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# Adult Literacy Development and Economic Growth

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## Introduction

Each year, the U.S. government invests about \$500 million in Title II of the Workforce Investment Act (WIA) to provide training that improves the English language, literacy, and math skills of adults and helps high school dropouts study for the General Educational Development (GED) test or other high school equivalency programs. States, local governments and private sources contribute another \$1.5 billion dollars each year. These funds provide educational opportunities to almost 3 million adults each year. The investment in WIA programs is meant to build human capital (skills and credentials) that is thought to bring a positive return on investment for both the funding sources and the adults who invest their time.

A major justification for these investments in adult basic skills programs is the strong relationship among educational attainment, basic skills and economic productivity. A human capital argument links increased levels of basic skills to more employment and higher productivity and earnings. This argument has been made repeatedly over the past quarter century in such well-known documents as *A Nation at Risk* (National Commission on Excellence in Education, 1983), *America's Perfect Storm* (Kirsch, Braun, Yamamoto & Sum, 2007) and *Reach Higher, America* (Council for the Advancement of Adult Literacy, 2008).

Adult education programs have traditionally defined their target populations in terms of educational attainment rather than skill level, with high school completion or non-completion (i.e., dropping out) as the key characteristic. The case for investment in adult education programs has therefore been built on associations between high school completion and economic snapshots of employment, earnings and poverty, such as the following:

- ♦ The unemployment rate for dropouts age 25 and older was 14.6% in 2009, compared to an unemployment rate of 9.7% for high school graduates and GED recipients who did not go to college. Median weekly earnings in 2009 for adults age 25 and over working full-time were \$454 for dropouts and \$626 for high school graduates and GED recipients with no college (U.S. Department of Labor, 2010).
- ♦ Per capita annual earnings in 2008 for adults age 25 and over were \$23,376 for dropouts, 70% of the per capita earnings of \$33,618 for high school graduates and GED recipients who did not go to college (U.S. Census Bureau, 2009a). The average male dropout earned \$27,553, 69% of the \$39,835 per capita earnings of high school graduates and GED recipients who did not go to college, (U.S. Census Bureau, 2009b). Female dropouts earned an average of \$16,254, 63 percent of the \$25,851 earned on average by female high school and GED recipients who did not go to college (U.S. Census Bureau, 2009c).
- ♦ On average, each dropout over his or her lifetime will cost the nation about \$260,000 in lost earnings, taxes and productivity compared with a high school graduate who does not go to college (Amos, 2008).
- ♦ In 2006-2008, high school dropouts were more than twice as likely to be living in poverty as high school graduates who did not go to college—24 percent compared with 11 percent (U.S. Census Bureau, 2009).
- ♦ Rank and Hirschl (2001) found that 74 percent of dropouts spend one or more years in poverty between the ages of 25 and 75, based on analyses of the data from the Panel Study of Income Dynamics between 1968 and 1992.
- ♦ Two in five youth between the ages of 16 and 24 who drop out of school receive public assistance (Bridgeland, DiIulio & Morison, 2006).

Descriptive data such as these, however, are only partially related to the mission of adult education. They are clearly related to economic contrasts between high school dropouts and graduates but are less clearly related to the economic effects of basic skills development in adults. Because levels of education and functional literacy are highly correlated, comparisons between levels of educational attainment tend to confound the effects of schooling with the effects of basic skills development. Economists who work with data sets that measure both schooling and

skills have been able to disentangle the returns to education and to adult literacy levels. Macroeconomic analyses of the relationships between historical changes in literacy skills and broad measures of national productivity have provided evidence of the independent contributions of schooling and literacy (Coulombe, Tremblay & Marchand, 2004; Johnston, 2004; Kirsch et al., 2007). Eric Hanushek and colleagues have examined the role of education and cognitive skills (primarily reading and math test scores) in cross-national studies of economic growth (Hanushek & Wößmann, 2007; Hanushek, Jamison, Jamison & Woessmann, 2008). Looking at the economic growth of 50 countries since 1960 in terms of their historical changes in educational attainment and test scores, Hanushek et al. (2008) found that economic growth is strongly dependent on cognitive skills even after accounting for differences in educational attainment and other important variables. Economic growth in the United States, they conclude, is negatively affected by our mediocre levels of tested cognitive abilities. Their analyses indicate that the economic problems we face require more than just training a larger group of highly skilled individuals; we also need to raise the basic skill levels of the entire population to remain economically vibrant. It will not suffice to increase our graduation rates. We must also increase the learning of individuals going through school so that when they do graduate from high school or college, their cognitive skills are at higher levels than they are now (Hanushek et al, 2008).

These findings at the national and international levels have counterparts at the individual level as well. Looking at the microeconomic level, Green and Riddell (2003) found that literacy and schooling each influence individuals' earnings. When literacy levels are taken into account, the estimated returns to schooling are lower than estimated returns when differences in literacy are not considered, (with obvious implications for investing in effective adult literacy programs as well as in K–12 schools). Sum (1999) also found independent contributions of adult literacy and educational attainment on individuals' employment and earnings. Green and Riddell (2003) further found that the effects of adult literacy and schooling on earnings do not interact with each other, and that the effect of adult literacy on earnings does not vary across different segments of the earnings distribution. Tyler, Murnane and

Willett (2000) looked specifically at low-education adults and found that cognitive skills affect labor market earnings even among high school dropouts.<sup>1</sup>

A number of researchers have looked specifically at the joint effects of literacy and obtaining a GED credential on the earnings of high school dropouts (Cameron & Heckman, 1993; Murnane, Willett & Boudett, 1995; Tyler, 2004). Although the various studies agree that high school dropouts who receive a GED credential subsequently earn more than high school dropouts without GEDs, Tyler's work in particular indicates that this advantage *does* interact with skill level. Tyler (2004) found that only those dropouts with relatively low levels of skill benefit from increased earnings associated with receipt of the GED credential.

An important limitation in previous research is that individuals' literacy proficiency is measured at only a single point in time (even when growth of earnings is measured longitudinally). Since there is accumulating evidence that skill levels are not constant across the adult lifespan (Green & Riddell, 2007; Reder & Bynner, 2009; Willms & Murray, 2007), a longitudinal study that follows development of both sides of this equation, skills and income, should provide a better measure of the relationship between them. This paper reports findings from a longitudinal study that measured changes in skill levels and how those changes are related to changes in the earnings of high school dropouts. Although improved economic outcomes are often the rationale for investing in basic skills programs to raise adult literacy levels, there has been little data or research that follows changes in both individuals' assessed literacy proficiencies and their employment and earnings. The research reported here offers new insights about the relationship between changes in adult literacy and changes in employment and earnings.

This paper will first describe the design and methodology of the Longitudinal Study of Adult Literacy (LSAL) and then present the key findings from LSAL about individuals' literacy growth over time and about changes in their employment and earnings over the same time

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1 A well-known longitudinal study in adult education, the "Tipping Point Research" in Washington State (Prince & Jenkins, 2005), is not included in this review because it examines the relationships among college credits, credentials and income but does not include a proficiency measure.

periods. Analyses of these data will lead into statistical modeling of the relationship between changes in literacy proficiency and earnings. The paper will then examine other models in an attempt to sort out the directionality and reciprocity of influences between literacy and earnings. The paper concludes with a discussion of the findings and their limitations along with suggested directions for future research.

## The Longitudinal Study of Adult Learning

Details of the design and methodology of the Longitudinal Study of Adult Learning (LSAL) are available in other publications (e.g., Reder, 2007, 2009a; Reder & Strawn, 2001a), but there are several key points about LSAL's design to keep in mind. LSAL was designed to start with a representative sample of the high school dropout population that is likely to participate in adult education programs at a fixed point in time and then follow that population over time, rather than following a single, narrowly defined age cohort of dropouts. Though following a single cohort of dropouts makes sense from the "pipeline" perspective of K–12 schools, once youth and adults have dropped out of school, policies, programs and opportunities tend to spread out across many age cohorts. Most adult education programs and employers, for example, interact with dropouts of a wide age range. For this reason, LSAL wanted to understand this population more holistically as programs or employers might encounter them.

LSAL followed a population of high school dropouts who were ages 18–44 at the beginning of the study, proficient but not necessarily native English speakers and residents of the Portland, Oregon, metropolitan area at the time the study began in the fall of 1998. Though this is a broadly defined dropout population, it does exclude some dropouts. To be sure, there are dropouts younger than 18 or older than 44 at a given point in time. LSAL could not support a sample large enough to include those over 44, but most participants in adult education programs are under 45. Furthermore, LSAL did not have sufficient resources to develop and administer survey and skills assessment instruments in languages other than English.

The sampled panel was statistically representative of a local (Portland, Oregon) dropout population rather than of a national one. This gives LSAL certain methodological advantages compared with a nationally representative study, yet it may limit the ability to generalize some findings. The methodological advantage of following a locally representative population is that most of its members attended the same school systems as children and encountered the same local labor market and adult education opportunities. These shared contexts of growing up and living adult lives allow the study to cast into relatively sharper relief any differences in individuals' family, schooling and work histories. Nationally representative panels, on the other hand, are usually designed in ways that they cannot be statistically representative of *any* local community (i.e., too few cases are sampled in any one locale) but contrasts between large regions of the country may be informative.

Some of the defining characteristics of LSAL's population changed over time. Everyone's age increased each year of the study. Some individuals received alternative high school credentials such as GEDs or even college degrees, whereas others moved outside of the Portland area. LSAL continued to follow individuals regardless of changes in residence and educational credentials.

A statistically representative sample of this high school dropout population was drawn within two sampling frames: a random-digit-dialing frame and an adult education program participant frame within the Portland metropolitan area. Sampled households were called and screened for members in the defined target population. The sample consisted of 496 individuals from the random-digit-dialing frame and 444 from the enrolled student frame. The resulting LSAL sample of 940 individuals was weighted so that population statistics could be estimated from the dual-frame sample data (Dinh, 2001). In addition to the formal sample of 940 respondents, 39 pilot subjects took part in LSAL. These pilot subjects were used for instrument development, interviewer training and in-depth qualitative studies.

### ***Interviews and assessments***

The LSAL conducted a series of six periodic interviews and skills assessments in respondents' homes. Respondents were paid for each of these sessions. The six sessions or "waves" of data were collected according to the following schedule:

Wave 1: 1998–1999

Wave 2: 1999–2000

Wave 3: 2000–2001

Wave 4: 2002–2003

Wave 5: 2004–2005

Wave 6: 2006–2007

Individuals were interviewed at about the same time in each wave so that there was approximately constant spacing among individuals' successive interviews and assessments (e.g., a respondent interviewed in February 1999 in Wave 1 was interviewed during February in each succeeding wave). LSAL staff maintained regular contact with respondents between waves, and about 90 percent of the original sample was retained in the study through Wave 5. Although data collection has been completed for Waves 1–6, the data from Wave 6 are still being processed and analyzed. Analyses in this paper are based on either Waves 1–4 or Waves 1–5, as explained below.

The population had an average age of 28 and was evenly divided among males and females. Approximately one-third were members of minority groups, about one in ten were born outside of the United States, about one-third describe themselves as having a learning disability and one in three reported having taken special education classes while they were in school.

Individuals dropped out of school for a variety of reasons. The most common reasons given were that they were bored with, did not like or did not fit in at school (29 percent) or had problems with academic performance (26 percent). Reasons related to employment while in school (17 percent), problems with personal relationships (15 percent), family problems (10 percent) and health or pregnancy reasons (9 percent) were also frequently reported.

The in-home sessions consisted of in-depth personal interviews and skills assessments. The sessions typically took about 90 to 120 minutes with about 60 to 90 minutes of structured and open-ended interview questions

followed by 30 minutes of assessment. Skills assessments included a standardized functional literacy assessment (alternate forms) administered in each wave and other measures administered once on particular waves, such as oral vocabulary, reading fluency and writing samples. The data collected fall into three major categories: *background information* (demographics, family-of-origin characteristics and K–12 school history, including reasons for leaving school); *special modules*, sets of detailed questions asked in a particular wave about a special topic (e.g., turbulence in everyday life, self-directed learning, health status, health care utilization, learning disabilities); and *repeated measures*, questions or assessments asked in each wave to capture information about change over time (functional literacy assessment; literacy practices; self-ratings of literacy abilities; participation in basic skill programs; other learning activities; GED testing and credentials; postsecondary education and training; employment, job characteristics and earnings; household and family composition; life goals and aspirations). In addition to information collected through personal interviews and assessments, information linked to Social Security numbers (SSNs) about individuals' program participation, education and employment/earnings was collected (with permission from the individual).

The instrumentation was carefully developed to yield data useful for the intended analytical purposes. For example, the Test of Adult Literacy Skills (TALS), developed by the Educational Testing Service (ETS), was selected as the functional literacy instrument because (1) it is not used in adult education programs (thus the planned comparisons of program participants and nonparticipants would not be contaminated by differential familiarity with the test), and (2) it is parallel with other large national and international assessments used for research and policy making. Similarly, many of the questionnaire items were taken from background questionnaires from these other large-scale assessments, so that the LSAL population can be systematically compared with other adult populations of interest.

**Literacy assessments**

The skills assessments included a standardized functional literacy assessment in each wave. The functional literacy assessment used was the Document Literacy scale of the TALS, which is administered in a constructed response format (rather than multiple choice format), to assess adults' abilities to extract and process written information in a variety of everyday document formats, such as forms, maps, tables, text displays, labels and so forth. These written documents are processed as part of performing simulated everyday literacy tasks. The difficulty of the questions is a combination of the difficulty of the text and the difficulty of the literacy task required to answer the question. Respondents are assigned proficiency scores on a 0–500 point scale based on the simulated literacy tasks they are able to perform correctly using a full information scaling program.<sup>2</sup> The TALS instruments are similar to instruments used in the 1992 National Adult Literacy Survey (NALS), the 2003 National Assessment of Adult Literacy (NAAL), the International Adult Literacy Survey (IALS), the Adult Lifelong Learning (ALL) survey and numerous state-level surveys of adult literacy conducted in the United States. Two TALS Document test forms, Form A and Form B, were randomly assigned for administration to respondents in Wave 1 and were alternated thereafter for a given subject from wave to wave. The developers of the instrument analyzed LSAL's item-level responses and concluded that the responses fit the Item Response Theory (IRT) model well and that the fitted item parameters were longitudinally stable (K. Yamamoto, personal communication, July 17, 2003).

**Use of computers at work**

In each interview, subjects were asked about a number of activities they might do as part of their current or most recent job, including the use of computer and information technologies. Individuals were asked each time they were interviewed about whether they read and wrote email as part of their job and if they searched for information on the Internet as part of their job. For each of these questions answered affirmatively, a follow-up question was asked about how often they typically did so: rarely, less

than once a week, once a week, a few times a week, every day. Responses were combined into a scale ranging from 0 (never) to 5 (every day) for each of the two items and the two were added to form a 0 to 10 point scale.

**Administrative data: Unemployment****Insurance (UI) hours and wages**

Individual subjects were asked to consent to release of their SSN-matched administrative data from state agencies to assist the research project. Individuals who agreed signed an informed consent and provided their Social Security number. Approximately 88 percent of the panel provided this release. Administrative records from Oregon and Washington state employment agencies were matched to provide hours and wages reported quarterly by employers for each consenting LSAL subject. For those who consented, 28 quarters (seven years, 1997–2003) of unemployment insurance (UI) hours and wages data from Oregon and Washington were collected.<sup>3</sup>

As might be expected, the composition of the SSN-matched population differed slightly from that of the non-consenting population of LSAL subjects. Among those who did not consent, immigrants are overrepresented, as are individuals with lower literacy proficiency scores and those whose parents have lower levels of education. There were no significant differences between consenters and non-consenters in gender, race or ethnicity, prevalence of learning disabilities, engagement in literacy practices or in years of schooling completed (before dropping out). Zero values were imputed for individuals for a given quarter for which they had no income or hours reported by either

<sup>2</sup> Thanks go to Irwin Kirsch of the Educational Testing Service for providing this scoring program.

<sup>3</sup> My appreciation goes to the staff of the Oregon Office of Community Colleges and Workforce Development, the Oregon Employment Department, the Washington State Board of Community and Technical Colleges and the Washington State Employment Security Department for their cooperation and assistance with this data matching.



Oregon or Washington during that quarter.<sup>4,5</sup> For the analyses conducted here, the administrative earnings data for 1997–2003 were adjusted with Consumer Price Index (CPI) deflators into constant 1997 dollars.

## Results

Results are presented in five sections. The first section presents literacy proficiency data. The second section develops growth curve models to characterize the systematic changes in proficiency observed over time during the study. These growth curves enable examination of individual differences among starting proficiency levels and changes in their proficiency levels over time. These individual differences, along with other individual characteristics such as age and gender, will be important determinants of employment and earnings trajectories.

The third section of results looks at individuals' employment and earnings trajectories between 1997 and 2003, with particular attention to how those trajectories depend on individuals' literacy growth curves and background characteristics. Individuals who started at higher

proficiency levels experienced higher earnings and more growth in earnings over time than individuals who started at lower proficiency levels. Furthermore, individuals who experienced literacy proficiency *growth* (loss) over time also tended to experience increased (decreased) employment and earnings over that same time period. Both of these trends were more pronounced during recessionary periods, suggesting that some important dynamics linking literacy proficiency and earnings are more active during downturns in the economy and labor market.

The fourth section of results describes some statistical models used to examine the relationships between literacy and earnings suggested by the descriptive data presented in the third section. Models are developed that enable us to consider how individuals' earnings trajectories depend on their literacy and other background characteristics. The fifth section explores some of the key findings through a different analytical lens. It discusses important issues about the directionality and reciprocity of the relationships between literacy proficiency and earnings.

### Literacy proficiency

Although the LSAL population was limited to adults with relatively little schooling (at the time the study began), the range of their assessed proficiencies was quite broad. In terms of the standard reporting levels used for Document Literacy in the National Assessment of Adult Literacy (NAAL), the LSAL population at Wave 1 scored at the levels shown in Table 1.

**Table 1. Initial proficiency levels of LSAL population.**

NAAL Performance Level	Proficiency Range	Percentage of LSAL Population
Below Basic	0–204	5%
Basic	205–249	21%
Intermediate	250–334	65%
Proficient	335–500	9%

LSAL: Longitudinal Study of Adult Learning; NAAL: National Assessment of Adult Literacy.

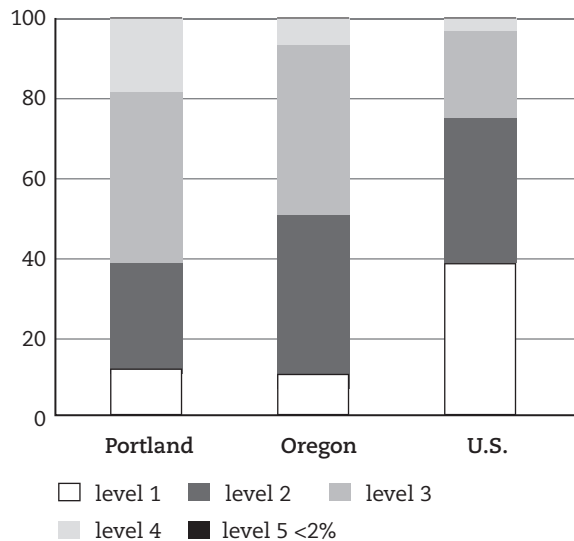
4 A few individuals with no UI-covered income during a given quarter may have been employed in Oregon or Washington but not in UI-covered occupations or industries. Approximately 92 percent of all paid employment was UI-covered during the years 1997–2003 (S. C. Williams, personal communication, June 30, 2010). Major exceptions include certain self-employed, agricultural, government and religious workers. A few other individuals moved to and may have worked in third states. Because we also have interview-based information about individuals' employment and income histories, we can address such potential biases within UI-coverage. Initial indications are that these biases are relatively small and do not alter the principal findings reported here.

5 Of the 822 individuals who provided this consent, 62 had no UI-covered employment reported at any time during the seven-year administrative window (1997–2003) and are not included in analyses of UI data. Although some of these individuals may not have worked at all during the seven-year period, other individuals evidently gave us erroneous social security numbers that failed to match state administrative records. These two patterns are indistinguishable in the administrative records. There would be some bias introduced by treating all these individuals as if they had no employment for the seven years, as well as a different bias introduced by omitting them. Comparison of the interview-reported weeks worked in the previous year for the group providing unmatched SSNs and those refusing to provide SSNs are not significantly different, so the unmatched SSN group was omitted from the data rather than assuming they all had no employment over the seven-year period.

A small percentage of this population performed at the lowest (Below Basic) level, and a small percentage scored at the highest proficiency level (Proficient). Most of the LSAL population scored at the Basic and Intermediate levels. Figure 1 compares the distribution of Wave 1 proficiencies in the LSAL population with those of matched Oregon statewide and U.S. national subpopulations (i.e., high school dropouts, ages 18–44, proficient but not necessarily native speakers of English). The distribution of proficiencies shown in the left panel, from LSAL Wave 1 in 1998, closely matches that of the statewide Oregon Literacy Survey collected eight years earlier in 1990. The similarity of these distributions provides a measure of confidence in the overall reliability of these large-scale assessments despite being carried out in different projects, by different organizations and using different sampling procedures and test forms.

The proficiency distributions in both of these Oregon populations are quite different from that of the corresponding national population shown in the right panel, taken from the National Adult Literacy Survey in 1992. There are relatively fewer adults at lower proficiency levels and relatively more adults at higher levels in Oregon than in the matching U.S. subpopulation. Reder and Edmonston (2003) carefully examined the higher literacy levels in Oregon, characteristic of the entire adult population rather than just the age- and education-restricted subpopulation shown in Figure 1. They wanted to know whether the differences were genuine literacy differences or due to demographic differences between Oregon and other parts of the United States, to procedural differences between the surveys or to other factors. After a careful review, they concluded that even after taking demographic differences into account, there are significant differences in literacy levels between the Oregon and U.S. populations. This paper will return to these differences when considering generalization of findings from LSAL to other populations.

**Figure 1.** Document Literacy proficiency of comparable target populations in Portland (Longitudinal Study of Adult Learning, Wave 1, 1998), Oregon (Oregon Literacy Survey, 1990) and the comparable U.S. population (National Adult Literacy Survey, 1992).



Comparing the results of LSAL and the Oregon Literacy Survey, collected some eight years apart, Reder and Edmonston (2003) concluded that there had been little overall change in levels of literacy in the target population. The initial NAAL report (U.S. Department of Education, 2005) also found little overall change in literacy levels between 1992 and 2003 in the adult population of the United States as a whole. Neither of these studies, however, considered *individual* change, something that can be considered with the LSAL data because of the study's repeated measurement of individual adults' literacy proficiencies over substantial periods of time.

The relatively small increase in population literacy level over time does not imply that corresponding literacy changes at the individual level are uniformly small (Reder & Edmonston, 2000). Many factors can affect the amount of individual gain (or loss) of proficiency over time, and the overall population change could be close to zero if the gains in proficiency of some individuals are offset by the losses experienced by others. This is exactly what happened within the LSAL population over time (Reder, 2009a).

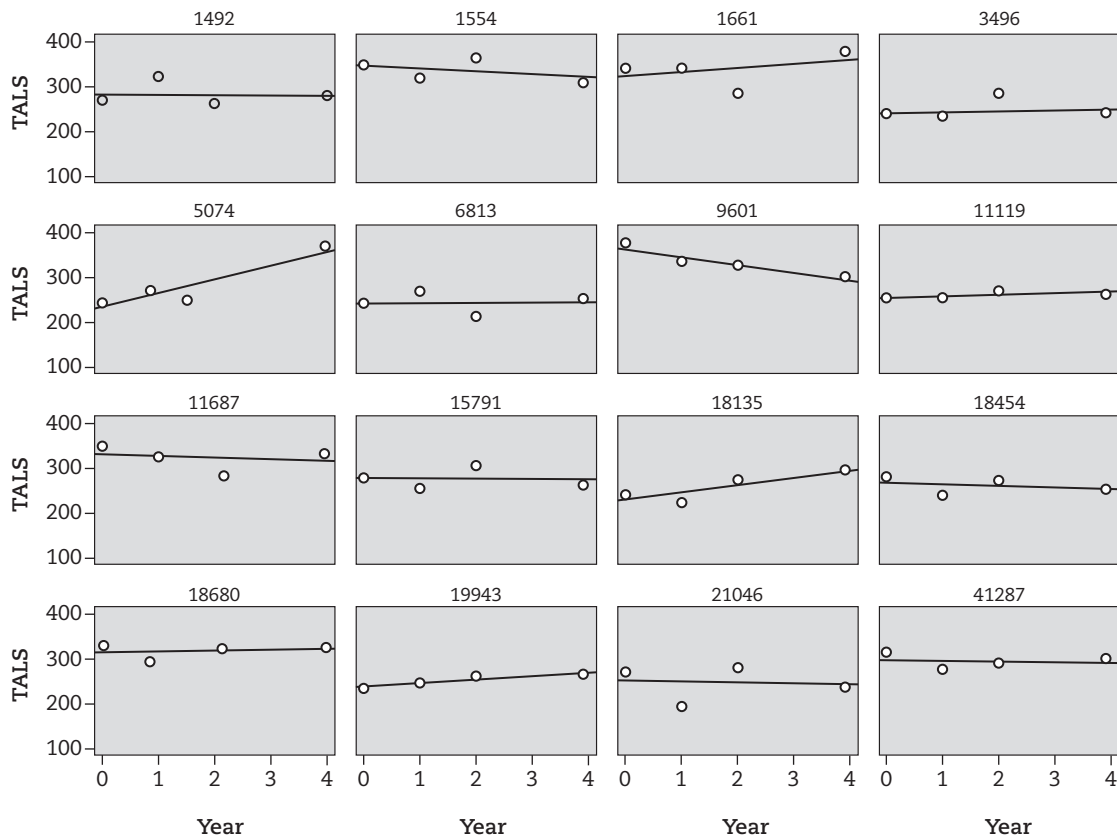
**Growth curves of individual changes in proficiency over time**

To examine individual change, the study applied growth curve modeling (Raudenbush & Bryk, 2002; Singer & Willett, 2003) to the repeated TALS measures from Waves 1–4. This analysis first constructed growth curves for the literacy proficiency of individual adults over time. Figure 2 shows such growth charts for 16 randomly selected individuals from the LSAL sample. The literacy proficiency scores are plotted for each individual at the four time points of measurement: 0, 1, 2 and 4 years after the study began. The lines drawn for each individual are the ordinary least squares (OLS) regression lines fitted to that individual’s data. These illustrative cases present a broad range of overall proficiency levels and a considerable

range of apparent rates of change in proficiency over the four-year period. Some individuals, such as cases #5074 and #18135, display apparent positive growth (i.e., proficiency gains) over time, whereas others, such as #9601 and #11687, exhibit apparent negative growth (i.e., proficiency losses) and yet others, such as #3496 and #6813, show relatively little proficiency change over time.

The repeated measures of individuals’ proficiencies over time shown in Figure 2 underline the importance of not viewing literacy proficiency as a fixed or unchanging attribute of the individual. Some of the variation in an individual’s assessed proficiency reflects the measurement error that is inevitably present in such testing, but there is also systematic change in some individuals’ proficiencies over time, representing learning and development during

**Figure 2.** Literacy proficiency scores for Waves 1–4 for 16 randomly selected cases from the Longitudinal Study of Adult Learning sample. Each point is a Test of Adult Literacy Skills (TALS) proficiency score for the person at a given point in time. Lines shown are the best-fitting (ordinary least squares) regression lines for the individual’s data.



adult life. Some literacy development may be maturational in origin; some may be triggered by participation in educational programs. Other development may be triggered by key life history events such as marriage, becoming a parent and so forth (Reder, 2009b). When examining relationships between literacy and labor market experiences, it is essential to conceptualize proficiency as a changeable rather than a fixed entity across adult life.

The empirical growth plots shown in Figure 2 are a good heuristic tool for examining changes in proficiency over time. These data suggest—and statistical analyses confirm—that linear growth curves are appropriate models of change in proficiency over the four-year time period. Figure 2 presents an impressive variability among the individually fit ordinary least squares (OLS) regression lines, with widely varying initial proficiency levels (the initial value or intercept of the line) as well as widely varying rates of change in proficiency over time (the slopes of the individual lines). The fluctuations of the individual data points around the regression lines indicate that there is a fair amount of measurement error present on each assessment occasion.

Reder (2009a) developed linear growth curves for individuals' LSAL Wave 1–5 data. This paper re-estimates them for Waves 1–4 to match more closely the time scale of the microeconomic data that extend through 2003, corresponding to Wave 4 rather than Wave 5. Technical details of the growth curve estimation procedures used are available elsewhere (Reder, 2009a). The basic linear growth model, fitted to the Wave 1–4 data, has a statistically significant but relatively small *average* rate of proficiency growth, 1.4 scale points per year ( $t = 3.019$ ,  $p = .003$ ). Over the four years of observation, this averages about 6.0 scale points of growth. This modest overall rate of growth is generally consistent with findings of small but statistically significant gains in test scores reported by programs using short-term pre-test and post-test comparisons of administrative data (Beder, 1999; Brooks et al., 2001; Rose, 2009). Analyses of LSAL proficiency growth, however, reveal that this small average growth rate belies a considerable heterogeneity of growth rates among individuals, with some individuals experiencing higher rates of growth and others much lower rates of growth, as suggested by Figure 2.

To capture this diversity in development, the study estimated individual growth curve parameters for each person. Their linear growth curves are characterized by two parameters: a person-specific *intercept* (initial proficiency level) and a person-specific *slope* (rate of proficiency change).<sup>6</sup> For the Wave 1–4 data, the estimates of the parameters of individuals' initial status range from 107 to 352 with a mean of 273, while estimates of their parameters for rate of change range from –1.3 to 4.3 scale points per year with a mean of 1.4 scale points per year.

### *Employment and earnings*

This section presents the employment and earnings data for the LSAL population: quarterly employment and earnings data series for 1997–2003 (corresponding to Waves 1–4 of the LSAL data). For these seven years, there are 28 quarters of data reported for each individual, identified in the figures below as quarters 1–28. Two important structural features will be evident in the time pattern of data across these 28 quarters. There is *seasonality*, with regularly varying levels of employment and earnings across the four quarters of each year. There is also a *recession* that is evident in the markedly reduced overall levels of employment and earnings in the years 2000 to 2003<sup>7</sup> (quarters 13–28). The paper will thus refer to two overall time periods within the seven years of data: an initial three-year period from 1997 to 1999

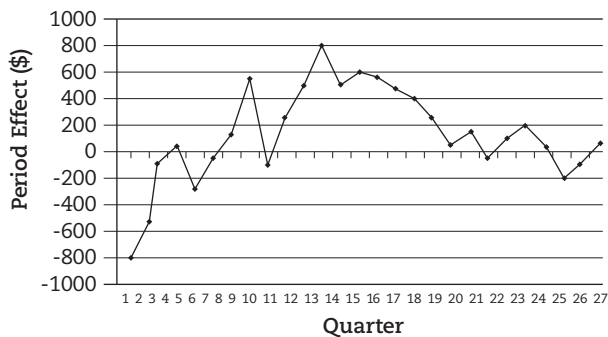
6 Although the OLS regression lines shown in Figure 2 provide reasonable initial estimates of these individual growth curve parameters, they are usually not the best estimates of individual growth curve parameters. Standard statistical methods are employed to estimate individual growth curve parameters using multilevel models of change (Raudenbush & Bryk, 2002; Singer & Willett, 2003). These are model-based *empirical Bayes* estimates (Morris, 1983) of individual growth curve parameters. They are similar to but more efficient than the OLS estimates, being based on both the individual's own data and the relationship of the individual's data to the overall data set. They are the best linear unbiased predictors (Singer & Willett, 2003). These person-specific intercepts and slopes are assumed to be random variables with known distributions in the sampled population. Statistical models explored how individuals' characteristics affect the intercepts and slopes of their literacy proficiency growth curves (Reder, 2009a).

7 This is the so-called "dotcom bust," which was particularly pronounced in Portland. Portland experienced very low levels of unemployment during the boom times in the local high technology industry during the late 1990s, followed by a large collapse of that sector starting in 2000.

(quarters 1–12) and a four-year recessionary period from 2000 to 2003 (quarters 13–28).

Figure 3 shows the estimated overall *period effects*, quarter-by-quarter, for earnings during this seven-year period. The estimated period effect for a quarter is relative to the last quarter of the period (i.e., quarter 28). These are the estimated net effects associated with each specific time period, looking across variations among time and persons in quarterly earnings.<sup>8</sup>

**Figure 3.** Period effects estimated by fixed-effects Tobit model of quarterly earnings, for quarters 1–27 (1997–2003). Period effects are relative to quarter 28 (effect of 0).



A positive value for a quarter indicates that earnings were higher in that quarter than for the baseline quarter 28, whereas a negative value indicates that earnings were relatively lower in that period. The shape of the period effect curve in Figure 3 reflects an initial prerecession period in which earnings appear to have been steadily rising (despite the seasonal fluctuations evident in the figure), followed by a recessionary period during which earnings appear to have been steadily falling (again, with some superimposed seasonality). Statistical tests indicate that both seasonality and the separation of time into two different earnings growth periods (one being quarters 1–12 and the

other being quarters 13–28) are statistically significant features of these quarterly earnings data.<sup>9</sup>

Figure 4 shows the quarterly employment rate for the LSAL population. The percentage of the population who had *some* UI-covered employment in a quarter is plotted for each of the 28 quarters in the seven-year period between 1997 and 2003. The somewhat irregular or jagged appearance of the curve is a periodic quarterly oscillation reflecting the seasonality of employment experienced by this population. A slightly increasing overall employment trend in 1997–1999 is superimposed on this seasonality pattern, followed by a sharply decreasing trend between 2000 and 2003. The sharp decrease in employment levels between 2000 and 2003, from peaks of around 70 percent to a low of just over 50 percent, corresponds with the national recession that took place in the United States at that time, which was particularly pronounced in the Portland area. During that time period, the Portland metropolitan area went from having one of the nation's lowest unemployment rates to one of the nation's highest.<sup>10</sup> Judging from Figure 4, the low-educated LSAL population was particularly hard hit by this recession. Although this recessionary period was not anticipated during the planning and design of LSAL, it offers a good opportunity to follow the employment and economic

<sup>8</sup> These period effects are estimated by fixed-effects Tobit panel models in which each individual has a person-specific earnings level and each of the 28 quarters has a period-specific effect on earnings. These models predict quarterly earnings for a particular person in a particular quarter that depend on both that individual's fixed effect and that quarter's fixed effect.

<sup>9</sup> These tests were made by comparing the goodness of fit of various fixed-effects Tobit panel models. The first test compared the most general earnings quarterly model having 27 period-specific estimated parameters, one for each period, with a simpler special case model that has five estimated parameters: a linear growth rate during the initial phase, a linear growth rate during the recessionary phase and three seasonality parameters. Comparing these two nested models with a likelihood ratio test yielded a test statistic:  $\chi^2 = 28.4$ ,  $df = 22$ ,  $p > .10$ . The more parsimonious model was thus retained, having only five parameters for the seasonality and two piecewise linear earnings growth processes. Next, the retained five-parameter model was compared with the simpler special case model that has only a single linear growth process. The likelihood ratio test yields  $\chi^2 = 94.1$ ,  $df = 1$ ,  $p > .10$ . The two-piece process model, though more complicated, fit the data better and was retained. Finally, this retained five-parameter model was compared with the simpler special-case model that dropped seasonality:  $\chi^2 = 34.4$ ,  $df = 3$ ,  $p > .10$ . The simpler model was thus rejected and the two-phase piecewise linear growth model with seasonality was retained.

<sup>10</sup> The Bureau of Labor Statistics data, for example, show that the unemployment rate in the Portland-Beaverton-Vancouver metropolitan statistical area (MSA) was 3.7 percent in December 1999 compared with 7.3 percent four years later in December 2003.

fortunes of an adult education population as it was buffeted by a tightening labor market.

**Figure 4.** Percentage of LSAL population employed during a quarter, 1997–2003. Individuals with any UI-covered employment during a quarter are counted as employed in that quarter.

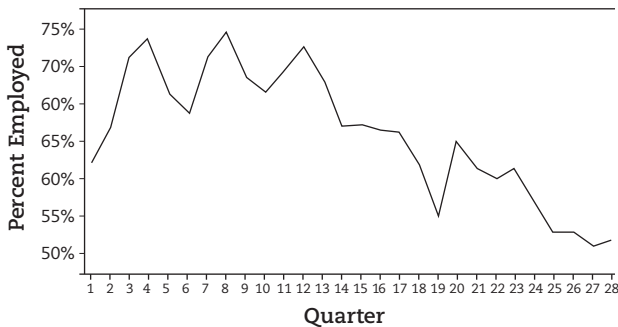
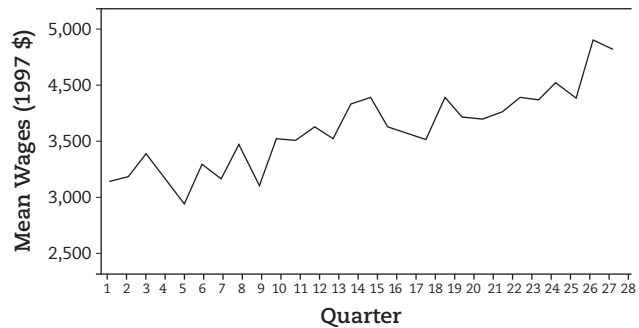


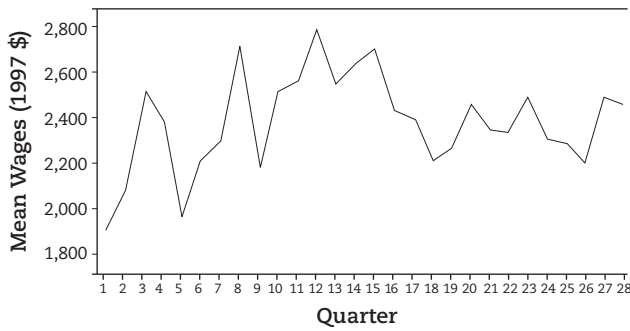
Figure 5 displays the quarterly earnings of individuals in the LSAL population who had *some* UI-covered earnings during that quarter. The steadily rising *conditional earnings* trend, in contrast to the distinct recessionary period evident in the employment data, suggests that the recession may have had its most noticeable negative effects on the employment component rather than the wage component of quarterly earnings. Notice that the seasonality effects are evident in these conditional quarterly earnings data, albeit apparently reduced in amplitude when compared with the quarterly employment data. The substantial increase in average earnings for those who remain in employment is quite impressive. However, there is a substantial reduction in the numbers employed during the recession from which this average is calculated (Figure 4). The rapid rise in earnings for those remaining employed during the recession period could be the by-product of lower-paid workers selectively losing employment or of workers who remain employed receiving higher wages, or both.

**Figure 5.** Mean conditional quarterly wages, 1997–2003. This includes only individuals in the LSAL population who had some UI-covered employment during the quarter.



If those without UI-covered employment are included in the calculations of average quarterly earnings (assigning them zero earnings for those quarters in which they were not employed), then the same 760 individuals contribute data for each quarter. The resulting average earnings data are shown in Figure 6. As expected, the seasonality amplitude that is evident increases considerably in overall (unconditional) earnings. Seasonality is more conspicuous in employment rates (Figure 4) and overall unconditional earnings (Figure 6) than in conditional earnings (Figure 5). The distinctiveness of the recessionary period is also clear in Figure 6 but not in Figure 5. Figure 6 presents a sharply rising trend in average earnings during 1997–1999 followed by a leveling off (or perhaps a mild decline) during the recessionary period of 2000–2003.

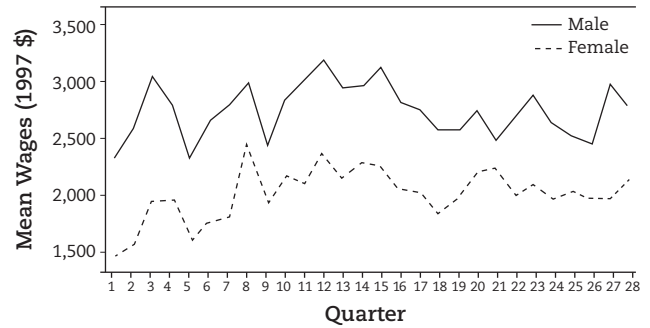
**Figure 6.** Mean quarterly wages, 1997–2003. This includes individuals in the LSAL population who had some UI-covered employment as well as those without any UI-covered employment in that quarter.



Since the overall or unconditional earnings data (averaged in Figure 6) encompass both quarterly employment and earnings for individuals, the analyses will concentrate on those data. The individual differences in earnings trajectories over the seven-year period are of primary interest in this paper. Many individual characteristics, of course, can potentially influence earnings. Some of these potential predictors are graphically illustrated through group comparisons based on specific individual characteristics. The joint influence of a larger set of individual characteristics on earnings trajectories will be examined in statistical models.

Figure 7 shows average unconditional quarterly earnings by gender. These are the same data shown in Figure 6, disaggregated by gender. The two earnings curves in Figure 7 appear to follow similar trajectories, with men earning on average substantially more than women in each quarter. There is little apparent difference in this figure in the rates of increase of men’s and women’s average quarterly earnings. Seasonality is evident in both the men’s and women’s earnings, as is a distinction between the 1997–1999 period in which average earnings steadily rose and the 2000–2003 recessionary period in which average earnings leveled off.

**Figure 7.** Mean quarterly wages, 1997–2003, for men and women.



Figures 8 and 9 disaggregate average quarterly earnings by literacy proficiency. As was shown in the previous section, LSAL’s repeated measures of literacy proficiency can be modeled as a family of linear growth curves, with each individual’s data characterized by two estimated growth parameters, an initial status (intercept) and a rate of change (slope). Figure 8 disaggregates the average quarterly earnings by proficiency intercept (initial proficiency level), whereas Figure 9 disaggregates those data by proficiency slope (proficiency growth rate).

**Figure 8.** Quarterly earnings, 1997–2003, by proficiency level.

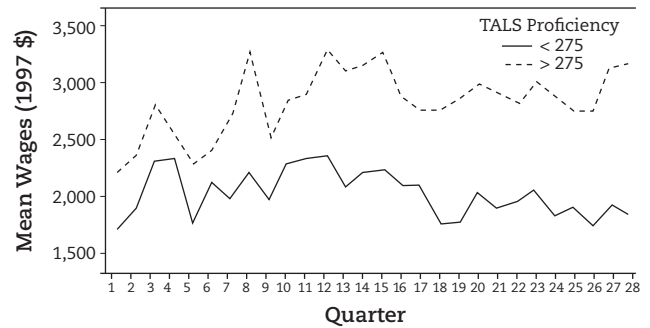


Figure 8 breaks down the average quarterly earnings according to whether the individual’s proficiency intercept is greater or less than 275, which was chosen for reasons explained below. Although the statistical models considered in the next section treat proficiency intercept as a continuous variable, it is convenient here for illustrative purposes to subdivide the intercept data into just two

contrastive groups. The 275 cut point used in Figure 8 is the median value of the proficiency intercepts in LSAL, dividing the population into two equal-sized groups. Interestingly, the scale score of 275 has been identified in previous research and by a number of state, national and international organizations as a key proficiency threshold for success in today's labor market (Comings, Sum & Uvin, 2000; Kirsch et al., 2007). Figure 8 shows that those with initial proficiencies below 275 have diminishing average quarterly earnings over time, while those with initial proficiencies above 275 have steadily increasing average quarterly earnings over the same time period, such that the earnings of the two groups steadily diverge over time.

**Figure 9.** Quarterly earnings, 1997–2003, by proficiency growth rate.

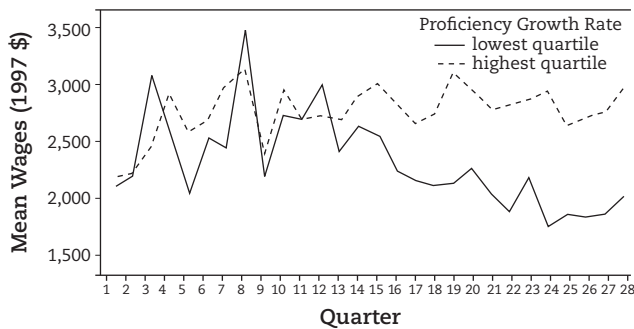


Figure 9 disaggregates the average quarterly earnings data by individuals' estimated proficiency slope parameters (i.e., their estimated rate of proficiency growth). For illustrative purposes, individuals' slope parameters were divided into four quartiles, and the average quarterly earnings for the lowest and highest ranking quartiles are plotted in Figure 9. There is apparently little overall difference in earnings between the two groups up until the recessionary period, at which time the two groups sharply diverge.<sup>11</sup> Individuals with the highest proficiency growth rates exhibit increasing wages during the recessionary period of 2000–2003, whereas those with the lowest proficiency growth rates (many of whom, in fact, lost proficiency) exhibit steadily decreasing wages during the

recessionary period. Thus not only does the proficiency level of the individual seem to affect earnings growth, the rate of proficiency change itself also affects that earnings growth during periods when the labor market tightens.

### *Statistical models of earnings trajectories*

The study developed a modeling framework to explore and test the statistical significance of some of the key features of the earnings data that have just been presented. This framework describes individual differences or heterogeneity in earning trajectories over the seven-year period from 1997–2003 and provides an opportunity to look at heterogeneity associated with literacy. It considers both the individual characteristics already examined graphically (i.e., gender and literacy growth) as well as other individual characteristics including age, education, minority status, place of birth and learning disabilities.

Presenting all the technical details of the statistical models and their results is well beyond the scope of this paper. The general framework and main results are described in this paper. The framework builds on the previous analysis that suggested that changes in individuals' earnings between 1997 and 2003 were generated by a two-piece linear growth process with seasonality. The first period of growth occurred over quarters 1–12 (1997–1999) when individuals' quarterly earnings grew at one person-specific rate, followed by a second period during quarters 13–28 (2000–2003) in which their earnings grew at a second person-specific rate. The model posits two distinct growth processes for earnings, one operating before and one operating after the economic downturn in 2000–2003. The growth processes in earnings are assumed to reflect changes in individuals' experience, basic skills, accumulated human capital and other time-dependent processes. Quarter-by-quarter seasonality effects are superimposed on these growth processes, reflecting seasonal variations in labor market conditions. Individuals are assumed to have person-specific initial levels of earnings, and it is further assumed that quarterly earnings grow at

<sup>11</sup> Although Figure 9 contrasts the top and bottom quartiles of the growth rate distribution, the underlying statistical models involve the entire range of values of the proficiency growth rate.



two person-specific rates over time: one rate applies during quarters 1–12 and a second rate during quarters 13–28.<sup>12</sup>

The key results for quarterly earnings are readily described in terms of the values of individuals' starting levels and two growth rates over quarters 1–12 and 13–28, respectively.<sup>13</sup> The mean growth rate for log quarterly earnings during 1997–1999 is significantly positive, indicating that quarterly earnings tended to increase during this period, whereas the mean value for the growth rate for 2000–2003 is significantly negative, indicating that quarterly earnings tended to decrease over that period (in part because of the increasing numbers of individuals who were not working and contributing zeroes to the average quarterly earnings). This pattern of differential mean growth rates for quarterly earnings in the 1997–1999 and 2000–2003 periods is consistent with the trends shown in Figure 8.

Although this represents the overall picture for the LSAL population, there are significant individual differences among the earnings trajectories that are very important to understand. The statistical models indicate that individuals' three earnings parameters—their starting level and their two growth rates for earnings—depend significantly on their literacy characteristics (i.e., on the intercepts and slopes of their proficiency growth curves) and other characteristics: age, gender, minority status, birthplace, education and learning disabilities. Our primary focus here is on individual differences in earnings

trajectories associated with literacy. It is important, however, to examine those relationships in multivariate settings where the effects of other background characteristics are statistically controlled.

Individuals' literacy intercepts—their proficiency levels at the beginning of LSAL—are significantly and positively associated with the initial levels of their quarterly earnings. The mean level of expected initial quarterly earnings increases by 0.008 log units for each scale point of increasing literacy proficiency. A 10-point score increase, for example, is predicted to result in a  $10 \times .008 = 0.08$  log unit increase in quarterly earnings, equivalent to an 8 percent increase in average earnings. A 100-point increase is predicted to be associated with a 0.8 log unit or an 80 percent increase in quarterly earnings. This positive relationship is consistent with the body of previous cross-sectional research on the relationship of literacy proficiency to employment and earnings (Coulombe et al., 2004; Green & Riddell, 2007, 2003; Sum, 1999; Tyler, 2004).

A new result here is that literacy proficiency also predicts individuals' earnings *growth* during the 2000–2003 period. The coefficient for the literacy intercept (initial literacy level) on the earnings growth rate for the 2000–2003 recessionary period is 0.0006, indicating that for each additional 10 scale points of initial literacy proficiency, the expected earnings *growth* rate per quarter is 0.006 log units or 0.6 percent higher than the expected rate for otherwise comparable individuals. This enhanced growth rate affects earnings growth each quarter over the 12 quarters comprising the 2000–2003 period, resulting in a moderate increase in expected earnings. The proficiency intercept coefficient for the earnings growth rate during the earlier 1997–1999 period, although trending positive, is not statistically significant in this model. The data in Figure 8 above suggest that there may be significant differences between the earnings growth rates for relatively high and low proficiency adults in both time periods.

The *slopes* of individuals' literacy growth curves also have important effects on their quarterly earnings trajectories. The slopes of individuals' literacy proficiency growth curves positively predict their initial levels of quarterly earnings, even after the effects of their initial literacy proficiencies and other background characteristics are statistically controlled. Furthermore, the literacy slopes may

12 This framework uses Tobit—also known as censored regression—panel models that econometricians have developed to handle earnings distributions that contain a large number of zero values. The study applies these models with the unconditional quarterly earnings data in which individuals not employed during a quarter are treated as having zero income for that quarter, as shown in Figures 6–9. To explore heterogeneity, random parameters Tobit panel models (Greene, 2007, Chapter 28) are used. The basic idea behind these models is that three key parameters of the earnings trajectory—the intercept (i.e., the initial earnings level) and the growth rates for the two periods—are random variables with distributions that depend on individual characteristics of interest, such as gender, age, literacy and so forth. By explicitly modeling the dependence of these random parameters on individual characteristics of interest, the study explores its primary research question about the relationship between literacy and earnings growth.

13 Quarterly earnings were transformed for these analyses into log (earnings+1) so that those with no quarterly earnings would have a log value of 0.

also positively predict, in this multivariate setting, the rate of earnings growth during the recessionary (2000–2003) period. Although the proficiency slope is not a significant predictor of the rate of earnings growth during the 1997–1999 period, it *may* be a significant predictor of earnings growth during the recessionary period 2000–2003.<sup>14</sup> These relationships are apparent in the earnings growth between the high and low literacy proficiency slope groups as shown above in Figure 9.

**Reciprocity and directionality of effects**

These results indicate that both the level of literacy proficiency and the rate of proficiency growth during a high school dropout’s adult life are significantly associated with earnings trajectories. An individual’s literacy has effects on both the levels of the individual’s earnings at fixed points in time as well as on the rates at which the earnings grow over time. The key findings are summarized in Table 2. The table shows how quarterly earnings trajectories between 1997 and 2003 are related to the two parameters of individuals’ literacy growth curves—the initial literacy level and the literacy growth rate (slope). The relationship is specified in terms of how the parameters of the literacy growth curve influence the three parameters specifying individuals’ quarterly earnings trajectories: the starting level of earnings and the two growth rates for earnings, one that applies during the pre-recession period and one during the recession.

As Table 2 indicates, literacy has a positive relationship with the starting level of individuals’ earnings as well as with the individuals’ earnings growth rate during the recession period, but not during the prerecession period.

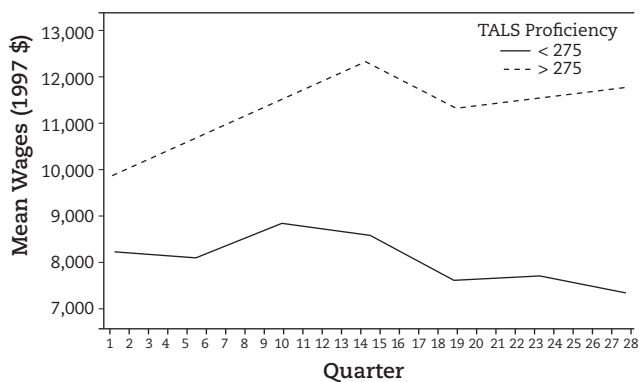
**Table 2. Summary of effects in a random parameters Tobit model for quarterly log earnings**

Predictor	Parameter of Quarterly Earnings Trajectory		
	Starting Level	Growth Rate, 1997–1999	Growth Rate, 2000–2003
Initial Literacy Level	+		+
Literacy Growth Rate	+		+?

+ indicates a significant, positive relationship ( $p < .05$ ); +? Indicates a marginally significant, positive relationship ( $p = .053$ ).

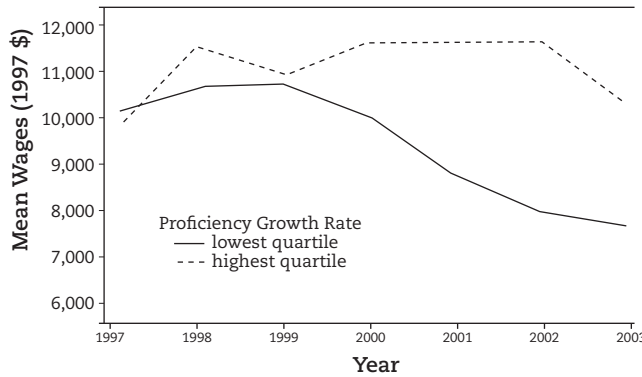
To fix attention on these key relationships, Figures 8 and 9 are redrawn in annualized terms. The amounts each person earned in the four quarters of each year are summed into annual earnings for the given year. Aggregating earnings across the four quarters of the year in this way, of course, removes the quarter-by-quarter seasonality from the data. The results are charted in Figures 10 and 11. These figures show quite clearly the substantial magnitude of the effects of different levels of literacy proficiency and of different rates of literacy proficiency change on earnings and earnings growth.

**Figure 10. Annual earnings by year, 1997–2003, by proficiency level.**



14 The test statistic for the proficiency slope being a significant predictor of earnings growth during the recessionary period has a marginal value: the coefficient of proficiency slope on (log) earnings growth rate is .00476, with a standard error of .00246, generating a *t* value of 1.93 ( $p = .053$ ). Using a conventional  $p < .05$  criterion, the hypothesis that this coefficient is significantly different from 0 would thus barely be rejected. Given the error present in estimating individual growth rates, it is not surprising that the apparently strong underlying relationship evident in Figure 9 could have marginal statistical significance. We thus offer a cautionary tone here.

**Figure 11.** Annual earnings, 1997–2003, by proficiency growth rate.



The effects that link literacy and earnings are estimated from essentially correlational analyses, so care is appropriate in attributing causality to these relationships. Only a randomized controlled trial (RCT) could *prove* causality. The plausibility of a causal relationship can only be considered here in light of the LSAL data and statistical modeling. In some instances, a clear temporal ordering or *directionality* between variables is such that there is little question about whether changes in one variable *could* be causally linked to changes in another variable. For example, the initial level of literacy proficiency is measured in 1998, well before an earnings growth rate is established for 2000–2003.<sup>15</sup> For other variables that are not temporally ordered, reciprocal causation may be plausible between the two variables. For example, the rate of literacy proficiency growth and the rate of earnings growth are not temporally ordered over the same time horizon. It is plausible that the rate of literacy proficiency might affect an individual’s work opportunities and thus an individual’s earnings; reciprocally speaking, the rate of earnings growth might influence individuals’ motivation in the workplace that could in turn affect their learning and thus the rate of their proficiency growth. There is thus the possibility for *reciprocal* causation between literacy growth and earnings

<sup>15</sup> *Unobserved variables* that are temporally prior to both literacy and earnings could be causally linked to each variable and thereby responsible for the observed correlation between the two; temporal ordering can be used to eliminate the possibility of a direct causal relationship leading from a temporally later variable to a temporally prior one.

growth. The four effects connecting literacy and earnings in our model are shown in Table 3 according to their attributes of directionality (temporal ordering) and reciprocity.

**Table 3. Directionality of effects in a random parameter Tobit panel model of quarterly earnings.**

Parameter of Literacy Growth Curve	Parameter of Quarterly Earnings Trajectory		
	Starting Level	Growth Rate, 1997–1999	Growth Rate, 2000–2003
Initial Level	Reciprocal effects	No effects	Temporally ordered: literacy level -> earnings growth
Growth Rate	Temporally ordered: earnings level -> literacy growth	No effects	Reciprocal effects*

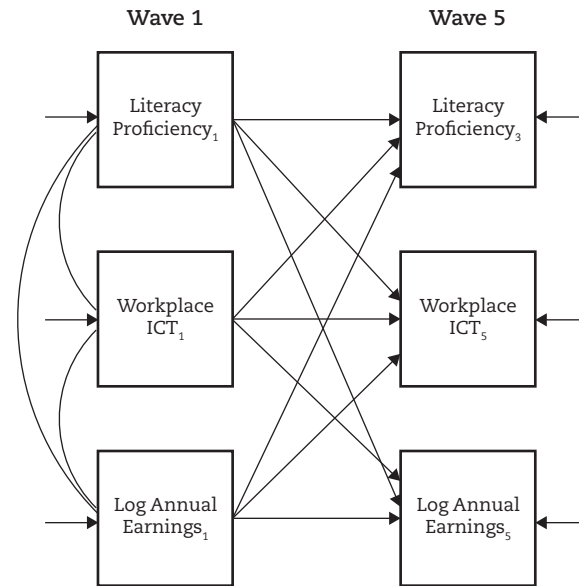
\*marginally significant ( $p = .053$ )

Given the importance of temporal ordering and possible reciprocal effects in the relationship between literacy and earnings, the study will try to approach these issues with a different analytical lens. The analytical approach taken here builds on the work of Kohn and Schooler (1978, 1982) who studied reciprocal effects between workplace experiences and various measures of psychological functioning. Structural equation models can explore possible directional and reciprocal influences between literacy and earnings using the classic simplex modeling approach developed by Humphreys (1960), Jöreskog (1979) and others. That approach is used here to look at relationships among three variables of interest—literacy proficiency, (log) annual earnings and use of information and computer technology (ICT) at work—at two different points in time, Wave 1 (1998) and Wave 5 (2004). Two snapshots are compared, one taken at Wave 1 and another six years later at Wave 5. The third variable, the use of ICT at work, was added to this model because it has frequently been suggested as a driver of increasing demands for basic skills in the workplace. Previous research with LSAL established that use of technology grew

markedly during the course of the study and suggested a relationship between literacy proficiency and the use of technology (Bynner, Reder, Parsons & Strawn, 2010; Strawn, 2008). The addition of this time-varying measure of technology use at work may help illuminate the longitudinal relationship between earnings and literacy.<sup>16</sup>

A simplex model was developed to examine how relationships among the three variables change between the snapshots taken at the two time points. In this simplex model, each of the three variables is allowed to influence the other two, so that reciprocal influences or effects are allowed among the variables between Waves 1 and 5. These can be *lagged effects*, that is, the effect of a variable at Wave 1 on its own Wave 5 value, as well as *cross-lagged effects* between a variable at Wave 1 and another variable at Wave 5. Wave 1 values are assumed to be predetermined within this simplex framework, with correlations allowed among the three measures at Wave 1. These potential lagged effects, cross-lagged effects and correlations are shown in Figure 12.

**Figure 12.** Simplex model of changes in literacy, technology and earnings measures from Wave 1 (1998) to Wave 5 (2004) in the Longitudinal Study of Adult Literacy.



The cross-lagged effects between each variable at Wave 1 and the other variables at Wave 5 are of central interest. Given that the lagged effects of each variable are already taken into account in the model, a significant cross-lagged effect would reflect the influence of one variable on another (e.g., the effect of earlier levels of literacy proficiency on later levels of earnings). The simplex model shown in Figure 12 is estimated by structural equation modeling. Statistical tests are used to evaluate the estimated path coefficients and the overall goodness of fit of the model to the data.<sup>17</sup>

Several alternative specifications of the general simplex model shown in Figure 12 were estimated. The first specification is the full simplex model, a *fully saturated* model, in which there are lagged effects for each variable and cross-lagged effects among all the variables. In a fully saturated model, there is a set of path coefficient values that will fit the observed covariance data perfectly. Thus the goodness of fit for the fully saturated model is not of interest (i.e., it will be perfect), but the fitted values of the lagged and

<sup>16</sup> The remainder of this section is statistical in nature, the key results of which are illustrated in Figures 12 and 13. For readers not conversant with the statistical modeling described in the remainder of the section, here is a less technical summary. Figure 12 shows possible influences among the three variables of interest, each of which was measured at two points in time some six years apart. Statistical tests confirm that the value of each variable measured at the earlier time point is a significant predictor of its value six years later —these influences are represented in Figure 13 by the arrows leading from each variable at Wave 1 straight across to the same variable at Wave 5. These findings are not surprising; they reflect the relative stability of these variables over time. More interesting are the arrows in Figure 13 leading from literacy proficiency at Wave 1 leading to ICT use at Wave 5 and to earnings at Wave 5. These represent the significant influences of literacy proficiency at one point in time on these other variables at a later point in time. Notice that there are no such arrows leading from ICT or Earnings at Wave 1 to other variables like literacy at Wave 5: those influences were found to be statistically nonsignificant.

<sup>17</sup> The *Mplus* statistical package, Version 5.2, was used to conduct the modeling (Muthén & Muthén, 2007).

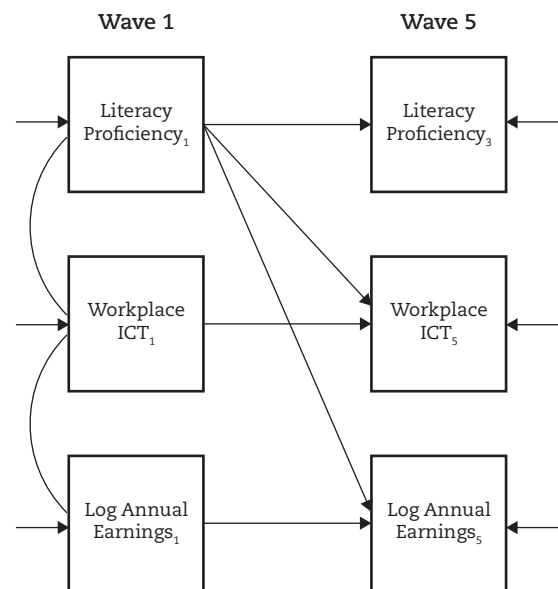
cross-lagged coefficients that produce that perfect fit are of considerable interest and guide subsequent specifications of the model.

A second specification of the simplex model is shown in Figure 13. The model diagrammed in Figure 13 includes only the statistically significant lagged and cross-lagged effects. The final model, estimated with individuals' other background characteristics controlled—age, gender, birthplace, years of schooling, race or ethnicity and learning disabilities—has a high degree of goodness of fit for the LSAL covariance data: the root mean square error of approximation (RMSEA) is .014 and the Tucker-Lewis index (TLI) is 0.98.<sup>18</sup>

As expected, each of the three lagged effects is positive and statistically significant; the value of each variable at Wave 1 is a moderate to strong predictor of its value six years later at Wave 5. The effect sizes for predicting the later value of a variable from its earlier value, a measure of its stability over time, are .63 for literacy proficiency, .23 for use of ICT in work and .18 for (log) annual wages. Clearly literacy proficiency is the most stable variable of the three.

Only two of the six cross-lagged effects are significant. The prior (Wave 1) level of literacy proficiency positively predicts subsequent (Wave 5) earnings and ICT use at work beyond what can be explained in terms of the prior values of those variables. Literacy at Wave 1 positively predicts Wave 5 earnings after the lagged effect of Wave 1 earnings is taken into account:  $t = 3.37, p = .001$ . The effect size for this cross-lagged influence from literacy proficiency to earnings is .23, larger than the aforementioned lagged effect of the prior value of earnings on its later value. Literacy also has a significant cross-lagged effect on later levels of use of ICT at work:  $t = 3.60, p < .001$ . The effect size of this cross-lagged effect of literacy on use of ICT in the workplace is .25, similar to the lagged effect size of ICT use on its later value.

**Figure 13.** Simplex model of changes in literacy, technology and earnings measures from Wave 1 (1998) to Wave 5 (2004) in the Longitudinal Study of Adult Literacy, showing only statistically significant lagged, cross-lagged and correlation effects.



The cross-lagged effects from Figure 12 that are *not* significant in Figure 13 are also of considerable interest. Although literacy proficiency influences future levels of earnings and use of ICT at work, neither of those variables has a significant cross-lagged effect on literacy or on each other. Of particular interest is the finding that although literacy proficiency influences future levels of earnings (with current level of earnings controlled), the reciprocal effect of earnings on proficiency is not significant ( $t = 0.148, p = .88$ ). Although these structural equation models cannot *prove* an underlying causality, they do indicate decisively which patterns of causal effects are consistent with the observed data. The results provide no evidence of reciprocal effects between literacy and earnings; instead, the results indicate that the LSAL data are consistent with a unidirectional influence of literacy proficiency on earnings.

<sup>18</sup> RMSEA values less than 0.06 and TLI values larger than 0.95 are generally considered to indicate good fit (Hu & Bentler, 1999).

## Discussion

This final section of the paper summarizes and discusses the major findings, considers the study limitations and suggests promising research directions.

### Major findings

**Literacy proficiency matters.** The study found strong relationships between literacy proficiency and earnings among high school dropouts. This replicates Tyler's (2004) finding and extends it to all high school dropouts within a population rather than just those who take GED tests. Given the large number of high school dropouts continuing to come out of our K–12 systems, we should not lose sight, amid the many calls for school reform efforts to reduce dropout rates, of dropouts' needs to improve their basic skills *after* they have left school.

LSAL makes it clear that dropouts' basic skills can, indeed, improve after they leave school. Reder (2009a) showed that dropouts' literacy development is influenced by a range of maturational, programmatic and life history events. More research is needed to clarify the mechanisms and processes through which literacy proficiency develops in adulthood.

**Literacy proficiency affects earnings growth.** In the panel models of individual earnings, the initial level of literacy proficiency affects both the initial level of earnings *and* the rate of subsequent earnings *growth* for the individual. Although a cross-sectional relationship between initial levels of proficiency and initial levels of earnings is consistent with previous research, the relationship identified here between initial proficiency level and earnings growth is an important new result. It suggests that literacy affects the economic return on work experience, possibly reflecting the role that literacy proficiency plays in gaining access to continuing and postsecondary education or workplace training. Literacy proficiency may also affect what individuals are able to learn and accumulate through work experience (i.e., their

accumulation of human capital). Future research, discussed below, can help clarify the mechanisms involved here.

**Literacy growth matters.** The panel data and models show that, above and beyond the effects of literacy proficiency *level* on earnings, the rate of proficiency *growth* affects earnings. With the effects of initial literacy level statistically controlled within the panel models, the literacy growth rates for individuals influence their earnings, both the starting level of their earnings and possibly the rate of growth of their earnings. Further analysis and research could deepen understanding of these fairly substantial effects. It could be, for example, that growth in literacy proficiency is a proxy for important omitted variables that influence the rates of both literacy and earnings growth. Noncognitive skills and motivational and dispositional attributes are believed to influence earnings along with cognitive abilities (Heckman, Stixrud & Urzua, 2006; Pryor & Schaffer, 1999). If such noncognitive attributes influence the rate of adults' proficiency development as well as their earnings growth, the omitted noncognitive variables could bias estimates of the relationship between literacy growth and earnings growth.

**The relationship of literacy and earnings is unidirectional and not reciprocal.** The simplex structural equation models of changes in literacy and earnings make it clear that the relationship between literacy and earnings is unidirectional, leading from literacy to earnings and not vice versa. Although we cannot prove causality, the LSAL data point to a unidirectional effect of literacy on earnings. There is no evidence of a reciprocal effect between literacy and earnings in the LSAL population (i.e., that changes in earnings lead to changes in literacy proficiency).

An important question is the extent to which the effects of literacy on earnings observed in the LSAL data reflect employee productivity growth rather than selection effects. Additional research is needed to resolve this matter clearly, but there is a body of previous cross-sectional research that does suggest

that literacy affects earnings through enhanced productivity. Raudenbush and Kasim (1998) analyzed the NALS data and examined wage premiums for literacy skills (with education and many other variables statistically controlled) in a variety of occupations. They found larger skill premiums in knowledge-intensive occupations, suggesting that it is the application of literacy skills that matters for productivity. Boothby (2002), working with the Canadian IALS data, analyzed cross-sectional wage variations in terms of education and literacy skills within various occupations. Boothby found wage premiums in jobs where the incumbent appeared to have more skills than the minimum required for the job, which should only be the case if literacy indeed confers direct productivity benefits.

**The relationship between literacy and earnings varies with labor market conditions.** When the LSAL was being designed, there was no expectation that there would be a major recession in the Oregon economy during the study. The unexpected downturn provided a rich opportunity to examine the impact of a tight labor market on a low-education population. The LSAL population was, indeed, heavily buffeted by the economic downturn between 2000 and 2003. Employment rates plummeted during the period, flattening per capita earnings for the LSAL population, earnings that had been steadily increasing in the immediately preceding years. Per capita earnings for those who remained employed during the downturn continued to rise steadily throughout the period. The panel models analyzed these earnings trends in terms of a two-piece growth process, with different rates of earnings growth applying in each of the two periods.

The random parameters panel model examined the heterogeneity among individuals' earnings growth rates for the pre-recession and recession periods. Literacy proficiency has a statistically significant effect on earnings growth rates during the recession period but not during the pre-recession period. This is an example of how the relationships among skills, employment and earnings vary with prevailing

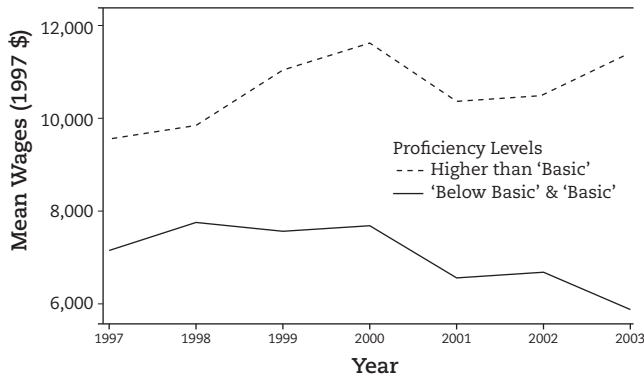
labor market conditions (e.g., Pryor & Schaffer, 1999). The finding here that labor market sorting in terms of literacy proficiency seems to happen during periods of rising unemployment appears to be very important. The LSAL data indicate that the role of literacy is particularly important (at least for low-education workers) in tight labor markets. It is possible, for example, that the restructuring of work processes and the introduction of new technologies that may be stimulated by economic downturns may effectively increase the demand for literacy in workplaces. Identifying the extent to which this is happening and the underlying mechanisms involved would require additional analysis and research.

#### *Limitations*

This study has a number of important limitations. First, there is a limitation of population. LSAL followed a locally rather than a nationally representative population. The pros and cons of this were discussed when the population and sampling for the study were described earlier in the paper. The findings may depend on characteristics of the local population, schools and labor market. This limitation is important to keep in mind when generalizing findings to other populations and locales. One important difference was pointed out earlier in the paper: literacy levels of the LSAL dropout population, although very similar to those of the corresponding Oregon statewide population, are considerably higher than those of the corresponding national population. There are relatively more high-skilled dropouts and relatively fewer low-skilled dropouts than in the corresponding national dropout population. These compositional differences in literacy proficiency between the Oregon and the national populations are evident at all levels of education, not just among dropouts (Reder & Edmonston, 2003). Whether such differences might affect fundamental relationships between literacy and earnings is unclear. A solid base of cross-national studies finds similar underlying relationships among literacy and economic growth across a diverse set of countries with widely varying distributions of literacy proficiency (Organisation for Economic Cooperation and Development & Statistics Canada, 2000). Given the breadth of these relationships at least among the Organisation for Economic Co-operation

and Development (OECD) countries, it seems unlikely that the fundamental relationships would vary markedly within a country, but this remains an open question.

**Figure 14.** Annual earnings by year, 1997–2003, by proficiency level.



Although the LSAL dropout population has relatively high levels of proficiency, there are numerous low-skilled dropouts in the LSAL population, and it may be helpful to illustrate one of the paper's key findings for the lower-skilled segment of the population. Figure 14 displays mean annual earnings from 1997 to 2003 by proficiency level, with one curve for individuals at low levels of proficiency (Below Basic or Basic literacy proficiency) and another curve for individuals with higher levels of proficiency. Although there are relatively fewer individuals in the lower proficiency group in Oregon than in other parts of the United States, it is nonetheless clear that in Oregon, low-skilled dropouts have a very different fate in the labor market than higher-skilled dropouts, and that this difference is accentuated during times of rising unemployment.

Other limitations related to population are that adults over the age of 45 and adults with poor English language skills were not studied by LSAL. Although non-native speakers of English were approximately 10 percent of the defined LSAL population, these were pre-screened to be proficient English speakers.

A second type of limitation pertains to the time period considered in this paper, 1997–2003. Major differences were observed in the literacy-earnings relationship between the period before the recession, 1997–1999, and the recessionary period, 2000–2003. Although most of

the United States experienced the same general economic downturn that Portland did, some caution is appropriate in generalizing the findings to other time periods, such as to the recession now in progress in the United States. It will be interesting to see, as additional data become available, the extent to which the findings of this paper are applicable to other time periods.

A third limitation may be the coverage that UI data provides about employment and earnings. Although UI hours and wages data are generally considered to provide comprehensive information, not all types of employment are covered. Certain self-employed, government, agricultural and undocumented workers, among others, are systematically excluded from UI reporting. Under-the-table work is also omitted. Such employment and earnings were not included in the administrative data matched to LSAL participants. Because LSAL also collected information about employment and earnings in the face-to-face interviews, it is possible to compare changes in covered employment (i.e., through the administrative data) with changes in non-covered work such as self-employment. Consider, for example, whether individuals who lost UI-covered employment during the recession tended to move into self-employment. In general, the answer appears to be negative: at the beginning of the recessionary period in 2000, 11.5 percent of the LSAL population reported some self-employment in the preceding year, compared with 8.8 percent two years later. Thus self-employment declined along with UI-covered employment during this period. In general, the interview-based reports of employment and earnings do not suggest a strong bias or lack of generality in the trends observed within the UI-based data series.

These and other limitations notwithstanding, the central findings of this paper seem reasonably well established. Literacy is a strong driver of earnings growth among high school dropouts. During periods of rising unemployment, literacy skills protect incumbent workers who have relatively little education, while the earnings of their low-skilled counterparts plummet. The literacy proficiencies of youth and young adults continue to increase after they leave school, but there is little evidence in LSAL that the work experiences available to dropouts are involved in that development.



### ***Further research needs***

Given the importance of literacy and literacy growth for productivity and earnings, it is essential to broaden the research base about how literacy develops in adulthood. Previous LSAL research makes it clear that many dropouts' literacy continues to develop after they leave school and that a variety of mechanisms are involved in that development (Reder, 2009a; Smith, 2009). Adult education programs appear to have complex effects on literacy development. On one hand, programs do not appear to have direct, short-term effects on proficiency development.<sup>19</sup> On the other hand, recent findings from LSAL suggest that programs may have longer-term impacts on proficiency development, mediated by the growth of literacy practices over time (Reder, 2009b). Some research indicates that adult education programs have direct, short-term impact on literacy practices (Purcell-Gates, Jacobson & Degener, 2004; Reder 2009b). Further research is needed about the ways in which adult education programs affect the growth of literacy practices across the individual's lifespan and how adults' increased engagement in everyday literacy practices leads to proficiency growth over time. The interconnection among key life history events, program participation and literacy development is one promising approach to these issues. Reder (in press) has shown strong relationships between program participation and life history events and perceived measures of literacy development. Desjardins (2001, 2003) also suggested some interesting approaches that might be taken to such research, with the goal of broadening our understanding of the "life-wide" benefits of adult learning on both our economic and our social well-being.

Additional research is needed on how literacy affects productivity in the workplace, especially for low-education workers. The findings of this study indicate that literacy proficiency influences both productivity (i.e., earnings) and the use of ICT on the job, but that neither of those variables influences the development of literacy proficiency.

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<sup>19</sup> Administrative reports of proficiency gains among adult education program participants, often taken as evidence of program impact, may reflect proficiency gains being experienced by young adults regardless of their participation in programs. Since administrative data such as these typically do not include non-participating adults as controls, it is easy to misinterpret gains observed among program participants (Beder, 1999; Reder 2009a; Smith 2009).

These results may reflect the nature of the jobs to which dropouts have access. For example, in LSAL, very few dropouts, received any basic skills or job-specific training in the workplace after starting their jobs. Nevertheless, both LSAL findings and other research suggest that literacy is having direct effects on productivity at work. Perhaps literacy proficiency affects the ways in which workers are able to accumulate human capital through work experience. This would certainly be consistent with the paper's findings that literacy proficiency influences subsequent use of ICT on the job and that literacy proficiency influences the rate of earnings growth over time. Further research could help clarify these mechanisms and guide the development of cost-effective workplace literacy programs in which employers would invest. Estimates of the return on investment (ROI) to both public and private funding of workplace literacy programs might be particularly useful in efforts to improve public policy and increase employers' investments in such programs.

Additional research is needed to understand why the relationship between literacy and productivity among dropouts is much stronger during economic downturns than during periods of economic growth. Productivity continues to increase for high-skilled dropouts who tend to stay employed during periods of rising unemployment, while the employment and earnings of low-skilled dropouts are drastically reduced. Further research can help us determine the extent to which this pattern generalizes to other locales and economic cycles (including the current recession).

These research directions can be pursued through additional analyses of the existing LSAL data as well as through new longitudinal studies. Many variables collected in the LSAL interviews can deepen our understanding of the relationships we have identified between literacy and earnings. Among these are detailed information about individuals' occupations, their uses of literacy and numeracy skills and ICT in the workplace, their postsecondary education and training experiences and measures of their noncognitive skills and work-related aspirations and motivations. All of these variables are implicated in the analyses conducted to date, and future research with the LSAL data should take advantage of them.

A new wave of LSAL data has been collected but not yet analyzed, extending the time horizon from six to eight years. This wave (Wave 6) will extend information about individuals' literacy, educational and economic development, data that will be invaluable in future analyses. It is also important, of course, to conduct additional longitudinal studies that will examine the relationships between literacy and economic development in a range of other geographical settings and economic contexts, replicating and extending the work of LSAL.

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