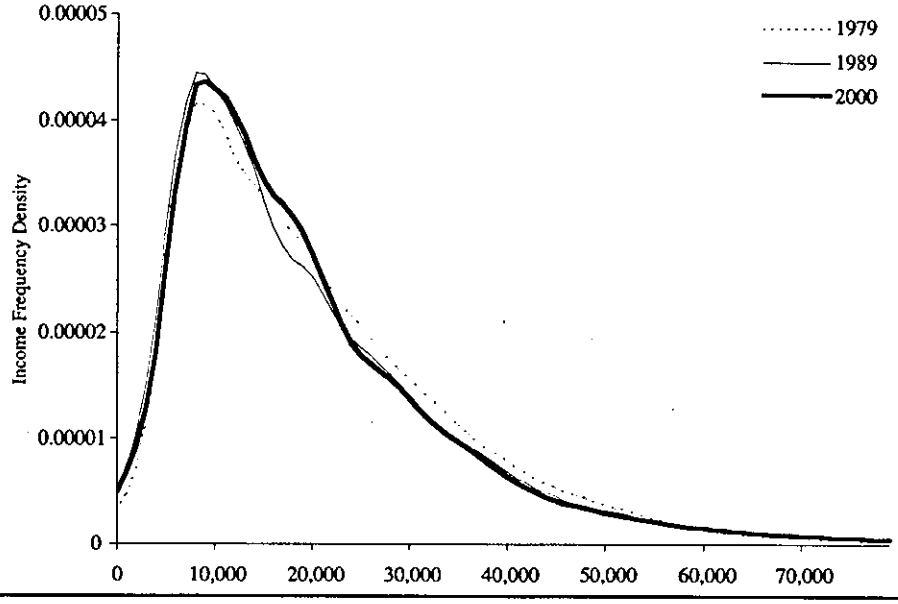
FIGURE 7

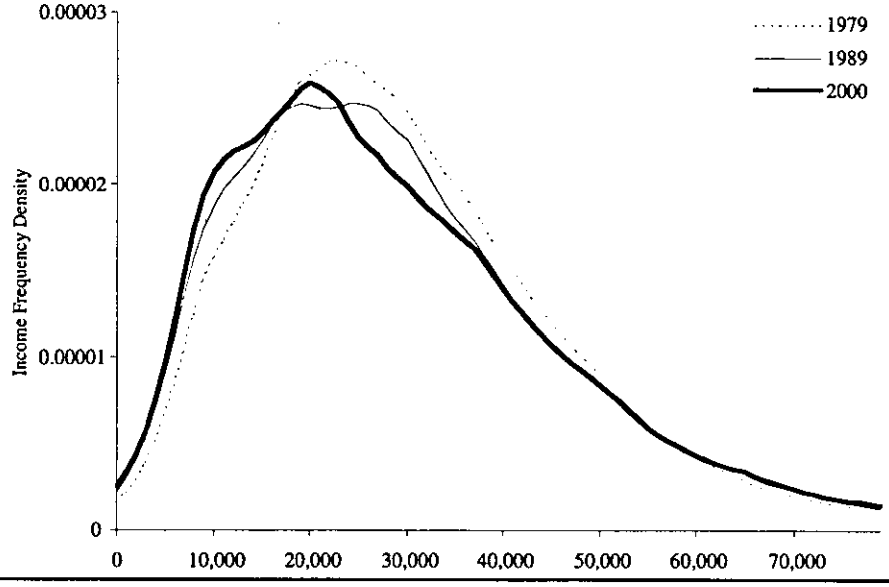
The Income Distribution in the United States Population in 1979, 1989, and 2000: Working Age (25–61) Individuals with Less than a High School Education



Individual Equivalent Pre-tax Post-Transfer Household Income, 2000 Dollars

FIGURE 8

The Income Distribution in the United States Population in 1979, 1989, and 2000: Working Age (25–61) Individuals with a High School Education Only



Individual Equivalent Pre-tax Post-Transfer Household Income, 2000 Dollars

Figure 8 shows the distribution for those with only a high school education. These results are worse than those without a high school education. The distribution of those with only a high school education moved significantly to the left between 1979 and 1989 and this population made no progress between 1989 and 2000. These results together with those in Figure 7 suggest that those with a high school education or less did somewhat better in the 1990s than in the1980s, but that it is more the decline in the shares of these two population (and the concomitant rise in the share of those with more than a high school education) in the 1990s than improvements in the returns to education of those still in these groups, that improved average income and reduced income inequality over this period.

These figures confirm the contrast between the distributional benefits of economic growth in the 1980s and 1990s. The entire income distribution moved to the right over the 1990s as did the conditional distributions for African Americans, single mothers with children and those living in household receiving welfare payment.

Kolmogorov-Smirnov Tests of the Significance of Distributions Shifts

The changes in the distribution of income provided above appear to be significant in most cases but to test whether the shifts in the distribution were statistically significant, we employ the Kolmogorov-Smirnov statistic. This test considers the null hypothesis that the distribution in one period is equal to the distribution in another period or H_0: $F_1(x) = F_2(x)$.

Table 9 provides statistics for comparisons between the years 1979–1989, 1989–2000, and 1979–2000 for the entire distribution as well as for each of the subgroups we have considered in the paper. Almost all of the tests indicate that the changes in the income distribution that have occurred in the past two decades are statistically significant at the 1% level with few exceptions. For those populations where this is not the case, p-values are reported.

Conclusion

Over a typical business cycle in the post-World War II period in the United States, rising incomes were generally associated with falling levels of inequality. That relationship appeared to have ended in the mid–1970s. During the 1980s, income growth was associated with increased income inequality. The middle of the distribution declined in the 1980s. While the vast majority of those people lived in households that became better off, a small but significant group became worse off. Overrepresented groups who experienced reductions in their living standards in the face of a prolonged economic expansion included African Americans, single mothers with younger children and those living in households receiving welfare.

This paper shows that the economic gains of the 1990s business cycle were more evenly distributed. In aggregate, the entire distribution of income shifted upwards over this period with pronounced improvements in the incomes of

African Americans, single mothers with younger children and those living in households receiving welfare payments.

The only group we observed who did not gain over the two decades of our analysis were working age persons with a high school education or lower. But importantly this population fell from 64% of the working age population in 1979 to 44% of the population in 1990 and even this population experience substantial gains in the growth years of the 1990s.

The 1990s appear to mark a return to a period where increases in economic growth are generally accompanied by a decline or at least no substantial increase in income inequality. It is too soon to conclude that the business cycle of the 2000s will yield similar results. It is good news, however, that the 1990s appear to be more representative of the period following World War II when increasing income was accompanied by decreasing inequality than of the period between the mid–1970s and the 1980s. This is particularly encouraging from a distributional perspective since this re-forged relationship appears to be strongest among many of the groups whose misfortunes made the largest contributions to increasing inequality in the 1980s, particularly welfare recipients, single mothers with younger children, and African Americans.

Appendix

We use the public-use Current Population Annual Demographic Survey (CPS) data to derive consistently top coded data for 1980–2001. Our objective was to create top codes that consistently capture the same percentile of the income of our sample across all years. Because total household income is not asked as one question but is the sum of each of the individual sources of income in the household, this required us to create a consistent top code for each of these sources of income over all years. Our strategy was to find the year at which the top code for a given source was at the lowest point in the distribution of income within that source and then to use that percentile as our cutoff point for all years. This strategy was complicated by the fact that the sources of income in the CPS have changed over time and we had to make some decisions with respect to how to combine these new categories. Furthermore, our values are sensitive to the years over which we are doing our comparisons since it is possible that the addition or subtraction of a year will change the most restrictive year in the data.

Consistent Sources of Income. In survey year 1988, the Census Bureau, began providing income in more detailed source categories: (a) labor income was divided into two categories, primary source (if the primary source of earned income was from labor), and the sum of secondary labor income sources (b) self-employment income was divided into two categories, primary source (if the primary source of earned income was from self-employment), and the sum of secondary self-employment income sources (c) farm income was divided into two categories, primary source (if the primary source of earned income was from farming), and the sum of secondary farm income sources (d) unemployment compensation, worker's compensation, and veteran's benefits were divided into three separate categories, (e) dividends and rental income were divided into two separate categories, (f) alimony and child support were divided into two separate categories. They also created a few new sources: (g) two sources of private retirement income, (h) two sources of private disability income, (i) two sources of private survivor's income, and (j) and other income category. For these new sources of income (retirement, disability, survivor's and other income) respondents were asked to specify the exact source (e.g., private insurance benefits). Our first step was to merge the post–1987 source data into the pre–1988 source categories by recombining sources that were divided and allocating the new sources of income (e.g., company or union pension was assigned to retirement income.)

Consistent Percentiles. Our second step was to calculate the percentage of individuals subject to top coding in each year for each of our source categories. To do so for the post–1987 source data that we recombined, we used the sum of the top codes of the recombined sources. (See Burkhauser et al, 2003 for a detailed discussion of these issues.) In 1996, rather then assign the top code for all persons at or above the top code, the Census Bureau estimated a cell mean for those above the labor earnings, farm income and self-employment income top codes based on their individual characteristics. The Census Bureau followed the same procedure in 1999 for other private sources of in-

come. To remain consistent with previous years, we continued to use the top coded values rather than the cell mean values in our data set. For each source, we imposed the most restrictive top code on all years, such that the top code hit the distribution at the same percentile in every year. Table 1A contains the percentage of the distribution affected by the top code and the year in which the most restrictive top code occurred for each source. The earliest constraining year is 1979 for retirement income and the most recent is 1999 for interest and dividends. The top codes hit self employed income at the lowest percentile of all our sources—3.6% of these values are top coded. But for wage and salary income, which is by far the most important source of income, the percentage top coded is only 1.2%.

Consistent Household Income. Our last steps were to sum each individual's sources of income to obtain his or her personal income and then to sum these values across all household members to obtain household income.

Comparing Levels and Trends in Gini Coefficients 1979–2000. Figure 1A shows Gini coefficients derived from our time-consistent public-use data and those from the internal CPS data and the public use version of that CPS data reported in DeNavas-Walt and Cleveland (2002). In our series, there is no spike in earnings inequality in either 1993 or 1995. We use regression analysis to test whether our time-consistent Gini coefficients are significantly different from the Gini coefficients provided by the Census Bureau based on internal CPS data. The regression estimates the levels of the two Gini series, their time trends and changes in their level and trend after 1992. The dependent variable (y) is the Gini value of full time year-round earnings expressed as a percentage. There are six explanatory variables: a constant, which is the level of the time-consistent Gini; a time trend ($t = 1, 2, \ldots 22$), which is the trend in the time-consistent Gini; a Gini source variable ($d = 1$ if the internal data, otherwise 0), which controls for the difference between levels in the two Gini measures; (d) and (t) interacted, which controls for the difference between the trends in the two Gini measures; (d) interacted with an indicator variable for post–1992 years (u),

TABLE 1A

Percentage of the Distribution above the Top Code and Year of the Most Restrictive Top Code for Each Income Source, 1979–2000.

Income Source	Percentage	Year
Wages and Salaries	1.2	1980
Self Employment Income	3.6	1980
Farm Income	2.2	1980
Social Security Income	0.5	1980
Supplemental Security Income	1.9	1994
Public Welfare and Assistance	0.5	1995
Workers' and Unemp. Comp., Vet. Ben.	0.2	1985
Interest Income	0.9	1999
Dividends and Rental Income	1.5	1999
Retirement Income	0.2	1979
Alimony and Child Support	0.2	1998

Source: Authors' computations from March CPS Annual Demographic Files and data from DeNavas-Walt and Cleveland (2002), Table A–3.

which controls for divergence between levels after 1992; and (d) interacted with (t) and (u), which controls for divergence between trends after 1992. The null hypotheses are that the trends are unchanged overall and after 1992. The test statistics are adjusted for the autocorrelation resulting from using the same people to compute both the internal and time-consistent Gini values. The estimated equation, with t-statistic in parentheses, is:

$$Y = 36.5 + 0.17\,t + 3.59\,d + 0.08d\,t + 1.58\,d\,u + -0.043\,d\,t\,u$$
$$(133) \quad (7.9) \quad (7.8) \quad (1.6) \quad (1.0) \quad (-.046)$$

The internal data Gini is significantly larger than the time-consistent Gini. This is not surprising since we have top coded (consistently) a greater portion of the upper tail of the earnings distribution. However, the trends in the two series are not significantly different, overall and after 1992. Hence the trends in earnings inequality are not significantly different in the two series either post–1992 or pre–1993. Importantly, the internal Gini coefficient jumped significantly in 1993 while our time-consistent Gini coefficient did not. Note that the unadjusted public use CPS data reported in Figure 1A cannot be used to trace the internal data for the reasons discussed above (See Burkhauser et al 2004 for detail).

Notes

We thank J.S. Butler and Mary C. Daly for their comments on earlier versions of this paper.

1. In the United States, the family (all married or blood relatives who live in a common dwelling) or the household (all residents living in a common dwelling) are the sharing units most often used by those estimating income inequality or poverty rates. Income within the sharing unit is assumed to be shared equally and some degree of returns to scale in the use of that income is assumed to be experienced by those who live together. Each individual in the sharing unit is then assigned a family or household size-adjusted income value. Atkinson, Rainwater, and Smeeding (1995) and Burkhauser, Crews, and Daly (1997) argue that assuming a family level sharing unit will produce a bleaker picture of the income distribution because this assumption will treat a larger number of individuals as single-person households even when they reside and share the benefits of living with others. Burkhauser, Crews, Daly, and Jenkins (1999) show that the changes found by researchers in the distribution of income in the 1980s are similar using either a family or household sharing unit.
2. Burkhauser, Butler, Feng, and Houtenville (2004) argue that despite the changes in the methods the Census Bureau has used to collect and report earnings between 1975 and 2001 (see Ryscavage, 1995; Polivka, 1996; Jones and Weinberg, 2000) in the March CPS data, these data can be used to consistently estimate trends in earnings inequality. We extend the top coding procedure Burkhauser et al (2004) used to capture earnings to capture household size-adjusted income. Our income measure produces Gini coefficients that are significantly lower than those for the full sample since we are systematically cutting off the upper tail of the distribution of income in all years, but as we show in the appendix there is no significant difference in the trends between the Gini coefficients produced by the Census Bureau based on their internal CPS data and our Gini coefficients both before the major change in their top coding rules in 1992 and afterward. (See: DeNavas-Walt and Cleveland, 2002: 20–22, Table A–3, for internal Census Gini values.) Our results mirror the results found by Burkhauser et al. (2004) with respect to earnings. Hence we believe our income trends provide an accurate measure of income inequality in the United States between 1979 and 2000. (See the Appendix for more details of this analysis.)

3. The formula used for this calculation is $Y_a = Y_u/F^{\theta}$. Here, Y_a is the adjusted household income used in the analysis. Y_u is the unadjusted household income. F is household size. Θ is the adjustment for household size. We assume $\theta = 0.5$. As discussed in Karoly and Burtless (1995: 382), this implies that a four-person household needs twice as much income as a one person household to attain the same level of consumption.
4. The starting and ending years of a business cycle are to some degree arbitrary. We take advantage of a clear trend in income to define our peak, trough, and peak years of the 1980s and 1990s business cycles. Because employment and income lag changes in economic growth these years do not necessarily match business cycles defined by changes in macroeconomic growth.
5. The welfare reform legislation of 1996 had a profound effect on the employment earnings of single mothers with children aged 17 and younger. For a detailed discussion of the law and its effects on single mothers see Blank (2002).
6. These estimates are based on Epanechnikov kernels with adaptive bandwidths.

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The impact of various policy measures on employment in the Netherlands

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This report gives an overview of a static structural microeconomic model of the Dutch labor market that has been developed within the framework of the MIMOSA project (Micromodel strategisch arbeidsmarktonderzoek). The MIMOSA project is a cooperation of OSA Institute for Labour Studies and CentER Applied Research. OSA Institute for Labour Studies, RWI Raad voor Werk en Inkomen (Council for Work and Income) and Stichting Instituut GAK financed the research project.

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1. Introduction

This report presents the prototype model developed as a pilotstudy of the MIMOSA-project. MIMOSA aims at developing a dynamic microsimulation model for the Dutch labour market as a flexible and reliable tool for policy analysis. Here, emphasis will be on policy measures that alleviate (in)voluntary unemployment in the Netherlands. In spite of the increased employment in the Netherlands during the last two decades, a large group of persons is still voluntary or involuntary unemployed. In order to arrive at effective policy measures it is necessary to get insight in the causes of unemployment. Besides problems with respect to the matching of supply of and demand for labor, two categories of causes exist:
1. The productivity trap (or involuntary unemployment)
A person has a too low productivity as compared to the wage to be paid by an employer. Various elements might play a role here. One can think of an insufficient level of education, a loss of skills and motivation due to unemployment, outdated knowledge, or physical or mental disablement. It is of importance here to know how the productivity trap is connected to education and experience, and how this can be solved by a reduction of the minimum wage costs, by generic policy measures or by specific measures for well-defined groups.
2. The poverty trap (or voluntary unemployment)
A person has insufficient incentives to do paid labor. The wage income to be earned is – in combination with the fixed costs of work – too low to accept a job, in view of the other household income and/or benefits to be received. This can be influenced by (the lack) of sanctions. Besides, discouragement effects may be present. Minimum wages play a role as their level also determines the minimum benefit level in the Netherlands.

The productivity trap is at work at the lower end of the labor market and can be alleviated by lowering minimum wage costs. One can think here of a reduction of the gross (minimum wage) or the use of labor costs subsidies. The poverty trap can be suppressed by making work financially more attractive. This can be done by lowering taxes and other levies (like social insurance contributions) on wages or by extra (tax) facilities for working persons as compared to persons receiving a benefit.

There is a vast research literature on the impact of minimum wages on employment via the productivity trap. For a recent overview, see Brown (1999). The larger part of the literature refers to the United States. Until the 1980s the main conclusion was that minimum wages negatively affect employment, which is in line with theory on perfect competition. However, it is also noticed that the impact (at least in the US) is limited, be it that larger effects are found for young (low-educated) persons. The reported elasticity with respect to teenage employment is in the range of –0.1 to –0.3. The view with respect to this, changes in the early 1990s due to the findings for the fast-food industry by Card and Krueger. Card and Krueger (1994) – applying differences in differences – did not find a negative impact of an increase of the minimum wage on employment in the services sector. Instead of an expected decrease, they find a small increase in employment due to the 18 percent increase in the minimum wage in New Jersey in 1992. This analysis has been repeated for more states and during a longer time period in Card and Krueger (1995). Again, this study does not find a negative impact of increasing minimum wages on teenage employment. Also for the United Kingdom zero or positive effects have been found; see Machin and Manning (1994) and Dickens et al. (1999). Machin and Manning's (1994) findings have been based on

regressions using aggregated data from the U.K. Wage Councils. Including GDP growth as an explanatory variable limits the positive impact to Catering, whereas the impact is zero or negative for the other three groups (Retail, Clothing and Hairdressing). Dickens et al. (1999) also use data from the U.K. Wage Councils. They take into account supply shocks (via sector and year dummies) and demand shocks (via sales variables) and find a significant positive effect of increases of the minimum wage on employment. All these studies refer to imperfect markets (monopsony) in order to explain these findings.

However, several recent studies have reported negative effects of minimum wages on employment in the US (see e.g. Currie and Fallick, 1996 and Burkhauser et al. 2000) and France (see Abowd et al., 2000 and Kramarz and Philippon, 2001). In contrast with e.g. Card and Krueger (1995), Burkhauser et al. (2000) control for macroeconomic effects and robustness of the model, using monthly data for 51 states during the period January 1979 - December 1997. They find a negative elasticity of teenage employment with respect to the minimum wage, which varies between –0.2 and –0.6. The aforementioned US studies use aggregated data. Currie and Fallick (1996) use individual-level panel data for 1979, 1980 and 1981 in order to analyze the increase in the federal hourly minimum wage from USD 2.90 to USD 3.10 in January 1980 and from USD 3.10 to USD 3.35 in January 1981. They find a significant negative effect of the increases of the minimum wage on youth employment. Kramarz and Philippon (2001) use micro data and study the impact of changes of total labor costs on the transition from employment to unemployment and vice versa for France. For the former they report an elasticity of –1.5, implying a large negative effect of increasing minimum wages on employment. The same approach has been followed by Abowd et al. (2000) for France and the United States. For France their results are comparable to those of Kramarz and Philippon (2001); for the US they do not find employment effects of a higher minimum wage.

For the period 1985-1989, Van Soest and Kapteyn (1990) found that lowering minimum wages by 10% resulted in an employment gain of a bit more than 100,000 jobs in the Netherlands. This implies an elasticity of about –0.2.

The impact of minimum wages on employment via the poverty trap runs by means of the reservation wage. If benefits are (positively) related to the development of the minimum wage, the reservation wage will increase when the minimum wage is raised. As a consequence, a potential employee will be less inclined to accept a job offer. As a result the probability to become or to remain voluntarily unemployed will increase. This holds both under perfect competition and imperfect competition. So, if benefits are positively related to the minimum wage, an increase of the minimum wages affects employment via the higher benefits in a negative way as a consequence of a lowering of the labor supply. With respect to the impact of benefits on labor supply, a lot of literature is present. For the United States, we mention the overview by Moffit (1999). For the Netherlands, the country that is the subject of this study, the elasticity is about –0.2; see Graafland (2000, p. 218).

As said, here we look at various instruments that are able to combat the poverty and productivity trap in the Netherlands using micro data for the 1990s. Our analysis is based on a structural microeconometric model, in which labor supply, labor demand, wage formation and minimum wage costs are dealt with simultaneously. So, the employment decision is the result of considerations at the level of both individuals

and firms. We determine how the productivity trap and poverty trap affect this process. In this way we are able to look at the impact of various labor policy instruments on both the supply and demand side. We proceed as follows. Section 2 describes the data used and the definition of voluntary and involuntary unemployment. Section 3 gives the model and section 4 the estimation results. In section 5 we look at the impact of various labor market policies. Finally, section 6 concludes.

2. The data

The data are drawn from the 1990 up to and including 2001 waves of the Dutch Socio-Economic Panel. This panel consists of about 5000 households in each wave and is representative of the Dutch population excluding people living in institutional households. We limit ourselves to persons aged 16 to 65 years. Moreover, we require:

- if a partner is present, both partners are younger than 65 years of age
- if a partner is present, both partners filled in the questionnaire
- the respondents are still in the household in the next year and filled in the questionnaire in both years, as the income data refer to the year before
- persons are available for the labor market; so, persons not available (NA) for the labor market (see below) have been excluded from the analysis.

Children aged 18 years and over and living with their parents have been considered as separate decision units and, as a consequence, they have been treated as separate observations.

The analysis refers to three groups: employed persons, involuntary unemployed persons and voluntary unemployed persons. The group of employed persons (WORK) consists of all persons with a paid job and not belonging to the group not available (NA). Persons with a part-time job and looking for additional work have been classified as being employed. The category NA refers to students, persons receiving full-time disability benefits, persons receiving pensions or other retirement benefits and persons in mandatory military services, unless such a person is working for 20 hours or over per week. In the latter case one is employed. People who are not employed or unavailable are either voluntary or involuntary unemployed. The distinction has been based on search behavior. Involuntary unemployed (IU) persons are those who are actively looking for a job, and have applied for a job at least once in the last two months. Moreover, if a job has been offered they are prepared to get started in that job within two weeks. If one does not meet these requirements one has been classified as being voluntary unemployed (VU).

Table 2.1 gives an overview of the distribution by the 3 categories WORK, IU and VU over the years 1990-2000. During this period we have 56,709 observations: 27,586 refer to men and 29,123 to women. For an overview of the exogenous variables by year, see Appendix 2.

Table 2.1: Observed proportion of unemployed and employed persons in the Dutch Socio-Economic Panel by year and sex (and total number)

	Voluntary unemployed VU %	Involuntary unemployed IU %	Paid job WORK %	Number N
		Men		
1990	2.56	3.44	94.00	2613
1991	2.20	4.00	93.80	2480
1992	2.60	3.58	93.82	2647
1993	2.79	4.68	92.53	2637
1994	4.24	5.77	89.99	2585
1995	4.34	4.66	91.00	2616
1996	3.44	5.90	90.65	2581
1997	3.50	4.80	91.70	2457
1998	3.47	3.47	93.06	2382
1999	3.84	2.93	93.24	2318
2000	3.00	2.90	94.10	2270
1990/2000	3.27	4.23	92.50	27,586
		Women		
1990	42.08	6.42	51.50	2759
1991	40.39	5.32	54.29	2614
1992	36.08	6.17	57.74	2781
1993	33.94	6.46	59.61	2764
1994	29.16	10.07	60.77	2755
1995	27.59	9.07	63.34	2762
1996	24.56	10.98	64.46	2705
1997	24.60	8.94	66.46	2570
1998	23.41	8.58	68.01	2523
1999	21.87	8.27	69.86	2463
2000	19.87	6.68	73.45	2427
1990/2000	29.68	7.91	62.42	29,123

3. The model

We apply a structural, static model of the labor market, which consists of four parts. The first part describes the demand side and gives the reservation wage for the employer (or the productivity of the potential employee as seen by the employer). The second part describes the market wage, which is a function of the reservation wage of the employer. We assume that both are independent of the number of hours worked by the employee. The third part describes the individual's preferences. It shows how an individual chooses the number of working hours, given the market wage and the tax and social security system. We assume that the individual maximizes his or her utility that depends on income and leisure. For persons with a partner we allow that the

hours decision is also determined by the number of hours worked by the partner and by the partner's income. This gives us the labor supply of individuals. The fourth part introduces the minimum wage costs for the employer. We now describe these four blocks.

3.1. Reservation wage of the firm

The demand side of the labor market has been described by the productivity equation F^*, which can be considered as the amount that a firm is prepared to pay per hour at maximum. The equation reads as follows:

$$ln\ F_i^* = \beta_0 + \beta_1 ZF_{i1} + \ldots + \beta_m ZF_{im} + e_{iF} \qquad (3.1)$$

Here F_i^* is the gross reservation wage rate of the firm for individual i. This maximum amount to be paid by the employer is determined by the marginal productivity of the potential employee. The variables $ZF_{i1}, \ldots, ZF_{im}$ are observed characteristics of individual i that affect his or her productivity; e.g. age, sex and level of education. However, the amount that a firm is prepared to pay probably also depends on the economic situation. We therefore include the unemployment rate and an indicator for the business cycle as explanatory variables. We also included time dummies to capture possible changes in the production structure. Unobserved characteristics that influence productivity, like firm-specific skills that are not expressed by education or experience (or age), are included in the error term e_{iF}.

3.2. Wage rate

The wage rate has been based on the productivity equation. We assume that the employer approximately knows the individual's productivity. Therefore, the wage rate can be set equal to the (unobserved) productivity. Moreover, we introduce dynamics by linking the wage rate to the labor market situation (*MR*). This has been measured by the number of involuntary unemployed divided by the sum of this number and the number of employees (all in the preceding year), in which we distinguish between 18 segments. The segments are determined by level of education (low, middle, high), age (≤ 30 years, 31-45 years, > 45 years) and sex. The coefficients with respect to *MR* have been based on Van Soest and Kalwij (1996, p. 39). So, we have for the wage rate W^*:

$$ln\ W_i^* = ln\ F_i^* + ?_s MR_s(-1) + e_{iME} \qquad (3.2)$$

in which s is the segment individual i belongs to. Combining (3.1) and (3.2), we have a number of explanatory variables that describe the economic situation. At first, there are the total unemployment rate and the business cycle that both refer to the macroeconomic situation. We expect these to have a negative impact when the economic situation deteriorates: employers will be inclined to pay less, whereas employees will be less demanding. Secondly, we have *MR* that refers to labour market tensions for various subgroups. This variable also reflects – albeit in an indirect way – the impact of changes in the replacement ratio: a change in the latter affects labour supply (see below) and this results in an adjustment of *MR*. Finally, we have added time dummies in order to take into account changes in e.g. the production structure.

The observed wage rates have been calculated from the reported labor income and the number of worked hours. Measurement errors will be present for various reasons. The measurement error has been included in the model by adding an extra error term e_{iME}

to eq. (3.2). We assume that this error term is distributed normally with expectation 0 and standard deviation s_{me}.

3.3. Labor supply

Next to the reservation wage of the firm, the reservation wage of the individual plays a role. The latter describes the supply side of the labor market. The reservation wage has implicitly been modeled via the individual preferences. The preferences of individuals are expressed by a direct utility function. We distinguish two groups. Group I only considers his or her own labor supply. This refers to singles, single parents, children living with their parents, other household members not being head or partner, and members of non-family households. Group II takes into account the labor supply by the partner. These are married or cohabiting men and women. Utility has been modeled as a function of (own) worked hours (h) and the net income per week (y), and for group II also the number of hours worked by the partner (hp). In the latter case income y includes the partner's income. We use a flexible utility function, quadratic in worked hours and income:[1]

$$U(v) = v'Av + b'v \qquad (3.3)$$

with

$v = (y,h)'$ group I

$v = (y, h,hp)'$ group II

A is a 2x2 (group I) or 3x3 (group II) matrix, b is a two (group I) or three dimensional (group II) vector. To allow the utility function to vary with taste shifters the parameters may vary with a vector X of individual and household characteristics. As taste shifters we use age, sex, number of children, age of the youngest child, level of education and dummies for single parents and persons living at their parents. We also use the unemployment rate and a business cycle indicator in order to reflect the impact of the macroeconomic situation on labor supply. The impact of these variables is not straightforward. For example, economic deterioration might result in a higher labor supply if people become more worried with respect to possible future labour market problems. For that reason they might decide to work more hours. On the other hand, it might disencourage people who are involuntary unemployed and, as a consequence, these persons might withdraw from the labour market and become voluntary unemployed.[2]

As it will be difficult to disentangle effects of X via the various parameters, we limit ourselves to the parameter $b_k = X'\beta_k$, $k=2$ for group I and $k=2,3$ for group II. As a consequence, the marginal utility of leisure only depends on X through the additive term $X'\beta$. The head of the household and his or her partner use a joint utility function. The labor supply decision is modeled in this way as a joint decision of both partners.

The quadratic utility function is as flexible as other utility functions applied within this context (see e.g. the overview in Blundell and MaCurdy, 1999). Van Soest, Das and Gong (2002) have extensively looked at the flexibility of a quadratic specification.

[1] When leisure is used in stead of worked hours, we get the same specification for the preferences; the parametrization only changes.

[2] One could also include time dummies in order to capture the role of social and societal changes (and possibly also changes in job characteristics, adaptations by employers facilitating paid labor and care for children and family, and so on). However, these appeared to be insignificant.

They compare a quadratic specification with the more restrictive linear specification and the more flexible specifications based on third, fourth and fifth order polynomials. They conclude that the linear specification is too restrictive and that a quadratic function is sufficient in order to estimate the relevant economic parameters. A more flexible form is preferred from a statistical point of view, but the resulting labor supply elasticities and the consequences from tax changes do not differ significantly.

The data give information on various types of unemployment benefits. However, this only holds for those persons who are actually unemployed. Unemployment benefits depend on labor history and age and have a limited duration (at most five years for persons above the age of 40). Due to the static nature, labor history is not available in the model. We therefore only take into account the social assistance a household receives when household income (excluding family allowances) is below the official poverty line. As a consequence, unemployment benefits are ignored.[3] On the other hand, other income (including family allowances) has been included. The income of other household members has been left out of consideration. This implies that labor supply of children living with their parents does not depend on the parents' earnings and labor supply of parents is independent from the children's earnings.

Following Van Soest (1995), utility maximization has been approached by replacing the actual choice set by a finite number of points. Utility maximization takes place by finding the best point in this finite set. To that end we do not need to require that the tax system and benefits system is piecewise linear or convex. The specification allows for incorporation of fixed costs of working. In this way, we also avoid the critique by MaCurdy et al. (1990) that the range of elasticities that can be obtained are limited by constraints on the chosen labor supply model. As we maximize utility over a finite set, we do not need to rely on tangency conditions or duality theory and do not need to base the model upon the Kuhn-Tucker conditions. Since the error term (see below) follows a continuous distribution, the probability that more points have optimal utility is zero. So, a unique solution exists and this solution is coherent.

We normalize the full-time working week at 40 hours. For both single and joint decision makers we use eleven points ($n=11$). These correspond with no working (0 hours) and working for 4, 8, 12, ..., 40 hours, respectively. Joint decision makers maximize their joint utility function on the basis of the hours worked by both partners. If both are not involuntary unemployed, their joint choice set consists of 121 points: each partner can work during 0, 4, 8, 12, ..., 36 or 40 hours and all combinations are feasible. Net income y now is the sum of the labor income of both plus possible additional income and / or social assistance minus income tax payments and social insurance contributions.[4] If one of both partners is involuntary unemployed, utility is maximized over the set of working hours, under the restriction that the unemployed partner does not work. In this case, we only have a choice set of 11 instead of 121 points.

Finally, we introduce fixed costs of working (*fcw*). Models without fixed costs of working generally underpredict the number of non-workers and overpredict the number of (small) part-time jobs. One way to repair this is the inclusion of fixed costs of working; see Van Soest (1995). This makes not working more attractive than

[3] Sensitivity analyses shows that this assumption hardly affects the results.
[4] The net income has been derived from the gross wage using standard tax-deductable items.

working a few hours per week. We model the fixed costs as a combination of individual and household characteristics (Z_1, ..., Z_r) and a constant:

$$fcw = d_0 + d_1Z_1 + ... + d_rZ_r \qquad (3.6)$$

One has to bear in mind that we do not have any specific information with respect to these fixed costs. This means that we introduce these as an unobserved latent variable. This variable refers to both actual costs (like travel costs and costs of day care) and immaterial costs (like factors that limit the acceptation of a paid job; think of time and search costs). We cannot distinguish between these components in the model. As explanatory variables we use the same variables that were used as taste shifters, except the economic climate indicators. Instead of these latter variables, we include time dummies. The development in the parameter values of these time dummies reflects social developments that affect these fixed costs (in a positive or negative way). One can think of the availability of child care facilities inside or outside the workplace, travel costs, time costs of traffic congestion, and so on.

The fixed costs are incorporated in the utility function by replacing income y_j by $y_j - fcw_j$ if individual j works.

GEV I errors have been added to the utility values of all alternatives in the finite choice set. The errors can be considered as the random part of the evaluation of each alternative. Various reasons can be mentioned here. A first interpretation is the presence of unobserved job characteristics. Secondly, they can be considered as comparable to optimization errors. In this way non-zero probability has been given to choices that are not optimal for any value of the random preference term. This might occur in a non-convex or discontinuous budget set, where some points on the budget frontier may result in low household income in comparison with adjacent points. Thirdly, it facilitates simulated maximum likelihood estimation by smoothing the approximation of the likelihood. In this way, the incorporation of the error term can be seen as a smoothing device; see e.g. Keane and Moffitt (1998). We now get:

$$u(v_j) = U(v_j) + e_j, \quad j=0, ..., n \qquad (3.4)$$

This is similar to a multinomial logit model. The probability that an individual chooses alternative j, conditional on wage rate, tax and benefit rules, exogenous variables and random preferences has now been given by:

$$P\{j\} = exp\ \{U(v_j)\} / ?_k\ exp\{U(v_k)\},\ j=0, ..., n \qquad (3.5)$$

The probabilities for persons without a partner can be determined in an analogous way.

3.4. Minimum wage

We apply the gross legal minimum (youth) wage M. In practice the applied minimum may deviate from the legal minimum wage. One reason for this is that the legal minimum wage refers to the amount to be paid per week and the weekly number of hours in a full-time job differs over branches. Another reason is the existence of salary scales, of which the lowest wages are above the minimum wage. Moreover, it is possible that firms pay less than the minimum wage as a consequence of illegal practices or ignorance. We therefore introduce T^*, the minimum wage rate that is relevant for the employer. This variable will not be observed in practice. We assume

that its logarithm depends on the logarithm of the gross legal minimum wage, the level of education and an error term following a normal distribution with mean 0 and standard deviation s_t^{educ}. We now can determine the probability that the individual's productivity is above the minimum wage that is of importance for the employer. For each level of education we have: $P(ln\ F^* > ln\ T^* | ln\ F^*) = F([ln\ F^* - a + \beta\ ln\ M] / s_t)$, in which F equals the distribution function of the standard normal distribution. This implies that we allow the possibility of offering a job to someone with productivity below the legal minimum wage. It also allows the possibility of not offering a job to a person with productivity above the minimum wage. The probability of a job offer increases with productivity and decreases with the minimum wage relevant for the employer.

3.5. Productivity, preferences and minimum wage

On the basis of the foregoing we are able to derive the following probabilities for each individual:

1. the probability that a person will be prepared to work against the legal minimum wage or the market wage, if higher; in this case his or her reservation wage (R^*) is below the maximum of the legal minimum wage rate and the offered wage rate W^*: $R^* < max(M, W^*)$
2. the probability that a person's productivity (as required by the employer) is above the minimum wage relevant for the employer: $F^* > T^*$.

This gives us the following four possibilities:

1. $R^* > max(M, W^*), F^* < T^*$ (A+P)

The individual has a reservation wage above the maximum of the legal minimum wage and the market wage. Therefore he or she will not be prepared to work: the poverty trap (A) applies. Productivity is below the minimum wage relevant to the employer, so that the productivity trap (P) also applies.

2. $R^* > max(M, W^*), F^* \geq T^*$ (A)

The individual has a reservation wage above the maximum of the legal minimum wage and market wage. Therefore he or she will not be prepared to work and the poverty trap (A) applies. Productivity is above the minimum wage relevant to the employer: the productivity trap does not apply and the individual is voluntary unemployed.

3. $R^* \leq max(M, W^*), F^* < T^*$ (P)

The individual has a reservation wage below the maximum of the legal minimum wage and his or her market wage. The poverty trap therefore does not apply. However, productivity is below the minimum wage relevant to the employer, so that the productivity trap (P) applies. This person is involuntary unemployed.

4. $R^* \leq max(M, W^*), F^* \geq T^*$ (W)

The individual has a reservation wage below the maximum of the legal minimum wage and his or her market wage. The poverty trap therefore does not apply. Productivity is above the minimum wage relevant to the employer and the productivity trap does not apply. This person will work (W).

We now determine for each person for each group the probability that s/he is in that group. The poverty trap has been considered here in a broad sense. Usually this concerns people who enjoy a benefit and do not want to work. Here, it also refers to, for example, persons who do not receive any benefit, but do not work at all, because their partner has a sufficiently high income or assets are large enough to live from.

3.6. Estimation

The model has been estimated using all observations in the sample with the exception of those who are not available for the labor market (see section 2). We apply simulated maximum likelihood. This is among other things due to the point that unobserved wages for unemployed persons have been replaced by predictions. The prediction errors will be substantial. One possibility is to integrate out the disturbance term of the wage equation in the likelihood. However, this may be computationally burdensome in case of partners. We therefore approximate this integral by a simulated mean. For each individual whose wage is unknown, we take R draws from the distribution of the error term(s) in the wage equation(s) and compute the average of the R likelihood values, conditional upon the drawn error. This estimator is a special case of smooth simulated maximum likelihood. It is asymptotically equivalent to maximum likelihood for large R, see Hajivassiliou and Ruud (1994). Our results have been based upon $R = 10$. In former applications using similar models it appeared that this is enough to get reliable estimates; see Van Soest (1995) and Van Soest and Das (2001).

4. Results

In this section the estimation results have been shown. Estimation refers to the period 1990-2000. In the tables we distinguish between joint decision makers (persons with a partner) and single decision makers (persons without a partner: singles, single parents and children living at their parents, et cetera). The model has been estimated simultaneously, albeit seperately for joint (45,094 observations) and single decision makers (11,615 observations). The loglikelihood amounts to –86,152.60 for joint decision makers and –25,297.27 for single ones.

4.1. Productivity and market wage rate

The wage rate is determined by the productivity (as valued by the firm), the labor market situation and a normally distributed error component; see Table 4.1 for the estimation of the log hourly wage rate. The table shows that productivity increases by level of education. Maximum productivity is reached at the age of 51 years for men with a partner. Thereafter productivity decreases very slowly. Productivity at the age of 60 is only one percent below maximum productivity. For the other persons the maximum productivity has been reached at the age of 40 years. The productivity of these groups declines a bit faster. At the age of 60 it is 5% below the maximum for married women and 9% for singles.

Table 4.1: The estimates for the wage equation (ln)

	Men joint		Women joint		Men single		Women single	
	est.	t-val	est.	t-val	est.	t-val	est.	t-val
Constant	-8.317	-21.58	-7.035	-17.15	-20.469	-40.27	-20.112	-38.79
Ln (age)	5.890	28.18	5.399	23.00	12.742	43.41	12.477	42.12
Ln (age) **2	-0.750	-26.14	-0.734	-22.20	-1.724	-40.66	-1.697	-40.24
D edl 2	0.043	6.09	0.032	3.74	0.078	4.33	0.092	4.85
D edl 3	0.185	31.96	0.264	31.75	0.212	11.60	0.312	17.08
D edl 4	0.402	51.80	0.491	48.09	0.367	17.43	0.518	23.76
D edl 5	0.528	53.93	0.634	38.42	0.366	15.77	0.657	23.08
D edl 6	0.228	17.03	0.269	13.57	0.257	7.091	0.314	7.35
Dummy 90	0.107	---	0.161	---	0.181	---	0.090	---
Dummy 91	0.110	---	0.165	---	0.070	---	0.115	---
Dummy 92	0.102	---	0.156	---	0.228	---	0.181	---

Dummy 93	0.077	---	0.133	---	0.389	---	0.428	---
Dummy 94	0.030	---	0.033	---	0.173	---	0.126	---
Dummy 95	0.025	2.53	0.007	0.60	0.056	---	-0.006	---
Dummy 96	-0.013	---	0.001	---	0.032	1.81	0.014	0.88
Dummy 97	-0.021	-2.75	0.008	0.81	0.039	2.05	0.014	0.76
Dummy 98	-0.035	-3.68	-0.022	-1.65	0.077	3.07	0.028	1.23
Dummy 99	-0.001	-0.04	-0.023	-1.13	0.150	4.29	0.082	2.35
Dummy 00	0.099	6.03	0.043	2.00	0.093	2.48	0.145	3.92
Unempl rate	-1.220	-2.24	-1.047	-1.55	0.161	0.15	3.153	3.08
Business cycle	-0.326	-0.98	0.957	2.23	11.295	16.09	13.54	18.71
s_F	0.250	---	0.250	---	0.250	---	0.250	---
s_{me}	0.285	400.65	0.388	331.87	0.338	157.10	0.361	180.70

D edl x = dummy for level of education x (1=lowest, 5=highest, 6=unknown)

When the economic climate deteriorates, it is straightforward that productivity is underestimated by the firm: the firm will be careful and will try to prevent from overestimating productivity. Therefore, we expect a negative impact of the unemployment rate and a positive effect of the business cycle.[5] This has been found for female joint decision makers. For male joint decision makers the sign for the business cycle indicator is negative, but insignificant, whereas single decision makers have the wrong sign for the unemployment rate. However, both economic indicators have to be taken into account simultaneously. For realistic combinations of the two indicators (e.g. the realizations) this results in decreasing employer's reservation wages when the economic climate deteriorates. The variance of the error component has been set in such a way that the model reproduces the observed wage distribution as good as possible. The estimated values for s_{me}, the standard errors of the measurement error in the observed wage rates are rather large.

4.2. Utility function

Table 4.2 gives the parameter estimates for the utility function. The coefficients on the squared hours terms and the interaction terms of hours and income cannot be interpreted separately. The combination of both determines the elasticities of hours worked; see below. A negative coefficient on an interaction of an exogenous variable with hours implies a positive effect on the marginal utility of leisure and, as a consequence, a negative effect on labor supply. This, for example, holds for the number of children up to and including 3 years of age for joint decision makers. The marginal utility of leisure is larger, the larger the number of children in this age bracket. So, young children negatively affect the labor supply of both men and women with a partner. For older children this only holds for the female partner. The presence of children – and in particular young children – also negatively influences the labor supply of single mothers. High-educated men with a partner have a somewhat lower labor supply as compared to married or cohabiting men with low or middle education. For women with a partner the reverse holds.

The unemployment rate and the economic climate indicator also affect utility. Both have of course to be looked at simultaneously. But, the picture is different for men and women. These economic indicators imply a positive impact on working hours for men and a negative impact for women. Discouragement effects might play a role for women, whereas men are apparently inclined to work extra hours during economic bad times.

[5] We use the *Conjunctuurindicator* of the CPB Netherlands Bureau for Economic Policy Analysis.