Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Income Tax Records

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March 1998

We are grateful for many discussions with Rene Morissette and for comments from Robert Barsky, John Bound, Julie Berry Cullen, Steven Haider, Aloysius Siow, and seminar participants at the University of Toronto, the University of Michigan, CIRANO, NBER, and the University of Western Ontario. The research support of Statistics Canada and SSHRC (Baker, grant no. 410-96-0187) is gratefully acknowledged. All views expressed in this paper are the authors' and do not necessarily reflect the views of Statistics Canada. Correspondence to: baker@chass.utoronto.ca or gsolon@umich.edu.

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Abstract

Several recent studies have found that earnings inequality in Canada has grown considerably since the late 1970's. Using an extraordinary data base drawn from longitudinal income tax records, we decompose this growth in earnings inequality into its persistent and transitory components. We find that the growth in earnings inequality reflects both an increase in long-run inequality and an increase in earnings instability. Our large sample size enables us to estimate and test richer models than could be supported by the relatively small panel surveys used in most previous research on earnings dynamics. For example, we are able to incorporate both heterogeneous earnings growth and a random-walk process in the same model, and we find that both are empirically significant.

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I. Introduction

Scores of studies have documented the growth of earnings inequality in developed Western economies since the late 1970's. Although a large proportion of this literature has focused on the United States,[1] numerous studies have examined changes in Canada's earnings distribution.[2] The Canadian studies do not agree in every detail, but by and large they indicate that earnings inequality has increased substantially, though perhaps not quite as dramatically as in the United States. They also find that the return to education in Canada, unlike the return in the United States, has increased little if at all. That is, the increase in Canadian earnings inequality has occurred mainly within education groups, rather than between them. Another contrast with the United States is that a larger share of Canada's growth in annual earnings inequality has arisen from increased dispersion in annual work hours rather than in hourly wage rates.

A few recent U.S. studies (Gottschalk and Moffitt, 1994; Moffitt and Gottschalk, 1995; Buchinsky and Hunt, 1996; Gittleman and Joyce, 1996; Haider, 1997) have stressed the importance of decomposing the growth in earnings inequality into persistent and transitory components. On one hand, if the increase in earnings inequality has been driven mainly by a rise in returns to education and other persistent worker attributes, then the observed increase in cross-sectional inequality signifies increased inequality in long-run earnings. In this scenario, the

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[1] See, for example, Bound and Johnson (1992), Katz and Murphy (1992), and the recent survey articles by Gottschalk (1997) and Johnson (1997).

[2] See, for example, Bar-Or, Burbridge, Magee, and Robb (1995), Beach, Slotsve, and Vaillancourt (1996), Beaudry and Green (1997), Blackburn and Bloom (1993), Davis (1992), DiNardo and Lemieux (1997), Freeman and Needels (1993), Gottschalk (1993), Morissette and Berube (1996), Picot (1996), and Richardson (1997).

chronically rich have gotten richer and the chronically poor poorer. On the other hand, if the increase in cross-sectional inequality has been driven mainly by a rise in the transitory component of earnings variation, then long-run inequality may have increased very little. In this scenario, the chronically rich have not gotten richer in the long run, and the chronically poor have not gotten poorer, but there has been an increase in year-to-year "churning" through the ranks of the annual earnings distribution.[3] As it turns out, the message of the U.S. studies is that *both* components of earnings inequality have increased. In Haider's words, "annual inequality increased because of fairly equal increases of a persistent component and an instability component."

In this paper, we decompose Canada's growth in earnings inequality into persistent and transitory components. To what extent does Canada's increasing inequality reflect greater year-to-year earnings fluctuation, and to what extent does it arise from an increased dispersion in permanent earnings? Given the integration of the U.S. and Canadian economies, one might expect to find the same answer as in the U.S. literature. The rise in long-run inequality in the United States, however, has been tied to a large increase in the return to education, which has not taken place in Canada.

To perform the decomposition for Canada, we use an extraordinary data base, developed by Statistics Canada, containing almost two decades of longitudinal earnings information drawn from income tax records. The large sample size and the accuracy of the employer-reported earnings enable a detailed accounting of the sources of growing earnings inequality in Canada. Furthermore, they make possible the estimation of richer models than can be identified with the relatively small-scale panel surveys available for U.S. research, and they provide unprecedented

[3] As noted by Haider, however, even purely transitory increases in earnings dispersion can have welfare costs. For example, transitory earnings declines can force consumption reductions for liquidity-constrained individuals even if their permanent earnings are unaffected.

leverage for testing competing models of earnings dynamics. For example, we incorporate both heterogeneous earnings growth and a random-walk process in the same model, and we find that both are empirically significant.

In the next section, we provide a detailed description of the data base. In Section III, we develop econometric models of earnings dynamics and discuss our estimation methods. Section IV contains our empirical results, and Section V summarizes and discusses the main findings.

II .Data

A. Data Base

The data base we use was developed by Statistics Canada from the T-4 Supplementary Tax File maintained by Revenue Canada.[4] This file is a one-percent random sample of all individuals who received a T-4 supplementary tax form, and filed a tax return (a T-1 form), in at least one year between 1975 and 1993. T-4's are issued by employers for any earnings that (1) exceed a certain annual threshold and/or (2) trigger income tax, contributions to Canada's public pension plans, or unemployment insurance premiums.[5] The annual threshold (condition 1) was equal to $250 for the years 1975-1988 and $500 for 1989-1993. This provision likely superseded the requirements of condition 2 in the vast majority of cases in which T-4's were issued over the sample period.[6] To obtain a sample which is consistent over time, we exclude all forms with

[4] The construction of the data base is described in Morissette and Berube (1996). Our description draws heavily on this source.

[5] The data include incorporated self-employed individuals who pay themselves a salary, but not other self-employed workers. The self-employed presumably have more volatile earnings than most workers, and their share of the Canadian work force has trended slightly upwards over our sample period. Our finding below that earnings instability has increased in Canada is all the more striking in light of our failure to encompass all of the self-employed.

[6] Income tax is deducted whenever an employee's annual income (earnings plus interest income, dividends, etc.) exceeds his or her personal exemption. In most cases, the underlying annual earnings should be higher than the

annual earnings less than $250 in 1975 dollars. The resulting threshold equals, for example, $645 in 1989 and $738 in 1993. Therefore, annual earnings is the sum of earnings from all jobs held by an individual in a given year that paid at least $250 in 1975 constant dollars.

This measure of earnings has several advantages over its counterparts in survey data and other administrative files. Most importantly, it is based on employers' reports under the provisions of the income tax laws. Therefore, the earnings variable should be free of the measurement error often observed in survey data due to, for example, recall error, rounding error, and top-coding. Also, missing values should be of limited concern to the extent that tax compliance is widespread, or that evasion is more typically an individual (rather than employer) infraction and/or involves other types of income. Note that, unlike other tax-file-based data, the earnings measure is not obtained from tax returns (the T-1 form). This is important as the decision to file a return is not exogenous, and the incentives for doing so may change over time, which could introduce selection effects to the data.[7] In the T-4 file, the only information taken from T-1 forms is the birth date and sex of the individual. To obtain this information, it is necessary that he or she filed a tax return at least once in the sample period. While it would be preferable to have data that are completely independent of an individual's decision to file a return, this is a much weaker requirement than consecutive filing over the sample period.

current year's threshold. Public pension plan contributions are owed on earnings which exceed the year's basic exemption, which ranged from $700 in 1975 up to $3500 in 1993. Finally, unemployment insurance contributions are made whenever employment exceeds certain time (15 hours per week in 1993) or earnings ($149 per week in 1993) thresholds. It is possible that an individual could be issued a T-4 form for weekly work that triggered unemployment insurance contributions even though annual earnings do not exceed the annual threshold ($250 or $500). We expect that these cases are of limited importance.

[7] Of particular concern in the present context is the introduction during the late 1980's of the Goods and Services Tax, which included a new refundable tax credit for low-income Canadians. In a study based on tax returns, such as Beach and Finnie (1997), the resulting change in the population of return-filers could be confounded with changes in the earnings distribution.

The target group in our sample selection is males between the ages of 25 and 58. These individuals will likely have already completed most of their schooling, and are too young to be strongly affected by the trend to earlier retirement.[8] In constructing our analysis sample, we refine Haider's (1997) revolving balanced panel design to take advantage of the very large size of the T-4 file. We begin by identifying the nineteen two-year birth cohorts who are between the ages 24 and 59 for at least nine years in the period 1975 through 1993, and select all males who had positive earnings in each year that the age requirement is met.[9] We then discard the first and last years of earnings for each individual. This is done to ensure that a consistent selection criterion is applied to each year of positive earnings; that is, we only include years of positive earnings which are bordered by years of positive earnings. The concern is that, without this requirement, the earnings variances in the first and last years will be inflated by labour market entry, retirement, or migration in or out of Canada. The end result is a balanced earnings panel for each cohort, with the panel length varying across cohorts. Our overall analysis sample contains 32,105 individuals, and the sample size *for each cohort* rivals the pooled sample sizes available in common longitudinal data sets. Table 1 contains a summary of the cohorts/panels which are included through this process.

A fully balanced panel design is not appropriate for the current purpose because average age and time will be perfectly collinear, and it will be difficult to separate the effects of age and time on earnings inequality. Our inference is based on an aggregate panel in which the (balanced)

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[8] There has been a strong increase in school enrolment among individuals 17-24 over this period (Morissette, 1997), which might affect our inference if we included younger males. Application for a public pension in Canada can be made as early as age 60.

[9] Individuals are identified in the T-4 file by their Social Insurance Number (SIN). We will lose track of a person if he changes his SIN in the sample period. This might lead us to mistakenly infer that an individual leaves when this change takes place.

cohort panels are stacked. As is evident in the second column of Table 2, the age range in this larger sample remains approximately constant over much of the sample period, thus breaking the direct link between time and age, though the sample does age somewhat between 1976 and 1981 and again between 1987 and 1992.

An alternative approach would be to use an unbalanced sample design in which any years of positive earnings for individuals satisfying the age requirements in the sample period would be included. The obvious advantage here is that the resulting panel is more representative of individuals with positive earnings at a point in time. In practice, however, unbalanced panels can pose difficult estimation problems for the types of models used here.[10] In addition, the various sample moments for a given cohort are based on somewhat different samples, so that measured changes over time may confound sample composition effects with true time and life-cycle effects.[11] Our approach avoids those problems and still allows the separation of time and age effects. Its most obvious shortcomings are the possible selection effects of focusing on individuals with at least nine consecutive years of positive earnings, and that earnings covariances of different orders are observable for different numbers of cohorts who, in turn, face different selection criteria. For example, sixteenth-order covariances are observed only for the nine cohorts born in 1934/35 through 1950/51. The individuals in these cohorts have nineteen consecutive years of positive earnings. In contrast, first-order covariances are observed for all cohorts, which include individuals who have as few as nine consecutive years of positive earnings. We can check

[10] Moffitt and Gottschalk (1995) provide evidence of the sorts of problems encountered with unbalanced panels in this context.

[11] An obvious example is that the variances for years t and s would be based on different samples. A more subtle example is that the variance in year t would be estimated on the basis of all individuals with positive earnings in that year, but the estimated autocovariance between years t and s would be based on only those positive earners in year t who also had positive earnings in year s.

the sensitivity of our results to some of these selection effects by changing the weights assigned to different cohorts included in the aggregate panel. Some direct evidence of how the aggregate balanced panel represents the target population of males aged 25 to 58 is provided in the next subsection.

B. Overview of Trends in Inequality

In the third and fourth columns of Table 2, we present the sample size and variance of log earnings for all the individuals in our pooled analysis sample. For example, in 1976 this includes the selected individuals in cohorts born in 1924/25 through 1950/51. The variance shows a clear upward trend over our sample period, and it displays substantial cyclical movements as well. To recognize the latter, it helps to know that the Canadian labor market was fairly stable from 1976 through 1981, with annual unemployment rates ranging between 7.2 percent and 8.4 percent. Unlike the United States, Canada did not experience a recession in 1980. It was hard hit by the 1982 recession, however, with unemployment rising to 11.0 percent in 1982 and 11.9 percent in 1983. Unemployment gradually receded afterwards, but leaped again to 10.4 percent in 1991 and 11.3 percent in 1992.

The variance series in the fourth column is plotted as the solid line in Figure 1. The variance rises by more than a third in the 1982 recession and then falls gradually in the expansion of the late 1980's, although it never reaches its pre-recession levels. In the recession of the early 1990's, the variance rises again, this time to a new high. This time-series behavior of earnings dispersion in our data set is altogether consistent with the patterns reported by the Canadian studies cited in footnote 2. Most of those studies are based on Canada's Survey of Consumer Finances (SCF), and it is reassuring that the SCF data and our data based on tax reports tell the same story. The advantage of our data set is that, because of its longitudinal aspect, we will be able to sort the trend toward greater earnings inequality into its persistent and transitory components.

In the remaining columns of Table 2, we provide some evidence of how the trends in our revolving balanced panel represent the experience of our target population. In the fifth and sixth columns, we present the sample sizes and variances of log earnings when we maintain the same age ranges as in our analysis sample but include all individuals with positive earnings in a given year. In many years, the sample size almost doubles, as do the variances. Next, in the seventh and eighth columns, we examine the sample of individuals aged 25 to 58 who had positive earnings in a given year. In this step we focus on a constant age interval, so the sample does not age over time. While there are some minor discrepancies from the previous two columns, it is clear that the requirement of positive earnings in consecutive years, rather than marginal aging over time, accounts for the differences in the variances between our analysis sample and the sample of all males aged 25 to 58.

Our revolving balanced sample approach leads to smaller estimates of the variance of log earnings, but they appear to be smaller than the variances in the other samples by a roughly fixed factor of one-half. This suggests that the variances in the alternative samples may follow similar patterns over time. This is important since our primary focus is on changes in earnings inequality over time, rather than its absolute level. In Figure 1, we also graph the time pattern of variances in our two comparison samples. As expected, they appear to shadow the variances in our analysis sample. In fact, the correlation coefficient between the variances in our analysis sample and the sample with the same age restrictions but all individuals with positive earnings is 0.957. Likewise, the correlation coefficient between the variances in the analysis sample and the sample of individuals 25-58 with positive earnings is 0.943.[12] The primary discrepancy appears on a cyclical basis, with the variance in the analysis sample growing relative to the variance in the larger samples during recessions. This pattern is unsurprising because lower earners presumably are especially prone to drop out of the unbalanced larger samples during recessions.[13] This sample composition effect dampens the countercyclicality of earnings dispersion in the unbalanced samples. In the analysis sample, which reduces the sample composition effect by following the same workers over time, the true countercyclicality of earnings dispersion is more apparent.[14]

Overall, although the level of earnings dispersion is much lower in the analysis sample, all three samples show similar behavior over time. Where they differ the most, in their cyclical amplitudes, the analysis sample probably provides a more accurate picture. At the least, it should provide a useful depiction of earnings inequality among those men with relatively stable employment careers.

In Figures 2 and 3, we present some detail on how different age groups within our analysis sample fared over the period. In Figure 2, we plot mean log earnings for five-year age categories, normalizing each series to equal 1 in 1979 to provide a common basis of comparison across the series of different lengths. For example, as documented in the second column of Table 2, the complete age group 26-30 is visible in the analysis sample only between 1976 and 1987, while the age group 51-55 is visible only from 1979 to 1992. Mean log earnings for the different groups moves in tandem up until 1982, but then we observe divergence. For example, by 1987 (the last

[12] Furthermore, there is similar coherence in other moments. The correlation coefficients between mean log earnings in the analysis sample and the other two samples are 0.999 and 0.997 respectively.

[13] For a discussion of U.S. evidence on the greater employment cyclicality of low earners, see Solon, Barsky, and Parker (1994).

[14] The U.S. evidence discussed in Solon, Barsky, and Parker (1994) suggests that the countercyclicality of dispersion in annual earnings arises mainly from countercyclicality in the dispersion of annual hours, rather than in the dispersion of hourly wage rates. We are not aware of Canadian evidence on this point.

year for the 26-to-30-year-olds) the difference in average log earnings between 46-to-50-year-olds and 26-to-30-year-olds has increased roughly 2.1 percent over its level in 1979. Further changes are observed in the late 1980's and early 1990's. The difference in log earnings between 31-to-35-year- olds and 46-to-50-year-olds is up 1.2 percent in 1987 and 2.6 percent by 1992.

In Figure 3, we provide complementary information about the variance of log earnings. Again we normalize each series to equal 1 in 1979. Corresponding to the effects of the recession on the means, there is a sharp increase in the variances in 1982 which is particularly severe for younger workers. In 1983, the variance for 26-to-30-year- olds is up 80 percent over its level in 1979, while the increase for older workers is on the order of 25 to 30 percent. The recession of the early 1990's also has the greatest effect on the young. Between 1989 and 1992, the increases in the variances for 31-to-35-year-olds and 36-to-40-year-olds are 68 percent and 42 percent respectively. In contrast, the increase over the same period is 29 percent for 41-to-45-year-olds, 37 percent for 46-to-50-year-olds, and 4 percent for 50-to-55-year-olds.

One previous study, by Morissette and Berube (1996), has used the same tax data we use to generate preliminary evidence on the extent to which the growth in annual earnings inequality reflects an increase in persistent inequality. To get a measure of persistent inequality, Morissette and Berube take a sample of workers within each of a variety of age ranges as of 1975, they sum the workers' earnings over the 1975-1984 period, and then they calculate several dispersion measures for the ten-year earnings total.[15] Then they perform the same exercise for the 1984-1993 earnings total and compare the dispersion measures between the two ten-year periods. For example, for men ages 35-44 as of 1975, the coefficient of variation in the 1975-1984 total of

[15] Surprisingly, Morissette and Berube base their tabulated results on total *nominal* earnings with no discounting. They report in a footnote, however, that they obtain qualitatively similar results for real earnings discounted annually by 3 or 7 percent.

earnings is 0.512. For men 35-44 as of 1984, the coefficient of variation in the 1984-1993 earnings total is 12 percent higher at 0.573. Regardless of age range or dispersion measure, Morissette and Berube find greater dispersion in the later period.

Morissette and Berube's evidence strongly suggests that the persistent component of earnings variation did increase between 1975-1984 and 1984-1993, but this finding leaves some important questions unanswered. First, a comparison of two ten-year periods does not pinpoint the timing of the increase in persistent earnings inequality, and this creates some ambiguity in how to interpret the comparison. For example, to what extent does the difference between periods reflect a secular trend or a difference in business cycle conditions? As Morissette and Berube acknowledge, "Since the unemployment rates observed since the mid-eighties were higher than those of the mid-seventies, one possibility is that the increase in long-term inequality that we found simply reflects a cyclical effect. Because we have been comparing two periods and thus have been using only two observations, we have been unable to control for such an effect." Second, their evidence does not provide a direct indication of whether (or when) the transitory component of earnings variation also increased. The remainder of our paper develops and estimates models designed to answer these questions.

III. Econometric Models and Estimation Methods

A. Models

Earnings dynamics and their implications for the connection between current and lifetime income have long been of central concern in numerous areas of economic research. Research on the distinction between the inequality observed in annual cross-sections of earnings and inequality in long-run earnings is just one such area. Another classic example is the research, going back at least to Friedman (1957), on the difference in the response of consumption to changes in transitory versus permanent income. Still another example is the recent research showing that the intergenerational correlation in earnings appears far greater for long-run measures of earnings than it does for single-year measures (Altonji and Dunn, 1991; Solon, 1992; Zimmerman, 1992).

Because of its recurring importance in many research areas, earnings mobility has been the subject of a voluminous empirical literature.[16] To explain the connection between the models in the literature and the models estimated in this paper, we will begin with a rudimentary version of the canonical variance-components models of earnings dynamics and then embellish it in order to allow for changes over time in both the persistent and transitory components of earnings variation.

Let Y_{ibt} denote the log earnings in year t of the i^{th} sample member born in year b. Then

(1) $$Y_{ibt} = \mu_{bt} + y_{ibt}$$

expresses Y_{ibt} as the cohort-specific mean μ_{bt} in year t plus an individual-specific deviation y_{ibt} from that mean. Most previous studies of earnings dynamics have attempted to partial out μ_{bt} with preliminary regression adjustments for year and age (or experience) effects and then have estimated models for the dynamics of y_{ibt}. By doing so, they have characterized both the cross-sectional variance and the year-to-year mobility in relative earnings within a cohort.

A stripped-down version of the commonly used models for y_{ibt} is

(2) $$y_{ibt} = \alpha_{ib} + v_{ibt}$$

[16] See Atkinson, Bourguignon, and Morrisson (1992) for an elegant survey of the literature up through most of the 1980's. See Baker (1997) and Haider (1997) for more recent analyses and for references to other studies since the late 1980's. Aside from the study by Beach and Finnie (1997) cited in footnote 7, the only other study of Canadian earnings dynamics of which we are aware is Kennedy (1989), which uses a small sample of earnings histories drawn from a Canada Pension Plan administrative file. Kennedy does not explore how the transitory and persistent components of earnings variation have changed over time.

where the permanent earnings component α_{ib} has population variance σ_{α}^{2}, the transitory component v_{ibt} has variance σ_{v}^{2} and is serially uncorrelated, and α_{ib} and v_{ibt} are orthogonal to each other. A nice feature of this exceedingly simple model is that it provides a clear representation of the distinction between inequality in current and permanent earnings. The variance in current relative earnings y_{ibt} is

(3) $$Var(y_{ibt}) = \sigma_{\alpha}^{2} + \sigma_{v}^{2},$$

which exceeds σ_{α}^{2}, the variance in the permanent component of earnings, by σ_{v}^{2}, the variance of transitory earnings.

This rudimentary model, however, possesses several weaknesses that render it inappropriate for our purposes. To begin with, it does not allow for changes in earnings inequality over time. Following Moffitt and Gottschalk (1995) and Haider (1997), a simple way to incorporate such changes is with the enhanced model

(4) $$y_{ibt} = p_t \alpha_{ib} + \lambda_t v_{ibt}$$

where p_t and λ_t are the respective year-specific factor loadings on the permanent and transitory components of relative earnings. Then the variance of y_{ibt} becomes

(5) $$Var(y_{ibt}) = p_t^2 \sigma_{\alpha}^{2} + \lambda_t^2 \sigma_{v}^{2}.$$

As this expression shows, an increase in either factor loading generates increased dispersion in current earnings. The character of the change in inequality, however, depends critically on which factor changes. A rise in p_t increases inequality in long-run earnings as well as in current earnings. The relative advantage of workers with chronically high earnings increases, as does the relative disadvantage of those with chronically low earnings. On the other hand, if λ_t increases without any change in p_t, inequality in current earnings rises because of an increase in year-to-year volatility, but there is no increase in the variance of the permanent component of earnings.

Since an increase in either factor loading increases the variance of y_{ibt}, variances by themselves cannot identify which component of inequality has changed. What does identify the source of the increased cross-sectional inequality is changes in observed autocovariances. In an era when p_t rises to a higher level, the autocovariances grow along with the variances. Indeed, if p_t increases without a change in l_t, the autocovariances grow in greater proportion than the variances, so the autocorrelations increase. In other words, the increase in cross-sectional inequality is accompanied by a decrease in mobility. In contrast, if l_t increases without a change in p_t, the rise is variances is *not* accompanied by a rise in autocovariances, and the autocorrelations decline. Although this point is particularly clear in the context of the model in equation (4), it does extend to more complex models. Heuristically, an increase in p_t preserves the order of individuals in the earnings distribution, but spreads them out further, and this greater spread persists from year to year. An increase in l_t leads to more scrambling of individuals' order in the annual earnings distribution, and the scrambling gets redone every year.

Although the model in equation (4) does incorporate changes in both the persistent and transitory components of earnings inequality, it still overlooks several important features of earnings dynamics that have been documented in the previous literature. First, several studies have found evidence of persistent heterogeneity across individuals not only in their levels of earnings, but in their growth rates.[17] Second, some earnings shocks have permanent effects,[18] and

[17] See Baker (1997) and the references therein. This finding of growth heterogeneity is to be expected, since the sources of life-cycle earnings growth -- such as human capital investment and schemes to elicit work effort -- presumably do vary across individuals.

some of the more recent literature on earnings dynamics has modeled such earnings variation with a random-walk component (MaCurdy, 1982; Abowd and Card, 1989; Moffitt and Gottschalk, 1995). Third, most studies have found that the transitory component is serially correlated. Fourth, several studies have found that the variance of the transitory component is a U-shaped function of age or experience.[19]

To encompass these aspects of earnings dynamics, we generalize the model in equation (4) to

(6) $$y_{ibt} = p_t[\alpha_{ib} + \beta_{ib}(t-b-26) + u_{ibt}] + \varepsilon_{ibt}$$

where

(7) $$u_{ibt} = u_{ib,t-1} + r_{ibt},$$

(8) $$\varepsilon_{ibt} = \rho\varepsilon_{ib,t-1} + \lambda_t v_{ibt},$$

and

(9) $$Var(v_{ibt}) = \gamma_0 + \gamma_1(t-b-26) + \gamma_2(t-b-26)^2.$$

In equation (6), β_{ib} is the deviation of the individual's idiosyncratic earnings growth rate from the average growth rate of his cohort (which already was subsumed in the μ_{bt} term in equation (1)). This individual-specific growth rate β_{ib} is expressed as a coefficient of years since age 26, so the variance in the individual-specific intercept α_{ib} reflects variance across individuals' earnings profiles as of age 26, and the variance in β_{ib} influences how the variance across earnings profiles evolves after age 26. We will denote the variance of β_{ib} as σ^2_β and the covariance between α_{ib}

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[18] One good example is the earnings losses suffered by displaced workers. See Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997). Another example, stressed by Farber and Gibbons (1996), is the wage impact of the arrival of new information about workers' productivities.

[19] See Gordon (1984), for example.

and β_{ib} as $\sigma_{\alpha\beta}$. If workers' choices about human capital investment involve trade-offs between early earnings levels and opportunities for subsequent earnings growth, $\sigma_{\alpha\beta}$ may be negative (Mincer, 1974; Lillard and Weiss, 1979; Hause, 1980).

In equation (7), which specifies a random-walk component in earnings growth after age 26,[20] r_{ibt} is a "white noise" innovation with variance σ_r^2. The random-walk innovation r_{ibt}, unlike the transitory innovation v_{ibt} in equation (8), accommodates any permanent re-ordering of workers in the earnings distribution. One way to distinguish the random-walk component from the heterogeneous-growth component is that the former implies that the cross-sectional log earnings variances should rise linearly over the life cycle, while the latter implies a quadratic pattern. Equation (8) incorporates serial correlation of the transitory component via a first-order autoregressive process generalized to include year-specific factor loadings on the innovation v_{ibt}. This specification assumes that, if year t is a year with unusually large innovations in the transitory earnings component (e.g., a recession year), the impact on the transitory variance in subsequent years dies out gradually. In addition, equation (9) allows the variance of v_{ibt} to be a quadratic function of age.[21]

While this model imposes a great deal of structure on earnings dynamics, it significantly generalizes previous models by allowing for multiple sources of nonstationarity (with respect to both calendar time and stage of life cycle). Like the models of Moffitt and Gottschalk (1995) and

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[20] Any such growth up through age 26 is subsumed in the α_{ib} term.

[21] We have experimented with a cubic specification, but the estimated coefficient of the cubed term was tiny and statistically insignificant. We also have tried extending our AR(1) specification in equation (8) to an ARMA(1,1) specification, but, given the complexity of the rest of our model, this appears to ask too much even of our rich data set. Unless we restrict other parts of our model, the estimation of the model with the ARMA(1,1) specification does not converge. The restrictions required to obtain convergence (e.g., restricting the initial transitory variances to be the same for different cohorts) are not economically appealing, and the results make very little sense.

Haider (1997), ours goes beyond earlier models by allowing for changes over calendar time in both the persistent and transitory components of earnings inequality. Our model extends Haider's by incorporating age-related heteroskedasticity of the transitory variance and a random-walk component. Relative to Moffitt and Gottschalk's preferred model, ours adds both age variation in the transitory variance and heterogeneity in growth rates. Because previous researchers have had to rely on U.S. panel surveys with relatively small sample sizes, they have been unable to identify models with many sources of nonstationarity, and they therefore have had to make arbitrary choices about which varieties to include. For example, they have included either a random walk or heterogeneous growth, but not both. Our access to a large sample observed over many years enables us to identify richer models and to examine empirically which sources of nonstationarity play important roles in the earnings process. Consequently, in addition to generating evidence about the nature of growing earnings inequality in Canada, our study also responds to Atkinson, Bourguignon, and Morrisson's (1992) comment that distinguishing among competing models of earnings mobility "is important and tests of alternative specifications should be conducted. However, we have found few tests of that type in the literature we have reviewed."

B. Estimation Methods

We begin by estimating μ_{bt} in equation (1) with the sample mean log earnings for cohort b in year t. We then treat the deviation of observed log earnings Y_{ibt} from that mean as our measure of y_{ibt}. This simple "de-meaning" procedure adjusts for year, age, and cohort effects on average earnings in a less restrictive way than the preliminary regressions typically used, which assume that the age and cohort patterns within any year can be well approximated by a low-order polynomial in age or experience.

Next, for each of our nineteen sample cohorts (born 1924/25 through 1960/61), we construct the sample autocovariance matrix of y_{ibt}. For the nine cohorts observed for the entire 1976-1992 sample period, these are 17×17 matrices; the matrices for the other cohorts have smaller dimensions. (At the beginning of Section IV, we will display and discuss these matrices for a few selected cohorts.) Then we list the distinct elements of the sample autocovariance matrix for cohort b in a vector C_b, which contains 153=$(17 \times 18)/2$ elements for each of the nine cohorts observed for the full sample period and fewer elements for the others. For purposes of standard error estimation, we also construct the matrix of fourth sample moments for each cohort.

We stack the nineteen C_b vectors into an aggregate vector C, which contains a total of 2077 sample moments. These are the data to which we fit the model of earnings dynamics described above. We estimate the model's parameters by generalized method-of-moments (GMM), i.e., by minimizing the distance between the observed sample moments in C and the corresponding population moments implied by our model.

In particular, write the population analog to C as C^* and express our model's moment restrictions as $C^* = f(\theta)$ where θ is the vector containing all the parameters in our model. For example, our model in equations (6)-(9) implies that one element in C^*, the variance of y_{ibt} in 1986 for the cohort born in 1950/1951, is

$$(10) \qquad Var(y_{i,1950/51,1986}) = p^2_{1986}(\sigma^2_\alpha + 100\sigma^2_\beta + 20\sigma_{\alpha\beta} + 10\sigma^2_r) + \rho^2 Var(\varepsilon_{i,1950/51,1985})$$
$$+ \lambda^2_{1986}(\gamma_0 + 10\gamma_1 + 100\gamma_2)$$

where 10 and its multiples appear because we count this cohort as 10 years past age 26 in 1986.

As ugly as this expression is, writing it out here serves at least two purposes. First, its complexity makes clear why we are not writing out the rest of the moments! Second, the dependence of the cohort’s overall 1986 variance on its transitory variance in 1985 illustrates that the autoregressive process in equation (8) induces a recursive structure in the moments. If one traces the recursion back to the first year of the cohort’s sample period (in this instance 1976), this raises the question of what the cohort’s transitory variance is in that year. In the previous literature on earnings dynamics, it has been common to restrict the initial transitory variance to be the same for individuals of different ages. In our richer model, which recognizes that earnings volatility varies across cohorts because they are at different stages of the life cycle and have lived through different times, this restriction becomes untenable. We therefore treat the initial transitory variances of the nineteen cohorts as nineteen additional parameters to be estimated.

Once $C^* = f(q)$ is specified, then GMM chooses $\hat{q}$ to minimize a distance function

$$(11) \qquad D = [C - f(\hat{q})]' W [C - f(\hat{q})]$$

where W is a positive definite weighting matrix. The asymptotically optimal choice of W is the inverse of a matrix that consistently estimates the covariance matrix of C. As explained by Altonji and Segal (1996) and Clark (1996), however, this approach can produce seriously biased estimates of q in finite samples. We therefore follow the practice of the most recent literature and use the identity matrix as the weighting matrix. This approach, often called “equally weighted minimum distance estimation,” just amounts to using nonlinear least squares to fit $f(\hat{q})$ to C. Finally, we use standard methods for estimating the covariance matrix of $\hat{q}$ on the basis of the fourth moments in the sample.[22]

IV. Results

In lieu of deluging the reader with all 2077 sample moments, in Tables 3 and 4 we display the sample autocovariance matrices for just the cohorts born in 1926/27, 1942/43, and 1958/59. For all three cohorts (as well as the other sixteen not shown), the autocorrelation patterns in the upper right triangles of the matrices are similar to those reported in U.S. studies based on the Panel Study of Income Dynamics. Like Baker (1997) and Haider (1997), we find autocorrelations of around 0.8 at the first order, followed by gradual declines at higher orders.[23]

Because these three cohorts are at different stages of the life cycle during our 1976-1992 sample period, they illustrate important life-cycle patterns in earnings dynamics as well as some salient trends and cyclical patterns. The 1958/59 cohort, which is in its mid twenties in its first years in the sample, initially shows very large variances (on the main diagonal), which subsequently decline as the cohort settles into its mature career path. The lower autocorrelations displayed by this young cohort suggest that its higher variances are driven at least partly by high *transitory* variation. At the other end of the life cycle, the 1926/27 cohort shows rising variances as it approaches retirement age during its last years in the sample. These obvious patterns suggest the importance of including age-varying parameters in econometric models of earnings dynamics.

The year effects apparent in these matrices echo the patterns already discussed in connection with Table 2 and Figures 1 and 3. The sample variances rise dramatically with the 1982 recession and then recede a little in the late 1980's before rising to new heights during the recession of the early 1990's. The upper-right triangles of the matrices display one more pattern not visible in the earlier tables and figures -- there is no striking secular trend in the

[22] See Chamberlain (1984) for a general discussion of GMM estimation and inference, and see the appendix to Abowd and Card (1989) for a detailed application to earnings dynamics models.

[23] We also have calculated sample autocovariance matrices for the first difference of y_{ibt}. These show autocorrelation patterns quite similar to those reported in Abowd and Card (1989) and Baker (1997).

autocorrelations. As explained in Section III, an increase in only the transitory variance component would cause the autocorrelations to decline, and an increase in only the persistent component would make them rise. The absence of any strong trend in the autocorrelations suggests that the upward trend in earnings inequality was generated by increases in *both* components.

To investigate these patterns more formally, we proceed to GMM estimation of the earnings dynamics model laid out in Section III. Table 5 shows the resulting estimates. In the first two columns are the parameter estimates and associated standard error estimates for the model described in equations (6)-(9). Recall that this model incorporates a persistent component, composed of terms capturing individual-specific heterogeneity in the age/earnings profile as well as a random walk, plus a transitory component following an AR(1) process with age-based heteroskedastic innovations. Furthermore, each component's variance is shifted over time by a separate year-specific factor loading.

The estimates of σ_α^2 and σ_β^2 in the first two rows express the heterogeneity in the intercept and slope of the age/earnings profile. They are generally smaller than the estimates found in studies of U.S. men. For example, our estimated standard deviation in earnings growth rates, $\hat{\sigma}_\beta = \sqrt{0.000090} = 0.0095$, is a bit less than half of the most comparable estimates in Baker (1997) and Haider (1997). Baker and Haider, however, do not allow for a random-walk component, age-related heteroskedasticity in the transitory innovations, or differences across cohorts in their initial transitory variances, so all of the age structure in earnings dispersion necessarily gets loaded into the growth heterogeneity part of their models. Our significantly positive estimate of σ_r^2 in the fourth row indicates that the random-walk component also plays a role, and, as will be seen below, our results also point to substantial age-related heteroskedasticity in the transitory component.

Nevertheless, even our smaller estimate of s_b is both statistically and substantively significant. It implies that a worker with a growth rate one standard deviation above the mean would accumulate a 10 percent earnings advantage over the course of a decade. As in several previous studies (Lillard and Weiss, 1979; Hause, 1980; Baker, 1997; Haider, 1997), our estimate of s_{ab} in the third row is significantly negative, corresponding to a trade-off between earnings early in the career and subsequent earnings growth.[24]

In the next seventeen rows, we report the estimates of the year-specific factor loadings on the persistent component. For identification, the parameter for 1976 is normalized to equal 1. The estimated factor loadings are a little above 1 in the years immediately after 1976, and then they increase sharply in the recession of 1982. There is a gradual decay over the expansion of the late 1980's and then another sharp increase in the recession of the early 1990's. The countercyclicality of the estimated factor loadings is consistent with the U.S. evidence that the annual work hours of low-wage workers are especially sensitive to the business cycle (Solon, Barsky, and Parker, 1994). The upward secular trend in the estimated factor loadings, foreshadowed by the patterns in the empirical autocovariance matrices reported in Tables 3 and 4, suggests that the persistent component plays an important role in the increase in earnings inequality over the period. Even though the previous literature reports that the return to education in Canada did not increase appreciably over this period, more generally the return to persistent worker attributes did trend upwards. This finding accords with Morissette and

Berube's (1996) result that the dispersion in earnings summed over ten years increased from 1975-1984 to 1984-1993.

In the next section of the table, we report the estimated parameters for the transitory component. First are the estimates of the "initial variances," which capture the accumulation of the transitory process up to the start of the sample period for each cohort. As was shown in Table 1, age in the initial year (1976) declines monotonically for cohorts 1924/25 through 1950/51. In turn, the estimated initial variances for these cohorts display a vaguely U-shaped pattern, although there are spikes for some of the middle cohorts. The estimated initial variances for cohorts 1950/51 through 1960/61 document how the accumulation of the transitory process changed for 26-year-olds over the period. The clear message here is that dispersion has been increasing, as the variance estimates more than double from 1976 (cohort 1950/51) to 1986 (cohort 1960/61).

In the next block are the estimates of the autoregressive parameter r and the parameters of the quadratic in age for the variance of the innovations to the transitory process. Our $\hat{r} = 0.533$ is quite similar to Baker and Haider's most comparable estimates. The estimated parameters of the age quadratic are highly significant and suggest a U-shaped profile. This can be seen more clearly in Figure 4, where we graph the quadratic over the ages observable in our sample. There is an initial decline in the variance of the innovations as it falls more than 50 percent from the mid twenties to the early forties. As was suggested above, the variance flattens out in mid-age. Finally, it rises in the fifties although not to the levels observed at the beginning of the age profile. This pattern is consistent with other evidence in the literature (Gordon, 1984)

[24] We have experimented with estimating a more complex model with quadratic, instead of just linear, growth heterogeneity. The estimated variance of the coefficient of age squared turns out to be insignificantly *negative*, and the estimates of the other parameters hardly change at all.

and points to the importance of accounting for the systematic influence of age on transitory innovations to earnings.

In the final block of the table, we report the estimated year-specific factor loadings on the transitory innovation. Here we must use the normalization that the parameter for 1977 equals 1, since the variance of this component in 1976 is left unrestricted to identify the initial variances of the cohorts . Not surprisingly, here we see more cyclical variation than was apparent in the factor loadings for the persistent component, with the transitory factor loadings rising more dramatically in the recession of 1982.[25] There is next some recovery from the recession, a fairly flat profile over the expansion of the late 1980's, and finally another sharp increase in the recession of the early 1990's.

Just plotting the time series of p_t and λ_t is not sufficient to give a full characterization of the relative contributions of the persistent and transitory components to increases in earnings inequality. The relative roles of the two components depend not only on these two factor loadings but also on the relative magnitudes of the factors that they load, the initial transitory variances, and the autoregressive parameter. Therefore, in Figure 5 we use our estimates of all these parameters to decompose our estimated model's predicted variance of log earnings into its persistent and transitory components, holding age constant to abstract from any life-cycle considerations. The decomposition is performed for males 40 years old, which is approximately the midpoint of the ages observable in our sample, and it tells the story of individuals who in turn should be in the middle of their working careers.[26] In moving from year to year, the factor

[25] Haider (1997) reports a similar result for the United States.

[26] We also have performed the decomposition for ages 32 and 50. The results for age 50 are qualitatively very similar to those for age 40. The results for age 32 assign a somewhat larger portion of the growth in earnings inequality to the transitory component.

loadings on the two components change, as does the initial variance used in generating the transitory variance up to age 40.[27]

The first thing to note in Figure 5 is the increase in the total variance, primarily in steps corresponding to the recessions over the sample period. This, of course, duplicates the pattern seen earlier in Figure 1 (and in previous Canadian studies based on the Survey of Consumer Finances). The novel feature of Figure 5 is its decomposition of the total variance into persistent and transitory components. In the early years of the sample period, the persistent component accounts for about 70 percent of the inequality in annual earnings. The two components move remarkably similarly over time. Both components rise substantially in the recession starting in 1982, settle down during the recovery at a higher level than before the recession, and then leap to new heights in the recession of the early 1990's. Because the increases in the transitory and persistent components are of similar absolute magnitudes, the proportional share of the persistent component is slightly lower toward the end of the sample period than in the early years.

To check our reading of Figure 5, we apply least squares to estimate time-series regressions of the persistent and transitory components on a linear time trend and the unemployment rate. For the persistent series, the estimated time trend coefficient is 0.0035 (with estimated standard error 0.0004), and the estimated unemployment rate coefficient is 0.0069 (0.0014). The corresponding coefficient estimates for the transitory series are 0.0025 (0.0006) and 0.0078 (0.0019). These results corroborate our impression that the two series show similar cyclical movements and contribute similar amounts to the upward trend in annual earnings inequality.

[27] In fact, the initial variance changes every two years, corresponding to the cohort estimates reported in Table 5. For example, in 1976 we have a direct estimate of the variance of the transitory component for males aged 40 in

The results discussed so far are based on equally weighted minimum distance (EWMD) estimation of the model in equations (6)-(9). The EWMD estimates are consistent (given correct model specification), but they are not asymptotically efficient. The loss of efficiency arises partly because various sample moments are subject to different variances, which occurs partly because sample moments for different cohorts are based on samples of different sizes. The EWMD estimator effectively applies nonlinear least squares (rather than generalized nonlinear least squares) despite this heteroskedasticity across sample moments. As discussed in Section III, however, the asymptotically optimal GMM estimator, which would apply feasible generalized nonlinear least squares, may be subject to a severe finite-sample bias. An intuitively appealing alternative is to replace the identity weighting matrix used by EWMD with a different exogenous weighting matrix that weights the sample moments in proportion to their sample sizes.

The results from this weighted estimation approach are shown in the third and fourth columns of Table 5. A comparison of the estimated standard errors for the weighted estimates to those for the EWMD estimates shows that the weighted estimation does *not* succeed in producing more precise estimates. On further reflection, perhaps this should not be surprising. One of the effects of the weighting is to give greater prominence to the younger and shorter earnings panels of cohorts 1952/53 through 1960/61. This can be seen through a comparison of the cohort sample sizes in Table 1. While the moments in these panels are presumably more precisely estimated, they also convey less information about certain aspects of earnings dynamics. In particular, in the earnings distributions of the younger and shorter panels, it should be harder to distinguish what is permanent from what is transitory but serially correlated. The shorter panels

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the initial variance for cohort 1936/37. In 1978, we use the initial variance for cohort 1938/39, whose members are 40 in this year.

also provide less information on the U-shaped life-cycle profile of the transitory earnings variances.

In any case, although the parameter estimates in column 3 are somewhat different from those in column 1, they are not hugely so. To get a better view of the substantive importance of the differences, in Figure 6 we plot estimates of the persistent and transitory variance components based on the weighted parameter estimates. The persistent and transitory series in Figure 6 seem more volatile than the corresponding series in Figure 5, probably because they are estimated less precisely. Nevertheless, Figure 6 tells much the same story -- the persistent component accounts for about two-thirds of the total variance, the two components increase similarly during recessions, and they contribute in about the same degree to the secular increase in earnings inequality.

The weighting scheme does not change the story much, but another natural question is how sensitive the story about time trends is to the specification of the earnings dynamics model.[28] For example, is it necessary to estimate a model as complex as ours, or would the same story come through with a simpler model? The answer is that model specification can matter somewhat for some results. To illustrate, in the last two columns of Table 5, we report EWMD estimates of a more restrictive model that assumes away both growth heterogeneity and age-related heteroskedasticity in the transitory innovation. This model is statistically indefensible with our data because, as shown in the earlier columns of the table, the estimates of the eliminated parameters are highly significant. The Wald statistic for testing the joint null hypothesis that s_b^2, s_{ab}, g_1, and g_2 are all zero is 243.9, with a p-value that is zero to at least five decimal places.

Nevertheless, the simpler model is worth investigating because its restrictions have been imposed in several previous studies. For example, Moffitt and Gottschalk's (1995) preferred model excludes both growth heterogeneity and age-related heteroskedasticity of the transitory component, and we would like to know whether these restrictions are innocuous for purposes of identifying trends in earnings inequality.

Comparing column 5 to column 1, some parameter estimates change very little, and others change a lot. To explore how much the changes matter, in Figure 7 we plot the decomposition into persistent and transitory components based on the estimates of the restricted model. In the new figure, the persistent component accounts for a little less than two-thirds of the total variance at the beginning of the sample period. Unlike the preceding figures, Figure 7 shows the transitory component increasing by more than the persistent component so that, by the end of the sample period, the transitory component is just as large. Again checking our eyeball interpretation with a regression analysis, when we apply least squares to the regressions of the new persistent and transitory series on time and the unemployment rate, the estimated time trend coefficients are 0.0024 (0.0005) for the persistent component and 0.0051 (0.0004) for the transitory component. Thus, while the estimates from the more general model indicated that increases in the persistent and transitory components contributed about equally to the growth in earnings inequality, the simpler model imposing apparently false restrictions attributes most of the inequality growth to the transitory component.

To summarize, all of the estimates indicate that both the persistent and transitory components of earnings variation contributed to the growth in Canadian earnings inequality over

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[28] As discussed above, the estimation of parameters related to the life-cycle evolution of earnings (such as σ_{α}^{2}, σ_{β}^{2}, and $\sigma_{\alpha\beta}$) *is* affected by what other sources of nonstationarity are included in the model specification.

the 1976-1992 period, and our preferred estimates suggest that the two components' contributions were about equal. How does this finding compare to related evidence for the United States? Comparison across studies is complicated by differences in both data and model specification, but it is interesting that the most comparable U.S. studies -- Moffitt and Gottschalk (1995) and Haider (1997) – also conclude that the increase in earnings inequality has come in roughly equal proportions from increases in the persistent and transitory components of earnings variation. Perhaps the most pronounced difference between the results for the two countries appears in the trends in the mid 1980's. Haider estimates a considerable increase in the persistent component starting in 1984, despite the recovery from the 1982 recession. This is consistent with the large increase in the return to education that many U.S. studies have documented for that period. As noted in our introduction, several studies have suggested that Canada experienced less dramatic increases in the return to education, and accordingly our Figures 5-7 show no rise in the persistent component during the late 1980's. Over our full sample period, however, we do observe increases in the returns to some persistent earnings attribute of individuals. In any case, by the early 1990's, the two countries are found in similar positions, with new heights of annual earnings inequality generated by substantial rises in both persistent earnings dispersion and earnings instability.

V. Conclusions

Using an extraordinary data set drawn from longitudinal income tax records, we have verified that earnings inequality in Canada grew substantially over our sample period of 1976-1992, and we have decomposed this growth in inequality into its persistent and transitory components. Like some of the U.S. studies cited in our introduction, we have found that the two components grew by similar magnitudes. Thus, Canada's growth in annual earnings inequality signifies an increase in long-run inequality, as well as an increase in earnings instability.

What has caused the increases in both long-run inequality and instability is an important subject for continuing research. In the U.S. studies, the finding of increased persistent inequality was expected because the United States has experienced a large increase in the return to schooling. This increase has been thoroughly documented and has been attributed in large part to skill-biased technological change that has increased the relative demand for educated labor.[29] In Canada, however, there has been little increase in the return to education, so it was less clear whether Canada's increase in annual earnings inequality reflects a rise in long-run inequality. Now that we have found that it does, it is natural to ask why long-run inequality has increased in Canada without an increase in the return to schooling. Freeman and Needels (1993) conjecture that the wage impact of increased relative demand for educated labor has been offset in Canada by a dramatic increase in the supply of college-educated labor. If other skill attributes (e.g., intelligence) have not undergone similar increases in supply, though, skill-biased technological change could still increase the returns to those skills. Perhaps this is why the persistent component of earnings inequality has increased in Canada despite little change in the return to schooling.

The increase in earnings instability is even more puzzling, both in the United States and Canada. While the U.S. literature has intensively studied the increased return to schooling, it has just begun to speculate about the sources of rising volatility in earnings. Gottschalk and Moffitt (1994), as well as their discussants, do discuss various possible explanations for the U.S. increase

[29] DiNardo, Fortin, and Lemieux (1996), however, stress that changes in unionization and the relative minimum wage also have contributed to the rise in wage inequality.

in earnings instability, but they conclude, “We have not located any definitive explanation for the increased transitory variance.” For example, they consider whether the large decline in the unionization of the U.S. work force has played an important role, but they find this could be “only a small part of the explanation.” In Canada, de-unionization is even less promising as an explanation because union density has not declined nearly as much there as in the United States (Riddell, 1993).

Another possible source of increased earnings instability is a decline in job stability. The U.S. evidence, however, does not point to a clear-cut trend in that direction.[30] Similarly, the two Canadian studies of which we are aware -- Heisz (1996) and Green and Riddell (1997) -- do not find a broad trend toward shorter job duration, but instead find an increasing prevalence of both very short *and* very long jobs. Whether this polarization in the job tenure distribution can possibly explain much of Canada’s increase in earnings instability probably deserves some attention.[31]

Another possible factor, which seems to have been overlooked so far in the literature, is tax changes that have altered the incentives for income smoothing.[32] As detailed in Shoven and Whalley (1992), both Canada and the United States adopted a complex series of tax changes during the 1980’s. While some of these changes (such as the flattening of marginal tax rates) may have increased earnings volatility by reducing incentives for income smoothing, others (such as Canada’s elimination of income averaging) cut in the other direction. As in the case of changes in

[30] See Jaeger and Stevens (1998) and the references therein.

[31] Another empirical question relevant to this issue is whether the increased instability in annual earnings stems from increased instability in annual work hours or in hourly wages. Unfortunately, our data set does not permit a decomposition of annual earnings into its hours and wage components. This question, however, could (and should) be pursued in the U.S. context with data from the Panel Study of Income Dynamics.

[32] We thank Joel Slemrod for raising this possibility and Jack Mintz for discussing it with us.

the distribution of job tenure, the impact on earnings instability is not immediately obvious, but probably warrants further research.

The substantive focus of our paper has been on learning more (and raising additional questions) about the sources of Canada's increase in earnings inequality. Along the way, however, we also have tried to push the econometric envelope in the modeling of earnings dynamics. Thanks to the large size of our sample, we have had the opportunity to estimate more general models than could be identified in previous research on earnings mobility.

For example, several recent studies have modeled the fanning out of a cohort's earnings distribution over the life cycle with *either* heterogeneous earnings growth *or* a random walk, but limited sample sizes have prevented these studies from incorporating both in the same model. We have succeeded in estimating the parameters of both of these aspects of the earnings process, and we have found that both are significant. This is a reassuring finding because there are good economic reasons to expect both aspects to be present. Persistent differences across individuals in their intensity of human capital investment, for example, *ought* to lead to heterogeneity in earnings growth.[33] Job losses and other shocks that cause permanent earnings changes *ought* to generate a random-walk aspect in the earnings process. In addition, we have found that the volatility of transitory earnings innovations varies significantly with stage of the life cycle. When researchers specify models that arbitrarily rule out some of these factors, they run the risk of falsely attributing some of the nonstationarity apparent in earnings data to only those sources of nonstationarity that remain in their models.

[33] It therefore is surprising that Abowd and Card's (1989) influential study claims an "absence of any permanent individual components of variance in the rate of growth of earnings or hours." As explained in Baker (1997),

Abowd and Card fail to detect the heterogeneity of earnings growth because their samples are small and because they view the data only in first differences.

References

Abowd, John M., and David Card, "On the Covariance Structure of Earnings and Hours Changes," Econometrica, March 1989, 57, 411-45.

Altonji, Joseph G., and Thomas A. Dunn, "Relationships among the Family Incomes and Labor Market Outcomes of Relatives," Research in Labor Economics, 1991, 12, 269-310.

Altonji, Joseph G., and Lewis M. Segal, "Small-Sample Bias in GMM Estimation of Covariance Structures," Journal of Business and Economic Statistics, July 1996, 14, 353-66.

Atkinson, A. B., F. Bourguignon, and C. Morrisson, Empirical Studies of Earnings Mobility, Chur: Harwood Academic Publishers, 1992.

Baker, Michael, "Growth Rate Heterogeneity and the Covariance Structure of Life-Cycle Earnings," Journal of Labor Economics, May 1997, 15, 537-79.

Bar-Or, Yuval, John Burbridge, Lonnie Magee, and A. Leslie Robb, "The Wage Premium to a University Education in Canada, 1971-1991," Journal of Labor Economics, October 1995, 13, 762-94.

Beach, Charles M., and Ross Finnie, "Polarization and Earnings Mobility among Workers in Canada, 1982-1994," unpublished, Queen's University, 1997.

Beach, Charles M., George A. Slotsve, and Francois Vaillancourt, "Inequality and Polarization of Earnings in Canada, 1981-1992," unpublished, Queen's University, 1996.

Beaudry, Paul, and David Green, "Cohort Patterns in Canadian Earnings: Assessing the Role of Skill Premia in Inequality Trends," unpublished, University of British Columbia, 1997.

Blackburn, McKinley L., and David E. Bloom, "The Distribution of Family Income: Measuring and Explaining Changes in the 1980s for Canada and the United States," in Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States, ed. David Card and Richard B. Freeman, Chicago: University of Chicago Press, 1993.

Bound, John, and George Johnson, "Changes in the Structure of Wages in the 1980's: An

Evaluation of Alternative Explanations," American Economic Review, June 1992, 82, 371-392.

Buchinsky, Moshe, and Jennifer Hunt, "Wage Mobility in the United States," Working Paper No. 5455, National Bureau of Economic Research, 1996.

Chamberlain, Gary, "Panel Data," in Handbook of Econometrics, volume 2, ed. Zvi Griliches and Michael D. Intriligator, Amsterdam: North-Holland, 1984.

Clark, Todd, "Small-Sample Properties of Estimators of Nonlinear Models of Covariance Structure," Journal of Business and Economic Statistics, July 1996, 14, 367-73.

Davis, Steven J., "Cross-Country Patterns of Change in Relative Wages," NBER Macroeconomics Annual, 1992, 7, 239-92.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," Econometrica, September 1996, 64, 1001-44.

DiNardo, John, and Thomas Lemieux, "Diverging Male Wage Inequality in the United States and Canada, 1981-1988: Do Institutions Explain the Difference?" Industrial and Labor Relations Review, July 1997, 50, 629-51.

Farber, Henry S., and Robert Gibbons, "Learning and Wage Dynamics," Quarterly Journal of Economics, November 1996, 111, 1007-47.

Freeman, Richard B., and Karen Needels, "Skill Differentials in Canada in an Era of Rising Labor Market Inequality," in Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States, ed. David Card and Richard B. Freeman, Chicago: University of Chicago Press, 1993.

Friedman, Milton, A Theory of the Consumption Function, Princeton: Princeton University Press, 1957.

Gittleman, Maury, and Mary Joyce, "Earnings Mobility and Long-Run Inequality: An Analysis Using Matched CPS Data," Industrial Relations, April 1996, 35, 180-96.

Gordon, Roger H., Differences in Earnings and Ability, New York: Garland, 1984.

Gottschalk, Peter, "Changes in Inequality of Family Income in Seven Industrialized Countries," American Economic Review, May 1993, 83, 136-42.

Gottschalk, Peter, "Inequality, Income Growth, and Mobility: The Basic Facts," Journal of

Economic Perspectives, Spring 1997, 11, 21-40.

Gottschalk, Peter, and Robert A. Moffitt, “The Growth of Earnings Instability in the U.S. Labor Market,” Brookings Papers on Economic Activity, 1994:2, 217-72.

Green, David A., and W. Craig Riddell, “Job Durations in Canada: Is Long-Term Employment Declining?” in Transition and Structural Change in the North American Labour Market, ed. Michael G. Abbott, Charles M. Beach, and Richard P. Chaykowski, Kingston: IRC Press, 1997.

Haider, Steven J., “Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991,” unpublished, University of Michigan, 1997.

Hause, John C., “The Fine Structure of Earnings and the On-the-Job Training Hypothesis,” Econometrica, May 1980, 48, 1013-30.

Heisz, Andrew, “Changes in Job Tenure in Canada,” Canadian Economic Observer, January 1996, 3.1-3.9.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan, “Earnings Losses of Displaced Workers,” American Economic Review, September 1993, 83, 685-709.

Jaeger, David A., and Ann Huff Stevens, “Is Job Stability in the United States Falling? Reconciling Trends in the Current Population Survey and Panel Study of Income Dynamics,” unpublished, Hunter College, 1998.

Johnson, George E., “Changes in Earnings Inequality: The Role of Demand Shifts,” Journal of Economic Perspectives, Spring 1997, 11, 41-54.

Katz, Lawrence F., and Kevin M. Murphy, “Changes in Relative Wages, 1963-1987: Supply and Demand Factors,” Quarterly Journal of Economics, February 1992, 107, 35-78.

Kennedy, Bruce, “Mobility and Instability in Canadian Earnings,” Canadian Journal of Economics, May 1989, 22, 383-94.

Lillard, Lee A., and Yoram Weiss, “Components of Variation in Panel Earnings Data: American Scientists 1960-70,” Econometrica, March 1979, 47, 437-54.

MaCurdy, Thomas E., “The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis,” Journal of Econometrics, January 1982, 18, 83-114.

Mincer, Jacob, Schooling, Experience, and Earnings, New York: National Bureau of Economic Research, 1974.

Moffitt, Robert A., and Peter Gottschalk, “Trends in the Autocovariance Structure of Earnings in the U.S.: 1969-1987,” Working Paper No. 355, Department of Economics, Johns Hopkins University, 1995.

Morissette, Rene, “The Declining Labour Market Status of Young Men,” unpublished, Statistics Canada, 1997.

Morissette, Rene, and Charles Berube, “Longitudinal Aspects of Earnings Inequality in Canada,” unpublished, Statistics Canada, 1996.

Picot, Garnett, “Working Time, Wages and Earnings Inequality among Men and Women in Canada, 1981-93,” unpublished, Statistics Canada, 1996.

Richardson, David H., “Changes in the Distribution of Wages in Canada, 1981-1992,” Canadian Journal of Economics, August 1997, 30, 622-43.

Riddell, W. Craig, “Unionization in Canada and the United States: A Tale of Two Countries,” in Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States, ed. David Card and Richard B. Freeman, Chicago: University of Chicago Press, 1993.

Shoven, John B., and John Whalley, ed., Canada-U.S. Tax Comparisons, Chicago: University of Chicago Press, 1992.

Solon, Gary, “Intergenerational Income Mobility in the United States,” American Economic Review, June 1992, 82, 393-408.

Solon, Gary, Robert Barsky, and Jonathan A. Parker, “Measuring the Cyclicality of Real Wages: How Important Is Composition Bias?” Quarterly Journal of Economics, February 1994, 109, 1-25.

Stevens, Ann Huff, “Persistent Effects of Job Displacement: The Importance of Multiple Job Losses,” Journal of Labor Economics, January 1997, 15, 165-88.

Zimmerman, David J., “Regression toward Mediocrity in Economic Stature,” American Economic Review, June 1992, 82, 409-29.

Table 1: Cohorts Included in the Working Sample

Birth Year	Sample Size	Years Observed	Age in Initial Year
1924/25	1219	1976-1982	52
1926/27	1272	1976-1984	50
1928/29	1170	1976-1986	48
1930/31	1054	1976-1988	46
1932/33	1013	1976-1990	44
1934/35	877	1976-1992	42
1936/37	1052	1976-1992	40
1938/39	1275	1976-1992	38
1940/41	1364	1976-1992	36
1942/43	1547	1976-1992	34
1944/45	1662	1976-1992	32
1946/47	2034	1976-1992	30
1948/49	1918	1976-1992	28
1950/51	1870	1976-1992	26
1952/53	2129	1978-1992	26
1954/55	2326	1980-1992	26
1956/57	2500	1982-1992	26
1958/59	2774	1984-1992	26
1960/61	3049	1986-1992	26
Total	32,105		

Notes: Source- Revenue Canada T-4 Supplementary Tax File. Age is defined by the older of the birth cohorts in each two year cohort.

Table 2: The Variance of Log Earnings in Various Samples

Year	Analysis Sample Ages	Analysis Sample		Individuals with Positive Earnings and Analysis Sample Ages		Individuals Aged 25-58 with Positive Earnings	
		N	Var(Y)	N	Var(Y)	N	Var(Y)
1976	25-52	19327	0.270	36789	0.597	41654	0.601
1977	26-53	19327	0.268	36235	0.614	42190	0.630
1978	25-54	21456	0.290	39539	0.629	42808	0.630
1979	26-55	21456	0.254	39592	0.603	44117	0.616
1980	25-56	23782	0.291	43484	0.644	45051	0.646
1981	26-57	23782	0.285	43332	0.647	46211	0.658
1982	25-58	26282	0.382	46325	0.745	46325	0.745
1983	26-57	25063	0.391	44006	0.772	46899	0.791
1984	25-58	27837	0.407	47855	0.798	47855	0.798
1985	26-57	26565	0.370	46119	0.777	49195	0.790
1986	25-58	29614	0.407	50286	0.790	50286	0.790
1987	26-57	28444	0.363	48599	0.766	51576	0.781
1988	27-58	28444	0.348	48611	0.765	53080	0.784
1989	28-57	27390	0.336	47037	0.765	54577	0.785
1990	29-58	27390	0.353	46489	0.768	55231	0.790
1991	30-57	26377	0.412	43618	0.815	54720	0.857
1992	31-58	26377	0.457	42231	0.846	54038	0.889

Notes: Source- Revenue Canada T-4 Supplementary Tax File.

Table 3: The Autocovariances, C_b, of the Log Earnings Residuals for the 1926/27 and 1958/59 Birth Cohorts

	Cohort Born 1926/1927								
	1976	1977	1978	1979	1980	1981	1982	1983	1984
1976	0.287	0.827	0.740	0.693	0.642	0.642	0.584	0.559	0.520
	(0.023)								
1977	0.231	0.272	0.813	0.747	0.695	0.689	0.641	0.598	0.566
	(0.016)	(0.019)							
1978	0.221	0.237	0.312	0.803	0.720	0.692	0.673	0.637	0.594
	(0.017)	(0.016)	(0.024)						
1979	0.198	0.207	0.239	0.284	0.839	0.782	0.726	0.689	0.630
	(0.014)	(0.014)	(0.017)	(0.021)					
1980	0.197	0.208	0.231	0.257	0.330	0.833	0.760	0.698	0.643
	(0.013)	(0.013)	(0.016)	(0.021)	(0.030)				
1981	0.202	0.211	0.227	0.245	0.281	0.346	0.804	0.732	0.659
	(0.013)	(0.014)	(0.016)	(0.020)	(0.025)	(0.028)			
1982	0.209	0.223	0.251	0.258	0.292	0.316	0.446	0.806	0.723
	(0.016)	(0.016)	(0.020)	(0.022)	(0.027)	(0.026)	(0.035)		
1983	0.218	0.227	0.259	0.267	0.292	0.313	0.392	0.530	0.829
	(0.018)	(0.016)	(0.022)	(0.023)	(0.028)	(0.027)	(0.032)	(0.043)	
1984	0.215	0.228	0.256	0.259	0.285	0.299	0.373	0.466	0.596
	(0.016)	(0.017)	(0.021)	(0.022)	(0.027)	(0.026)	(0.031)	(0.037)	(0.045)
	Cohort Born 1958/1959								
	1984	1985	1986	1987	1988	1989	1990	1991	1992
1984	0.526	0.716	0.591	0.540	0.501	0.443	0.411	0.386	0.350
	(0.022)								
1985	0.353	0.462	0.737	0.638	0.569	0.517	0.473	0.451	0.403
	(0.015)	(0.021)							
1986	0.283	0.331	0.435	0.756	0.609	0.552	0.508	0.472	0.436
	(0.013)	(0.014)	(0.021)						
1987	0.226	(0.011)	0.288	0.333	0.760	0.660	0.598	0.559	0.509
	(0.011)	(0.011)	(0.013)	(0.016)					
1988	0.207	0.220	0.229	0.250	0.325	0.753	0.627	0.578	0.526
	(0.011)	(0.011)	(0.010)	(0.012)	(0.016)				
1989	0.179	0.196	0.203	0.213	0.240	0.311	0.763	0.670	0.593
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.016)			
1990	0.168	0.181	(0.010)	0.195	(0.201)	0.240	0.318	0.738	0.631
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.012)	(0.016)		
1991	0.180	0.197	0.200	0.207	0.211	0.240	0.267	0.412	0.735
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.021)	
1992	0.174	0.188	0.197	0.202	0.206	0.227	0.244	0.324	0.471
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.015)	(0.024)

Notes: Source- Revenue Canada T-4 Supplementary Tax File. Standard errors in parentheses. Correlation coefficients are reported above the diagonal.

Table 4: The Autocovariances, C_b , of the Log Earnings Residuals for the 1942/43 Birth Cohort

	1976	1977	1978	1979	1980	1981	1982	1983	1984
1976	0.225 (0.017)	0.807	0.675	0.633	0.636	0.577	0.572	0.528	0.547
1977	0.178 (0.013)	0.216 (0.019)	0.783	0.694	0.695	0.633	0.623	0.560	0.578
1978	0.157 (0.010)	0.178 (0.012)	0.241 (0.018)	0.779	0.732	0.665	0.648	0.609	0.619
1979	0.148 (0.011)	0.159 (0.011)	0.188 (0.012)	0.242 (0.021)	0.772	0.674	0.640	0.586	0.580
1980	0.145 (0.010)	0.155 (0.010)	0.173 (0.012)	0.183 (0.012)	0.231 (0.017)	0.794	0.700	0.652	0.628
1981	0.140 (0.009)	0.150 (0.010)	0.167 (0.010)	0.169 (0.011)	0.195 (0.014)	0.261 (0.022)	0.757	0.674	0.646
1982	0.156 (0.010)	0.166 (0.013)	0.182 (0.012)	0.180 (0.011)	0.193 (0.012)	0.221 (0.016)	0.328 (0.025)	0.778	0.699
1983	0.149 (0.011)	0.154 (0.010)	0.177 (0.013)	0.171 (0.012)	0.186 (0.012)	0.204 (0.015)	0.264 (0.017)	0.351 (0.026)	0.781
1984	0.151 (0.012)	0.156 (0.011)	0.176 (0.013)	0.166 (0.011)	0.175 (0.012)	0.192 (0.013)	0.233 (0.015)	0.269 (0.019)	0.338 (0.027)
1985	0.146 (0.009)	0.147 (0.010)	0.169 (0.012)	0.169 (0.012)	0.177 (0.012)	0.185 (0.012)	0.221 (0.013)	0.238 (0.014)	0.253 (0.016)
1986	0.140 (0.009)	0.140 (0.009)	0.160 (0.010)	0.159 (0.011)	0.166 (0.011)	0.177 (0.011)	0.209 (0.013)	0.218 (0.013)	0.227 (0.014)
1987	0.139 (0.009)	0.146 (0.010)	0.165 (0.012)	0.160 (0.011)	0.165 (0.012)	0.174 (0.011)	0.203 (0.013)	0.213 (0.015)	0.224 (0.015)
1988	0.137 (0.009)	0.142 (0.010)	0.160 (0.011)	0.159 (0.011)	0.167 (0.012)	0.173 (0.012)	0.200 (0.013)	0.201 (0.013)	0.213 (0.014)
1989	0.135 (0.009)	0.139 (0.010)	0.155 (0.011)	0.154 (0.011)	0.159 (0.011)	0.172 (0.013)	0.201 (0.013)	0.203 (0.014)	0.208 (0.014)
1990	0.132 (0.010)	0.133 (0.010)	0.150 (0.011)	0.149 (0.012)	0.151 (0.011)	0.161 (0.011)	0.194 (0.013)	0.199 (0.014)	0.203 (0.014)
1991	0.129 (0.009)	0.136 (0.010)	0.148 (0.010)	0.151 (0.011)	0.153 (0.010)	0.165 (0.011)	0.211 (0.014)	0.201 (0.013)	0.208 (0.013)
1992	0.135 (0.009)	0.136 (0.010)	0.153 (0.011)	0.147 (0.010)	0.155 (0.011)	0.168 (0.011)	0.216 (0.015)	0.209 (0.015)	0.211 (0.013)

Notes: Source- Revenue Canada T-4 Supplementary Tax File. Standard errors in parentheses. Correlation coefficients are reported above the diagonal.

Table 4: (cont.)

	1985	1986	1987	1988	1989	1990	1991	1992
1976	0.577	0.568	0.549	0.517	0.516	0.494	0.464	0.433
1977	0.596	0.578	0.590	0.547	0.540	0.510	0.497	0.446
1978	0.647	0.628	0.632	0.584	0.571	0.546	0.512	0.473
1979	0.647	0.623	0.610	0.580	0.568	0.541	0.523	0.455
1980	0.690	0.663	0.644	0.623	0.598	0.560	0.540	0.490
1981	0.681	0.667	0.641	0.607	0.610	0.563	0.552	0.501
1982	0.726	0.702	0.666	0.625	0.635	0.604	0.627	0.573
1983	0.755	0.708	0.674	0.608	0.618	0.599	0.576	0.537
1984	0.818	0.752	0.725	0.657	0.646	0.623	0.610	0.552
1985	0.283 (0.020)	0.848	0.793	0.723	0.717	0.676	0.637	0.598
1986	0.235 (0.014)	0.271 (0.017)	0.851	0.749	0.755	0.709	0.669	0.597
1987	0.225 (0.015)	0.236 (0.015)	0.284 (0.020)	0.827	0.766	0.712	0.690	0.612
1988	0.215 (0.014)	0.218 (0.014)	0.246 (0.017)	0.312 (0.025)	0.825	0.752	0.701	0.632
1989	0.211 (0.014)	0.217 (0.014)	0.226 (0.015)	0.255 (0.018)	0.306 (0.024)	0.831	0.739	0.668
1990	0.202 (0.014)	0.207 (0.014)	0.213 (0.015)	0.236 (0.016)	0.258 (0.017)	0.315 (0.021)	0.799	0.697
1991	0.199 (0.012)	0.205 (0.013)	0.216 (0.015)	0.230 (0.015)	0.240 (0.015)	0.263 (0.017)	0.345 (0.024)	0.789
1992	0.209 (0.014)	0.204 (0.013)	0.214 (0.014)	0.232 (0.015)	0.243 (0.015)	0.257 (0.017)	0.305 (0.019)	0.433 (0.033)

Table 5: Estimates of Earnings Dynamics Models

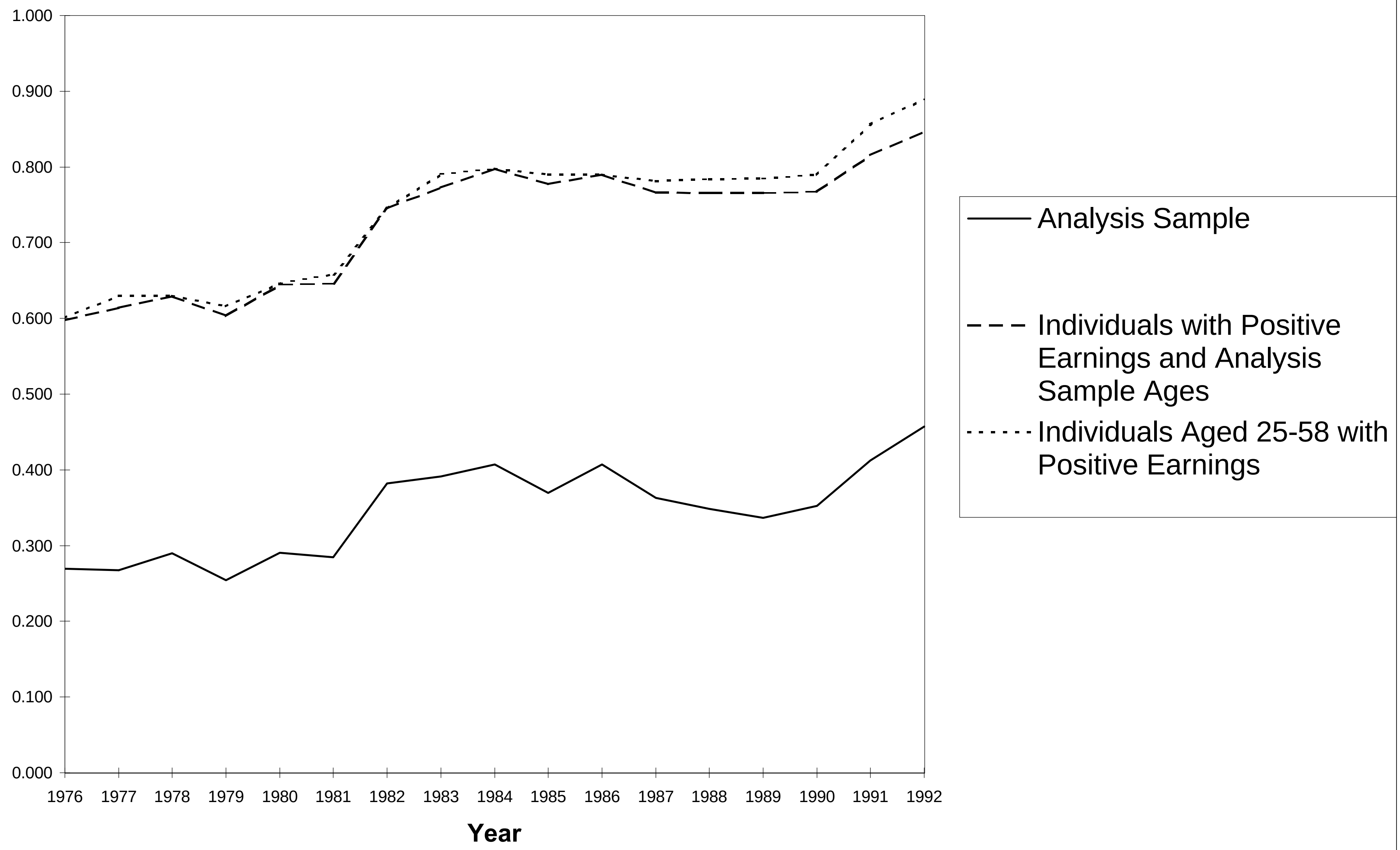
	Equally-Weighted Minimum Distance Estimates		Sample-Size-Weighted Minimum Distance Estimates		Equally-Weighted Minimum Distance Estimates	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
			Persistent Component			
s_{a}^{2}	0.135	0.007	0.156	0.021	0.095	0.004
s_{b}^{2}	0.000090	0.000033	0.000184	0.000055		
s_{ab}	-0.0032	0.0004	-0.0040	0.0009		
s_{r}^{2}	0.0067	0.0007	0.0059	0.0008	0.0032	0.0004
p_{76}	1.000		1.000		1.000	
p_{77}	1.035	0.012	0.951	0.063	1.023	0.013
p_{78}	1.027	0.015	0.908	0.064	1.010	0.017
p_{79}	1.005	0.015	0.883	0.063	0.986	0.018
p_{80}	1.029	0.017	0.919	0.065	1.013	0.021
p_{81}	1.050	0.017	0.964	0.067	1.042	0.023
p_{82}	1.143	0.020	1.139	0.077	1.147	0.029
p_{83}	1.124	0.021	1.142	0.075	1.112	0.030
p_{84}	1.125	0.021	1.124	0.072	1.117	0.031
p_{85}	1.122	0.022	1.140	0.068	1.104	0.030
p_{86}	1.111	0.022	1.141	0.066	1.091	0.031
p_{87}	1.098	0.023	1.116	0.061	1.061	0.031
p_{88}	1.105	0.023	1.108	0.057	1.071	0.031
p_{89}	1.126	0.024	1.125	0.055	1.086	0.032
p_{90}	1.127	0.024	1.146	0.054	1.098	0.031
p_{91}	1.234	0.026	1.276	0.057	1.212	0.033
p_{92}	1.253	0.027	1.315	0.057	1.229	0.033
			Transitory Component			
$s_{24/25}^{2}$	0.132	0.038	0.099	0.062	0.172	0.044
$s_{26/28}^{2}$	0.084	0.031	0.056	0.048	0.109	0.036
$s_{28/29}^{2}$	0.115	0.033	0.096	0.055	0.125	0.039
$s_{30/31}^{2}$	0.070	0.029	0.058	0.050	0.076	0.034
$s_{32/33}^{2}$	0.070	0.027	0.062	0.047	0.063	0.031
$s_{34/35}^{2}$	0.126	0.039	0.127	0.067	0.136	0.042
$s_{36/37}^{2}$	0.084	0.029	0.084	0.047	0.083	0.032
$s_{38/39}^{2}$	0.044	0.024	0.044	0.037	0.042	0.028

Notes: Source- Revenue Canada T-4 Supplementary Tax File.

Table 5 (cont.)

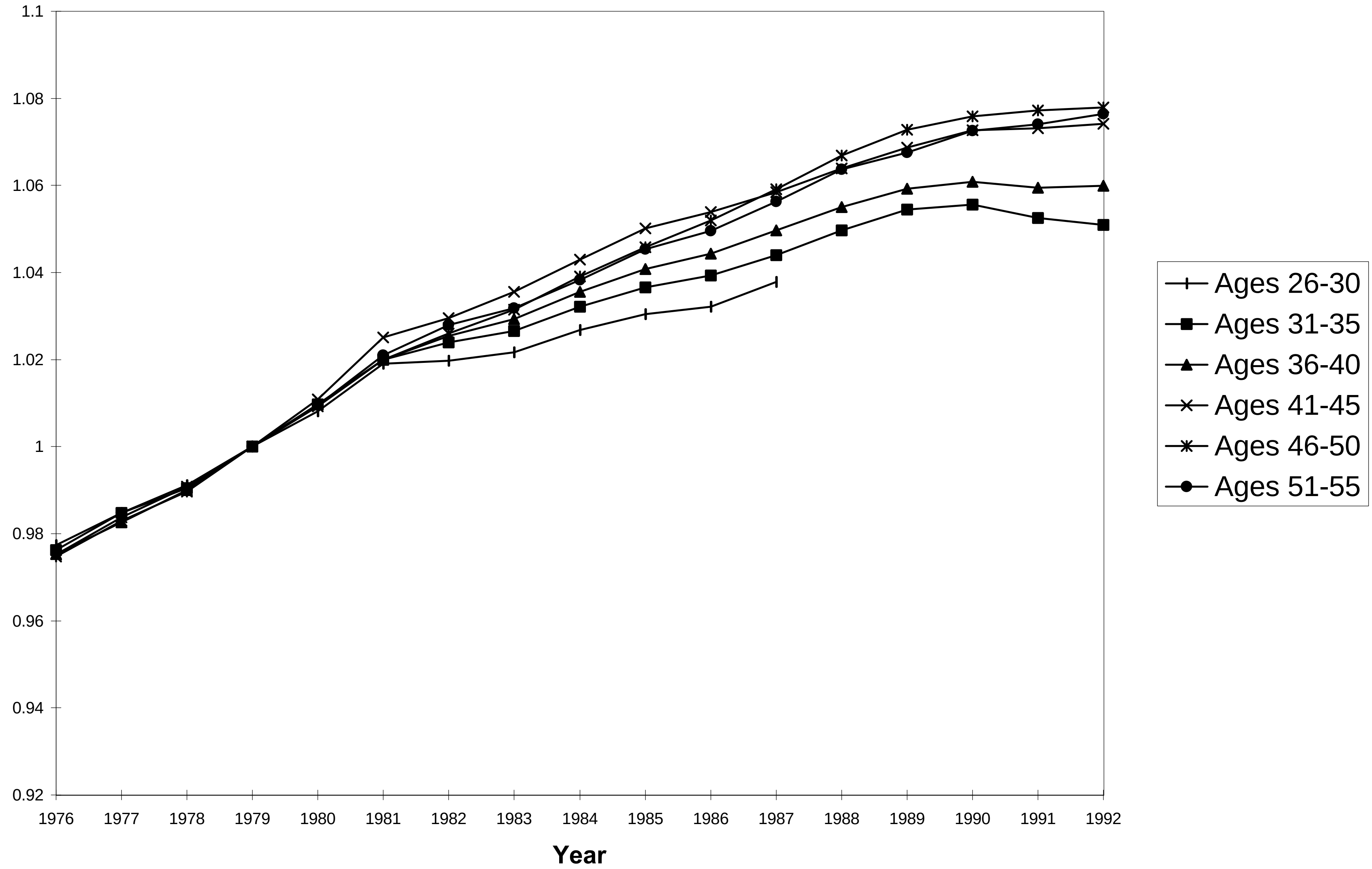
	Equally-Weighted Minimum Distance Estimates		Sample-Size-Weighted Minimum Distance Estimates		Equally-Weighted Minimum Distance Estimates	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
$\sigma^2_{40/41}$	0.066	0.025	0.066	0.037	0.072	0.028
$\sigma^2_{42/43}$	0.074	0.023	0.073	0.033	0.088	0.026
$\sigma^2_{44/45}$	0.054	0.025	0.052	0.034	0.077	0.031
$\sigma^2_{46/47}$	0.071	0.021	0.071	0.030	0.088	0.021
$\sigma^2_{48/49}$	0.090	0.021	0.084	0.031	0.106	0.022
$\sigma^2_{50/51}$	0.166	0.024	0.154	0.033	0.195	0.022
$\sigma^2_{52/53}$	0.156	0.025	0.185	0.025	0.190	0.023
$\sigma^2_{54/55}$	0.250	0.027	0.273	0.026	0.292	0.026
$\sigma^2_{56/57}$	0.293	0.026	0.268	0.024	0.360	0.026
$\sigma^2_{58/59}$	0.374	0.027	0.344	0.023	0.413	0.025
$\sigma^2_{60/61}$	0.386	0.025	0.337	0.021	0.427	0.023
ρ	0.533	0.012	0.445	0.011	0.717	0.011
γ_0	0.095	0.009	0.126	0.011	0.046	0.005
γ_1	-0.007	0.001	-0.007	0.002		
γ_2	0.00018	0.00002	0.00032	0.00008		
λ_{77}	1.000		1.000		1.000	
λ_{78}	1.135	0.060	1.101	0.063	1.096	0.056
λ_{79}	0.949	0.051	0.928	0.047	0.943	0.046
λ_{80}	1.067	0.061	1.000	0.062	1.035	0.057
λ_{81}	1.065	0.061	0.995	0.051	1.028	0.057
λ_{82}	1.398	0.079	1.212	0.064	1.291	0.070
λ_{83}	1.528	0.083	1.299	0.060	1.405	0.073
λ_{84}	1.387	0.079	1.193	0.060	1.188	0.064
λ_{85}	1.348	0.076	1.119	0.051	1.207	0.066
λ_{86}	1.348	0.077	1.110	0.054	1.208	0.065
λ_{87}	1.309	0.075	1.075	0.049	1.234	0.070
λ_{88}	1.294	0.074	1.056	0.048	1.209	0.065
λ_{89}	1.269	0.076	0.989	0.048	1.207	0.069
λ_{90}	1.415	0.080	1.073	0.052	1.299	0.068
λ_{91}	1.521	0.087	1.138	0.055	1.395	0.075
λ_{92}	1.732	0.095	1.270	0.059	1.655	0.086

Figure 1: The Variance of Log Earnings in Various Samples



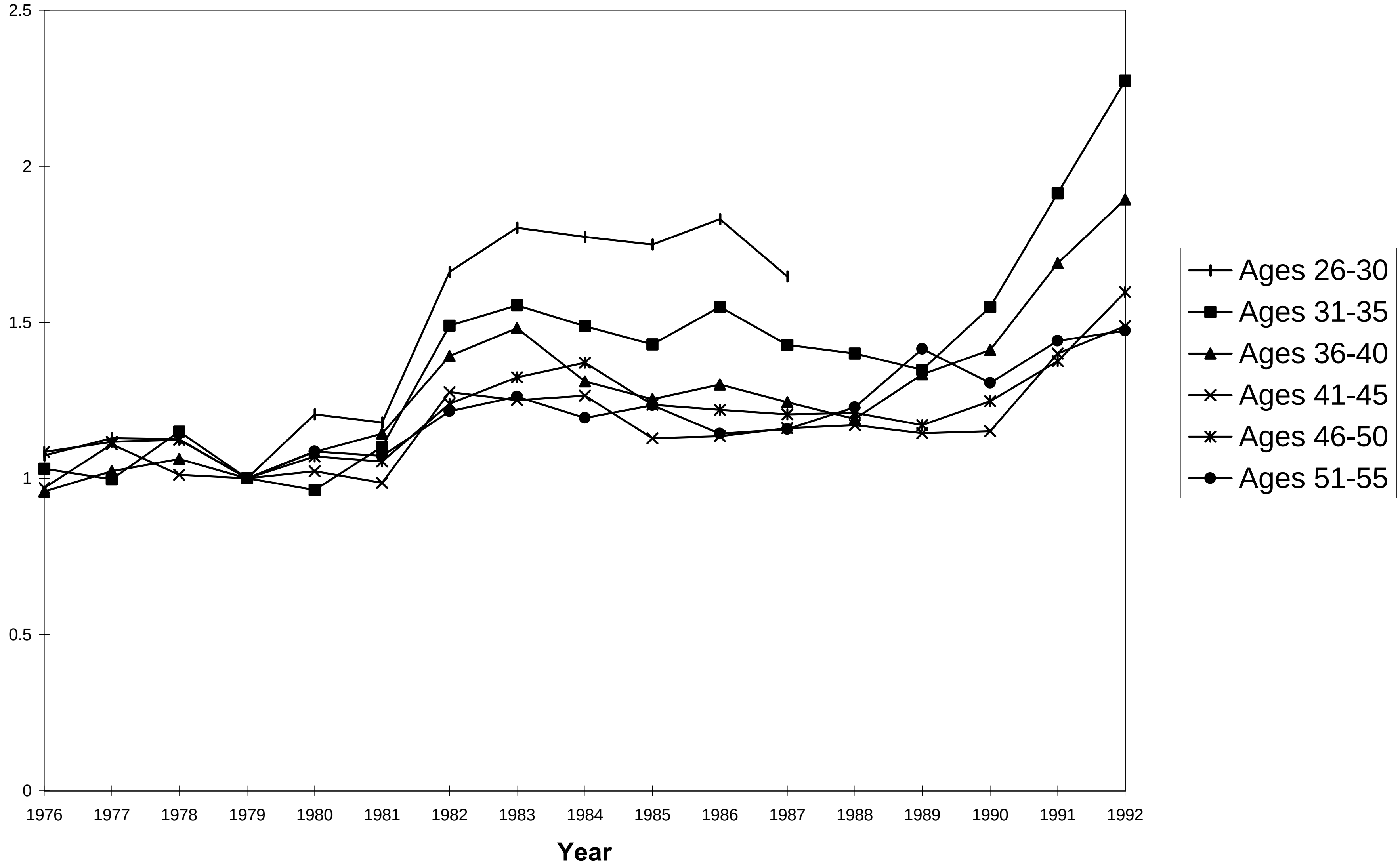
Note: Source- Revenue Canada T-4 Supplementary Tax File. See Table 2.

Figure 2: The Mean of Log Earnings by Age in the Analysis Sample



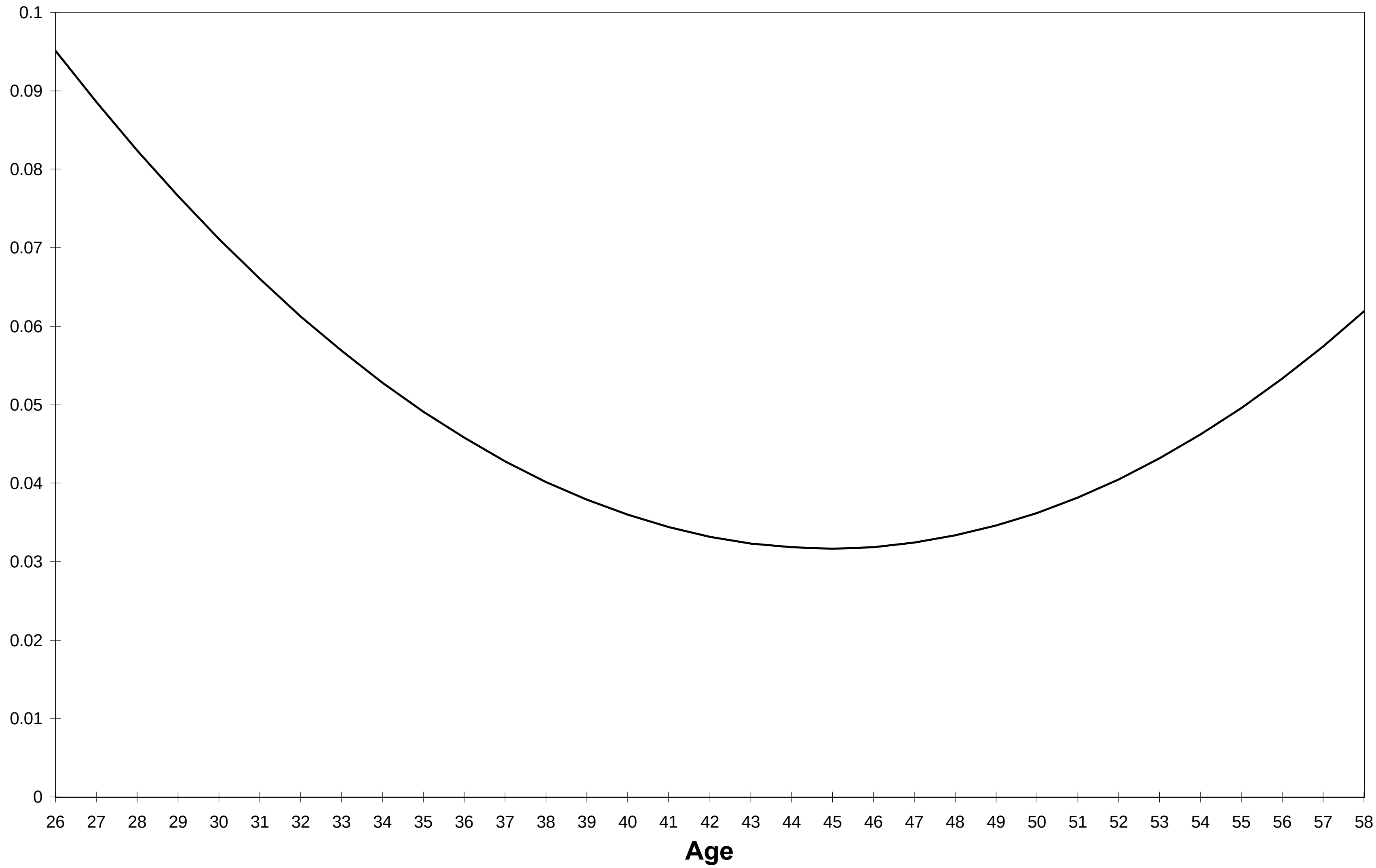
Notes: Source- Revenue Canada T-4 Supplementary Tax File. Mean Log Earnings for each age group is normalized to equal 1.0 in 1979.

Figure 3: The Variance of Log Earnings by Age in the Analysis Sample



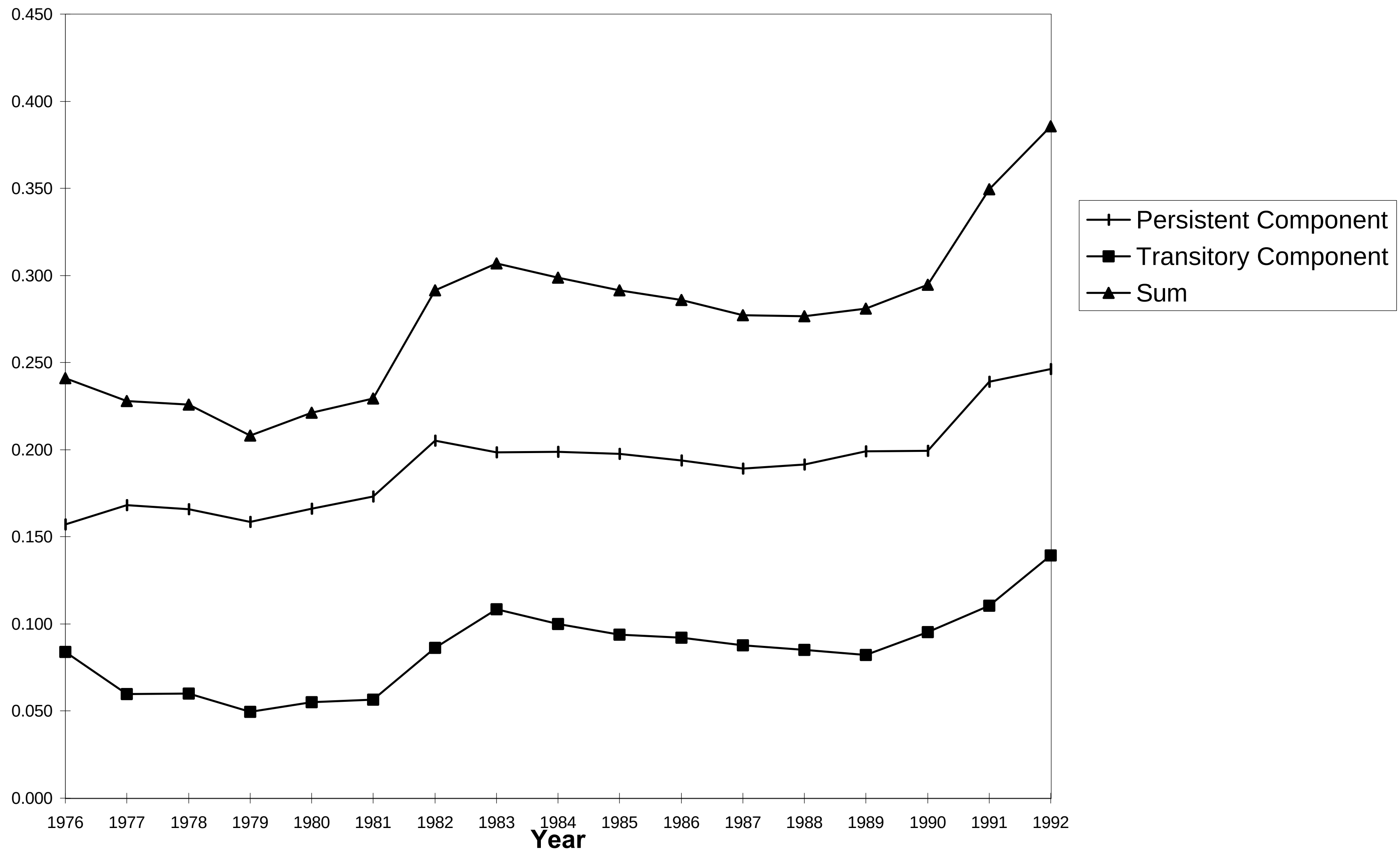
Notes: Source- Revenue Canada T-4 Supplementary Tax File. The variance of log earnings for each age group is normalized to equal 1.0 in 1979.

Figure 4: The Age Profile of the Transitory Variance.

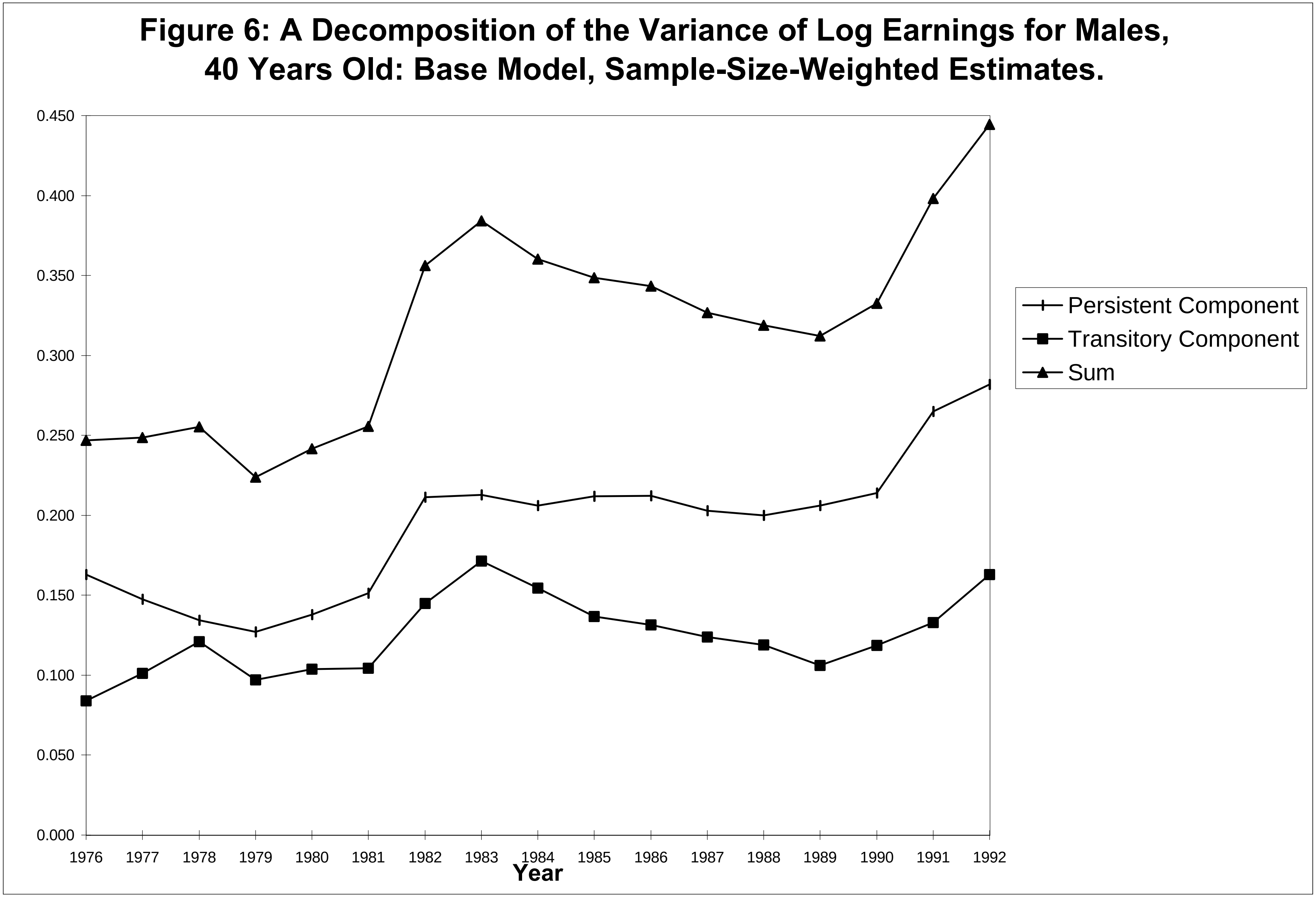


Notes: The age profile is constructed from the estimates reported in the first column of table 5.

Figure 5: A Decomposition of the Variance of Log Earnings for Males, 40 Years Old: Base Model, Equally-Weighted Estimates.

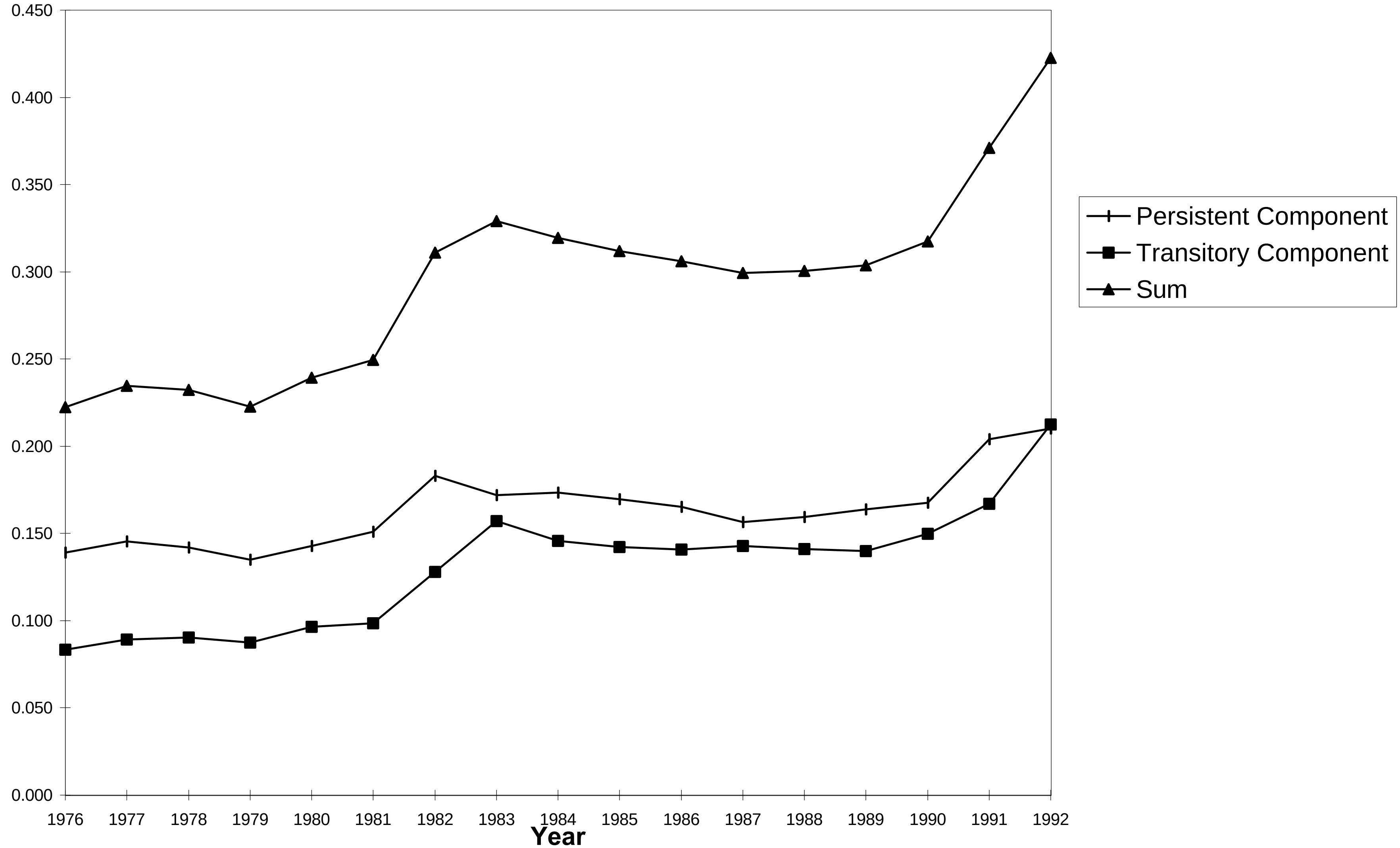


Notes: The decomposition is constructed using the estimates reported in the first column of table 5.



Notes: The decomposition is constructed using the estimates in the third column of table 5.

Figure 7: A Decomposition of the Variance of Log Earnings for Males, 40 Years Old: Restricted Model, Equally-Weighted Estimates.



Notes: The decomposition is contructed using the estimates in the fifth column of table 5.