*aw5
              -0.466*noelw+0.225*spsecw +0.079*certdipw
              +0.145*univw+0.002*uiw +0.005*&pminub;

        ub=exp(fz&j + durb);
        end;
run;
proc sort data=subad1;
        by descending prob&j;
run;

data subad1;
        set subad1;
        minub&j=min(52,ub);
run;

data subad1;
```

```
        set subad1;
        wminub&j=uniwgt*minub&j;
run;

data subad1;
        set subad1;
        bastot&j + wminub&j;
run;

data subad1;
        set subad1;
        if bastot&j > &buw then
        minub&j=0;
run;

data subad1;
        set subad1;
        bemp&j=max(0,52-nlfw-minub&j);
run;

data subad1;
        set subad1;
        if minub&j > 0 then uflag&j=1;
        else uflag&j=0;
run;

%mend adj1;



%macro adj2(j,pminub);

data subad1;
        set subad1;
        if hsex=1 then
        llm= -2.206 +0.215*atl +0.002*que +0.133*pra +0.109*bc
                -0.617*manadm -0.402*profes -0.251*salserv -0.217*cleric
                -0.363*farm +0.793*a1 +0.698*a2 -0.346*a4 -0.968*a5 +0.156*noel
                -0.143*spsec -0.181*certdip -0.458*univ +0.274*single
                +0.090*&pminub;

        else if hsex=2 then
        llm= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
                +0.310*manadm -0.113*profes +0.512*salserv +0.267*cleric
```

```
        +0.251*farm +0.738*a1 +0.497*a2 -0.467*a4 -1.202*a5
        -0.171*noel +0.099*spsec -0.068*certdip -0.109*univ
        +0.028*single + 0.074*&pminub;

    else if hsex=3 then
    llm= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
        +0.310*manadmw -0.113*profesw +0.512*salservw
        +0.267*clericw +0.251*farmw +0.738*aw1 +0.497*aw2 -0.467*aw4
        -1.202*aw5 -0.171*noelw +0.099*spsecw -0.068*certdipw
        -0.109*univw+ 0.074*&pminub;

    rllm= llm + rv&j; /* s.e.e=1.814 */
    prob&j= 1 /(1 + exp(-rllm));


run;
proc sort data=subad1;
    by descending prob&j;
run;

%mend adj2;


%macro adj3(j,pminub);

data subad1;
    set subad1;

    if hsex=1 then
    do;

    durb=2.592 +0.150*atl +0.075*que -0.014*pra -0.34*bc
        -0.336*manadm-0.172*profes +0.057*cleric -0.243*salserv
        +0.092*farm+0.07*a1 + 0.219*a2 -0.157*a4 -0.202*a5
        -0.004*noel+0.190*spsec +0.004*certdip +0.283*univ
        +0.029*single+0.013*&pminub + 0.0003*ui;

                /* Adjustment factors (Males): */

        /* (NAIRU)    1981. log(13.7/23.2)+3.119=2.592 */
           /*     1982. log(18.0/13.7)+2.592=2.865 */
           /*     1983. log(23.2/18.0)+2.865=3.119 */
           /*     1984. log(22.9/23.2)+3.119=3.106 */
           /*     1985. log(23.2/22.9)+3.106=3.119 */
```

```
                    /*      1986. log(21.5/23.2)+3.119=3.043 */
                    /*      1987. log(22.2/21.5)+3.043=3.075 */

/* Initially the intercept is aligned with a.d. as 3.229+log(25.31/28.26)=3.119 */


    ub=exp(mz&j+durb);
    end;

    else if hsex=2 then
    do;

    durb=1.768 +0.140*atl +0.118*que +0.166*pra -0.149*bc
          +0.245*manadm+0.504*profes -0.009*cleric +0.082*salserv
          -0.339*farm-0.409*a1 +0.219*a2 +0.346*a4 -0.036*a5
          -0.466*noel+0.225*spsec +0.079*certdip +0.145*univ
          -0.320*single+0.005*&pminub +0.002*ui;


                    /* Adjustment Factors (Females & Wives) */

                /* (NAIRU)      1981. log(14.7/19.9)+2.071=1.768 */
                    /*      1982. log(16.4/14.7)+1.768=1.877 */
                    /*      1983. log(19.9/16.4)+1.877=2.07 */
                    /*      1984. log(19.8/19.9)+2.07=2.065 */
                    /*      1985. log(19.7/19.8)+2.065=2.06 */
                    /*      1986. log(18.8/19.7)+2.06=2.013 */
                    /*      1987. log(18.6/18.8)+2.013=2.002 */

/* Initially the intercept is aligned with a.d as 2.286+log(23.96/29.71)=2.071 */

    ub=exp(fz&j +durb);
    end;

    else
    do;

    durb=1.768 +0.140*atl +0.118*que +0.166*pra -0.149*bc
          +0.245*manadmw+0.504*profesw -0.009*clericw +0.082*salservw
          -0.339*farmw-0.409*aw1 +0.219*aw2 +0.346*aw4 -0.036*aw5
          -0.466*noelw+0.225*spsecw +0.079*certdipw +0.145*univw
          +0.002*uiw +0.005*&pminub;

    ub=exp(fz&j +durb);
```

```
        end;

        /* Constrained unemployment weeks */

        minub&j=min(ub,52);
 run;

%mend adj3;


/* ADJUSTMENT PERIODS: UNEMPLOYMENT FLAG ASSIGNMENT */

%macro adj4(j,buw);

data subad1;
        set subad1;

        /* (1) Bastot is the cumulative weighted constrained u weeks
              for NAIRU
           (2) Individuals are already sorted in a descending probability order */

  /* Weighted unemployment weeks */

        wminub&j=uniwgt*minub&j;
run;
data subad1;
        set subad1;
        bastot&j+ wminub&j;
run;
data subad1;
        set subad1;
        if bastot&j <= &buw then uflag&j=1;
        else uflag&j=0;
run;
data subad1;
        set subad1;
        if uflag&j=0 then minub&j=0;
run;
data subad1;
        set subad1;
        bemp&j=max(0,52-nlfw-minub&j);
        emp&j=max(0,52-nlfw-minub&j);
        minu&j=minub&j,
```

```
run;

%mend adj4;

        /* SIMULATION */

%macro b1(j,pminu,pminub);

data subad1;
        set subad1;

        if hsex=1 then
        llm1= -2.206 +  0.215*atl +0.002*que + 0.133*pra + 0.109*bc
                -0.617*manadm -0.402*profes -0.251*salserv -0.217*cleric
                -0.363*farm +0.793*a1 +0.698*a2 -0.346*a4 -0.968*a5
                +0.156*noel -0.143*spsec -0.181*certdip -0.458*univ +0.274*single
                +0.090*&pminu;

        else if hsex=2 then
        llm1= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
                +0.310*manadm -0.113*profes +0.512*salserv +0.267*cleric
                +0.251*farm +0.738*a1 +0.497*a2 -0.467*a4 -1.202*a5
                -0.171*noel +0.099*spsec -0.068*certdip -0.109*univ
                +0.028*single + 0.074*&pminu;

        else if hsex=3 then
        llm1= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
                +0.310*manadmw -0.113*profesw +0.512*salservw
                +0.267*clericw+0.251*farmw +0.738*aw1 +0.497*aw2 -0.467*aw4
                -1.202*aw5-0.171*noelw +0.099*spsecw -0.068*certdipw
                -0.109*univw+ 0.074*&pminu;


        rllm1=llm1 + rv&j;
        sprob&j= 1 /(1 + exp(-rllm1)); /* Shock probability */


        if hsex=1 then
        llm2= -2.206 +  0.215*atl +0.002*que + 0.133*pra + 0.109*bc
                -0.617*manadm -0.402*profes -0.251*salserv -0.217*cleric
                -0.363*farm +0.793*a1 +0.698*a2 -0.346*a4 -0.968*a5
                +0.156*noel -0.143*spsec -0.181*certdip -0.458*univ +0.274*single
                +0.090*&pminub;
```

```
        else if hsex=2 then
        llm2= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
              +0.310*manadm -0.113*profes +0.512*salserv +0.267*cleric
              +0.251*farm +0.738*a1 +0.497*a2 -0.467*a4 -1.202*a5
              -0.171*noel +0.099*spsec -0.068*certdip -0.109*univ
              +0.028*single + 0.074*&pminub;

        else
        llm2= -2.362 +0.136*atl +0.080*que -0.097*pra +0.069*bc
              +0.310*manadmw -0.113*profesw +0.512*salservw
              +0.267*клericw+0.251*farmw +0.738*aw1 +0.497*aw2 -0.467*aw4
              -1.202*aw5-0.171*noelw +0.099*spsecw -0.068*certdipw
              -0.109*univw+ 0.074*&pminub;

        rllm2= llm2 + rv&j; /* Note: s.e.e=1.814 */
        bprob&j= 1 /(1 + exp(-rllm2)); /* Base probability */

run;

%mend b1;


%macro b2(j,int3,int4,pminu,pminub);

data subad1;
        set subad1;
        if hsex=1 then
        do;
        dur= &int3 +0.150*atl +0.075*que -0.014*pra -0.34*bc -0.336*manadm
        -0.172*profes +0.057*cleric -0.243*salserv +0.092*farm +0.07*a1
        +0.219*a2 -0.157*a4 -0.202*a5 -0.004*noel +0.190*spsec +0.004*certdip
        +0.283*univ +0.029*single +0.013*&pminu +0.0003*ui;

        durb=2.592 +0.150*atl +0.075*que -0.014*pra -0.34*bc
              -0.336*manadm-0.172*profes +0.057*cleric -0.243*salserv
              +0.092*farm+0.07*a1 + 0.219*a2 -0.157*a4 -0.202*a5
              -0.004*noel+0.190*spsec +0.004*certdip +0.283*univ
              +0.029*single+0.013*&pminub + 0.0003*ui;

                        /* Adjustment factors (Males): */

                /* (NAIRU)    1981. log(13.7/23.2)+3.119=2.592 */
                   /*         1982. log(18.0/13.7)+2.592=2.865 */
                   /*         1983. log(23.2/18.0)+2.865=3.119 */
```

```
                    /*      1984. log(22.9/23.2)+3.119=3.106 */
                    /*      1985. log(23.2/22.9)+3.106=3.119 */
                    /*      1986. log(21.5/23.2)+3.119=3.043 */
                    /*      1987. log(22.2/21.5)+3.043=3.075 */

/* Initially the intercept is aligned with a.d. as 3.229+log(25.31/28.26)=3.119 */


    u=exp(mz&j + dur);
    ub=exp(mz&j + durb);
    end;

    else if hsex=2 then
    do;
    dur= &int4 +0.140*atl +0.118*que +0.166*pra -0.149*bc
         +0.245*manadm+0.504*profes -0.009*cleric +0.082*salserv
         -0.339*farm-0.409*a1 +0.219*a2 +0.346*a4 -0.036*a5
         -0.466*noel+0.225*spsec +0.079*certdip +0.145*univ
         -0.320*single+0.005*&pminu + 0.002*ui;

    durb=1.768 +0.140*atl +0.118*que +0.166*pra -0.149*bc
         +0.245*manadm+0.504*profes -0.009*cleric +0.082*salserv
         -0.339*farm-0.409*a1 +0.219*a2 +0.346*a4 -0.036*a5
         -0.466*noel+0.225*spsec +0.079*certdip +0.145*univ
         -0.320*single+0.005*&pminub +0.002*ui;


                    /* Adjustment Factors (Females & Wives) */

                /* (NAIRU)    1981. log(14.7/19.9)+2.071=1.768 */
                    /*      1982. log(16.4/14.7)+1.768=1.877 */
                    /*      1983. log(19.9/16.4)+1.877=2.07 */
                    /*      1984. log(19.8/19.9)+2.07=2.065 */
                    /*      1985. log(19.7/19.8)+2.065=2.06 */
                    /*      1986. log(18.8/19.7)+2.06=2.013 */
                    /*      1987. log(18.6/18.8)+2.013=2.002 */

/* Initially the intercept is aligned with a.d as 2.286+log(23.96/29.71)=2.071 */

    u=exp(fz&j + dur);
    ub=exp(fz&j + durb);
    end;

    else
```

```
        do;
        dur= &int4 +0.140*atl +0.118*que +0.166*pra -0.149*bc
               +0.245*manadmw+0.504*profesw -0.009*clericw +0.082*salservw
               -0.339*farmw-0.409*aw1 +0.219*aw2 +0.346*aw4 -0.036*aw5
               -0.466*noelw+0.225*spsecw +0.079*certdipw
               +0.145*univw+0.005*&pminu + 0.002*uiw;


        durb=1.768 +0.140*atl +0.118*que +0.166*pra -0.149*bc
               +0.245*manadmw+0.504*profesw -0.009*clericw +0.082*salservw
               -0.339*farmw-0.409*aw1 +0.219*aw2 +0.346*aw4 -0.036*aw5
               -0.466*noelw+0.225*spsecw +0.079*certdipw +0.145*univw
               +0.002*uiw +0.005*&pminub;

        u=exp(fz&j +dur);
        ub=exp(fz&j +durb);
        end;

        /* Constrained unemployment weeks */

        minu&j=min(u,52);
        minub&j=min(ub,52);

 run;

%mend b2;


/* FIRST PERIOD BASE UNEMPLOYMENT FLAG ASSIGNMENT */

%macro b3(j,buw);

proc sort data=subad1;
        by descending bprob&j;
run;
data subad1;
        set subad1;

        /* (1) bastot is the cumulative weighted constrained u weeks
               for NAIRU */

        wminub&j=uniwgt*minub&j;
run;
data subad1;
```

```
        set subad1;
        bastot&j+ wminub&j;
run;
data subad1;
        set subad1;
        if bastot&j <= &buw then uflag&j=1;
        else uflag&j=0;
run;
data subad1;
        set subad1;
        if uflag&j=0 then minub&j=0;
        minu&j=minub&j;
run;
data subad1;
        set subad1;
        emp&j=max(0,52-nlfw-minu&j);
        bemp&j=max(0,52-nlfw-minub&j);
run;

%mend b3;

        /* PERIODS 2-7  */

%macro b4(j,buw,suw);

data subad1;
        set subad1;

        wminu&j=uniwgt*minu&j;
        wminub&j=uniwgt*minub&j;
run;
proc sort data=subad1;
        by descending bprob&j;
run;
data subad1;
        set subad1;
        bastot&j + wminub&j;
run;
data subad1;
        set subad1;
        if bastot&j <= &buw then uflag&j=1;
        else uflag&j=0;
run;
proc sort data=subad1;
```

```
        by descending sprob&j;
run;
data subad1;
        set subad1;
        lostot&j+wminu&j;
run;
data subad1;
        set subad1;
        if  lostot&j <=&suw  then sflag&j=1;
        else sflag&j=0;
run;
data subad1;
        set subad1;
        if uflag&j=0 then minub&j=0;
        if sflag&j=0 then minu&j=0;

        if uflag&j=0 and sflag&j=1 then los&j=1;
        else los&j=0;
run;
data subad1;
        set subad1;
        emp&j=max(0,52-nlfw-minu&j);
        bemp&j=max(0,52-nlfw-minub&j);
run;

%mend b4;


        /* SIMULATION: MACRO PARAMETERS */

%macro sim1;

/* 1981: ADJUSTMENT and BASE UNEMPLOYED; NO LOSERS */

        %adj1(00,40749975,hwun);
        %adj2(0,minub00);
        %adj3(0,minub00);
        %adj4(0,40749975);

        %b1(1,minu0,minub0);
        %b2(1,2.592,1.768,minu0,minub0);
        %b3(1,40749975);

%mend sim1;
```

```
%macro sim2;

 /* 1982: BASE UNEMPLOYED AND LOSERS */

        %b1(2,minu1,minub1);
        %b2(2,2.865,1.877,minu1,minub1);
        %b4(2,40749975,52732674);

%mend sim2;

%macro sim3;

/* 1983: BASE UNEMPLOYED AND LOSERS */

        %b1(3,minu2,minub2);
        %b2(3,3.119,2.07,minu2,minub2);
        %b4(3,40749975,56567777);

%mend sim3;

%macro sim4;

/* 1984: BASE UNEMPLOYED AND LOSERS */

        %b1(4,minu3,minub3);
        %b2(4,3.106,2.065,minu3,minub3);
        %b4(4,40749975,53691449);

%mend sim4;

%macro sim5; /* 1985: BASE UNEMPLOYED AND LOSERS */

        %b1(5,minu4,minub4);
        %b2(5,3.119,2.06,minu4,minub4);
        %b4(5,40749975,50335734);

%mend sim5;

%macro sim6;

/* 1986: BASE UNEMPLOYED AND LOSERS */

        %b1(6,minu5,minub5);
        %b2(6,3.043,2.013,minu5,minub5);
```

```
        %b4(6,40749975,45541854);

%mend sim6;

%macro sim7; /* 1987: BASE UNEMPLOYED AND LOSERS */

        %b1(7,minu6,minub6);
        %b2(7,3.075,2.002,minu6,minub6);
        %b4(7,40749975,42186139);

%mend sim7;



        /* UNEMPLOYMENT SIMULATION */
%sim1;
%sim2;
%sim3;
%sim4;
%sim5;
%sim6;
%sim7;

        /* CORRELATION ANALYSIS */

proc corr data=subad1;
        var  uflag00 uflag0-uflag7;
        weight uniwgt;

        title 'BASE INCIDENCE CORRELATIONS';
run;

proc corr data=subad1;
        var uflag1 sflag2-sflag7;
        weight uniwgt;

        title 'SHOCK INCIDENCE CORRELATIONS';
run;

proc corr data=subad1;
        var  minu0-minu7;
        weight uniwgt;
```

```
        title 'SHOCK DURATION CORRELATIONS';
run;
proc corr data=subad1;
        var  minub00 minub0-minub7;
        weight uniwgt;

        title 'BASE DURATION CORRELATIONS';
run;


        /* FREQUENCY CHECK */

proc freq data=subad1(keep= uflag00 uflag0-uflag7
                los2-los7 uniwgt);
        weight uniwgt;

        title 'UNEMPLOYMENT FREQUENCIES';
run;




        /* INCOME CALCULATION */

/* (1) SHOCK INCOME: EMPLOYMENT EARNINGS AND/OR UIB */


%macro i1(j,pminu,pemp,aqw,ppqw,pqw,pbqw,bqw,poqw,oqw);

data subad1;
        set subad1;

        if atl=1 or que=1 then
          do;

                if &pminu > 0 then
                do;
                if  &pemp >= &aqw then
                inc&j=wage&j* emp&j +
                0.6*wage&j*min(minu&j,min(52-&pminu,50));
                else
```

```
        inc&j=wage&j* emp&j;
        end;

        else
        do;
        if emp&j >= &aqw then
        inc&j=wage&j* emp&j + 0.6*wage&j*max(minu&j-2, 0);
        else
        inc&j=wage&j*emp&j;
        end;
end;
else if pra=1 then
do;
        if &pminu > 0 then
        do;
        if  &pemp >= &ppqw then
        inc&j=wage&j* emp&j + 0.6*wage&j*min(minu&j,min(52-
        &pminu,50));
        else
        inc&j=wage&j* emp&j;
        end;

        else
        do;
        if emp&j >= &pqw then
        inc&j=wage&j* emp&j + 0.6*wage&j*max(minu&j-2,0);
        else
        inc&j=wage&j* emp&j;
        end;
end;

else if bc=1 then
do;
        if &pminu > 0  then
        do;
        if &pemp >= &pbqw then
        inc&j=wage&j* emp&j +
        0.6*wage&j*min(minu&j,min(52-&pminu,50));
        else
        inc&j=wage&j* emp&j;
        end;

        else
        do;
```

```
            if emp&j >= &bqw then
            inc&j=wage&j* emp&j + 0.6*wage&j*max(minu&j-2,0);
            else
            inc&j=wage&j* emp&j;
            end;
      end;
      else
      do;
            if &pminu > 0  then
            do;
            if &pemp >= &poqw then
            inc&j=wage&j* emp&j + 0.6*wage&j*min(minu&j,min(52-
            &pminu,50));
            else
            inc&j=wage&j* emp&j;
            end;

            else
            do;
            if emp&j >= &oqw then
            inc&j=wage&j*emp&j + 0.6*wage&j*max(minu&j-2,0);
            else
            inc&j=wage&j*emp&j;
            end;

      end;
run;

%mend i1;


/* (2) BASE INCOME: EMPLOYMENT EARNINGS AND/OR UIB */

%macro i4(j,pminu,pemp,aqw,ppqw,pqw,pbqw,bqw,poqw,oqw);

data subad1;
      set subad1;

      if atl=1 or que=1 then
      do;
            if &pminu > 0  then
            do;
            if &pemp >= &aqw then
```

```
        incb&j=wnar&j*bemp&j+
        0.6*wnar&j*min(minub&j,min(52-&pminu,50));
        else
        incb&j=wnar&j*bemp&j;
        end;

        else
        do;
        if bemp&j >= &aqw then
        incb&j=wnar&j*bemp&j + 0.6*wnar&j*max(minub&j-2,0);
        else
        incb&j=wnar&j*bemp&j;
        end;
end;

else if pra=1 then
do;
        if &pminu > 0 then
        do;
        if &pemp >= &ppqw then
        incb&j=wnar&j*bemp&j+
        0.6*wnar&j*min(minub&j,min(52-&pminu,50));
        else
        incb&j=wnar&j*bemp&j;
        end;

        else
        do;
        if bemp&j >= &pqw then
        incb&j=wnar&j*bemp&j+0.6*wnar&j*max(minub&j-2,0);
        else
        incb&j=wnar&j*bemp&j;
        end;
end;

else if bc=1 then
do;
        if &pminu > 0 then
        do;
        if &pemp >= &pbqw then
        incb&j=wnar&j*bemp&j+
        0.6*wnar&j*min(minub&j,min(52-&pminu,50));
        else
        incb&j=wnar&j*bemp&j;
```

```
                end;

                else
                do;
                if bemp&j >= &bqw then
                incb&j=wnar&j*bemp&j+0.6*wnar&j*max(minub&j-2,0);
                else
                incb&j=wnar&j*bemp&j;
                end;
        end;

        else
        do;
                if &pminu > 0 then
                do;
                if &pemp >= &poqw then
                incb&j=wnar&j*bemp&j+
                0.6*wnar&j*min(minub&j,min(52-&pminu,50));
                else
                incb&j=wnar&j*bemp&j;
                end;

                else
                do;
                if bemp&j >= &oqw then
                incb&j=wnar&j*bemp&j+0.6*wnar&j*max(minub&j-2,0);
                else
                incb&j=wnar&j*bemp&j;
                end;
        end;
run;

%mend i4;


        /* INCOME SIMULATION  MACROS */


%macro sim8;

        %i1(1,minu0,emp0,10,14,14,13,13,13,13);
        %i1(2,minu1,emp1,10,14,12,13,10,13,10);
        %i1(3,minu2,emp2,10,12,10,10,10,10,10);
        %i1(4,minu3,emp3,10,10,10,10,10,10,11);
```

```
        %i1(5,minu4,emp4,10,10,11,10,10,11,11);
        %i1(6,minu5,emp5,10,11,11,10,10,11,13);
        %i1(7,minu6,emp6,10,11,11,10,10,13,13);

%mend sim8;

%macro sim10;

        %i4(1,minub0,bemp0,10,14,14,13,13,13,13);
        %i4(2,minub1,bemp1,10,14,14,13,13,13,13);
        %i4(3,minub2,bemp2,10,14,14,13,13,13,13);
        %i4(4,minub3,bemp3,10,14,14,13,13,13,13);
        %i4(5,minub4,bemp4,10,14,14,13,13,13,13);
        %i4(6,minub5,bemp5,10,14,14,13,13,13,13);
        %i4(7,minub6,bemp6,10,14,14,13,13,13,13);

%mend sim10;

        /* INCOME SIMULATION FOR BASE AND SHOCK CASES */


%sim8;
%sim10;

        /* PRESENT VALUE OF EMPLOYMENT EARNINGS= HUMAN
WEALTH */

data subad1;
        set subad1;

        /* PV of employment earnings: real rate=0.1775-0.123=0.0545
         Continuous discounting */

        /* Unweighted pv calculation */

        pvb1=netpv(0.0545,0,of incb1-incb7);
        pvs1=netpv(0.0545,0,of inc1-inc7);

run;

data wife(rename=( pvb1=pvbw1 pvs1=pvsw1 incb1=incbw1
                        uflag1=uflagw1 uflag2=uflagw2 uflag3=uflagw3
                        uflag4=uflagw4 uflag5=uflagw5 uflag6=uflagw6
                        uflag7=uflagw7
```

```
                    los2=losw2 los3=losw3
                    los4=losw4 los5=losw5
                    los6=losw6 los7=losw7) drop=hsex);


                set subad1(keep= pvs1 pvb1 incb1 los2-los7
                          uflag1-uflag7 famsno hsex);

        if hsex=3;
run;
data heads;
        set subad1;
        if hsex=3 then delete;
run;
proc sort data=wife;
        by famsno;
run;
proc sort data=heads;
        by famsno;
run;
data adhw;
        merge heads wife;
        by famsno;
run;
data adhw;
        set adhw;

        if pvbw1=. then pvbw1=0;
        if pvsw1=. then pvsw1=0;

        if incbw1=. then incbw1=0;
run;
proc sort data=ad2;
        by famsno;
run;
proc sort data=adhw;
        by famsno;
run;
data ad3;
        merge ad2 adhw;
        by famsno;
run;
data ad3;
        set ad3;
```

```
        wbhw=(pvb1*uniwgt)+(pvbw1*uniwgt);
        wshw=(pvs1*uniwgt)+(pvsw1*uniwgt);

        bhw=pvb1+pvbw1;
        shw=pvs1+pvsw1;

        hwratio=wshw/wbhw;

        hwloss=wbhw-wshw;
        totloss+hwloss;

run;
```

```
/* NON-HUMAN WEALTH SIMULATION */

     /* ALIGNMENT WITH NATIONAL BALANCE SHEET ACCOUNTS
*/

data finance;
     set ad3(keep=uniwgt famsno tliqas tdep tcsb cash mortout vownhom tstock
          pdebt cdebt bhw shw a1 a2 a3 a4 a5 atl que ont pra bc manadm
          profes cleric salserv farm other noel high spsec certdip univ   single
          hsex);
     vownhom=(vownhom/0.66)**(1/0.95);
     bond=((tliqas-tdep-tcsb-cash)/0.08)**(1/0.95);
     totliq=((tdep+cash)/0.24)**(1/0.95) + (tcsb/0.35)**(1/0.95);
     cpdebt=((cdebt+pdebt)/0.75)**(1/0.95);
     tstock=(tstock/0.08)**(1/0.95);
     mortout=(mortout/0.57)**(1/0.95);

run;
data finance;
     set finance;

     bond1=bond*((10.26-15.17)/15.17)+bond;
     mortout1=mortout*((12.47-17.79)/17.79)+mortout;

     bond1=bond1*((100-122.3)/122.3)+bond1;
     mortout1=mortout1*((100-122.3)/122.3)+mortout1;


     vownhom1=vownhom*((100-97.5)/97.5)+vownhom;
     tstock1=tstock*((1954.1-2400.3)/2400.3)+tstock;

     vownhom1=vownhom1*((100-122.3)/122.3)+vownhom1;
     tstock1=tstock1*((100-122.3)/122.3)+tstock1;


     totliq1=totliq*((100-122.3)/122.3)+totliq;
     cpdebt1=cpdebt*((100-122.3)/122.3)+cpdebt;

     /* STOCK */

     s2=((1958.1-1954.2)/1958.1+0.0403)/110.8*100;
     s3=((2552.4-1958.1)/2552.4+0.0322)/117.2*100;
     s4=((2400.3-2552.4)/2400.3+0.0370)/122.3*100;
```

```
s5=((2900.6-2400.3)/2900.6+0.0313)/127.2*100;
s6=((3066.2-2900.6)/3066.2+0.0299)/132.4*100;
s7=((3027.8-3066.2)/3027.8+0.0308+1)/138.2*100;

s=s2/1.0545 +s3/(1.0545)**2 +s4/(1.0545)**3
        +s5/(1.0545)**4 +s6/(1.0545)**5 +(s7)/(1.0545)**6;

/* BOND */

b=0.1517/110.8*100/1.0545
        +0.1517/117.2*100/1.0545**2
        +0.1517/122.3*100/1.0545**3
        +0.1517/127.2*100/1.0545**4
        +0.0988/132.4*100/1.0545**5
        +(0.0988+1)/138.2*100/1.0545**6;

/* MORTGAGE */

m=0.1779/110.8*100/1.0545
        +0.1779/117.3*100/1.0545**2
        +0.1247/122.3*100/1.0545**3
        +0.1247/127.2*100/1.0545**4
        +0.1247/132.4*100/1.0545**5
        +(0.0879+1)/138.2*100/1.0545**6;

/* LIQUID ASSETS */

klb= 1/200.7*100;
kls= 1/138.2*100;

/* HOUSE = 0.91 */

/* BASELINE NET WORTH */

bnet= bond1 + tstock1 + vownhom1+ klb*totliq1
        -mortout1 -klb*cpdebt1;

/* SHOCK NET WORTH */

snet= b*bond1 + s*tstock1 + 0.91*vownhom1 +
      + kls*totliq1 -m*mortout1 -kls*cpdebt1;

tbw=bhw+bnet;
tsw=shw+snet;
```

```
/* BASE: HOUSEHOLD TOTAL WEALTH */

wtbw=uniwgt*tbw;

/* SHOCK: HOUSEHOLD TOTAL WEALTH */

wtsw=uniwgt*tsw;

run;
```

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