Why is the U.S. Unemployment Rate So Much Lower?[1]

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[1]This title is intended to recall Hall (1970) ('Why is the Unemployment Rate So High at Full Employment?') and Summers (1986) ('Why is the Unemployment Rate So Very High Near Full Employment?'). The wording of this title reflects the recent decline in the unemployment rate in the United States. Explaining the cross-sectional behavior of unemployment, e.g. why the U.S. unemployment rate is so much lower than Europe's, is beyond the scope of this paper.

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Abstract

The U.S. unemployment rate is so much lower because the population is so much older. This paper argues that in the absence of the baby boom, the unemployment rate would neither have increased from 1957 to 1979, nor have fallen in the subsequent two decades.

The paper also considers other demographic changes. The most quantitatively significant is the increased educational attainment of the labor force. Since more educated workers have lower unemployment rates, it might appear that this should have (counterfactually) caused a secular decline in unemployment. However, there are theoretical reasons to believe that an increase in education will not translate into a reduction in unemployment, and independent empirical evidence to support this view.

> "In a well-known paper in one of the inaugural issues of the *Brookings Papers*, Robert Hall posed the question, 'Why is the Unemployment Rate So High at Full Employment?' [Hall (1970)] Hall, writing in the context of the 3.5% unemployment rate that prevailed in 1969, answered his question by explaining that the full-employment rate was so high because of the normal turnover that is inevitable in a dynamic economy . . . . Today [in 1986], four years into an economic recovery, the unemployment rate hovers around 7%. Over the past decade, it has averaged 7.6% and never fallen below 5.8%. . . . While some of the difference between recent and past levels of unemployment has resulted from cyclical developments, it is clear that a substantial increase in the normal or natural rate of unemployment has taken place." — Summers (1986)

1. Introduction

In November 1997, the US unemployment rate fell to 4.6%, the lowest level since 1973. This monthly report was not a fluke; the aggregate unemployment has remained below 4.7% for six months, for the first time since 1970. Figure 1 documents the decrease in unemployment during the past nineteen years, following decades of secular increases. The unemployment rate fell by 63 basis points (hundredths of a percentage point), from 5.66% just before the second oil shock in 1979 to 5.03% at the end of the long expansion in 1989. It has fallen by an additional 43 basis points since then. This prompted Federal Reserve Chairman Alan Greenspan to ask in his semi-annual testimony to Congress whether there has been a structural change in the U.S. economy:

> We do not know, nor do I suspect can anyone know, whether current developments are part of a once or twice in a century phenomenon that will carry productivity trends nationally and globally to a new higher track, or whether we are merely observing some unusual variations within the context of an otherwise generally conventional business cycle expansion. — Greenspan (1997)

This paper argues that 'current developments are part of a once or twice in a century phenomenon', albeit one far more mundane than Greenspan suggests in his testimony.

The U.S. labor force has changed significantly during the past two decades, primarily due to the aging of the 'baby boom' generation. Because the teenage unemployment rate is several times higher than the aggregate unemployment rate, historical changes in the percentage of teenagers in the population have had a significant effect on the aggregate unemployment rate. I calculate that the entry of the baby boom into the labor market in the 1960s and 1970s raised the aggregate unemployment rate by about two percentage points. The subsequent aging of the baby boom has reduced it by about one-and-a-half percentage points. This is the bulk of the low-frequency fluctuations in unemployment since World War II.

This demographic story fits with other characteristics of the current expansion. For example, Greenspan (1997) notes that although consumers "indicate greater optimism about the economy," many do not perceive an unusually attractive labor market: "Persisting insecurity would help explain why measured personal savings rates have not declined as would have been expected ... ". An explanation for these apparently contradictory opinions, is that the probability of being unemployed conditional on demographic characteristics is higher now than during most other recent business cycle peaks, particularly for men. A forty two year old man sees that 3.7% of his peers are unemployed today, but remembers that when his father was about his age in 1973, only 2.0% of his father's peers were unemployed. He looks at his eighteen year old son, who is unemployed with 17.2% probability. He recalls that in 1973, only 13.9% of his peers were unemployed.

1.1 A Preliminary Calculation

A simple way of establishing the magnitude of the covariance between the unemployment and the baby boom, is through a linear regression of the aggregate unemployment rate at time t, U_t, on a constant and on the fraction of the working age population (age 16–64) in its youth (age 16–24), YouthShare_t.[3]

$$U_t = \underset{(0.0049)}{0.0211} + \underset{(0.0255)}{0.1895}\ \text{YouthShare}_t + \varepsilon_t,\ R^2 = 0.08$$

(Standard errors in parentheses.) The youth share of the working age population peaked at 23% in 1976, and has since declined to 16%. Thus the declining youth population is correlated with a 130 basis point reduction ($0.1895 \times (23\% - 16\%) \approx 1.3\%$) in the unemployment rate. If we include a time trend in the regression, the coefficient on youth population falls to 0.1589 (standard error 0.0224), and so the point estimate of the impact of the declining youth population is 110 basis points.

There are two problems with these calculations. First, they demonstrate that there is a correlation between the youth population and the aggregate unemployment rate, but do not establish any causal mechanism. Second, the result is sensitive to the precise specification. For example, if we define the youth share to be the fraction of the working age population between the age of 16 and 34, the coefficient on youth share rises considerably. The same back-of-the-envelope calculation implies that the aging of the baby boom reduced the aggregate unemployment rate by about 270 basis points! Thus one should be hesitant in interpreting these regressions structurally.

[3]Thanks to Greg Mankiw for suggesting this calculation.

1.2 Project Outline

The remainder of this paper gives a structural interpretation to the relationship between demographics and aggregate unemployment. Summers (1986) asserts, "There is no reason why the logic of adjusting for changes in labor force composition should be applied only to changes in" the age structure. The first goal of this paper (Section 2) is to document the disaggregated unemployment rate of different groups of workers. Using data based on the Current Population Survey, the source of official US unemployment statistics, I calculate the unemployment rate of workers grouped by their observable characteristics — age, sex, race, and education.

Next I follow Perry (1970) and Gordon (1982) in calculating how much of the recent decline in unemployment is attributable to these demographic factors and how much of the decline would have happened if all demographic variables had remained constant. To perform this counterfactual exercise, I maintain the hypothesis that the unemployment rate of each group of workers is unaffected by demographics. Any change in unemployment for a group of workers would therefore have happened in the absence of demographic changes; it is a 'genuine' change in unemployment. Any remaining changes in unemployment are 'demographic'. I find that the changing age structure of the population reduced the unemployment rate by more than 75 basis points since the business cycle peak in 1979. The increased participation of women has had virtually no effect on unemployment in the last two decades, while the increase in the non-white population raised unemployment moderately, by about 13 basis points. Finally, under the maintained hypothesis, the increase in education has been much more important: it has reduced the unemployment rate by another 99 basis points.

In summary, the aggregate unemployment rate fell by about 106 basis points since 1979. Under the maintained hypothesis, if labor force demographics had remained unchanged, the aggregate unemployment rate would have *increased* by about 55 basis points during that nineteen year period. I should not be asking why the aggregate unemployment rate is so low, but rather why the genuine unemployment rate is still so very high.

If this is a puzzle during the 80s and 90s, it is more so during the 60s and 70s, a time of rising aggregate unemployment. Summers (1986) calculates that increased education during the 60s and 70s should have reduced the unemployment rate by about one full percentage point, enough to outweigh all other demographic effects. He writes, "taking into account the changing composition of the labor force does not reduce and may even increase the size of the rise in unemployment [in the 60s and 70s] that must be explained." More generally, increases in education should have caused a sharp secular decline in unemployment in the U.S. and throughout the world over long time horizons. This has of course not happened, leading Summers to dismiss the relevance of demographic explanations of changes in unemployment.

A more rigorous method of dismissing demographic adjustments, would be to invalidate the maintained hypothesis, that the unemployment rate of different groups of workers is unaffected by demographics. The second goal of this paper is then to provide a framework for evaluating the hypothesis. I argue that there are good theoretical reasons to believe it is adequate with respect to changes in the age structure, but that it might be violated when there are changes in educational attainment.

Section 3 develops a simple model of youth unemployment with the key feature that the source is not that young workers have trouble finding jobs, but that new jobs are easily destroyed. Young workers are learning about their comparative advantage by experimenting, and so necessarily endure many brief unemployment spells. In contrast, many older workers are in extremely stable jobs. Now consider the effect of the baby boom. There are more young workers, and so more unemployment. If this gives rise to a proportional incentive to create jobs, it has no effect on the rate that young workers find jobs. The age-specific unemployment rate is unaffected by population dynamics, and it makes sense to demographically adjust the unemployment rate for age.

Section 4 points out that education may be quite different. First, employers may care about relative education more than the absolute level of education. Thus an increase in the fraction of college graduates may simply lead employers to increase the educational requirement of jobs. This says that a shift in the education distribution may have no real effects. Second, educational choice is endogenous and correlated with (unobserved) ability. More able workers are likely to have a lower unemployment rate for a given level of education, and an increase in education reduces the ability of the average worker with a given level of education. Therefore an increase in education will tend to raise the unemployment rate conditional on education, even if it has little or no effect on aggregate unemployment. A demographic adjustment for education would be unwarranted and potentially misleading.

Ultimately, the appropriateness of a demographic adjustment is an empirical issue, and so in section 5, I return to the data. I first test whether changes in a group's size are correlated with changes in the group's relative unemployment rate. The reduction in the population of high school dropouts is highly correlated with a relative increase in their unemployment rate. That is a prediction of the theory in Section 4, and implies that demographic adjustments for educational attainment are inappropriate.

Next I look at age. I find that when an age group gets larger, its unemployment rate increases relative to the aggregate unemployment rate. In particular, when the baby boom generation was young, the youth unemployment rate increased. It correspondingly fell as the baby boom aged. In terms of the model of youth unemployment, job creation did not keep pace with the increase in young workers. The maintained hypothesis *understates* the effect of the baby boom on aggregate unemployment.

In light of this evidence, I construct a series for the effect of the baby boom on unemployment. My new hypothesis, supported by the model in Section 3 and the data in Section 5, is that the unemployment rate of prime age workers was unaffected by the baby boom. Any movement in the aggregate unemployment rate that cannot be explained by movements in the prime age unemployment rate, is due to demographics. This includes both the direct effect under the original hypothesis of having more young workers, and the indirect effect that the baby boom apparently had on the youth unemployment rate. Figures 19 and 20 display the genuine and demographic fluctuations in unemployment. The baby boom explains a 190 basis point increase in unemployment from 1954 to 1980 and a 150 basis point decrease in unemployment from 1980 to 1993, which was moderated by about 30 basis points in the last five years. This is the bulk of the low-frequency fluctuations in unemployment since World War II.

1.3 Related Literature

An older literature looks at whether changes in the age and sex composition of the labor force could explain the increase in unemployment in the 1960s and 70s. Prominent papers include Perry (1970) and Gordon (1982). They found, as I confirm, that these variables have explanatory power. There are two significant differences between their papers and mine. First, they use a different method to calculate the demographic unemployment rate, as I explain in footnote 10. My demographic adjustment is suggested by the theory I develop in later sections of the paper, and requires less data than Perry's.

Second, these earlier papers focus on changes in the 'non-accelerating inflation rate of unemployment' (NAIRU), while I look at changes in the actual unemployment rate. I do this primarily for expositional simplicity. If one has a model connecting equilibrium unemployment and inflation in mind, these two objectives are likely to be almost equivalent. If the actual unemployment rate requires a demographic adjustment, then so surely must the unemployment rate associated with no wage-push inflation. Conversely, if demographics have no effect on unemployment, then they should have no effect on the NAIRU, in the absence of some other channel connecting demographics and inflation. In support of this idea, I show at the end of this paper (Figure 21, page 60) that my demographic adjustment of the unemployment rate is remarkably similar to Staiger, Stock, and Watson's (1997) non-structurally estimated series for the NAIRU.

Demographic adjustments to the unemployment rate have attracted less attention in recent years.[4] There are two apparent reasons. First, the aging of the baby boom should have led to a decline in the unemployment rate starting in 1980, but 1980–86 marked a period of very high unemployment. In response, early proponents of demographic adjustments stopped making them. For example, Gordon (1997) writes, " ... when I tested in the late 1980s to see whether the demographic changes of the 1980s ... had reduced the NAIRU accordingly, I found that it had not. Without any justification other than its empirical performance, I arbitrarily set the textbook NAIRU equal to 6.0 percent for the entire period after 1978." This paper argues that Gordon was too quick to abandon his model. High unemployment in the early 80s was a temporary phenomenon.

Second, and more to the point of this paper, the validity of demographic adjustments came under attack by Summers (1986), who argued that if one is going to adjust the unemployment rate for changes in the age and sex composition of the labor force, one logically must adjust it for changes in education. He shows that the effect of a demographic adjustment for education in the 1970s is larger in magnitude and opposite in sign to the effects emphasized by Gordon (1982). He concludes that demographics increase the unexplained change in unemployment. An important goal of this paper is then to examine his premise, that education and age adjustments are equally sensible. Moreover, to the extent that the reader does not believe my conclusion that demographic adjustments for education are unwarranted, we must ask why the aggregate unemployment rate has not fallen steadily during the twentieth century.

Finally, many other papers seek to explain why the U.S. unemployment rate has fallen so much, or alternatively why it in fact is not low by historical standards. Making a complete list of proposed explanations is beyond the scope of this paper. I mention only one, chosen because it may be as large in magnitude and as fundamental as demographics. Juhn, Murphy, and Topel (1991) note that the labor market participation of men has declined sharply over the last thirty years. For example, the participation of men age 35–44 declined from 97% in 1968 to 93% today. Part of the reason for this has to do with how we measure unemployment. There has been an increase in the number of 'discouraged' workers, who are without a job

[4] An exception is Council of Economic Advisors (1997). In a discussion of the NAIRU, the report notes, " ... about 0.5 percentage point of the decline in the NAIRU since the early 1980s can be attributed to demographic changes. The single most important demographic change is the aging of the baby-boom generation: the United States now has a more mature labor force, with smaller representation of age groups that traditionally have higher unemployment rates." It is not clear what other demographic changes are considered, although education must surely not have been, since I show in Section 2.4 that college enrollment is 'more important' than the aging baby boom. The reason the demographic adjustment is smaller in the Council's report than in this paper appears to be that they are focusing on a shorter time interval and ignoring the impact that the baby boom had on the youth unemployment rate.

and available for work, but who view job search as hopeless. They are not counted as unemployed, although this omission may seem somewhat arbitrary. The implications of this can be added to the implications of the demographic adjustment, leading us to conclude that by historical standards, the U.S. 'nonemployment' rate is quite high.

2. Disaggregating Unemployment

The U.S. Bureau of Labor Statistics (BLS) publishes its monthly unemployment report using data gathered in the Current Population Survey (CPS), a representative sample of about 50,000 households. This data can therefore also be used to calculate the unemployment rate of a group of workers sharing certain characteristics.[5] The BLS in fact publishes monthly official statistics on unemployment as a function of age, sex, and race.[6] Also, the BLS maintains annual observations of unemployment as a function of education. This section uses those data to characterize the unemployment experience of different groups of workers. I then reaggregate the data to construct series for the demographic and genuine components of unemployment.

2.1 Age

After years of depression and war, the birth rate in the U.S. reached unprecedented levels from 1946 to 1964, the baby boom (Ventura, Martin, Mathews, and Clarke, 1996). In 1940, eight percent of women aged 15–44 gave birth. At the peak of the baby boom, the birth rate rose to over twelve percent, but by 1975, it had fallen to less than seven percent, where it has remained.

One effect of the baby boom was a large increase in the fraction of young workers in the labor force in the late 1960s and 1970s, as Figure 2 documents. Because of the low birth rate during the Great Depression and World War II, only 6.1% of the labor force were in their teens in 1958. This increased steadily during the next sixteen years, until by 1974, nearly ten percent of the labor force was sixteen to nineteen years old. The teenage share then declined even more sharply, bottoming out at 5.4% in 1992, before climbing slightly in the last half decade. The share of young adults followed a similar pattern, with a natural small lag.

These demographic changes are important for aggregate unemployment, because the unemployment rate of young workers is much higher than the unemployment rate of adult workers. Figure 3 provides a graphical depiction of this fact. To be

[5]Throughout this paper, I use statistics for the unemployment rate of the civilian labor force.

[6]The data in this paper are available from the BLS website, `http://stats.bls.gov`, except where noted otherwise. The specific series used are available upon request.

more rigorous, the unemployment rate of workers in age group i, $u_t(i)$, is described well by an ARMA(2,2) process:

$$u_t(i) = \bar{u}(i) + \alpha_1(i)(u_{t-1}(i) - \bar{u}(i)) + \alpha_2(i)(u_{t-2}(i) - \bar{u}(i)) + \eta_t(i) \tag{1}$$
$$\eta_t(i) = \varepsilon_t(i) + \theta_1(i)\varepsilon_{t-1}(i) + \theta_2(i)\varepsilon_{t-2}(i)$$

where $\bar{u}(i)$ is the unconditional expectation of the unemployment rate of group i, and $\varepsilon_t(i)$ is white noise with variance $\sigma_t^2(i)$, allowing for heteroskedasticity. Table 1 shows the ARMA coefficients for four different groups of workers during the last forty years.[7] The coefficients have been stable and are remarkably consistent across groups. The unconditional unemployment rate of teenage workers is more than four times the unemployment rate of prime age workers, while the unemployment rate of workers in their early twenties is nearly three times as high.

To quantify the importance of the changing age structure of the labor force, I divide the labor force into seven age groups: $I = \{16–19, 20–24, 25–34, 35–44, 45–54, 55–64, 65+\}$. Define $\omega_t(i)$ to be the fraction of workers who are in group i at time t, so $\sum_{i \in I} \omega_t(i) = 1$ for all t. Let $u_t(i)$ denote the unemployment rate of age group i at time t. Then the aggregate unemployment rate at time t is

$$U_t \equiv \sum_{i \in I} \omega_t(i) u_t(i) \tag{2}$$

There are two ways that aggregate unemployment might fall. First, the unemployment rate of different groups of workers $u_t(i)$ might fall. Second, the population might shift towards groups with lower unemployment rates, so $\omega_t(i)$ increases for i with small $u_t(i)$ and decreases for i with large $u_t(i)$.

I want to understand how much of that change would have happened if demographics had remained the same. I will refer to this as the 'genuine' change in unemployment. A useful hypothesis is that if demographics had remained unchanged at some initial shares $\omega_{t_0}(\cdot)$, the disaggregate unemployment rates $u_t(\cdot)$ would have followed the same path that we observed from t_0 to t_1. This implies that the unemployment rate at time t_1 would have been

$$U^G_{t_1,t_0} \equiv \sum_{i \in I} \omega_{t_0}(i) u_{t_1}(i) \tag{3}$$

if demographics had remained the same from t_0 to t_1. The calculation of $U^G_{t_1,t_0}$ naturally depends on the choice of the base year t_0. An interesting candidate is

[7] The years from 1948 to 1957 were characterized by higher frequency cyclical fluctuations and the Korean War, so these results are sensitive to a choice of initial year before 1957. However, they are not sensitive to a choice of a later initial year.

August 1978 (78:08), as this is the demographically 'worst' point in recent U.S. history. That is, $U^G_{t_1,78:08} \geq U_{t_1}$ for all t_1 since World War II, as shown in Figure 4.

$U^G_{t_1,78:08}$ rose by 208 basis points from the peak of the expansion in 1969 to the peak in 1979, a period during which the aggregate unemployment rate U_t rose by 229 basis points. Thus genuine unemployment changes account for most of the action in the 1970s. In contrast, $U^G_{t_1,78:08}$ only declined by 25 basis points from 1979 to 1989 and by 12 basis points from 1989 to the present, about forty percent of the total decline in aggregate unemployment in the first interval, and less than thirty percent in the second interval.[8]

The obvious alternative is to ask how much the unemployment rate changed because of demographics. Maintain our hypothesis that demographics do not affect disaggregate unemployment rates. Then if the only changes in the economy from t_0 to t_1 were demographic, the unemployment rate at t_1 would be

$$U^D_{t_1,t_0} \equiv \sum_{i \in I} \omega_{t_1}(i) u_{t_0}(i) \tag{4}$$

Changes in U^D are 'demographic' unemployment changes. Figure 5 plots this series, again using a base of August 1978. $U^D_{t_1;78:08}$ rose by 90 basis points from its lowest level in 1954 to its peak in 1978, and has since declined by 78 basis points. About sixty five percent of the decline in unemployment from the peak in 1979 to the peak in 1997 is picked up by $U^D_{t_1;78:08}$.[9]

One problem with these measures of demographic change is that they depend on a choice of base year. To avoid this issue, I introduce a 'chain-weighted' measure of the change in unemployment attributable to demographics. Given an initial time period t_0, define for $t_1 > t_0$

$$\Delta_{t_1,t_0} = \sum_{t=t_0}^{t_1-1} \sum_{i \in I} (\omega_{t+1}(i) - \omega_t(i)) \left(\frac{u_{t+1}(i) + u_t(i)}{2} \right) \tag{5}$$

$\Delta_{t+1,t_0} - \Delta_{t,t_0}$ reflects the change in demographics from t to $t+1$. Thus Δ_{t_1,t_0} reflects the cumulative effect of changing demographics since period t_0. This series rose by 84 basis points from 1954 to its high point in August 1978, and has since fallen by 81 basis points (Figure 6). Since the 1979 business cycle peak, $\Delta_{t_1,48:01}$ declined by 76 basis points, 68% of the total decline in unemployment.

[8]Using a different base year gives similar results. For example, $U^G_{t_1,54:12}$ (using the demographically 'best' point as the base year) rose by 179 basis points in the 1970s and declined by 38 basis points in the last nineteen years. $U^G_{t_1,97:11}$ rose by 185 basis points and then declined by 38.

[9]Different base years give similar results. We can also let $u_{t_0}(i)$ equal the unconditional expectation of group i's unemployment rate, as estimated by an ARMA(2,2) like equation (1). This implies a 91 basis point increase in unemployment due to demographics from 1954 to 1978 and a subsequent 80 basis point decline.

Δ is not a perfect measure of demographics either,[10] since it may be affected by the cyclicality of labor market participation. For example, youth participation varies more with the business cycle, since prime age workers do not move in and out of the labor market very easily.[11] During the 1960s and 70s, when the youth population was increasing, this should have reduced the change in the weights $\omega(i)$ during recessions, since the secular increase in the share of youth was offset by their cyclical decrease in participation. It should have increased the change in the weights during expansions, since the two effects moved in the same direction. In calculating Δ, we multiply these weights by the current unemployment rate, which is higher during recessions. This would tend to moderate the change in Δ. This argument can be reversed to suggest that changes in Δ during the 80s and 90s are exaggerated. This may help explain why the 'simple' demographically adjusted unemployment series U^D changed by more than the chain-weighted series Δ in the 60s and 70s, and by less in the 80s and 90s. Still, Figure 2 demonstrates that the secular shifts in labor market shares swamp any cyclical variations, so this issue is unlikely to be quantitatively important.

Data problems may bias both demographic adjustments to zero. Suppose we divide the population into only two age groups, 16–24 and 25+. We find that Δ rose by 74 basis points from 1954 to 1978, and then declined by 73 basis points from 1978 to 1997. Any other division into two groups gives smaller changes. For example, with age groups 16-19 and 20+, we only observe half of the change in Δ during both time intervals. It is not surprising that aggregation reduces the measured demographic changes, since it is precisely the differences in disaggregate unemployment rates and the changes in labor market shares that result in demographic adjustments. If we could divide the population into more age groups, logic and evidence suggests that we would attribute more of the decline in unemployment to the changing age structure of the labor force.

[10] Both of my measures of the demographic unemployment rate differ from the measure suggested by Perry (1970) and used by him and Gordon (1982). Perry and Gordon weight different groups by their members' total annual earnings, and construct an alternative measure of unemployment using these weights. The demographic adjustment is then the difference between the actual unemployment rate and this series. I show in Section 3 that a simple model justifies the use of U^G to represent genuine changes in unemployment, and U^D or Δ to represent demographic changes. My theory does not suggest Perry's demographic adjustment.

[11] One way to quantify this is to look at the covariance between real GDP growth and labor market participation growth for different age groups. If a group moves out of the labor market during recessions, this should be positive. From 1948 to 1979, the covariance for teenage workers was eight times the covariance for workers age 45–54 and ten times the covariance for workers age 55–64. For the remaining four groups of workers, the covariance was actually negative. Since 1980, the covariance between these two series has become positive for all groups. Still, the covariance is three times as large for teenagers as for workers 20–24, and at least eight times larger than for the remaining five groups.

In light of these caveats, under the maintained hypothesis, the aging of the baby boom explains at least seventy percent of the decline in unemployment since 1979, leaving about thirty or forty basis points unexplained. The entry of the baby boom into the labor market had the opposite effect, but explains a smaller percentage of the larger increase in unemployment during the sixties and seventies.

2.2 Sex

Another dramatic trend has been the increasing participation of women in the U.S. labor market (Figure 7). This would have the potential to explain a change in the aggregate unemployment rate if women had a different unemployment rate than men. Historically this was the case, although the gap has disappeared during the last fifteen years (Figure 8). More precisely, both series are described by statistically identical ARMA(2,2) processes.

As this suggests, female participation cannot explain much of the change in unemployment. For example, divide workers up by sex and construct the chain weighted series Δ as in equation (5). This explains a 19 basis point rise in the unemployment rate from 1950 to 1979, and then virtually no change in the unemployment rate from 1979 to 1997 (Figure 9).

The behavior of U^D, defined in equation (4) depends strongly on the choice of base year. If we choose a year when women's unemployment is lower (higher) than men's, then U^D monotonically declines (increases). This highlights the disadvantage of U^D when the relationship between disaggregate unemployment rates is unstable. For this reason I use Δ as my primary measure of demographic unemployment.

One might be tempted to add the demographic changes reported here and in the first part of this section, in order to obtain the effects of the changes in the age and sex composition of the labor force — a 103 basis point increase in unemployment from 1954 to 1978, followed by an 81 basis point decline in unemployment from 1978 to 1997. That calculation is incorrect if there are any 'mix effects' between age and sex. For example, the increase in participation has been most dramatic for prime age women, who have a much lower unemployment rate than teenage women. Thus the increase in female participation may be double-counted as a relative decrease in teenage participation. Constructing Δ with fourteen age and sex groups, we find that age and sex jointly account for a 96 basis point increase in the unemployment rate from 1954 to 1978, followed by an 80 basis point decline in the unemployment rate from 1978 to 1997. Mix effects are quantitatively unimportant.

2.3 Race

The fraction of the labor force that is white was nearly constant from 1948 to 1971. Since then, it has declined from 89% to 84%. Figure 10 shows that most of the increase in labor force share has been for people who are neither white nor black. Conversely, the white unemployment rate is only slightly lower than the unemployment rate for this group (Figure 11). The big gap between black and white unemployment rates should have had little effect on demographics, since the black labor force share has been stable.

Dividing the labor force into three race categories, black, white, and other,[12] I find that Δ was constant from 1960 to 1977, and has since increased by sixteen basis points (Figure 12). The changing racial composition has slightly mitigated the decline in unemployment in the last two decades.

I do not expect that it is race *per se* that leads non-whites to have a high unemployment rate.[13] Instead, it is variables like poor schooling and poverty. A demographic adjustment for the changing race composition would be misleading, if the relationship between race, quality of school, and wealth is changing over time. Since the magnitude of the race adjustment is not very large, this distinction is economically not very important. In practice, I do not adjust the unemployment rate for the racial composition of the labor force.

2.4 Education

The final trend that I examine is the increased education of the U.S. labor force (Figure 13). Since 1970, the percentage of workers[14] with at least some college education has increased from 26% to 56%. The percentage with only a high school diploma increased from 38% in 1970 to 40% in the early 1980s, and has since fallen to 33%. The percentage with less than a high school diploma fell steadily from 36% to 11% during this time period.

Also, less educated workers have a much higher unemployment rate (Figure 14).

[12] Data limitations only allow me to divide the labor force into two groups, white and other, before 1972. Since whites and blacks account for 98.8% of the labor force in 1972, this is unlikely to be a problem. After 1972, separating out blacks and other non-whites is quantitatively important.

[13] Employer preference for hiring whites rather than blacks would give one direct link between race and unemployment. One implication of the the model in Section 4.1, is that if unemployment differences are due to discriminatory hiring, demographic adjustments to the unemployment rate are inappropriate.

[14] Throughout this section, I look at workers between the age of 25 and 64. A sixteen year old who works while in high school is probably quite different than an adult who dropped out of high school many years before. Since most workers have completed their education by age 25, I avoid complex aggregation issues by focusing on these workers.

The unemployment rate of workers with less than a high school diploma has been three to five times as high as the unemployment rate of workers with a college degree throughout this time period. The unemployment rate of those with a high school diploma has been two to three times as high. These differences have increased over time.

I can again construct the variable Δ as in equation (5), using the four education categories (Figure 15). I find that Δ has fallen by 99 basis points since 1979.[15] This is larger than the decline that can be explained by the changing age structure, so changes in education appear to be a promising explanation for the recent decline in aggregate unemployment. In fact, the sum of an age and education adjustment is a 175 basis point decline in unemployment during the 80s and 90s, while the actual unemployment rate only fell by 106 basis points.

I will argue in the remainder of this paper that this education adjustment is misguided. As indirect evidence for this claim, one can perform the same exercise in previous decades. My data show a decline in Δ of almost 60 basis points during the 1970s. Similarly, Summers (1986) calculates that the increase in education in the 1960s reduced the aggregate unemployment rate at a similar rate, about fifty basis points during the decade.[16] As Summers pointed out, if education 'explains' the unemployment decline during the last two decades, then it increases the mystery of why the unemployment rate was so very high in 1979.

There are two possible solutions to this issue. First, the problem could be ameliorated by the mix effects between age and education. Unemployment among college graduates may have been rising in the 1950s and 60s because most college graduates were young. This solution does not appear promising, because in looking at education, I have restricted attention to workers age 25–64. Empirically, the relationship between age and unemployment is weak for these workers, and so there is unlikely to be much overlap between the two demographic adjustments. Second, the maintained hypothesis, that changes in education do not affect unemployment conditional on education, may be false. The next two sections address the theoretical foundations of the maintained hypothesis, while the final section evaluates it empirically.

3. Youth Unemployment

Empirically, changes in the age and education composition of the labor force account for large changes in aggregate unemployment under the maintained hypothe-

[15]The annual change of about six basis points remains the same if we omit 1993 and 1994, the years that were affected by the redesign of the CPS.

[16]Summers effectively calculates the change in the gap between the actual unemployment rate and the genuine unemployment rate $U^G_{t_1,t_0}$, where the base year t_0 is 1965.

sis. Other demographic changes do not have as much potential explanatory power. Thus the remainder of this paper focuses exclusively on age and education.

This section develops a benchmark model of youth unemployment, in order to explore whether changes in the age structure of the population affect unemployment rates conditional on age. The model illustrates conditions under which the maintained hypothesis is satisfied, while simultaneously helping us to understand the bias that would be introduced by plausible violations of the hypothesis.

The premise of the model is that young workers do not have a particularly hard time finding jobs, but instead they have trouble keeping jobs. This is motivated by the fact that the mean and median unemployment durations in the U.S. are increasing functions of age. For example, the median unemployment duration of unemployed teenage workers during 1997 averaged 5.6 weeks, and the mean was 10.3 weeks. For workers between 55 and 64 years old, the median unemployment duration was 10.3 weeks and the mean was 21.9. This monotonic order surprisingly holds for the six working-age groups (16–19, 20–24, 25-34, 35–44, 45–54, and 55–64) and for every year since 1976, when the Bureau of Labor Statistics began reporting unemployment duration data.[17] Since more young workers are unemployed, but those who lose their jobs stay unemployed for shorter, it follows that young workers are much more likely to lose their jobs.[18]

I assume that young people lose their jobs more frequently not because they are young, but because they are inexperienced. More precisely, the hazard rate of job loss is decreasing in the length of time since the worker was last unemployed or out of the labor force, her 'job tenure'. Thus when an older worker loses her job, she is thrust back into the same situation as a younger worker. There are a number of theoretical justifications for this assumption. A new employee may be unsuitable for her job, but this can only be learned by trial-and-error. After surviving an apprenticeship, her job security increases. Moreover, as she stays on the job for a long period of time, she acquires specific human capital, making firing costly. Even if she quits her job to take a new one, she will tend to do so only if she expects it will enhance her job security. There is also an empirical justification for the assumption: it matches U.S. data.

[17]The fact that older workers stay unemployed for longer may be due to their superior access to unemployment insurance. This possibility goes beyond the model here.

[18]There is some controversy about this conclusion. Clark and Summers (1982) argue that youth unemployment duration is reduced by unemployed workers leaving and reentering the labor force, and that the source of youth unemployment is a core group of young workers who cannot find jobs.

3.1 Modeling Job Loss

I do not take a stand on why the hazard rate of job loss is decreasing, but instead set up a simple model with that property. A representative worker is 'born' unemployed. She looks for a job, and is hired with flow probability M. That is, during any interval of length t, an unemployed worker is hired with flow probability $1 - e^{-Mt}$. When she is hired, her marginal product is initially equal to some constant s. Thereafter, productivity follows a random walk in continuous time: productivity after t periods is $x(t) = s + \sigma Z(t)$, where $Z(t)$ is a standard Brownian motion. Thus after $\tau < t$ periods, $x(t)$ is a normally distributed random variable with with mean $x(\tau)$ and variance $\sigma^2(t-\tau)$. I assume that the job is destroyed when productivity falls below some threshold $\underline{x} < s$.[19] Following a separation, she looks for a new job, finding one with flow probability M. Productivity in the new job is again initially equal to s, and again follows a random walk. This repeats forever. The unemployment rate of workers at age t is equal to the probability that this representative worker is unemployed at age t. Later in this section, I endogenize the separation threshold $\underline{x}$ and the hiring rate M. However, it is simpler at this stage to treat these two variables as exogenous.

Under these assumptions, a match ends within t periods with probability

$$F(t) = 2\Phi\left(-\frac{s - \underline{x}}{\sigma\sqrt{t}}\right) \tag{6}$$

where Φ is the cumulative distribution of a standard normal random variable. Figure 16 depicts the match survival probability for one particular value of $(s - \underline{x})/\sigma$.

The intuition for this result is the 'Reflection Principal' (Karatzas and Shreve, 1991). Momentarily ignore the fact that matches are terminated when productivity reaches the threshold $\underline{x}$. Consider a sample path that first reaches $\underline{x}$ after t' periods. Given this, productivity at some time $t > t'$ is distributed normally with mean $\underline{x}$. Thus among sample paths that first reach the separation threshold after t' periods, only half of them have productivity less than $\underline{x}$ after $t > t'$ periods. Since t' was chosen arbitrarily, this is true for any $t' \in [0, t]$. Thus for sample paths that reached the separation threshold within t periods, exactly half of them have productivity less than the separation threshold after t periods. The fraction of sample paths that are below the separation threshold after t periods is

$$\Phi\left(-\frac{s - \underline{x}}{\sigma\sqrt{t}}\right)$$

This must be half of the fraction of sample paths that reach the separation threshold

[19] If $\underline{x} \geq s$, all matches are destroyed immediately upon creation, an uninteresting case.

within t periods, and hence half the fraction of matches that are terminated within t periods, $F(t)/2$.

The hazard rate of separation in a t-period-old match is $F'(t)/(1-F(t))$, depicted in Figure 17. This is increasing for small values of t, since a sample path is unlikely to fall from s to $\underline{x}$ in a very short period of time. It is decreasing for large values of t, since conditional on a match having survived for a long period of time, productivity is likely to be much larger than the separation threshold.

3.2 The Relationship between Unemployment and Age

Let $u(t)$ denote the probability that the representative worker is unemployed at age t. This must satisfy a backward-looking differential equation:

$$\dot{u}(t) = -Mu(t) + M \int_0^t u(\tau) F'(t-\tau)\, d\tau \tag{7}$$

with initial condition $u(0) = 1$. Unemployment decreases due to match creation and increases due to match separations. The flow probability that a worker is hired at age t is the flow probability that an unemployed worker is hired M times the probability that she is actually unemployed at t. The flow of separations depends on earlier hiring probabilities. She was hired at age $\tau \in [0, t]$ with flow probability $Mu(\tau)$. The flow probability that this job ends at t is $F'(t-\tau)$, where F is the probability that a match does not survive, given in equation (6).

One can show that $u(t)$ converges to zero over time, because everyone winds up in very good matches eventually. Also, simulations show that $u(t)$ is monotonically decreasing (Figure 18), although since the separation hazard rate is non-monotonic, I cannot prove this analytically.

A simpler model in which the flow probability of a separation is a constant $\delta > 0$ (e.g. Mortensen and Pissarides, 1994) would deliver the same qualitative predictions as this model. However, quantitatively the models are extremely different. In the Mortensen-Pissarides model, the unemployment rate moves exponentially towards its steady state value; half the gap between the actual and steady state unemployment rate is closed in $\log 2/(\delta + M)$ periods. For plausible parameters, this implies the unemployment rate of workers with one year of labor force experience will be indistinguishable from the unemployment rate of prime age workers. This would be an inadequate explanation for youth unemployment.

The (mostly) declining hazard rate of job loss in this model implies a much slower decline in unemployment as a function of age. In the example depicted in Figure 18, the unemployment rate of workers with one year's labor market experience is 24%. It declines to 12% after four years and 6% after sixteen years. The eventual 'steady state' unemployment rate is zero. Thus there is a quantitatively strong and persistent relationship between age and unemployment in this model which is absent from the simpler model. This is why a declining hazard rate of job loss is a necessary ingredient in a model that explains youth unemployment through differential rates of job destruction. The interesting point is that it appears to be a sufficient ingredient as well.

3.3 Demographic Adjustment

I am now in a position to ask whether the demographic adjustments U^D and Δ and the genuine unemployment rate U^G appropriately reflect the impact of changes in the age structure of the population. Let $N(t)$ denote the population measure of infinitely lived workers at time t. Each worker's life proceeds as described above. To avoid introducing aggregate uncertainty, assume that all the stochastic processes in the economy are independent. That is, the hiring probabilities of different workers are independent, and the stochastic process for the productivity of worker i in job j, $Z_{ij}(t)$, is independently distributed.

The sole source of aggregate fluctuations is variations in the population growth rate, $\dot{N}(t)/N(t)$. Applying equation (2) and the law of large numbers, the aggregate unemployment rate must equal

$$U_t = \int_0^\infty u_t(\tau)\frac{\dot{N}(t-\tau)}{N(t)}d\tau$$

$u_t(\tau)$ is the unemployment rate of τ-year-old workers in period t, as given by the solution to differential equation (7). $\dot{N}(t-\tau)$ workers were born τ periods ago, and the current population is $N(t)$. Thus the labor market share of τ-period-old workers is $\omega_t(\tau) = \dot{N}(t-\tau)/N(t)$.

Since the only shocks in this model are demographic, all fluctuations in unemployment should be attributed to demographics. It is easy to verify conditions under which our constructions from Section 2 behave correctly. Use (3), (4), and the continuous time limit of (5):

$$U^G_{t_1,t_0} = \int_0^\infty u_{t_1}(\tau)\frac{\dot{N}(t_0-\tau)}{N(t_0)}d\tau$$

$$U^D_{t_1,t_0} = \int_0^\infty u_{t_0}(\tau)\frac{\dot{N}(t_1-\tau)}{N(t_1)}d\tau$$

$$\Delta_{t_1,t_0} = \int_{t_0}^{t_1}\int_0^\infty u_t(\tau)\frac{d}{dt}\left(\frac{\dot{N}(t-\tau)}{N(t)}\right)d\tau dt$$

Now suppose the unemployment rate of workers conditional on their age does not vary over time, $u_t(\tau) = u_{t_0}(\tau)$ for all t, t_0 and τ. Simplifying the equations above yields three conclusions:

1. The genuine unemployment rate is constant over time t_1 for fixed initial time t_0: $U^G_{t_1,t_0} \equiv U_{t_0}$, so none of the changes in unemployment are genuine;

2. The demographic unemployment rate tracks the actual unemployment rate, $U^D_{t_1,t_0} \equiv U_{t_1}$, so all of the changes in unemployment are demographic; and

3. The chain-weighted unemployment rate tracks the change in the unemployment rate, $\Delta_{t_1,t_0} \equiv U_{t_1} - U_{t_0}$, again stating that all of the changes in unemployment are demographic.

All three constructions recognize that the change in aggregate unemployment is demographic. On the other hand, if the age-specific unemployment rates depend on the age distribution, and so vary over time, demographic adjustments are misleading.

In summary, the question of whether these constructions capture demographic changes well, is equivalent to the question of whether the disaggregate unemployment rates $u(\tau)$ are independent of the age distribution.[20] By equations (6) and (7), this requires that the age distribution not affect the hiring rate M and the threshold $\underline{x}$.[21]

3.4 Closing the Model

To see whether this is a reasonable assumption, I endogenize these two variables, following the general methodology of Pissarides (1985). I have already discussed workers' lifetime in some detail, and here I briefly outline the environment faced by firms. I assume firms use a constant returns to scale technology, and so without loss of generality I impose that a firm can employ at most one worker. It can either have a vacancy (and be looking for a worker) or have a filled job (and be producing). When a firm has a filled job, its productivity follows a random walk, as described before. The first issue is the determination of the separation threshold $\underline{x}$. My solution assumes that the economy is in steady state, but these results can all be generalized to non-stationary environments.

[20]This is certainly not the only model that ensures that disaggregate unemployment rates satisfy this property. For example, if heterogeneous workers choose to segregate themselves into separate labor markets, as in Acemoglu and Shimer (1997), a change in the distribution of workers changes the size of each labor markets, but has no effect on unemployment rates. I do not use this segregation model to study youth unemployment, since it focuses attention on job creation. As discussed before, the primary cause of youth unemployment is the high rate of job destruction.

[21]I assume that the technological parameters s and σ are unaffected by demographics.

The Separation Threshold

An employment relationship is terminated when it is in the mutual interest of the worker and her employer.[22] Let $\mathcal{W}(x)$ denote the expected present value of the firm's profits plus the worker's wages, discounted at the interest rate $r > 0$, as a function of current productivity x. Let $\mathcal{U}$ denote the worker's value following a separation, the expected present value of her future wages while she is unemployed; and $\mathcal{V}$ denote the firm's value, the expected present value of its future profits while it has a vacancy. These values do not depend on x, as this represents an idiosyncratic or match-specific shock. Then the match ends if $\mathcal{W}(x) \leq \mathcal{U} + \mathcal{V}$. Otherwise, the productivity process implies $\mathcal{W}(x)$ satisfies a second order differential equation:

$$r\mathcal{W}(x) = x + \tfrac{1}{2}\sigma^2 \mathcal{W}''(x)$$

The flow value of a match comes from its current productivity x plus the capital gain from changes in x. Although there is no drift in the stochastic process for productivity, variability of x raises the value if $\mathcal{W}$ is a convex function. The expected value of $\mathcal{W}$ next period is larger than $\mathcal{W}$ evaluated at the expected productivity, an application of Jensen's inequality.

The general solution to this differential equation is

$$r\mathcal{W}(x) = x + k_1 e^{-\frac{\sqrt{2r}}{\sigma}x} + k_2 e^{\frac{\sqrt{2r}}{\sigma}x}$$

for constants k_1 and k_2. We require two terminal conditions. First, if x is very large, the threat of a separation is remote. An additional unit of productivity must raise the value of a match by $1/r$. $\lim_{x\to\infty} \mathcal{W}'(x) = 1/r$, so $k_2 = 0$.

Next, observe that $\mathcal{W}$ is weakly increasing.[23] This verifies the optimality of a threshold rule. Now if productivity x is close to the threshold $\underline{x}$, it will fall below $\underline{x}$ in a short interval of time with probability close to 1. This property of Brownian motions implies that a small change in productivity near the threshold $\underline{x}$ will have almost no effect on the present value, $\mathcal{W}'(\underline{x}) = 0$. Thus

$$k_1 = \frac{\sigma}{\sqrt{2r}} e^{\frac{\sqrt{2r}}{\sigma}\underline{x}}$$

[22] A generous interpretation of this model would recognize that it allows for job-to-job movement. Suppose an employed worker takes a new job when it is in the mutual interest of her current and future employers and herself. This may be ensured by the structure of her contract, which can include 'breach of contract' penalties, such as vested pension plans (Diamond and Maskin, 1979; Diamond and Maskin, 1981). Then $x(t)$ should be interpreted as productivity after t periods, assuming the worker follows an optimal sequence of job-to-job moves.

[23] To prove this formally, use the fact the fact that the optimal 'stopping rule' for one value of x can also be used for a higher value x'. This must yield at least as high a value. Using an optimal termination rule must yield a still higher value.

so

$$r\mathcal{W}(x) = x + \frac{\sigma}{\sqrt{2r}} e^{-\frac{\sqrt{2r}}{\sigma}(x - \underline{x})} \tag{8}$$

Finally, the value of the match at the threshold must equal the sum of the values after a separation, $\mathcal{W}(\underline{x}) \equiv \mathcal{U} + \mathcal{V}$:

$$\underline{x} = r(\mathcal{U} + \mathcal{V}) - \frac{\sigma}{\sqrt{2r}} \tag{9}$$

Matches survive even after productivity passes below the myopic threshold $x = r(\mathcal{U} + \mathcal{V})$. The reason is that a separation destroys the option to take advantage of future productivity increases. The option is worth more when agents are patient (r is small) and when the variability of output is large (σ is large), since productivity is more likely to increase substantially in the near future.

Job Search and the Hiring Rate

I next turn to the job search process. This will allow me to determine the continuation values $\mathcal{U}$ and $\mathcal{V}$ and the hiring rate M.

An important question is how wages are determined in this environment. There is generally surplus when a new match is created, since the worker and firm are jointly better off matching instead of waiting for new partners. There are a number of ways that the surplus can be divided.[24] At this point choosing how is not very important. However, later in the paper it is convenient to use a 'multilateral' bargaining rule (Shimer, 1997), and so I introduce it now.

Multilateral bargaining focuses on the mechanics of the matching process. Every unemployed worker targets her job search towards one vacancy, selected at random. With exogenous flow probability π, the vacancy 'closes'. However, that does not guarantee the worker a job. Other unemployed workers may also be applying for the job opening, giving the firm an opportunity to hire one of the competing applicants. The multilateral bargaining rule is that the firm 'sells the job to the highest bidder'. This can equivalently be thought of as Bertrand competition or a second price auction between job applicants.[25] As a result, a worker's wage depends on the circumstances under which she was hired.

[24] For example, Pissarides (1985) sparked a literature that assumes wages are set by 'Nash bargaining'. A worker and firm divide the difference between the value of a match and the sum of their outside options. Let $\beta \in [0, 1]$ denote the workers' 'bargaining power'. Her value increases by $\beta(\mathcal{W}(s) - V - \mathcal{U})$ when she gets a job. The value of a firm jumps by $(1 - \beta)(\mathcal{W}(s) - V - \mathcal{U})$. The conclusions in this section would be unchanged by this bargaining rule.

[25] This wage setting procedure is equivalent to other 'job auctions' (Shimer, 1997). For example, workers may not know the number of competing applicants. They bid for jobs by committing to a

Since all workers are equally likely to apply for all job openings, the number of applicants for a given vacancy is a Poisson random variable with expectation q, equal to the ratio of the measure of unemployed workers to the measure of firms with vacancies. That is, the probability that $n \in \{0, 1, 2, \dots\}$ other applicants compete for a particular job is $q^n e^{-q}/n!$. In particular, when a worker's desired job vacancy closes, there are no other applicants with probability e^{-q}. In this event, she is hired and is able to extract all the surplus from the match. Her value jumps by $\mathcal{W}(s) - \mathcal{V} - \mathcal{U}$ upon being hired, where $\mathcal{W}(s)$ is the value of a new match. She may still be hired if there are other job applicants; however, if this happens, the firm is able to extract all the surplus. The firm's value jumps by $\mathcal{W}(s) - \mathcal{V} - \mathcal{U}$, while all the applicants' values are constant whether or not they are hired.

Putting this together, the value of an unemployed worker satisfies

$$r\mathcal{U} = y + \pi e^{-q}(\mathcal{W}(s) - \mathcal{V} - \mathcal{U}) \tag{10}$$

Here y represents a worker's exogenous unemployment benefit or value of leisure. With flow probability e^{-q} the worker is the only applicant for a vacancy when it closes, and so enjoys a capital gain. Similarly, the value of a vacant firm satisfies

$$r\mathcal{V} = -c + \pi \left(1 - e^{-q}(1+q)\right)(\mathcal{W}(s) - \mathcal{V} - \mathcal{U}) \tag{11}$$

where c is the cost of maintaining an open vacancy. When the vacancy closes, there is a probability e^{-q} of there being no applicants. The firm must reopen the vacancy. With probability qe^{-q}, the firm receives one application, and so hires the applicant; but she keeps the whole surplus. Otherwise the firm enjoys a capital gain. Equations (8), (9), (10), and (11) can be solved for the endogenous variables $\underline{x}$, $\mathcal{U}$, $\mathcal{V}$, and $\mathcal{W}$ as functions of the various parameters and the unemployment vacancy-ratio q.

Finally, since conditional on a vacancy closing with n other applicants, a worker is hired with probability $1/(n+1)$, the flow rate at which she is hired is

$$M = \pi \sum_{n=0}^{\infty} \frac{q^n e^{-q}}{(n+1)!} = \pi \frac{1 - e^{-q}}{q} \tag{12}$$

Thus M is a simple function of the unemployment-vacancy ratio q as well. If q does not depend on the age distribution of the population, the disaggregate unemployment rates do not depend on the age distribution, and a demographic adjustment for the baby boom is justified.

wage if they are hired, and the firm accepts the worker who demands the lowest wage. Although the analysis is more complex, since one must solve for the equilibrium (mixed) bidding strategy, the conclusions are unchanged. In particular, $\mathcal{U}$ and $\mathcal{V}$ are the same as with this wage setting rule. This is essentially an application of the Revenue Equivalence Theorem (Riley and Samuelson, 1981).

3.5 Conclusion

What does it mean for q to be independent of the age distribution? The most sensible interpretation is that job creation and labor demand are perfectly elastic. If free entry drives the value of a vacant job $\mathcal{V}$ to zero, one can solve for the equilibrium values of q and $\mathcal{U}$ with no reference to the age distribution. Essentially, changes in labor supply are accommodated by changes in labor demand, leaving the hiring rate M and separation threshold $\underline{x}$ unchanged.

The evidence on the elasticity of labor demand is mixed. More populous countries do not have higher unemployment rates, so the cross-sectional evidence is that labor demand is elastic. But it is less clear whether this is true within countries over medium time horizons. Katz and Murphy (1992) argue that from 1965 to 1980, wages tended to decrease for a group of workers when the size of that group increased, evidence for relatively stable labor demand curves. During the 1980s, wages tended to increase, suggesting that labor demand might have *overreacted* to labor supply shifts. Also, Krueger and Pischke (1997) argues that the U.S. 'employment miracle' is due to the ability of the labor market to absorb large changes in supply. They cite the wage *decreases* for young workers at the time that the 'baby bust' entered the labor force as supporting evidence. Another famous example is the large migration of Cubans to Miami, which had little effect on wages in Miami (Card, 1990). Thus the benchmark model offers a simple, plausible condition under which the baby boom should have had no effect on disaggregate unemployment rates, and the demographic adjustment performed in Section 2 is justified.

4. Low Skilled Unemployment

I now turn to the source of low skilled unemployment. Skilled workers have a lower unemployment rate because their skills are most useful while they are employed. The gap between their productivity while employed and while unemployed is large, and so the cost of searching for a job is relatively small compared to the potential reward. Similarly, firms will spend much more effort recruiting skilled workers. There is even an industry ('headhunters') that attempts to match skilled workers with jobs. Reinforcing this effect, the large gap between skilled workers' productivity s and reservation wage $\underline{x}$ implies that they are much less likely to be fired during downturns. In short, skilled workers are rarely fired, and have a relatively easy time finding a job when they are.

Since more educated workers tend to be more skilled, increases in education raise the fraction of the population in low unemployment categories. This suggests a demographic adjustment is merited. There are at least two objections to this reasoning. First, the absolute level of education may be less important than relative education attainment. An increase in the percentage of job seekers with a college degree not only increases the competition for jobs among college graduates, but puts workers with only a high school diploma at a further disadvantage. Thus the unemployment rate of all education levels may increase when all workers get more education, even if the aggregate unemployment rate is unchanged. A demographic adjustment would incorrectly interpret this as a demographic reduction in unemployment, and an offsetting genuine increase, and so is misleading.

Second, the fact that more educated workers tend to be more skilled does not imply that increases in education raise the skill level of the labor force. This point is crystallized by Spence's (1973) job market signaling model. If education is more costly for low ability workers, it may be used to indicate ability to future employers, and hence may be undertaken even if it conveys no direct benefit. Changes in the cost of education or the return to ability may then alter workers' education decision, but this has no effect on the skill distribution. More generally, if education is positively correlated with ability, the average college graduate today is less able than the average college graduate was twenty years ago. Again, a demographic adjustment for education overstates the true effect of a change in education.

4.1 A Model of Relative Educational Attainment

I begin by showing that if employers only care about workers' relative educational attainment education, demographic adjustments are extremely misleading.[26] I extend the model in Section 3 by assuming that when workers are born, they are randomly and independently assigned an educational attainment or schooling level $s \in S \subset \mathbb{R}_+$. Let $g : S \mapsto \mathbb{R}_+$ represent the atomless density of educational attainment.

I make two simplifications to the basic model. First, the population growth rate is a constant $\dot{N}(t)/N(t) \equiv \gamma > 0$. Second, when a type s worker gets a job, her productivity is equal to s and is constant thereafter. In the language of Section 3, $\sigma = 0$. As a result, jobs last forever, and I can ignore job destruction. With this assumption, it is obviously not true that more educated workers lose their jobs less frequently. However, it simplifies the analysis considerably: equation (8) implies that the value of a type s job is $\mathcal{W}^*(s) \equiv s/r$. This helps elucidate the main point, which is about relative rates of job creation. The analysis here could be extended to allow $\sigma > 0$ without qualitatively changing the results.

[26]This is related to the point by Blanchard and Diamond (1994) that if firms prefer to hire workers who have been unemployed for less time, a worker's relative, not absolute, unemployment duration affects her probability of finding a job. The model here is an extension of Blanchard and Diamond (1995) and Shimer (1997).

Balanced Growth Path

I look for a balanced growth path. On this path, the type dependent flow matching probabilities $M(s)$ are constant over time, so the unemployment rate of type s workers at age t is $e^{-M(s)t}$. Using the fact that age t workers comprise a density $\gamma e^{-\gamma t}$ of the labor force at any point in time, the unemployment rate of the average type s worker, aggregating across age cohorts, is

$$\tilde{u}(s) = \frac{\gamma}{\gamma + M(s)} \tag{13}$$

This is decreasing in the flow matching probability for obvious reasons. It is increasing in the population growth rate, since fast population growth increases the relative proportion of young workers.

It is also convenient to define the fraction of unemployed workers with schooling less than s:

$$\theta(s) = \frac{\int_0^s \tilde{u}(s')g(s')ds'}{U} \tag{14}$$

where $U \equiv \int_S \tilde{u}(s)g(s)ds$ is the aggregate unemployment rate.

Matching Probabilities

The job search process is a generalization of the process described in Section 3.3. In this stylized model, there is only one type of job, so college graduates and high school dropouts compete directly against each other for jobs. This represents a more realistic world of 'interlinked competition', in which college graduates compete against workers with some college education; and workers with some college education apply for other jobs, in which they compete against high school graduates; who are apply for still other jobs in which they compete against dropouts.

Job vacancies close with flow probability π. The number of other applicants is a Poisson random variable with expectation q. I assume that the most educated applicant always gets the job, and verify in the next paragraph that this 'ranking rule' is an equilibrium.[27] Thus s is hired with flow probability

$$M(s) = \pi e^{-q(1-\theta(s))} \tag{15}$$

[27]One can also prove that the equilibrium is unique. See Shimer (1997), which also argues that for a wide range of wage determination procedures, more productive workers will always be hired in preference to less productive ones. This contrasts with Blanchard and Diamond (1995), which shows that with the Nash bargaining rule described in footnote 24, lower quality workers may be ranked ahead of higher quality ones. The important distinction is whether the presence of workers who are not hired affects the wage of workers who are hired.

Since $\theta(s)$ is monotonically increasing, less educated workers are hired less frequently, and so have a higher unemployment rate.

Now return to the assumption that the most educated applicant is always hired. To verify this, I must generalize the multilateral bargaining game to this environment. If there is only one applicant s for a job, she retains the entire match surplus $\mathcal{W}^*(s) - \mathcal{U}(s) - \mathcal{V}$. If there are multiple applicants, the firm cannot extract the most educated applicant's entire value, but it instead extracts the value that it would get if it hired the second most educated applicant and retained the entire surplus. If the second highest applicant's type is s', then s enjoys a gain $(\mathcal{W}^*(s) - \mathcal{U}(s)) - (\mathcal{W}^*(s') - \mathcal{U}(s'))$. For s to be willing to outbid s', this must be positive.

Using this bargaining rule, one can prove that

$$r\mathcal{U}'(s) = M(s)\big(\mathcal{W}^{*\prime}(s) - \mathcal{U}'(s)\big) \tag{16}$$

Intuitively, the gain to a small increase in schooling ds, is that with probability $M(s+ds)$, a type $s+ds$ worker is hired, and in that event she keeps an extra bit of surplus $(\mathcal{W}^{*\prime}(s) - \mathcal{U}'(s))ds$. The fact that she is hired more often, $M(s+ds) - M(s) \approx M'(s)ds > 0$, is a second order effect. To the extent that $s+ds$ is hired more often than s, this happens only if she is hired in preference to some s' between s and $s+ds$. The value of the job to s' is nearly the same as the value to $s+ds$, so multilateral bargaining holds $s+ds$ nearly to her reservation value.

The return to education $\mathcal{U}'(s)$ is strictly positive but less than the productivity increase $\mathcal{W}^{*\prime}(s) \equiv 1/r$. This implies that the match surplus $\mathcal{W}^*(s) - \mathcal{U}(s) - \mathcal{V}$ is increasing in s, so more educated workers will always outbid less educated ones. The 'ranking rule' described here is in fact an equilibrium, and so the probability that a type s worker is hired is given by (15).

Effect of Demographics

Now I can address the effect of an increase in education on unemployment. I begin by showing that the aggregate unemployment rate does not depend on demographics g. Rewriting the education-specific unemployment rate (13) as $\tilde{u}(s) = 1 - M(s)\tilde{u}(s)/\gamma(s)$, the aggregate unemployment rate satisfies

$$U = \int_S \left(1 - \frac{M(s)\tilde{u}(s)}{\gamma}\right) g(s)ds$$

Expanding $M(s)$ and then using the fact that $\theta'(s) = \tilde{u}(s)g(s)/U$ yields:

$$U = 1 - \frac{\pi}{\gamma}\int_S e^{-q(1-\theta(s))}\tilde{u}(s)g(s)ds = 1 - \frac{\pi}{\gamma}\frac{e^{-q}}{q}U$$

This is easily solved for U with no reference to the schooling distribution g. Since changes in schooling have no effect on unemployment, any demographic adjustment is completely spurious.

Despite this, under the maintained hypothesis, demographic changes would lead us to make significant demographic adjustments. This is because demographic changes affect disaggregate unemployment rates, a violation of the maintained hypothesis. Consider the effect of a first order stochastic dominating 'improvement' in the schooling density from g_1 to g_2.[28] That is, for all $s \in \tilde{S} \subseteq S$,

$$\int_0^s g_1(s')ds' > \int_0^s g_2(s')ds' \tag{17}$$

with a weak inequality for $s \in S \setminus \tilde{S}$. I will prove that this raises all the type contingent unemployment rates,

$$\tilde{u}_1(s) < \tilde{u}_2(s) \text{ for all } s \in \tilde{S} \tag{18}$$

I omit the similar proof that the unemployment rates are equal for other $s \in S \setminus \tilde{S}$.

According to (13), my claim is equivalent to $M_1(s) > M_2(s)$ for all s; by (15), that is equivalent to $\theta_1(s) > \theta_2(s)$ for all s. So in order to find a contradiction, assume that $\theta_1(s) \leq \theta_2(s)$ for some s. By (14) and the fact that aggregate unemployment U is unchanged,

$$\int_0^s \tilde{u}_1(s')g_1(s')ds' \leq \int_0^s \tilde{u}_2(s')g_2(s')ds'$$

Subtract this from (17); multiply both sides by γ; and then again apply the relationship $\gamma(1 - \tilde{u}_i(s')) = M_i(s')\tilde{u}_i(s')$.

$$\int_0^s M_1(s')\tilde{u}_1(s')g_1(s')ds' > \int_0^s M_2(s')\tilde{u}_2(s')g_2(s')ds'$$

Now replace $M_i(s')$ using (15) and solve the resulting integrals to find $e^{-q(1-\theta_1(s))} > e^{-q(1-\theta_2(s))}$ or $\theta_1(s) > \theta_2(s)$, contradicting our hypothesis and establishing (18).

Now suppose one naïvely calculated the change in the 'genuine unemployment rate' as in Section 2:

$$U_{2,1}^G - U_{1,1}^G = \int_S g_1(s)(\tilde{u}_2(s) - \tilde{u}_1(s))ds = \int_{\tilde{S}} g_1(s)(\tilde{u}_2(s) - \tilde{u}_1(s))ds > 0$$

[28] I perform a comparative statics exercise here, while recent decades are probably better characterized by a transition to a new steady state. These results also hold along the transition path.

where the inequality is an application of (18). One would mistakenly interpret the increase in type-specific unemployment rates as a genuine increase in unemployment. Conversely, one would find that the 'demographic' decline in unemployment exactly offsets the 'genuine' increase: $U_{2,1}^D - U_{1,1}^D = -(U_{2,1}^G - U_{1,1}^G) < 0$. But we just proved that the aggregate unemployment rate is unaffected by demographics! Thus this model illustrates a case in which demographic adjustments are theoretical nonsense and extremely misleading.

The Difference between Age and Education

An important question is why this model describes the effect of changes in the schooling distribution, but cannot be altered to describe the effect of changes in the age distribution. That is, another potential explanation for youth unemployment is that firms hire older workers in preference to younger ones. The problem with this explanation is that it has the counterfactual prediction that older workers have a shorter unemployment duration. As I discussed at the start of Section 3, youth unemployment is a consequence of the short duration of jobs, not the length of unemployment spells. Thus an argument that 'relative age not absolute age' matters appears incorrect. Section 5 also provides empirical evidence that changes in schooling have very different effects than changes in the age distribution.

4.2 Endogenous Education

My analysis has glossed over one important issue: an increase in skills raises the value of a vacancy in the ranking model. In treating q as exogenous, I have implicitly assumed that labor demand is perfectly inelastic in the long run. The analytical proof of this is an algebraic mess, but the intuition is clear. The value of a firm is increasing in the skill of the second best applicant, since surplus is increasing in skill by equation (16). The expected skill level of this applicant is higher when the labor force is more skilled.

Making q endogenous and $\mathcal{V}$ exogenous through an elastic job creation condition clouds the analysis considerably. With elastic labor demand, the increase in the value of a vacancy will cause entry, which will reduce aggregate unemployment. Some of the disaggregate unemployment rates will decrease, although many will continue to increase. A demographic adjustment is still misleading, since one would conclude that there had been a sharp demographic decline in unemployment, partially offset by a genuine increase. However, it would be less misleading than the analysis in the text suggests.

Ability Bias

Fortunately, this issue is probably not very relevant, because a change in education is unlikely to have as large an effect on unemployment as Figure 14 suggests. The key reason for this, and another important difference between age and education, is that educational choice is endogenous. A number of theories predict that more able workers will opt for more education, so some of the unemployment rate differential attributed to education is in fact due to ability differences. Since we cannot observe workers' ability in the Current Population Survey, this problem is not easily corrected.

The basic issue is illustrated with another small extension to the model. When workers are born, they are endowed exogenously with an ability a drawn from a known density $\tilde{g}$. They are then given an option to invest in a unit of education ('go to college') at unit cost. If they go to college, they are left with skill $s = a + b$. If they do not make the investment ('drop out of high school'), $s = a$. The decision is irreversible. The rest of the model is unchanged. In particular, a worker's productivity is equal to her skill.

A college degree is worth more to a more able worker. The reason is that she will be employed more frequently, and therefore she makes better use of her educational investment. More formally, (16) implies that $\mathcal{U}'$ is increasing since M is increasing. Convexity of $\mathcal{U}$ implies that the slope of the secant $\mathcal{U}(a + b) - \mathcal{U}(a)$ is increasing in ability a. There is a threshold $\bar{a}$ such that workers with higher ability go to college, while those with lower ability drop out.

Since workers who go to college are more able and better educated, they are more skilled. Following the logic of the first part of this section, they are always hired in preference to dropouts, and so have a lower unemployment rate. However, this is not because they went to college. In this simple model, any college graduate is more able than all the dropouts, and so would have been hired in preference to them even if she had not gone to college. Likewise, if a high school dropout went to college, she would still be ranked below college graduates, and so would be unemployed more frequently. More to the point, despite the fact that the returns to education are positive and that college graduates have a lower unemployment rate than dropouts, the unemployment rate of college graduates would be the same if none of them went to college; and the unemployment rate of high school dropouts would be the same if all of them went to college.

To see why this matters, suppose there is a decrease in the cost of education or an increase in the returns to education. The threshold for attending college will fall. Since the marginal college graduate is of lower ability than the rest of the college graduates, this reduces the quality of the average college graduate. Since she is of higher ability than all the dropouts, it also reduces the quality of the average dropout. If we could observe workers' ability, we would realize that neither relative rankings nor unemployment rates conditional on ability have changed. We would conclude that there had been no change in unemployment, demographic or genuine. But since we observe education, not ability, we would see that unemployment has increased for both groups. A demographic adjustment would mistake this for a genuine increase in unemployment offset by a demographic decline. The fact that ability is unobservable leads to a further bias in the demographically adjusted unemployment rate.

Education as a Signal

Spence's (1973) signaling model affords an extreme case where education has no effect on skills, and so a change in the education distribution has no effect on the value of a vacancy.[29] People pay the high cost of a college degree and forgo years of labor income, because if they did not use this costly signal, they would be unable to obtain a high wage.

Suppose firms cannot observe applicants' skill but can observe how much they have invested in education, now a continuous choice variable $b \geq 0$. Applicants make wage demands, and the firm hires the applicant whom it expects will yield the most profit, retaining the expected profit from the second most attractive applicant. To do this, the firm must form beliefs about each applicant's skill based on its knowledge of her education and the relationship between skill and education. The most interesting case is a separating equilibrium, in which more skilled workers choose more education, $b = B(s)$ for some strictly increasing function B. This implies that upon observing education b, the firm can simply invert the education schedule B to calculate the implied skill. The firm believes that it has complete information, and so we can apply the analysis of the case with exogenous skill (Section 4.1). Firms always hire the most educated applicant, so the hiring rate as a function of education must satisfy an analog of equation (15):

$$\tilde{M}(b) = \pi e^{-q(1-\theta(B^{-1}(b)))}$$

where $B^{-1}(b)$ is the skill of a worker who chooses b units of education in equilibrium.

What keeps an unskilled worker from getting a lot of education and claiming that she is skilled? If she did so, she would be hired more rapidly, and more importantly, would be able to demand higher wages. The marginal value of an additional unit of

[29] Recent papers by Farber and Gibbons (1996) and especially Altonji and Pierret (1997) provide empirical support for the notion that firms 'statistically discriminate' on the basis of education, so education indeed serves as a costly signal. However, they conclude that education raises productivity as well.

education for an unemployed worker is the analog of equation (16):

$$\tilde{\mathcal{U}}'(b) = \frac{\tilde{M}(b)}{r + \tilde{M}(b)} \mathcal{W}'(B^{-1}(b))$$

This does not depend on a worker's skill.[30] Thus to sustain a separating equilibrium, we require that the cost of education depend on a worker's skill $C(b, s)$. More precisely, we need a single crossing property that the marginal cost of education is lower for more able workers. Given this restriction, a simple revealed preference argument implies that high skilled workers will opt for more education,[31] and strictly so if C is a continuously differentiable function (Edlin and Shannon, 1996).

Consider the effect of an increase in the returns to skill (skill-biased technical change), modeled as an increase in $\mathcal{W}'(s)$. To restore a separating equilibrium, all workers must endure more of the costly signal. Otherwise, it would pay unskilled workers to imitate the education choice of skilled workers. It is clear that this change in education can have no real effect on the economy, since it is simply a change in the expenditure on the costly signal. In particular, it gives firms neither more nor less of an incentive to create jobs. Despite this, because we cannot observe the decline in skill conditional on education, we would measure it as an increase in unemployment conditional on education. This is then misinterpreted as a genuine increase in unemployment, offset by the increase in expenditures on education, the costly signal.

5. How Much do Demographics Explain?

I have shown that there are theoretical reasons why demographic adjustments to the unemployment rate may or may not be appropriate, but ultimately this is an empirical question. If changes in a group's labor market share $\omega(i)$ do not affect any disaggregate unemployment rate $u(j)$, then $U^G_{t_1,t_0}$ is an accurate measure of what the unemployment rate would be at time t_1 if the demographics looked as they did in period t_0. $U_{t_1} - U^G_{t_1,t_0}$ measures how much the unemployment rate increased due to demographics. Similarly, $U^D_{t_1,t_0}$ is an accurate measure of what the unemployment rate would be if the only changes had been demographic, so $U^D_{t_1,t_0} - U_{t_0}$ is another measure of how much the unemployment rate increased due to demographics. To

[30] I am implicitly assuming that firms cannot punish workers who 'lie' about their skill by choosing the 'wrong' amount of education, $b \neq B(s)$. Firms must learn a worker's skill when they observe her productivity, and so I am imposing that contracts are incomplete.

[31] Proof: Take $s > s'$ who choose education b and b' respectively. Revealed preference implies $\tilde{U}(b) - C(b, s) \geq \tilde{U}(b') - C(b', s)$ and $\tilde{U}(b') - C(b', s') \geq \tilde{U}(b) - C(b, s')$. Add these inequalities and use the single crossing property to prove $b \geq b'$.

the extent that $U_{t_1} - U^G_{t_1,t_0} \neq U^D_{t_1,t_0} - U_{t_0}$, U^G and U^D are poor measures of genuine and demographic unemployment.

With a little algebraic manipulation, one finds that

$$\begin{aligned}\left(U_{t_1} - U^G_{t_1,t_0}\right) - \left(U^D_{t_1,t_0} - U_{t_0}\right) &= \sum_{i\in I}\left(\omega_{t_1}(i) - \omega_{t_0}(i)\right)\left(u_{t_1}(i) - u_{t_0}(i)\right) \\ &= \sum_{i\in I}\left(\omega_{t_1}(i) - \omega_{t_0}(i)\right)\left(\left(u_{t_1}(i) - U_{t_1}\right) - \left(u_{t_0}(i) - U_{t_0}\right)\right)\end{aligned}$$

If this number is positive, groups that increase their labor market share tend to have *relative* increases in unemployment.[32] The problem with using this as a measure of the quality of demographic adjustments, is that if demographic changes or relative unemployment rate changes are small, this inner product ('covariance') will be small. Therefore I construct a measure that normalizes by the size of these changes, analogous to a correlation:

$$\rho = \frac{(\vec{\omega}_{t_1} - \vec{\omega}_{t_0}) \cdot (\vec{u}_{t_1} - \vec{u}_{t_0})}{|\vec{\omega}_{t_1} - \vec{\omega}_{t_0}|\ |\vec{u}_{t_1} - \vec{u}_{t_0}|} \in [-1, 1]$$

where $\vec{\omega}$ and $\vec{u}$ are the vectors of labor market shares and disaggregate unemployment rates, and the vertical bars indicate the Euclidean length of the indicated vectors. If ρ is positive, then there is a relatively large increase in unemployment for groups that grow relatively larger. If ρ is negative, then groups that grow larger had a relative decline in unemployment. Only if $\rho = 0$ do U^G and U^D have the desired interpretations.

Table 2 shows the value of ρ obtained by dividing the population according to age and education. These estimates are fairly robust to changes in the time period. For example, changing the initial or terminal time by one year does not change the sign of any of the entries.

Education

I discuss the negative results for education, before moving on to the positive results for age. The second column of Table 2 shows that when an education category gets smaller, its members' unemployment rate increases relatively more. This reflects the disproportionate increase in unemployment for high school dropouts (Figure 13). This is inconsistent with a model in which the reduced supply of high school dropouts has made them a scarce resource.

[32] This is similar to the method used by Katz and Murphy (1992) to test for relative demand shifts.

However, it is consistent with the models suggested in Section 4. First, the ranking model tells us that the increase in a skill group's unemployment rate for a decrease in the relative ranking is larger in magnitude for groups that are unemployed more frequently, low skilled workers. To see this, differentiate equations (13) and (15):

$$\frac{\partial \tilde{u}(s)}{\partial \theta(s)} = -q\tilde{u}(s)(1-\tilde{u}(s))$$

Since $\tilde{u}(s)$ is decreasing in skill, the magnitude of this partial derivative is decreasing in s as long as the skill group's unemployment rate is less than 50%. Intuitively, the most skilled workers find jobs almost instantly, and so if they fall slightly down the ladder, they will suffer only a slight increase in unemployment (but a larger percentage increase).

A second explanation for the negative correlation, is that when high school dropouts comprised almost forty percent of the labor force in 1970, lack of a high school degree did not signal anything special. In contrast, now only the least skilled, lowest ability workers drop out of high school, leading to a precipitous drop in the quality of high school graduates. In summary, the maintained hypothesis that changes in education have no effect on unemployment rates conditional on education is false, making a demographic adjustment for changes in education severely overestimate the actual impact of changes in education. I conclude that the logic of adjusting for changes in labor force composition does not apply to changes in education, contrary to Summers (1986).

Age

The first column of Table 2 shows that from 1957 to 1989, age groups that increased in size had a correspondingly larger increase in unemployment. Looking back at Figure 2, this is saying that the youth unemployment rate increased disproportionately from 1957 to 1978; and then decreased disproportionately from 1978 to 1989. Since 1989, there has been a negative correlation between changes in labor market share and changes in unemployment. However, the magnitude is much smaller, and is exactly zero for the interval 1988–97.

The maintained hypothesis, that changes in age structure do not affect disaggregate unemployment rates, appears to be false. The baby boom caused an increase in youth unemployment, and so estimates like Δ and U^D *understate* the size of the demographic unemployment increase. The question is, by how much?

The theory in Section 3 provides some guidance. Suppose labor demand is not perfectly elastic, even in the long run. When the baby boom entered the labor market, there was a sharp increase in the number of unemployed workers, without a correspondingly large increase in the number of vacancies. From equation (12), the increase in the equilibrium unemployment-vacancy ratio q reduced the hiring rate M. However, it had an ambiguous effect on the separation threshold $\underline{x}$. To see why, recall that by (9), the separation threshold is increasing in $\mathcal{U}+\mathcal{V}$. Adding (10) and (11) implies[33]

$$r(\mathcal{U}+\mathcal{V}) = y - c + \pi\left(1 - qe^{-q}\right)\left(\mathcal{W}(s) - \mathcal{U} - \mathcal{V}\right)$$

Thus if qe^{-q} is increasing in q, as is the case for $q < 1$, an increase in the relative number of unemployed workers reduces $\mathcal{U}+\mathcal{V}$ and $\underline{x}$. If $q > 1$, qe^{-q} is decreasing in q, and so the separation threshold is increasing in q.

As the baby boom was gradually absorbed into the employed population, the unemployment-vacancy ratio slowly returned to its previous levels, restoring the old hiring rate and separation threshold. In short, the entry of the baby boom led to a temporary reduction in hiring rates, and perhaps a small change in separations. For prime age workers entrenched in stable jobs, this had little effect. However, it led to two decades of high youth unemployment.

A reasonable alternative hypothesis is that the unemployment rate of prime age workers, say the unemployment rate of workers age 35–64, was unaffected by the baby boom.[34] The part of aggregate unemployment that can be predicted by this series is 'genuine'. The orthogonal residual is 'demographic'. That is, I regress aggregate unemployment on a constant and the prime age unemployment rate, yielding

$$U_t = \underset{(0.0010)}{0.0051} + \underset{(0.0246)}{1.3531}\; u_t(\text{prime}) + \varepsilon_t,\;\; R^2 = 0.834$$

(Standard errors in parentheses.) Genuine unemployment is $0.0051+1.3531u_t(\text{prime})$ (Figure (19)). Notably, this is approximately the same in 1957, 1979, 1989, and 1998, as the prime age unemployment rate has not changed over long time horizons. The demographic unemployment rate at time t is the residual $\hat{\varepsilon}_t$ (Figure 20). The shape of the series looks very much like the age-adjusted series in Figures 5 and 6, but that the magnitude of the adjustment is much larger. A Hodrick-Prescott (HP) filter of

[33] Interpreting this expression is complicated by the fact that $\mathcal{W}(s)$ depends on $\mathcal{U}+\mathcal{V}$ through (8) and (9). Still, the joint gain from creating a new job, $\mathcal{W}(s)-\mathcal{U}-\mathcal{V}$, is decreasing in $\mathcal{U}+\mathcal{V}$.

[34] If q is much smaller than 1, the prime age unemployment rate may have dropped, because the decrease in job destruction from the reduced threshold outweighed the decrease in job creation from the reduced hiring rate. Under these conditions, the alternative hypothesis overstates the effect of the baby boom on unemployment. However, for $q \geq 1$, the unemployment rate of prime age workers unambiguously increased because of the baby boom. Job destruction increased and job creation fell. Then the analysis here understates the effect of the baby boom on unemployment.

the residuals removes the high frequency fluctuations and shows that the baby boom explains about a 180 basis point increase in demographic unemployment from 1959 to 1980, and more than a 145 basis point decline in demographic unemployment from 1980 to 1993, offset by a slight increase in the last five years.

Despite the crudeness of this measure of demographic unemployment, the result is robust. I illustrate this in three ways. First, the definition of prime age is not very important. Using the unemployment rate of workers age 35–54 or 35+ as our measure of prime age unemployment has no discernable effect on the demographic unemployment rate. Including younger workers age 25–34 in our measure reduces the magnitude of the residuals by about half, as would be expected if these workers still have some characteristics of youth.

Second, omitting extreme cyclical fluctuations in unemployment does not affect the result. I regressed an HP filtered series for aggregate unemployment on an HP filtered series for prime age unemployment.[35] The residuals are nearly identical to the HP filtered residuals in the basic regression.

Third, since female participation has increased enormously during these decades, I regressed aggregate unemployment on the unemployment rate of men age 35–64. The peak of the HP filtered residual increased by about fifty basis points compared to the basic regression, without any other substantial effect. According to this calculation, the demographic portion of unemployment rose by 250 basis points from 1953 to 1976, and has subsequently fallen by 200 basis points.

Any variant of these numbers is large. For example, compare my series for the demographic component of unemployment with Staiger, Stock, and Watson's (1997) non-structurally estimated series for the NAIRU (non-accelerating inflation rate of unemployment), which presumably represents some sort of equilibrium rate of unemployment. Figure 21 reproduces Staiger, Stock, and Watson's (1997) point estimate for the NAIRU and their 95% confidence interval. I then juxtapose the HP filtered residuals from Figure 20, renormalizing the mean of the residuals to 6%, which represents long-run average unemployment. My series for the demographic component of unemployment fits easily within the confidence interval, and actually reproduces their point estimate of the NAIRU quite well, except during the Vietnam War.

I conclude that changes in the age composition of the labor force explain the bulk of the rise in unemployment during the fifties and sixties, and the subsequent decline in the eighties and nineties. However, the simplest demographic story, that a group's unemployment rate is unaffected by the size of that group, is inadequate. The entry of the baby boom into the labor force led to an increase in youth unemployment, multiplying the size of the demographic shock from a direct effect of about eighty

[35] Thanks to Richard Rogerson for suggesting this calculation.

basis points (the estimate of the change in Δ from Section 2) to nearly two hundred basis points. The subsequent effect of the aging of the baby boom has been almost as important, again multiplying the size of the demographic shock from about eighty basis points to at least one hundred and twenty. The answer to why the U.S. unemployment rate is so much lower, is that the population is so much older.

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Age	16–19	20–24	25–34	35+
$\bar{u}(i)$	0.169 (0.009)	0.095 (0.007)	0.056 (0.005)	0.039 (0.003)
$\alpha_1(i)$	1.620 (0.070)	1.828 (0.064)	1.824 (0.078)	1.816 (0.073)
$\alpha_2(i)$	-0.632 (0.068)	-0.835 (0.063)	-0.831 (0.076)	-0.824 (0.071)
$\theta_1(i)$	-1.061 (0.062)	-1.048 (0.061)	-0.888 (0.083)	-0.861 (0.072)
$\theta_2(i)$	0.341 (0.044)	0.264 (0.035)	0.212 (0.049)	0.220 (0.045)
$\hat{\sigma}(i)$	0.008	0.005	0.002	0.001

Table 1: ARMA coefficients from equation (1), from October 1957 to November 1997. (Newey-West standard errors in parentheses.)

Year	Age	Education
1957–69	0.35	–
1969–79	0.29	-0.48
1979–89	0.44	-0.77
1989–97	-0.09	-0.24

Table 2: Measures of the correlation between a group's growth in labor market share and its relative growth in unemployment.
Comparisons are March-to-March for the indicated years. Data availability precludes calculating this for education from 1957–1970; the first entry is for 1970–79.

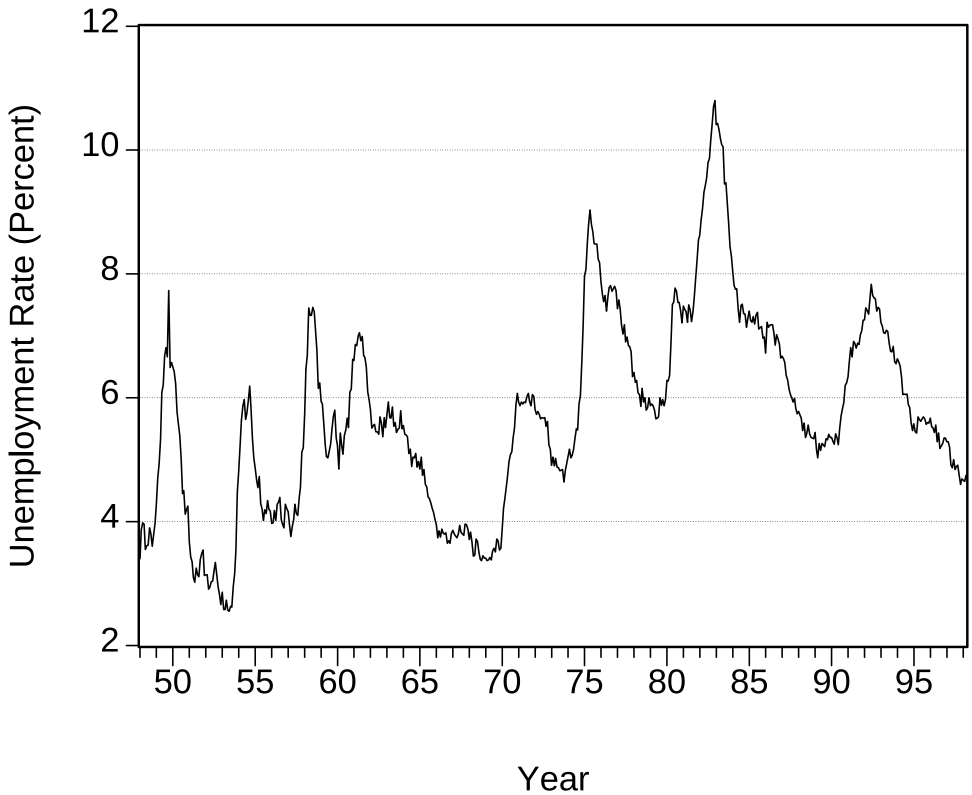

Figure 1: The aggregate unemployment rate is at the lowest sustained level since 1970, part of a downward trend since the early 80s.
Computed from seasonally adjusted labor force series based on the Current Population Survey.

Figure 2: During the late 1960s and 1970s, the share of young workers in the labor force increased dramatically, as the peak of the baby boom passed through its teens and early twenties.
Computed from seasonally adjusted labor force series based on the Current Population Survey.

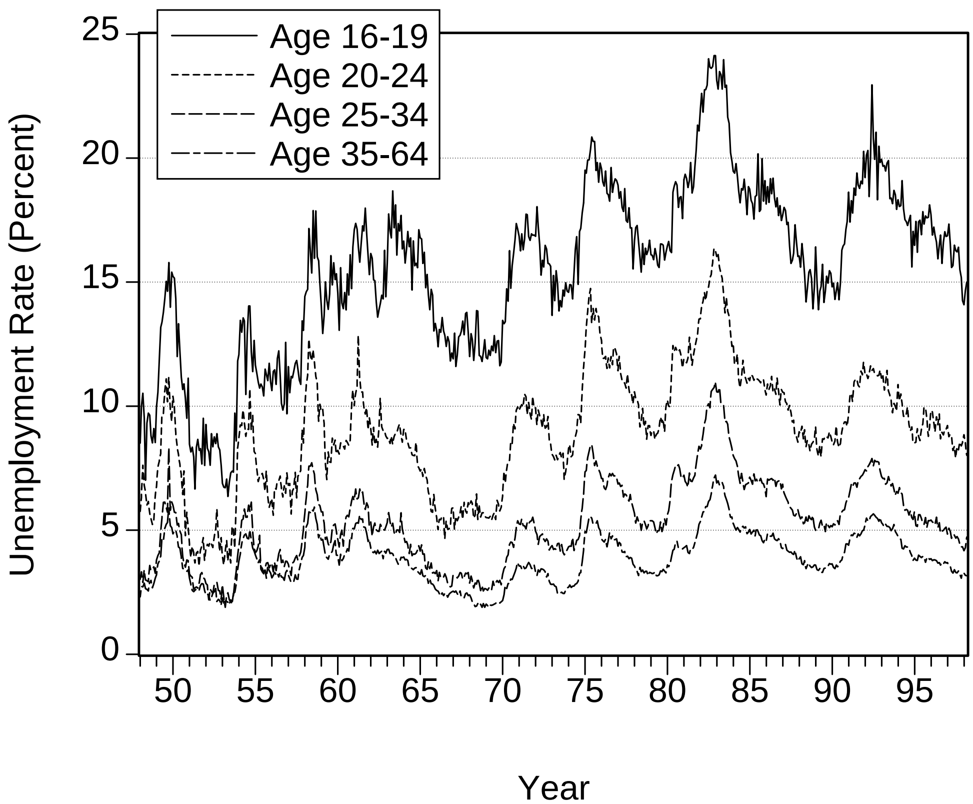

Figure 3: The unemployment rate of teenagers is typically at least three times the unemployment rate of workers over thirty five. The unemployment rate of young adults is typically about twice as high.

Computed from seasonally adjusted labor force series based on the Current Population Survey.

Figure 4: $U^G_{t_1,78:08}$ and U_{t_1} for seven age groups. Less than forty percent of the decline in aggregate unemployment during the last two decades is genuine.

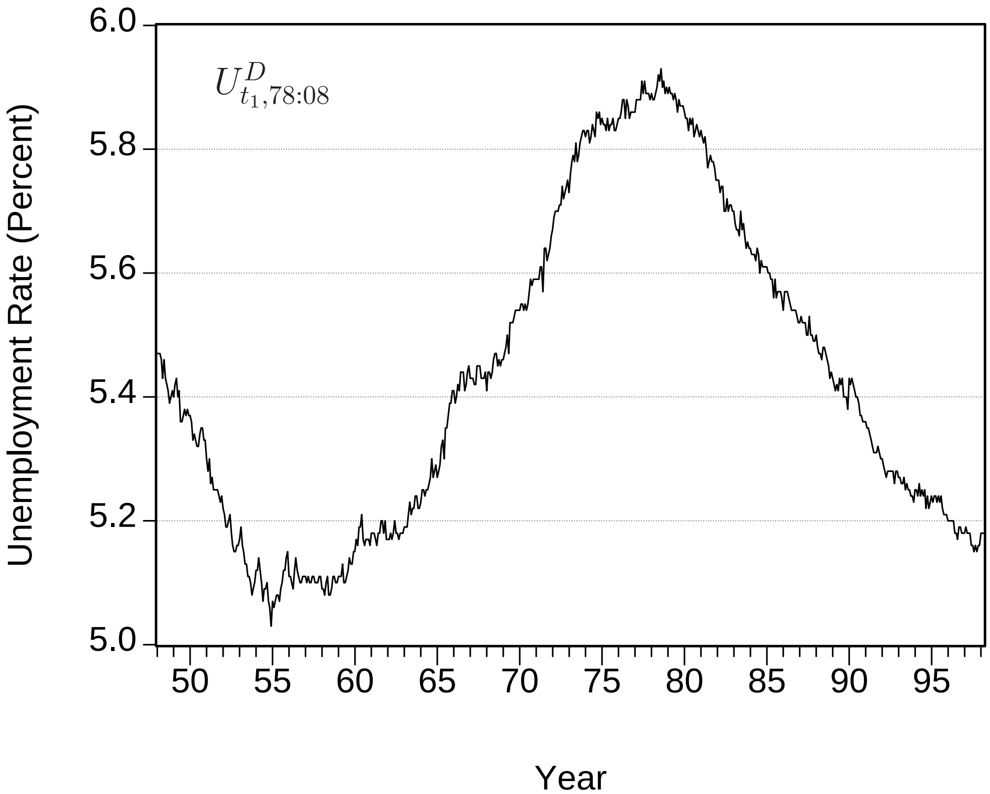

Figure 5: Demographic adjustment for seven age groups.

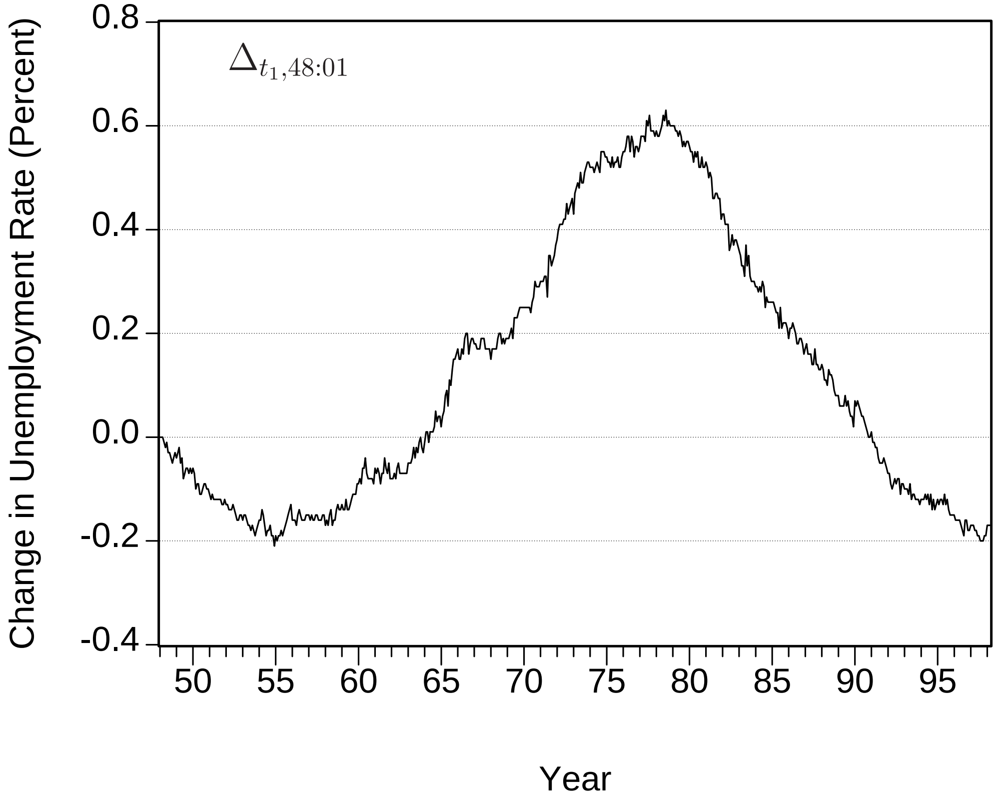

Figure 6: Demographic adjustment for seven age groups.

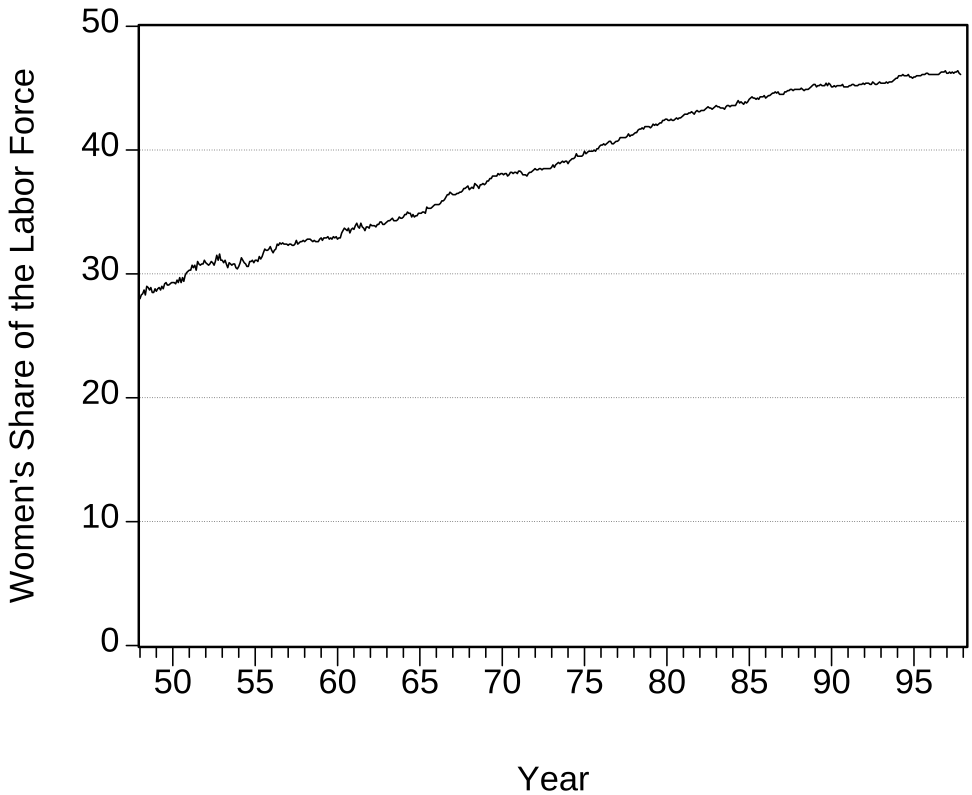

Figure 7: The fraction of the labor force that is female has steadily increased since World War II.

Computed from seasonally adjusted labor force series based on the Current Population Survey.

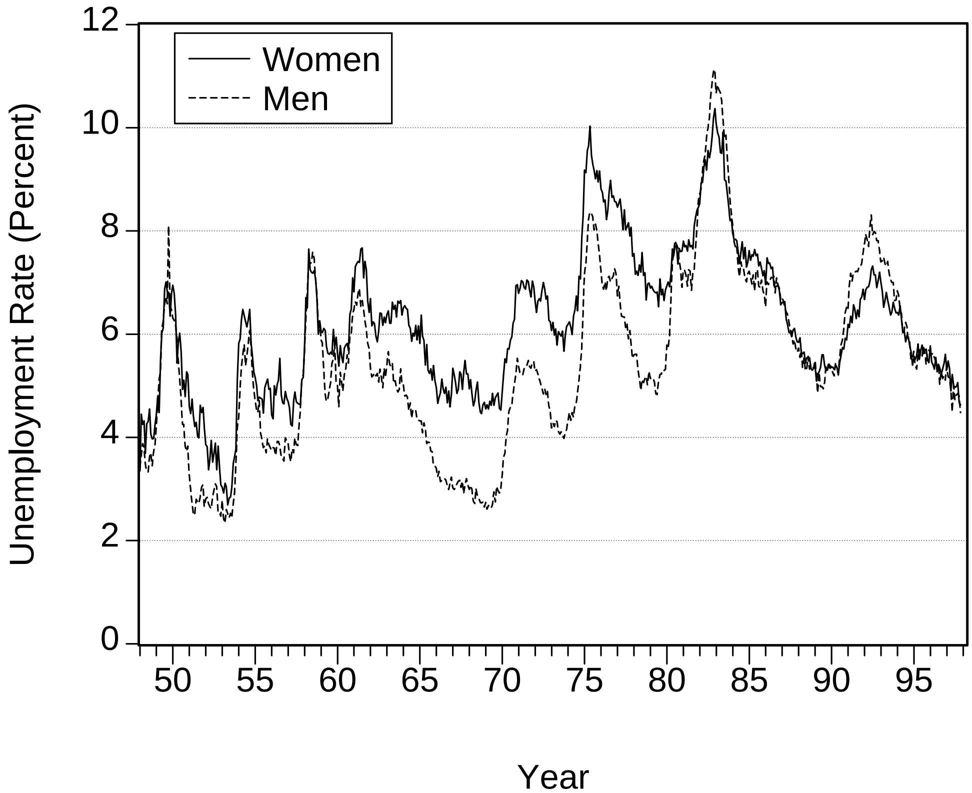

Figure 8: During the 1960s and 70s, the unemployment rate of men was about 2 percentage points below the unemployment rate of women, but that gap disappeared in 1980.
Computed from seasonally adjusted labor force series based on the Current Population Survey.

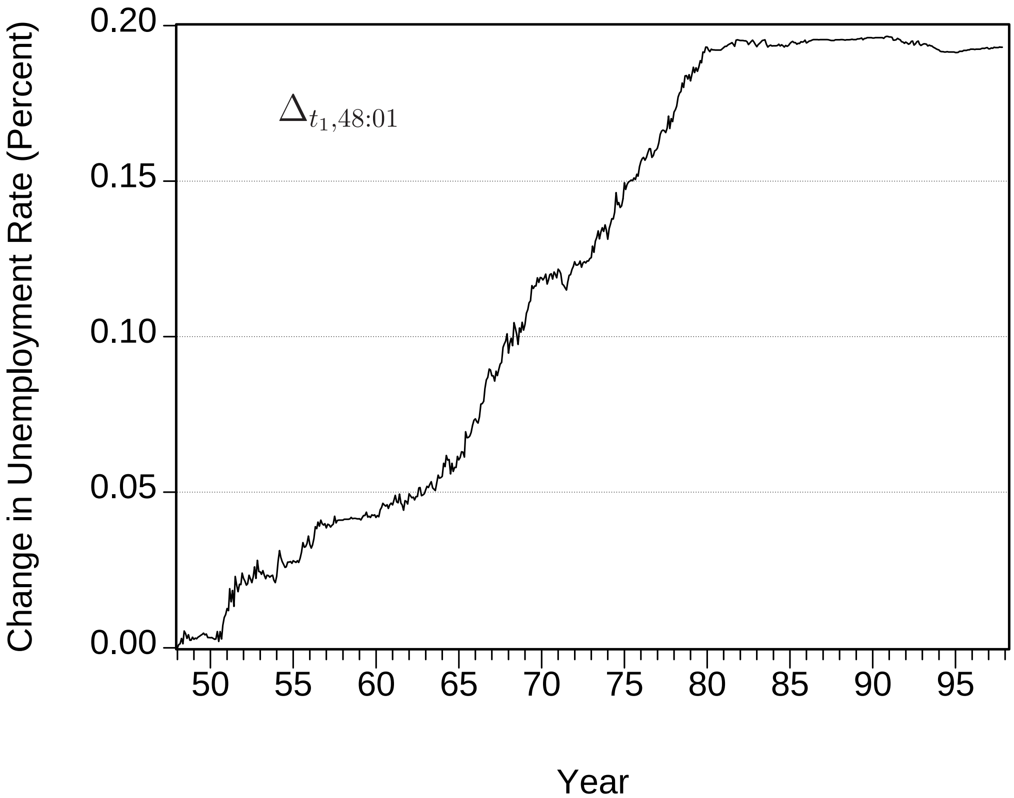

Figure 9: Demographic adjustment for increased female participation.

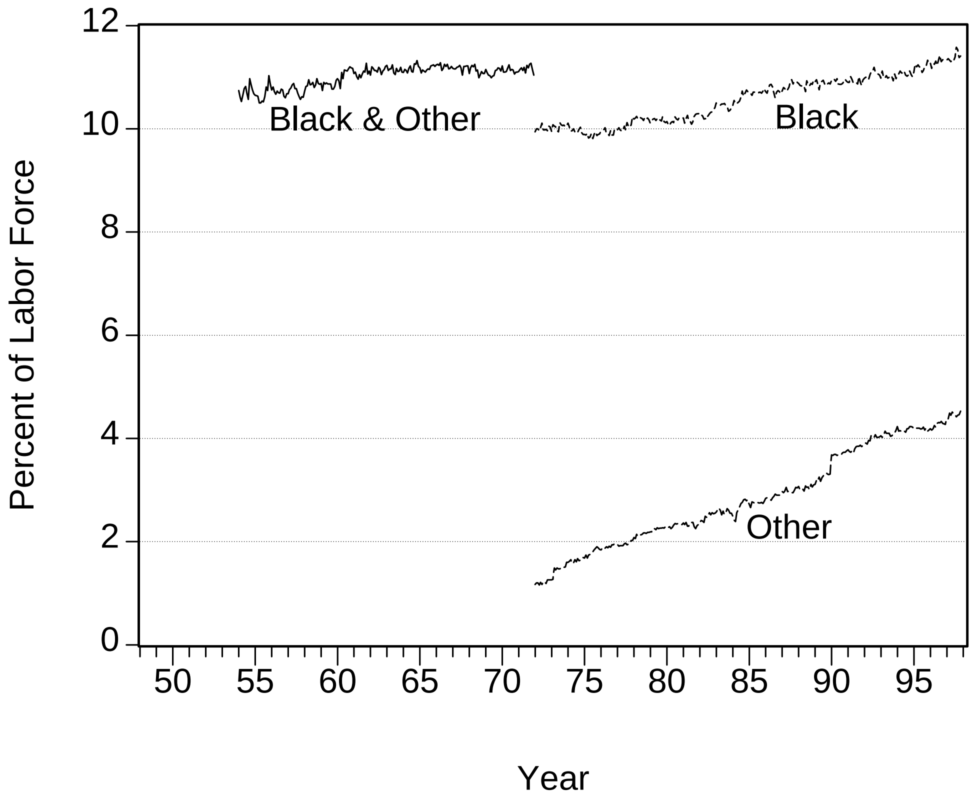

Figure 10: The fraction of blacks has increased by less than two percent, while the fraction of whites has declined by about five percent.
Computed from seasonally adjusted labor force series based on the Current Population Survey. Data limitations only allow me to divide the labor force into two groups, white and other, before 1972.

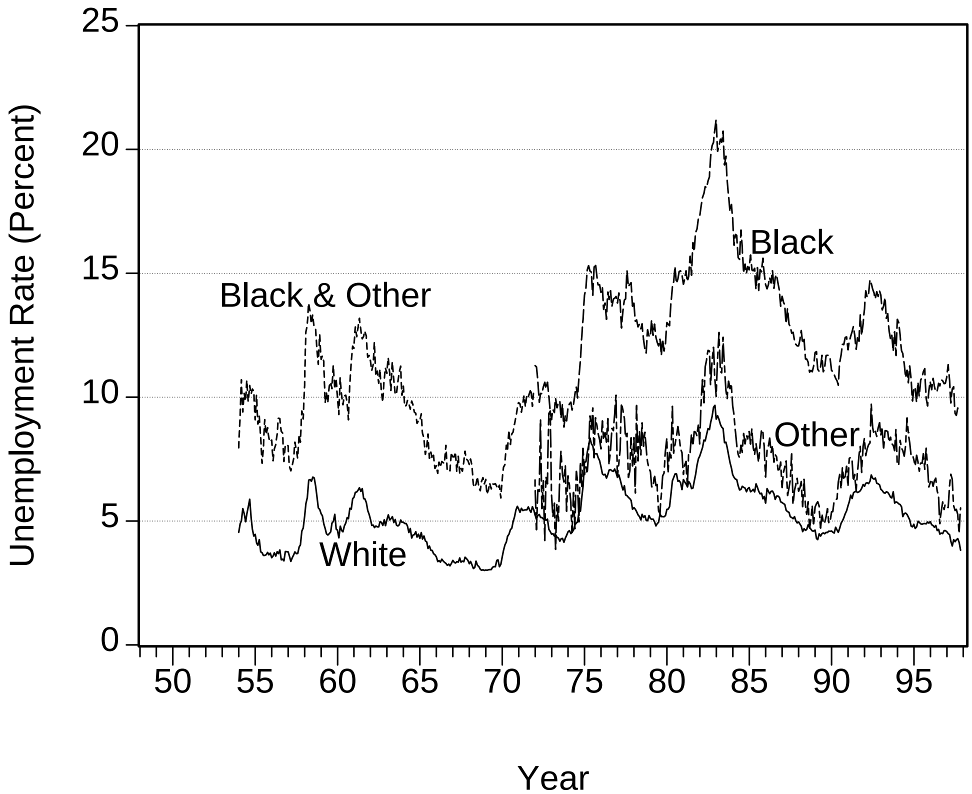

Figure 11: The black unemployment rate is much higher than the white unemployment rate.

Computed from seasonally adjusted labor force series based on the Current Population Survey. Data limitations only allow me to divide the labor force into two groups, white and other, before 1972.

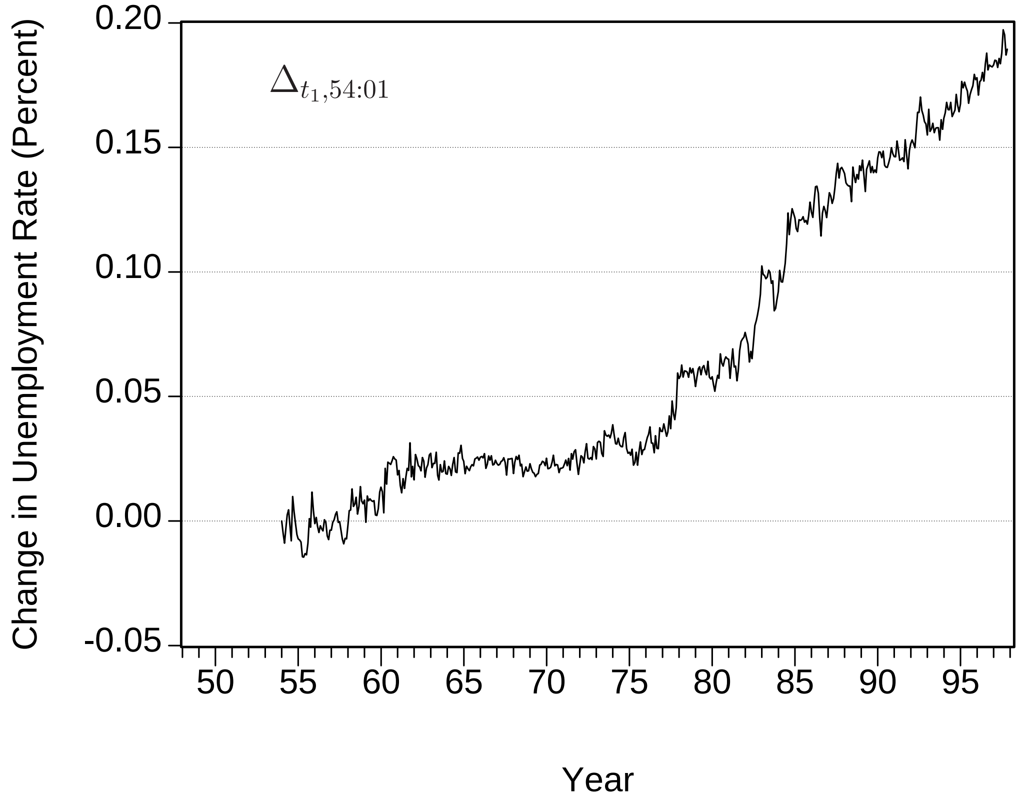

Figure 12: Demographic adjustment for increased non-white participation.
Computed from seasonally adjusted labor force series based on the Current Population Survey.

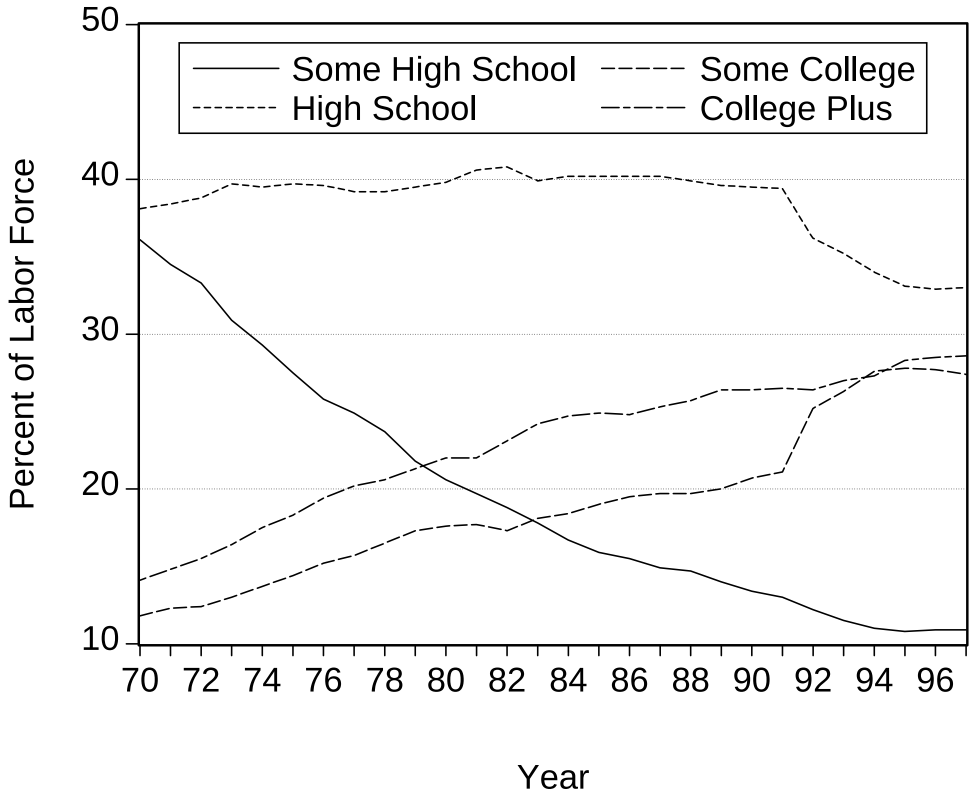

Figure 13: The fraction of workers with at least some college education has increased steadily since 1970, at the expense of workers with less than a high school diploma. Data are for March of each year. Since 1992, data on educational attainment have been based on the "highest diploma or degree received," rather than the"number of years of school completed." Data from 1994 forward are not directly comparable with data for earlier years due to the Current Population Survey redesign. I am grateful to Steve Haugen at the Bureau of Labor Statistics for providing me with this data.

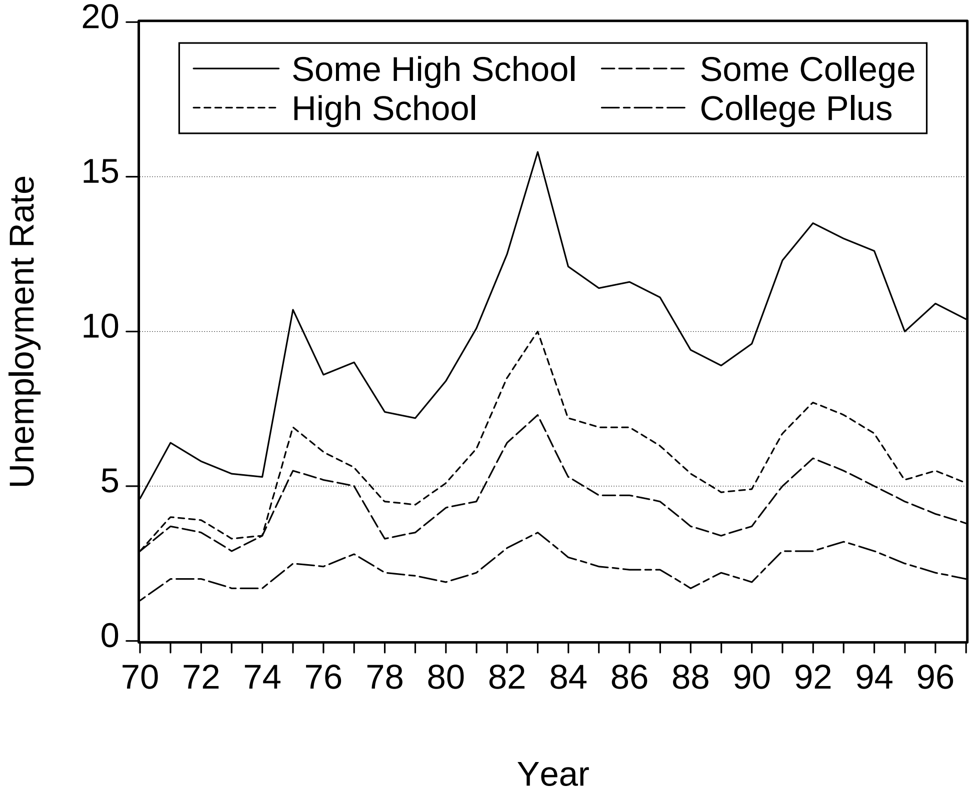

Figure 14: The unemployment rate of less educated workers is much higher than the unemployment rate of more educated workers; the gap has been growing recently. Data are for March of each year. Since 1992, data on educational attainment have been based on the "highest diploma or degree received," rather than the"number of years of school completed." Data from 1994 forward are not directly comparable with data for earlier years due to the Current Population Survey redesign. I am grateful to Steve Haugen at the Bureau of Labor Statistics for providing me with this data.

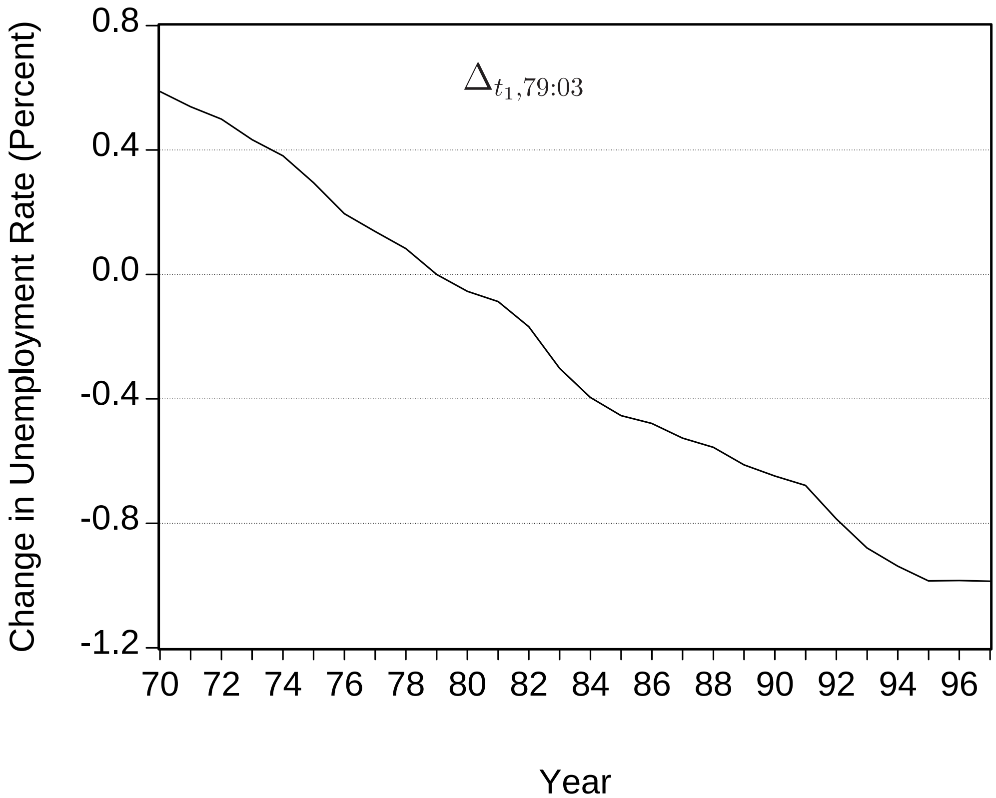

Figure 15: Demographic adjustment for increased education.

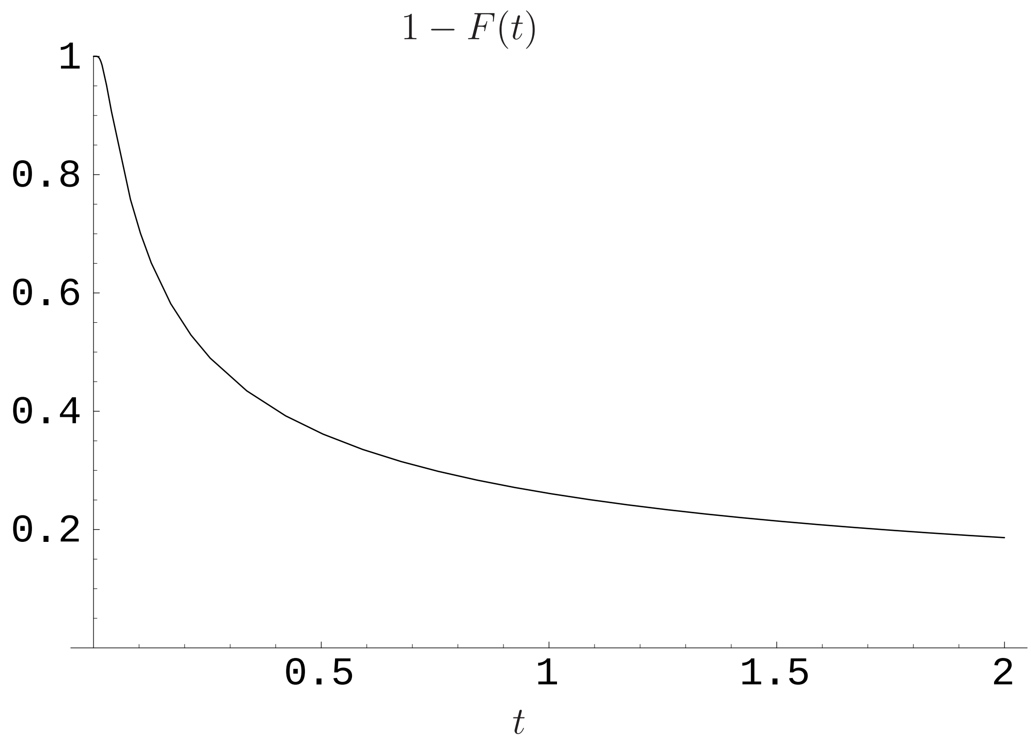

Figure 16: The probability of a match surviving from for t periods. This is drawn for $\frac{s-x}{\sigma}=\frac{1}{3}$.

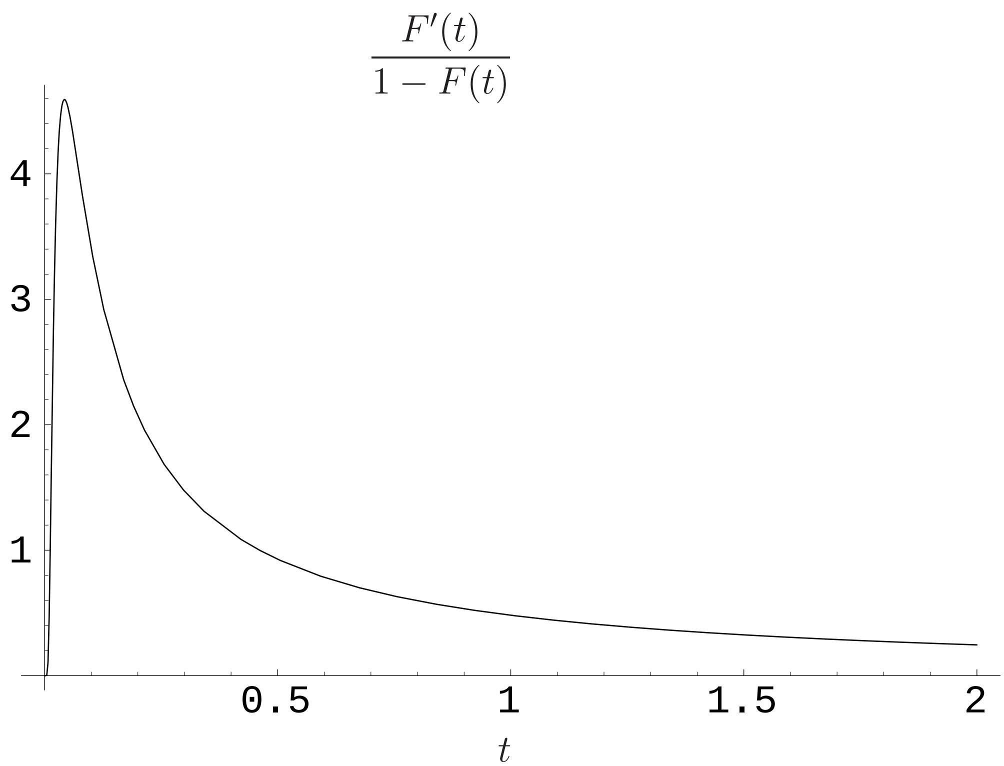

Figure 17: The hazard rate for match separations after t periods. This is drawn for $\frac{s-x}{\sigma} = \frac{1}{3}$.

Figure 18: The unemployment rate of a worker as a function of her labor market experience. This is drawn for $\frac{s-x}{\sigma} = \frac{1}{3}$ and $M = 5$.

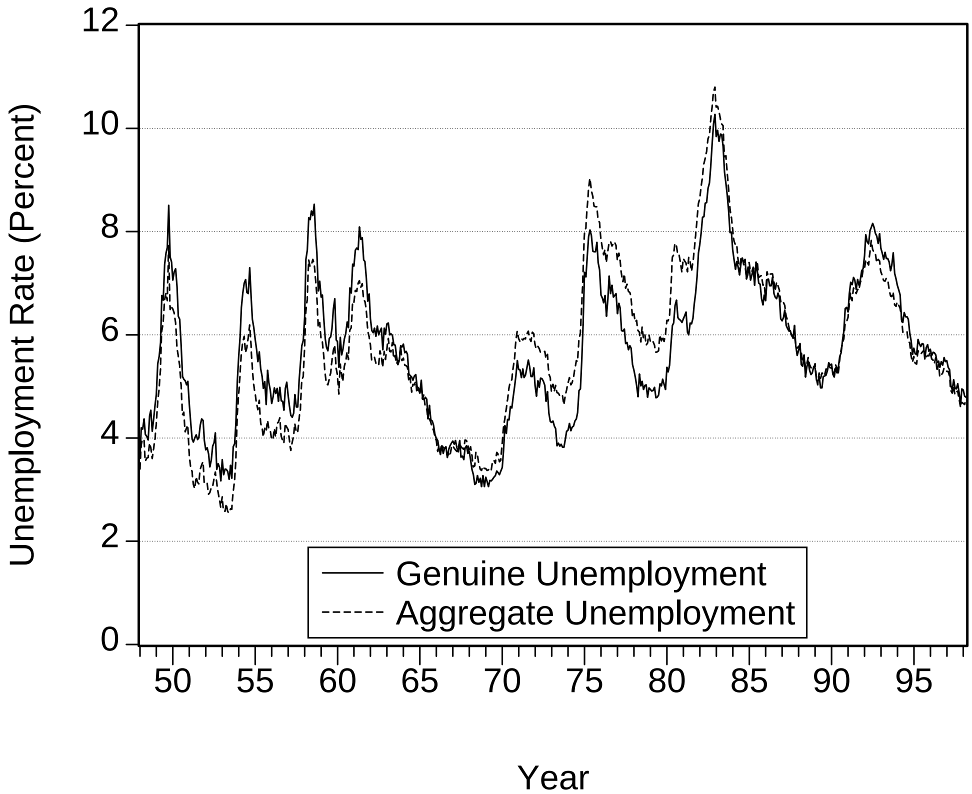

Figure 19: Genuine unemployment, defined as the part of unemployment that can be predicted from prime age unemployment. Prime age workers are age 35–65.

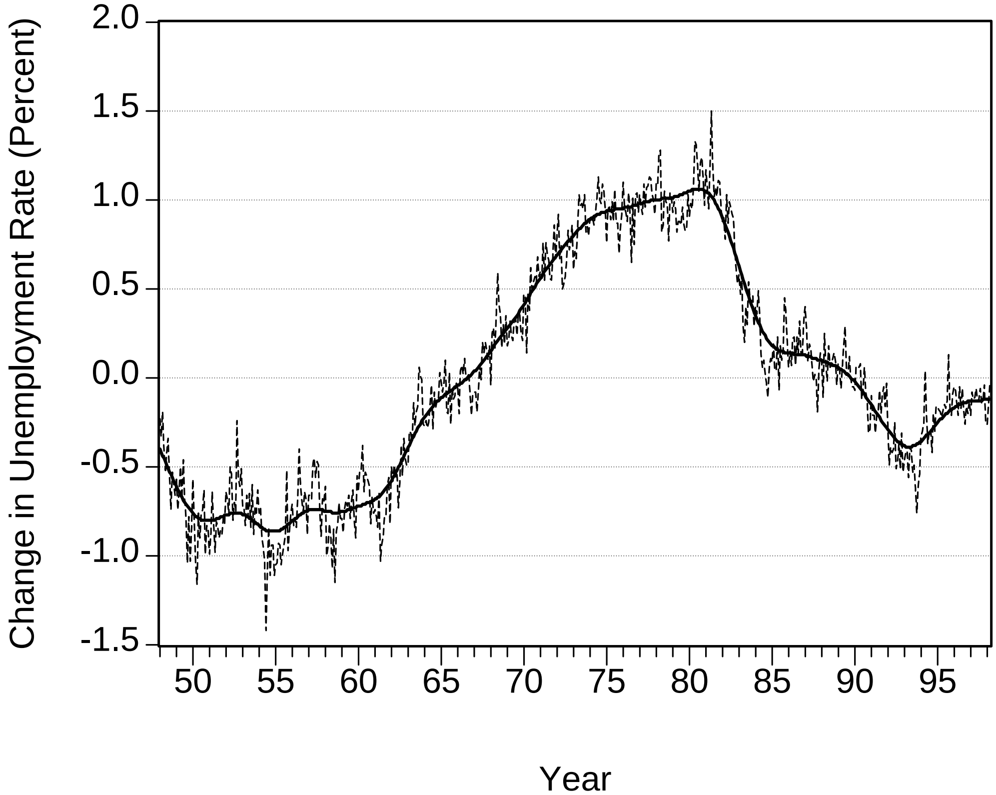

Figure 20: Changes in demographic unemployment, defined as the unpredictable residual, together with an Hodrick-Prescott filter of the residuals. Prime age workers are age 35–65.

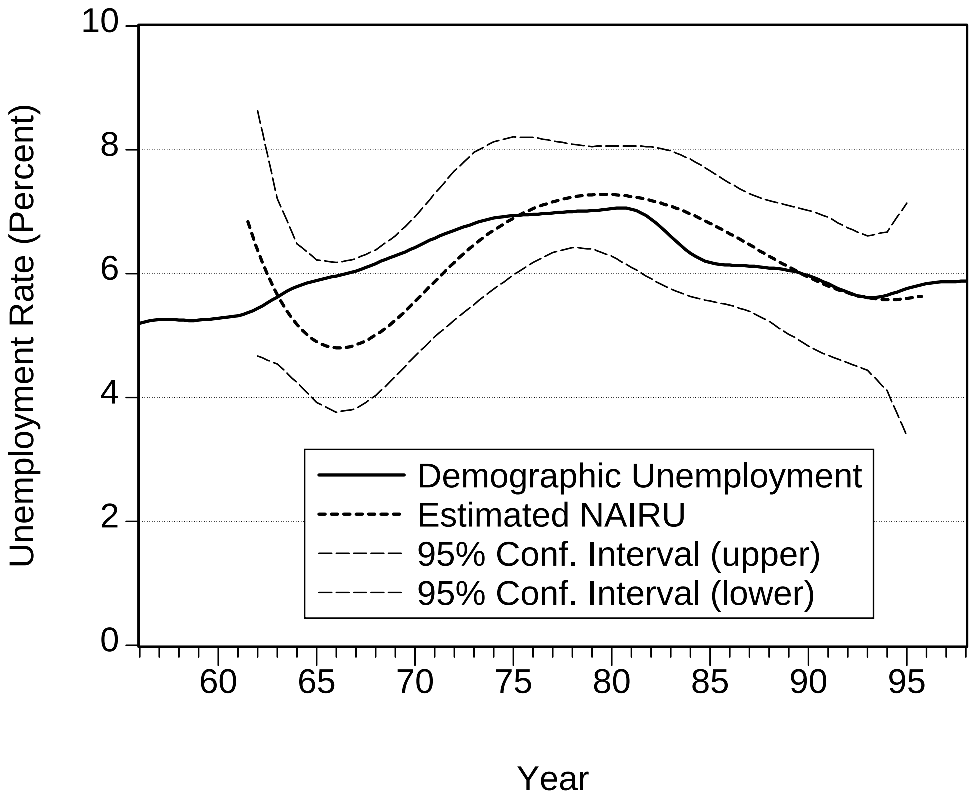

Figure 21: A smoothed series of demographic unemployment fit easily within Staiger, Stock and Watson's 95% confidence interval for the NAIRU.
Thanks to Mark Watson for providing me with their calculation of the NAIRU.