The Young, the Old, and the Restless: Demographics and Business Cycle Volatility*

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Abstract

We investigate the consequences of demographic change for business cycle analysis. We find that changes in the age composition of the labor force account for a significant fraction of the variation in business cycle volatility observed in the U.S. and other G7 economies. During the postwar period, these countries experienced dramatic demographic change, although details regarding extent and timing differ from place to place. Using panel-data methods, we exploit this variation to show that the age composition of the workforce has a large and statistically significant effect on cyclical volatility. We conclude by relating these findings to the recent decline in U.S. business cycle volatility. Using both simple accounting exercises and a quantitative general equilibrium model, we find that demographic change accounts for a significant part of this moderation.

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1. Introduction

The baby boom and subsequent baby bust in the U.S. resulted in dramatic shifts in the age composition of the American population. Japan, Germany, and other industrialized countries have experienced similarly dramatic demographic change during the postwar period, although the details regarding timing and magnitude differ from place to place. In this paper, we investigate the consequences of demographic change for business cycle analysis.

Recently, a great deal of attention has been devoted to studying the moderation in business cycle volatility in the U.S since the mid-1980s. However, less attention has been paid to the run-up in volatility that began in the mid-1960s. We propose demographic change as a framework that can rationalize the evolution of U.S. macroeconomic volatility over the last four decades. Moreover, we offer this framework as relevant for understanding the evolution of cyclical volatility observed in other industrialized economies during the postwar period. Specifically, we find that changes in the age composition of the workforce account for a significant fraction of the variation in business cycle volatility observed in the U.S. and the rest of the G7.

We establish the relationship between demographics and macroeconomic volatility in the following manner. First, we document important differences in the responsiveness of labor market activity to the business cycle for individuals of different ages. In previous work Clark and Summers (1981), Ríos-Rull (1996), and Gomme et al. (2004) showed, using postwar U.S. data, that the cyclical volatility of market work is U-shaped as a function of age. The young experience much more volatility of employment and hours worked than the prime-aged over the business cycle; those closer to retirement experience volatility somewhere in between. Our first contribution is to show that this is an empirical regularity for all G7 countries.

Specifically, we show in Section 2 that the volatility of market work is U-shaped as a function of age in these economies. For example, when averaged across countries, the standard deviation of cyclical employment fluctuations for 15 - 19 year olds is nearly six times greater than that of 40 - 49 year olds; as a result, although teenagers comprise only 6% of aggregate employment, they account for 17% of aggregate employment volatility. Similarly, the average employment volatility of 60 - 64 year olds is about three times greater than that of 40 - 49 year olds.

Given this observation, a natural conjecture is that the responsiveness of aggregate output to business cycle shocks will depend on the age composition of the workforce. For instance, suppose that the volatility of age-specific employment is unaffected by age composition. Then, when an economy is characterized by a large share of young workers, all else equal, these should be periods of greater cyclical volatility in market work and output than would otherwise occur. Our second contribution is to show that this is indeed the case.

During the postwar period, the G7 countries experienced substantial variation in business cycle volatility. Variation in the nature of demographic change across countries allows us to identify the effect of workforce age composition. In Section 3, we use panel-data methods to show that the age composition has a quantitatively large and statistically significant effect on measures of business cycle volatility. Because workforce composition is largely determined by fertility decisions made at least 15 years prior to current volatility, this allows us to obtain unbiased inference on the causal effect with standard econometric techniques.

In Section 4, we relate these findings to the recent literature on "The Great Moderation" – the decline in macroeconomic volatility experienced in the U.S. since the mid-1980s.[1] Through simple quantitative accounting exercises, we find

[1] See Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) for early papers identifying a change in output growth volatility. Blanchard and Simon (2001) argue that this moderation is part of a longer term phenomenon starting at least since the 1950s. The term "The

that demographic change accounts for roughly one fifth to one third of the moderation experienced in the US. Clearly, demographic change is not the sole factor responsible for this episode; nevertheless, demographic change constitutes a common factor relevant for understanding the evolution of business cycle volatility – not only in the U.S., but also in other G7 countries – over the past four decades.[2]

The results of our accounting exercises indicate that demographic composition plays an important role in the propagation of business cycle fluctuations. Our final contribution is to articulate this notion within a quantitative macroeconomic framework. In Section 5, we describe a simple variant of the standard real business cycle model that emphasizes the role of age as determining an individual's labor market experience. We show that the model is capable of accounting for differences in the volatility of hours worked across age groups, and demonstrate how variation in age composition manifests itself in variation of macroeconomic volatility. We provide concluding remarks in Section 6.

2. Differences in Market Work Volatility by Age

In this section, we analyze the responsiveness of market work to the business cycle for data disaggregated by age. We begin with an analysis of the U.S. and Japan, countries for which consistent information on hours worked by age is available. We supplement this with an "episodic" analysis, by documenting the response of the unemployment rate to postwar U.S. recessions for various age groups. We conclude the section with an analysis of how the volatility of employment differs by age in the sample of industrialized economies represented by the G7.

Great Moderation" is first used to describe this phenomenon by Stock and Watson (2002), and more recently by Bernanke (2004).

[2]See also Blanchard and Simon (2001) and Stock and Watson (2003) for analysis of changes in macroeconomic volatility in the G7.

2.1. Evidence on Hours Worked from the U.S. and Japan

Our approach to studying differences in business cycle volatility by age is similar to that of Gomme et al. (2004). We use data from the March supplement of the CPS to construct annual series of per capita hours worked from 1963 to 2005 for 15-to-19 year olds, 20-to-24 year olds, 25-to-29 year olds, and so on, proceeding in 5-year age groups to 60-to-64 year olds, and finally those aged 65 years and up. We also construct an aggregate series for all individuals 15 years and up. For Japan, we construct age-specific, annual time series covering 1972 to 2004, using data from the Annual Report of the Labour Force Survey. See Appendix A for detailed information on data sources used throughout the paper.

To extract the high frequency component of hours worked, we remove the trend from each series using the Hodrick-Prescott (HP) filter. Since we are interested in fluctuations at business cycle frequencies (those higher than eight years), we use a smoothing parameter of 10 for annual data.[3,4]

Table 2.1 presents results for the volatility of hours worked in the U.S. for various age groups. The first row presents the percent standard deviation of the detrended age-specific series. We see a distinct U-shaped pattern in the volatility of hours worked by age.

We are not interested in the high frequency fluctuations in these time series per se, but rather in those that are correlated with the business cycle. For each age-specific hours worked series, we identify the business cycle component as the projection on a constant, current detrended output, and on current and lagged detrended aggregate hours. Our measure of cyclical volatility is the percent standard

[3] Baxter and King (1999) show that this choice yields a very close approximation to the ideal high-pass filter for annual data. Throughout this paper, we have repeated our analysis of annual data using the band-pass filter proposed by Baxter and King, removing fluctuations less frequent than eight years. The results are essentially identical in all cases.

[4] Since much of the literature uses a parameter value of 100, we repeat the analysis of this subsection for this choice in Appendix B; the results are very similar and are not discussed here.

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	4.845	2.384	1.691	1.202	0.898	0.909	1.406	3.083
R^2	0.79	0.81	0.84	0.89	0.90	0.72	0.33	0.25
cyclical volatility	4.346	2.139	1.518	1.138	0.829	0.780	0.800	1.570
% of hours	3.24	10.33	12.86	25.38	23.29	17.20	4.82	2.88
% of hours volatility	11.14	17.49	15.44	22.86	15.84	10.61	3.04	3.58

Table 2.1: Volatility of Hours Worked by Age Group, US. HP filtered data.

deviation of these projections.

The second row of Table 2.1 reports the R^2 from the regression of detrended age-specific hours worked on aggregate output and hours. This is very high for most age groups, indicating that the preponderance of high frequency fluctuations are attributable to the business cycle. The exceptions are the 60 - 64 and the 65+ age groups. Here, a larger fraction of fluctuations are potentially due to age-specific, non-cyclical shocks.[5] The third row indicates the business cycle volatility of hours worked for each age group.

Compared to Row 1, the largest differences between "raw" and "cyclical" volatilities are for those aged 60 years and up, reflecting the discussion of the previous paragraph. Nevertheless, the U-shaped pattern remains. The young experience much greater cyclical volatility in hours than the prime-aged; the volatility of those close to or at retirement age is somewhere in between. Moreover, the differences in cyclical volatilities across age groups are large. The standard deviation of cyclical hours fluctuations for 15 - 19 and 20 - 24 year old workers is more than 5.5 and 2.5 times that of 50 - 59 year olds, respectively. Relative to the 50 - 59 year olds, hours worked is roughly twice as volatile for the 25 - 29 and

[5] Alternatively, the small fraction of individuals participating in the labor market may give rise to measurement error.

65+ age groups.[6]

The fourth row indicates the average share of aggregate hours worked during the sample period by each age group. The last row indicates the share of "aggregate hours volatility" attributable to each age group. Here, aggregate hours volatility is represented by the hours-weighted average of age-specific cyclical volatilities. What is striking is the extent to which fluctuations in aggregate hours are disproportionately accounted for by young workers. Although those aged 15 - 29 make up only 26% of aggregate hours worked, they account for 44% of aggregate hours volatility. By contrast, prime-aged workers in their 40s and 50s account for 41% of hours but only 26% of hours volatility.

These large differences by age remain when we undertake further demographic breakdowns. These results are presented in Appendix B and summarized here. We first disaggregate the U.S. workforce by age and educational attainment. For brevity, we present results only for two education groups: those with high school diplomas and less (less education), and those with at least some postsecondary education (more education). Several observations deserve mention.

First, there is a noticeable difference in the volatility of hours by education. Interestingly, the differences across education are much less pronounced for young workers than for the prime-aged. A simple average across 20 - 24 and 25 - 29 year olds indicates that those with less education have hours volatility that is 1.5 times that of those with more; by contrast, the difference across education groups is a factor of 3 for those aged 30 - 59. Finally, note that the U-shaped pattern remains for both education groups, with large differences by age. For instance, 20

[6] These results corroborate the findings of Gomme et al. (2004), and extend them to include data from the most recent recession. See also Clark and Summers (1981), Moser (1986), Rios-Rull (1996), and Nagypál (2004) who document differences in cyclical sensitivity across age groups. More broadly, the literature documents differences as a function of skill; see for instance, Kydland and Prescott (1993) and Hoynes (2000), and the references therein. Note that those studies are confined to the analysis of US data.

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	2.868	0.965	0.835	0.759	0.626	0.640	1.021	1.203
R^2	0.65	0.64	0.85	0.86	0.87	0.91	0.42	0.53
cyclical volatility	2.338	0.769	0.775	0.710	0.593	0.619	0.662	0.846
% of hours	2.21	10.18	11.77	23.34	24.19	18.67	4.92	4.73
% of hours volatility	7.17	10.88	12.67	23.02	19.93	16.06	4.52	5.75

Table 2.2: Volatility of Hours Worked by Age Group, Japan. HP filtered data.

- 24 year olds experience hours volatility roughly 3 times greater than 40 - 49 year olds, regardless of educational attainment. Indeed, 20 - 29 year olds with more education have greater volatility than prime-age workers with less education.

Appendix B also presents results disaggregated by age and gender. Again, the U-shaped pattern exists for both men and women. Moreover, the magnitude of volatility differences by age is roughly similar. Importantly, the differences across age groups within gender are much more pronounced than the differences across genders within age groups. An average across age groups indicates that males have 10% higher hours volatility over the cycle. On the other hand, 15 - 19 and 20 - 24 year olds experience hours fluctuations that are roughly 5.5 and 3 times more volatile than 50 - 59 year olds, for either gender. Gomme et al. (2004) discuss age differences with further demographic breakdowns (e.g., marital status, industry of occupation) for the U.S. Their results corroborate those presented here, indicating large and important differences in the volatility of hours worked by age.

Table 2.2 presents the same calculations as shown in Table 2.1 for Japan. As in the U.S., there is a distinct U-shaped pattern to both the raw and the cyclical volatility of hours worked as a function of age. Several differences between the two countries deserve mention.

First, the volatility of hours worked is smaller in Japan overall. Second, the age-specific regression R^2s for those aged 60+ are larger in Japan than in the U.S., indicating that hours fluctuations for these workers are more correlated with the business cycle. Third, the volatility of teenagers and those aged 65+ relative to the prime-aged is roughly similar to that found in the U.S. For the remaining age groups, the differences are not as pronounced, although significant volatility differences by age remain.

Finally, individuals over the age of 60 in Japan are much more significant contributors to the volatility of aggregate hours than those in the U.S. This is due to their larger hours share and their greater age-specific cyclical volatility. In fact, except for teenagers, the 65+ group experiences greater cyclical volatility in hours worked than any other age group.

2.2. Evidence on Unemployment from the U.S.

In this subsection, we provide additional evidence of the differences in business cycle sensitivity across age groups. In Figure 1, we present the average response of unemployment to a postwar U.S. recession. The unemployment rate data come from the BLS, cover the period 1948:I - 2004:II, and are available for the age groups presented. As in Jaimovich and Rebelo (2006), we define a recession as a period in which filtered real output falls below trend for at least two consecutive quarters. For this exercise we use the BP filter proposed by Baxter and King (1999) to isolate periodic fluctuations between 6 and 32 quarters.[7,8] Along the horizontal

[7] Relative to the high-pass filter, removing the high frequency fluctuations allows us to plot smoother unemployment rate responses. Otherwise, there are no substantive differences between the two filtering methods.

[8] This method identifies all of the NBER Dating Committee recessions, plus four additional episodes: 1962:II, 1967:II, 1986:III, and 1994:III. The timing of our recessions and those identified by the NBER is very similar. For the 10 recessions identified by the NBER, our procedure produces six whose starting date coincides with the peak quarter chosen by the NBER: 1948:IV, 1957:III, 1960:II, 1980:I, 1981:III, and 1990:III. For the other four, the starting dates are within

axis, date 0 represents the last quarter before output falls below trend. The figure tracks the BP-filtered age-specific unemployment rates for 20 quarters beyond this date. The solid line represents the recessionary response averaged across episodes, while the dashed lines represent 2-standard deviation bands. Unemployment rises quickly in response to a recession, and crosses above trend at date 2 (for all age groups except the 65+, which crosses at date 3). The response peaks at date 4 or 5, then slowly returns to trend.

This recessionary response is much stronger for young individuals. While the unemployment rate of 16 - 19 and 20 - 24 year olds increases by 1% above trend, the increase is only about 0.5% for prime-aged workers. Moreover, the 16 - 19 and 20 - 24 year olds experience average trough-to-peak responses of approximately 2.4% around trend. This compares with a trough-to-peak response of only 1% for prime-aged individuals. In summary, the unemployment rate response to a recession for young workers is roughly 2 to 2.5 times greater than that of prime-aged individuals.

2.3. Evidence on Employment from the G7

We provide further evidence on the differences across age groups in business cycle volatility by considering data for the G7 economies. Because hours worked data disaggregated by age are not available for all countries, we restrict our attention to employment. The data we analyze are from published and unpublished national government sources, and the OECD Labour Force Statistics database. The data are at an annual frequency, and the time coverage varies across countries. Again, see Appendix A for details.

We identify cyclical fluctuations in the data as we did in our analysis of hours

one quarter of the NBER dates (indicated in parentheses): 1953:III (II), 1969:III (IV), 1974:II (III), and 2001:II (I).

worked. For many of the G7 countries, the high frequency fluctuations of those aged 65 and older are largely orthogonal to the business cycle. For instance, from the regression of employment of the 65+ age group on aggregate employment and output, the R^2 for France is only 0.02. In Italy, employment for this group is actually negatively correlated with the cycle. As a result, for all countries except Japan, we omit those aged 65 years and up, and define aggregate employment as that among 15-to-64 year olds.[9] We retain this older group for Japan since their age-specific employment regression produces an R^2 of 0.7; this indicates that employment among the old is highly correlated with the cycle.

In Table 2.3 we present our results for HP-filtered data from the G7. For brevity, the information displayed is condensed relative to Tables 2.1 and 2.2. Because postwar aggregate employment volatility varies widely across countries, we normalize the age-specific measures by expressing them relative to the volatility of 40 - 49 year olds.

Again, the age profile of business cycle employment volatility can be characterized as roughly U-shaped, with large differences across age groups.[10] The young and old display greater cyclical sensitivity than prime-aged individuals. In all countries, the 15 - 29 year olds are substantially more volatile than those aged 30 - 59. This is particularly true for the continental European countries. Taking a simple average across all G7 countries, we find that while the young comprise 30% of aggregate employment, they account for approximately 50% of aggregate employment volatility. Large differences between the prime-aged and those over 60 are also evident in Europe and Japan. In each of these countries, this older group also contributes disproportionately to aggregate volatility.

To summarize, we find that age-specific differences in business cycle respon-

[9] Since the 65+ share of the labor force and employment is small, our results are unchanged if we include this group in our analysis.

[10] See Gomme et al. (2004) for similar results for several OECD countries.

		15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64
US	cyclical volatility	4.691	2.577	1.766	1.424	1.000	1.077	0.927
	% of empl.	6.72	12.30	12.89	24.82	22.27	16.38	4.62
	% of empl. volatility	19.04	19.15	13.76	21.35	13.46	10.66	2.59
Japan[A]	cyclical volatility	6.821	1.642	1.321	1.095	1.000	1.400	2.957
	% of empl.	2.91	10.77	11.45	22.75	23.22	17.96	10.93
	% of empl. volatility	12.54	11.18	9.56	15.73	14.67	15.89	20.42
Canada	cyclical volatility	4.198	2.327	1.693	1.311	1.000	0.907	1.174
	% of empl.	7.46	12.37	13.53	26.61	22.41	14.34	3.29
	% of empl. volatility	19.92	18.31	14.57	22.21	14.26	8.28	2.45
France	cyclical volatility	9.195	6.626	2.985	1.676	1.000	1.812	4.320
	% of empl.	2.75	10.36	13.70	27.27	25.21	17.49	3.21
	% of empl. volatility	10.06	27.32	16.27	18.18	10.03	12.61	5.52
Germany	cyclical volatility	3.222	3.426	2.550	1.643	1.000	1.264	7.073
	% of empl.	7.82	12.66	11.96	24.57	23.48	16.27	3.25
	% of empl. volatility	12.20	21.01	14.77	19.56	11.37	9.96	11.13
Italy	cyclical volatility	6.452	4.101	2.125	1.169	1.000	2.466	3.176
	% of empl.	7.70	8.41	12.45	28.05	24.43	15.94	3.02
	% of cyclical employment	22.93	15.91	12.20	15.13	11.27	18.13	4.43
UK[B]	cyclical volatility	5.464	3.351	2.072	1.654	1.000	1.502	2.350
	% of empl.	6.54	10.90	12.37	25.28	23.51	17.37	4.03
	% of empl. volatility	17.97	18.38	12.89	21.04	11.83	13.13	4.77

Table 2.3: Relative Business Cycle Volatility of Employment by Age Group. A: 60 - 64 age group replaced by 60+. B: 15 - 19 age group replaced by 16 - 19.

siveness of market work are an empirical regularity in our sample of industrialized economies. Our findings extend the results of Clark and Summers (1981), Ríos-Rull (1996), and Gomme et al. (2004) for the U.S. to the rest of the G7. That these economies differ greatly in terms of industry composition and the degree of labor market regulation makes this finding all the more striking. These results suggest that the age composition of the labor force is potentially a key determinant of the responsiveness of an economy to business cycle shocks. In the next section, we confirm this conjecture.

3. Age Composition and Business Cycle Volatility

We employ panel-data methods to study the relationship between cyclical volatility and demographics in the G7. Our identification comes from cross-country differences in the extent and timing of demographic changes. As a rough summary of these changes, Figure 2 presents birth rates for three of the G7 countries.

In the U.S. and Canada, the postwar baby boom led to an unusually large cohort of "20-something" labor market entrants in the mid- to late-1970s, and subsequently a large cohort of prime-aged labor market participants beginning around 1990. In France, Italy, and Germany, the baby boom was less pronounced, and changes in age composition have been less dramatic. Instead, declining fertility (which accelerated in the late-1960s) has resulted in a gradual aging of the labor force. The demographic experience of the U.K. falls somewhere in between those of North America and continental Europe, so the changes in age composition there are intermediate to those just described. In Japan, a sharp and rapid decline in fertility occurred after WWII, leading to a marked drop in the number of young workers entering the labor force after the early-1970s. In addition, population aging led to an increasing share of workforce participants over the age of 60; this has been particularly pronounced since 1980.

Figure 3 depicts the share of the labor force composed of individuals aged 15-29 years old for the same three countries as Figure 2. Comparing these two figures, it is clear that the primary factor driving changes in labor force composition since WWII is changes in fertility.

We use this variation in demographic change to determine the average impact of workforce age composition on business cycle volatility. The obvious related question is how changes in the age distribution affect output volatility in specific countries. Given the extensive literature on the moderation of U.S. business cycles experienced over the past 20 years, and the relevance of our results to this issue, we defer that discussion to the following sections.

Our baseline measure for the age distribution is the share of the labor force by various age groups. We look at labor force shares since this reflects our interest in the role of differential market work volatility by age in affecting macroeconomic volatility. We are able to interpret our empirical results as causal, insofar as labor force shares are exogenous to the determinants of business cycle volatility. The close correlation between Figures 2 and 3 indicates that the low frequency movements in workforce shares are driven by movements in population age composition. Since population composition is determined largely by fertility decisions made at least 15 years earlier, this component of labor force shares is exogenous to current business cycle conditions. This leaves the potential endogeneity of age-specific labor force participation rates and international migration to cyclical volatility unaccounted for. In our analysis (see below), we pursue two formal approaches to address these issues.

It is obviously difficult to obtain a direct, point-in-time measure of cyclical volatility or, more abstractly, an economy's responsiveness to business cycle shocks. Therefore, we consider the approach pursued in the literature by measuring cyclical volatility at quarter t as the standard deviation of filtered real GDP during a 41-quarter (10-year) window centered around quarter t. We adopt the HP filter with smoothing parameter 1600 as a benchmark; to demonstrate robustness, we also present results for volatility measures constructed with other filters and time windows.[11]

The benchmark regression we consider is:

$$\sigma_{it} = \alpha_i + \beta_t + \gamma \mathbf{share}_{it} + \varepsilon_{it}, \tag{3.1}$$

where σ_{it} is our measure of business cycle volatility for country i at year t, and $\mathbf{share}_{it}$ is the particular (vector of) labor force share measure(s) under consideration. We account for unobserved heterogeneity in volatility via the country fixed effect, α_i. We include a full set of time dummies, β_t, which allows us to control for time-varying factors affecting volatility that are common across countries. This also implies that our identification of γ is through age composition change that is not shared across countries over time.[12]

We are interested in this regression for the following reason. The estimated value of γ is informative with respect to the average effect of labor force shares on output volatility. However, it does not identify the specific economic mechanisms generating this relationship. For instance, changes in age composition can affect the volatility of market work (and thus, the volatility of output) in two ways. First, changes in the age structure have a direct composition effect, changing the relative shares of stable (prime-aged) and volatile (young and old) workers

[11] See Appendix A for data sources. Because of limitations in data availability, our time coverage differs from country to country, so our sample represents an unbalanced panel. Annual observations for labor force shares are available from national labor force surveys, and were obtained from various published and unpublished sources. Quarterly real GDP is used to construct the cyclical volatility measures; annual time series were constructed by selecting the value for the second quarter of each year. Essentially identical results obtain when we annualize by averaging over quarters.

[12] See Blanchard and Simon (2001) for a similar empirical specification, studying the relationship between inflation and output volatility.

in the aggregate. Second, changes in the age structure can have a more indirect effect, changing the volatility of hours and employment of specific age groups. Our benchmark regression does not identify the relative contributions of such direct and indirect effects, but identifies the sign and magnitude of the total effect. We return to this discussion in Section 4, after presenting results for our benchmark regression, given in equation (3.1).

3.1. A First Cut

The first specification we consider is one where **share** is the fraction of the 15 - 64 year old labor force accounted for by 15 - 29 year olds plus 60 - 64 year olds. Given the U-shaped pattern in market work volatility as a function of age documented in Section 2, we refer to this measure as the *volatile-aged* labor force share. We view this specification as a simple and informative "first cut" to illustrate the average effect of the age distribution on business cycle volatility in the G7. We discuss the robustness of our results to alternative definitions of the volatile-aged below, and we present results using a more detailed treatment of the age distribution in the following subsection.

Before proceeding to the regression analysis, Figures 4 and 5 present the time series of cyclical volatility, σ_i, and the volatile-aged labor force share, $\mathbf{share}_i$, for the U.S. and Japan, 1963 - 1999. Given our construction of σ_i, this includes output data from 1958 to 2004. In both countries, the two series track each other very closely. In the U.S., output volatility rose from the early 1960s to 1978, then fell from 1978 to present. This pattern is matched by the labor force share of the young. The hump in the labor force share that peaks in 1978 is due to the entrance of baby boomers into the workforce.

However, this correlation could be spurious, because of such factors as instability of oil prices and monetary policy in the 1970s. In this respect, a cross-country analysis disciplines our inference: in our panel regression, the effect of labor force shares is identified through differences in demographic change across countries. Consider Japan, which similarly experienced postwar moderation in output volatility and aging of the workforce, but with quite a different evolution. In contrast to the U.S., Japan's business cycle volatility fell beginning in 1971 and accelerated in the late 1970s. After stabilizing in the early 1980s, volatility has since risen. Again, this pattern is closely tracked by Japan's volatile-aged labor force share. The fact that these changes in demographics and volatility represent a "mirror image" of the U.S. strongly suggests that the correlation is not spurious.

Figures 6 and 7 present the same series for all G7 countries. In each panel, the scale of the vertical axes is identical in order to facilitate comparison. In six of the seven countries, business cycle volatility and the volatile labor force share clearly covary, although there is a slight phase shift in Canada. In France, unconditional evidence of this relationship is weaker, but relative to the other countries there is little change in volatility to explain.

Table 3.1 presents estimation results on γ, the average effect of the labor force measure on business cycle volatility. Column 1 presents our benchmark OLS estimate. The share of volatile-aged workforce participants has a positive effect on business cycle volatility. To interpret the magnitude of the coefficient estimate, a 10% increase in this labor force share would increase cyclical volatility by 0.40.[13] We estimate this effect to be significant at the 1% level.

The result in Column 1 suffers from autocorrelated residuals. This is due in part to the construction of our measure of cyclical volatility, which results in overlap of output data in consecutive observations of σ_{it}. To address this, we run standard tests on the regression residuals to determine the highest order of serial

[13] Again, we delay discussion of this result in relation to the U.S. Great Moderation to the following section.

	1	2	3	4	5	6	7
	HP$^{A,\bigstar}$	HP$^{A,\blacktriangle}$	HP$^{B,\blacktriangle}$	FD$^{A,\blacktriangle}$	FD$^{B,\blacktriangle}$	BP(hi)$^{A,\blacktriangle}$	BP(lo)$^{A,\blacktriangle}$
$\hat{\gamma}$	4.022***	4.022***	4.955***	2.090***	2.250**	2.345***	2.507***
	(0.792)	(1.134)	(1.500)	(0.693)	(0.996)	(0.704)	(0.936)
Nobs	207	207	213	207	213	180	180

A and B: 41 qtr and 21 qtr window used to construct dependent variable, respectively.
$\bigstar$ and $\blacktriangle$: OLS and Newey-West robust standard error, respectively.
** and ***: significant at 5% and 1% level, respectively.

Table 3.1: Effect of Volatile Group Shares on Business Cycle Volatility. All regressions include country fixed effects and time dummies. Standard errors in parentheses.

correlation. For the benchmark specification, we cannot reject a highest order of two. In Column 2, we report results when heteroskedasticity and autocorrelation-robust standard errors are constructed using the Newey-West estimator. Again, the effect of the labor force share on cyclical volatility is significant at the 1% level. The standard errors reported throughout the remainder of the paper are corrected in the same manner.

To illustrate robustness, Table 3.1 reports coefficient estimates when we change the way that cyclical volatility is measured. In Columns 3 and 5, we shrink the window of observations used to measure volatility, from 41 to 21 quarters. In Columns 4 and 5, we consider real output detrended by first-differencing; relative to the HP filter, this amplifies high frequency fluctuations. Finally, we take the frequencies that the HP filter passes (those higher than 32 quarters), and split them approximately in two: we isolate fluctuations with frequency between 2 and 16 quarters, and those between 17 and 32 quarters. We do this with the BP filter and, for brevity, report in Columns 6 and 7 only the results for the 41-quarter window (the results using the 21-quarter window are virtually identical). The estimated effect of the volatile-aged labor force share on all measures is positive and significant at either the 5% or 1% level. Finally, note that the magnitude of the coefficient estimates cannot be compared across columns since the definition of the dependent variable differs.

The results in Table 3.1 are potentially subject to endogeneity problems because any group's labor force share depends on its participation rate, which in turn may depend on (country-specific) shocks determining output volatility. Endogeneity bias results if the response of labor force participation to these shocks differs across age groups. To investigate this, we present instrumental variables (IV) results in which each country's volatile-aged labor force share is instrumented by its population share of 15 - 29 and 60 - 64 year olds.

The first column in Table 3.2, Panel A repeats our benchmark OLS result from Table 3.1. Column 2 presents our estimate when workforce shares are instrumented by population shares. Again, the effect of the volatile group's labor force share is positive and significant at the 1% level. In fact, the estimated coefficient changes little from our OLS result. Using the Hausman test, we cannot reject the hypothesis of no endogeneity bias in our original labor force measure.

Our second IV approach goes further toward addressing the possibility that the population age distribution is endogenous as well. This would occur if the response of international migration to shocks determining output volatility differed across age groups. To address this, we instrument our labor force measures by lagged birth rates. The motivation for this is straightforward. Excluding migration, an age group's share of the 15 - 64 year old population is determined by the distribution of births 15 to 64 years prior.[14] Since past fertility is almost certainly exogenous to current macroeconomic volatility, instrumenting by lagged birth rates allows us to obtain unbiased estimates of the causal impact of labor

[14] This ignores deaths among individuals under age 64, which is statistically negligible among G7 countries.

		endogeneity			*Blanchard - Simon*	
	1	2	3	4	5	6
	OLS	IV1	IV2	BP	OLS	IV2
A. annual						
$\hat{\gamma}$	4.022***	3.635***	3.946***	4.284***	5.430***	5.381***
	(1.134)	(1.424)	(1.138)	(1.203)	(1.095)	(1.089)
Nobs	207	207	207	207	203	203
B. 4-year						
$\hat{\gamma}$	4.306***	3.411*	4.272***	4.532***	5.728***	5.447***
	(1.427)	(1.987)	(1.422)	(1.596)	(1.390)	(1.379)
Nobs	55	55	55	55	53	53

* and ***: significant at 10% and 1% level, respectively.

Table 3.2: Effect of Volatile Group Shares on Business Cycle Volatility: Additional Robustness Checks. All regressions include country fixed effects and time dummies. Newey-West robust standard errors in parentheses.

force composition.

We instrument by projecting the volatile-aged labor force share on 20-year, 30-year, 40-year, 50-year, and 60-year lagged birth rates. The results are presented in Column 3 of Table 3.2. Again, the estimated effect is statistically significant at the 1% level, and the magnitude of the coefficient estimate is similar to the original OLS result.

Using population shares and lagged birth rates as instruments is problematic, though, if demographics affect cyclical volatility, independent of their influence on labor force composition. This is possible if, for example, differential demand for investment and durable goods or differential impacts of borrowing constraints across age groups have important business cycle effects. In this case, population measures may not constitute valid instruments for labor force shares.

Given this, we consider an alternative approach to addressing the potential endogeneity of labor force measures: we simply remove the medium and high frequency variation in the volatile-aged labor force share. Using the BP filter, we discard all fluctuations at frequencies greater than 20 years.[15] This corresponds to the view that endogeneity arises from unobserved shocks, simultaneously determining labor force shares and business cycle volatility. In this case, it should suffice to restrict our attention only to low frequency variation in workforce composition caused by factors such as demographic change that are orthogonal to cyclical volatility shocks. Column 4 of Table 3.2, Panel A reports the result of this exercise. Again, the coefficient estimate is positive and significant, and is very similar to our benchmark result.

In addition, we add to our benchmark specification the regressors considered by Blanchard and Simon (2001). Blanchard and Simon conclude that inflation volatility displays a strong, and potentially causal, relationship with output volatility. This conclusion is based on panel-data analysis similar to ours. In their analysis, output volatility is regressed on the mean and standard deviation of inflation, along with country and time fixed effects. The inflation volatility coefficient is found to be large and statistically significant.

As Blanchard and Simon acknowledge, concern arises from the endogeneity of inflation measures and output volatility. This bias makes inference problematic. Consequently, when we include measures of average inflation and inflation volatility in our analysis, we do not view the magnitude of the coefficient estimates as particularly informative. The point is simply to illustrate that our results are robust to concerns of spurious correlation between labor force composition and output volatility.[16] The OLS estimate from this exercise is reported in Column 5

[15] We implement this using the BP filter proposed by Christiano and Fitzgerald (2003). See Christiano and Fitzgerald for a discussion of the merits of their method for isolating fluctuations outside of the "business cycle frequencies" relative to Baxter and King (1999).

[16] The previous discussion on validity of population measures as instruments raises another possibility for spurious correlation: namely, that demographic change has affected cyclical volatility through channels unrelated to labor market considerations. Since inference on any hypothesis regarding the role of demographics likely relies on exogenous variation in population measures, it is very difficult to provide direct evidence to rule this out. However, the results of the following

of Table 3.2, Panel A; Column 6 reports the estimate when the labor force measure is instrumented by lagged birth rates. Including the inflation measures does not alter the sign or the statistical significance of the original findings (the results for the IV1 and BP exercises are virtually identical).

Our last experiment concerns the "spacing" or temporal frequency of observations. The demographic change underlying our inference is a gradual process. Consequently, perhaps meaningful variation in our labor force measure obtains only at longer time horizons. This concern is addressed in Panel B of Table 3.2. We repeat our analysis, this time with annual observations spaced four years apart.[17] Columns 1 through 4 present coefficient estimates for our benchmark OLS, IV, and BP-filtered cases, respectively. Note that this change does not substantively affect our results; in fact, it only serves to strengthen our conclusion of a positive link between the volatile group's labor force share and output volatility. Results from including inflation measures as regressors are also unchanged.

Finally, we consider alternative definitions of the volatile-aged labor force share guided by our results in Section 2. In the U.S. and Canada, despite the fact that 60 - 64 year olds display greater volatility than the prime-aged, their contribution to total employment volatility is smaller than their contribution to total employment. As such, we redefine the volatile-aged in these countries as only 15 - 29 year olds. Also, the results in Section 2 indicate that, unlike in other countries, in Japan the 65+ year olds are significant contributors to the volatility of aggregate hours and employment. Therefore, we redefine $\mathbf{share}_i$ for Japan as the fraction of the 15+ workforce accounted for by 15 - 29 and 60+ year olds. Considering these changes, both separately and simultaneously, does not change any of the results reported

subsection suggest that such spurious correlation is unlikely.

[17] We choose this relative to a more conventional 5-year spacing for practical reasons: given the unbalanced nature of our panel, this one-year drop in frequency results in a disproportionately large drop in the number of observations.

in Tables 3.1 and 3.2. Taken together, we interpret the results of this subsection as convincing evidence of a positive effect of the labor force share of volatile aged individuals on business cycle volatility.

3.2. Looking at the Entire Age Distribution

Up to this point the results indicate that periods with a larger share of age groups with cyclically sensitive market work tend to display greater business cycle volatility. In this section, we extend our analysis to include a more detailed look at the effect of the labor force age composition.

In particular, we use the entire age distribution of the labor force as the regressor in (3.1). This is motivated by our results in Section 2: namely, there is a U-shaped pattern in the cyclical volatility of hours and employment as a function of age. Our intent is to determine whether there is a similar U-shaped effect of age shares on aggregate output volatility. This would support our view that the shape of the entire age distribution affects the responsiveness of an economy to business cycle shocks, and that the crucial channel of influence is via differences in the cyclical sensitivity of market work across age groups.

We therefore alter our benchmark specification so that the regressor, **share**, is a vector of labor force shares: the shares of the 30 - 39, 40 - 49, 50 - 59, and 60 - 64 year old age groups. Because shares sum to one, we exclude the 15 - 29 year olds for the obvious reason. This implies that the coefficient on any particular age group represents the change in cyclical volatility that results from a shift of workforce share *out of* the 15 - 29 group, *into* that age group.

Row 1 of Table 3.3 presents our benchmark OLS result. Relative to our conjecture, the estimated coefficients have the expected sign and magnitude. A decrease in the share of 15 - 29 year olds in favor of any other age group reduces business cycle volatility. Moreover, the effect is U-shaped as a function of age. The smallest

		30 - 39	40 - 49	50 - 59	60 - 64	Nobs
1	OLS	-3.026^{*}	-4.058^{***}	-6.226^{***}	-0.716	207
		(1.672)	(1.489)	(2.086)	(4.371)	
2	IV1	-3.237^{**}	-4.177^{***}	-6.440^{***}	-0.588	207
		(1.680)	(1.485)	(2.165)	(4.448)	
3	IV2	-2.935^{*}	-4.010^{***}	-6.039^{***}	-1.018	207
		(1.676)	(1.500)	(2.077)	(4.406)	
4	BP	-2.745	-4.335^{***}	-6.769^{***}	-0.614	207
		(1.739)	(1.674)	(2.520)	(4.658)	
*, **, and *** significant at 10%, 5%, and 1% level, respectively.						

Table 3.3: Effect of the Age Distribution on Business Cycle Volatility, annual observations. All regressions include country fixed effects and time dummies. Newey-West robust standard errors in parentheses.

reduction in volatility comes from shifting young workforce members into the 60 - 64 age group, although this effect is not significantly different from zero. This is consistent with our results in Section 2, indicating that both the young and the old tend to contribute disproportionately to aggregate employment volatility in the G7. By contrast, shifting labor force shares out of the young and into prime-aged groups results in large and statistically significant reductions in cyclical volatility. Again, this is consistent with the U-shape in market work volatility.

We conduct additional experiments by varying the excluded age group, one at a time, from the regression. This allows us to determine the statistical significance of differences across age-group pairs. For brevity we do not report these results, but summarize them as follows: broadly speaking, the biggest differences in volatility effects are between either the 15 - 29 or 60 - 64 age groups (Set 1) and either the 40 - 49 or 50 - 59 age groups (Set 2). Across Set 1 and Set 2, the difference in coefficient estimates for any pair of age groups is large and statistically significant. On the other hand, for pairs within Sets 1 and 2, the estimated difference is small and insignificant. The 30 - 39 year olds represent an intermediate group. When this group is excluded, the coefficient is statistically significant at the 1% and 10% levels for the 50 - 59s and 15 - 29s, respectively, and is insignificant for the 40 - 49s and 60 - 64s.

Though the results are not reported here, we also experiment using different splits in age groups to ensure robustness. For instance, we split the young into 2 groups, those aged 15 - 24 and those aged 25 - 29. This has minimal impact on the results. Again, we obtain a U-shaped impact of workforce age shares on cyclical volatility. In fact, we find no significant difference between the estimated effect of 15 - 24 and 25 - 29 year olds. Other splits yield similar results, and maintain the U-shaped pattern. Finally, we repeat the robustness checks of the previous subsection by considering different definitions of business cycle volatility. Again, the results are not sensitive to the details of the detrending of output or the size of the window used in computing volatility.

In the remaining rows of Table 3.3 we report robustness checks that address the potential endogeneity of labor force shares. In Row 2 we present IV estimates using population shares as instruments; in Row 3 we present IV estimates using lagged birth rates (see the previous subsection for details). The results are hardly changed relative to Row 1. Again, in formal testing we cannot reject the hypothesis that the labor force shares do not suffer from endogeneity bias. Row 4 presents the results when we BP-filter the workforce shares to retain only fluctuations with periodicity greater than 20 years, as described in the previous subsection. Again, the effect on business cycle volatility is U-shaped as a function of age.

Table 3.4 presents the same estimates as Table 3.3, but using observations spaced 4 years apart. Again, we find significant age group effects and a U-shaped pattern in coefficient estimates as a function of age. Finally, we include measures of average inflation and inflation volatility in our analysis, although the results are not reported here. Again, our results regarding the sign and statistical significance

		30 - 39	40 - 49	50 - 59	60 - 64	Nobs
1	OLS	−3.394	−3.964*	−6.424**	2.730	55
		(2.455)	(2.065)	(2.817)	(6.555)	
2	IV1	−3.262	−3.901*	−6.283**	2.866	55
		(2.479)	(2.068)	(2.796)	(6.566)	
3	IV2	−3.193	−4.086**	−6.147**	2.633	55
		(2.436)	(2.066)	(2.741)	(6.524)	
4	BP	−2.789	−4.391*	−6.910*	3.371	55
		(2.513)	(2.327)	(3.680)	(7.192)	

* and ** significant at 10% and 5% level, respectively.

Table 3.4: Effect of the Age Distribution on Business Cycle Volatility, 4-year spaced observations. All regressions include country fixed effects and time dummies. Newey-West robust standard errors in parentheses.

of the coefficient estimates are unchanged.

We view this as strong support for our hypothesis that the age distribution of the labor force has important implications for business cycle volatility. Moreover, these results indicate the robustness of the U-shaped impact of age shares on business cycle volatility.

Given the U-shaped pattern documented in Section 2, we view this as convincing evidence that the influence of demographic composition on volatility operates through differences in the cyclical sensitivity of hours and employment across age groups. The pattern of market work volatility as a function of age represents a natural explanation for the U-shaped impact of age shares on business cycle volatility. Indeed, any other hypothesis regarding the impact of demographic composition on output volatility would need to rationalize this pattern.

4. The Great Moderation: Quantitative Accounting

Since the mid-1980s the U.S. has undergone a substantial decline in business cycle volatility, as shown in Figure 4. Indeed, determining the causes of “The Great

Moderation" is the objective of a growing body of literature. Potential explanations include a reduction in inflation volatility that is potentially related to improved monetary policy (see, for instance, Clarida, Gali, and Gertler, 2000; Blanchard and Simon, 2001; Stock and Watson, 2002); regulatory changes and financial market innovation related to household borrowing (Campbell and Hercowitz, 2006; Fisher and Gervais, 2006; Justiniano and Primiceri, 2006), changes that have reduced the volatility of production relative to sales (McConnell and Perez-Quiros, 2000; Ramey and Vine, 2006); and good luck, in the form of a reduction in the variance of business cycle shocks (Stock and Watson, 2002 and 2003; Justiniano and Primiceri, 2006; Arias, Hansen, and Ohanian, 2006).

In this section, we take a first step at quantifying the role of demographic change in accounting for the Great Moderation. In the following section, we discuss a quantitative theoretical approach which takes a specific stance on the impulses and propagation mechanisms generating cyclical fluctuations.

Our first exercise simply involves interpreting the coefficient estimates from our G7 panel regressions. Business cycle volatility peaks in the U.S. in 1978. This year coincides with the peak in the 15 - 29 year old labor force share at 38.5%. Cyclical volatility then falls rapidly during the 1980s, coinciding with a fall in the share of the young in the labor force as baby boomers enter their 40s and 50s. By 1999, the 15 - 29 year old share was only 27.1%, representing a level reduction of 11.4% from 1978. From our OLS estimates in Table 3.3, it follows that such a shift in workforce composition – from the 15 - 29 age group into the 40 - 49 age group – predicts a volatility reduction of $0.114 \times 4.058 = 0.463$. Given that our measure of cyclical volatility fell from 2.379 to 0.955 between 1978 and 1999, this change in age composition accounts for roughly 32% of the moderation between these two dates.

Finally, we present a simple decomposition exercise to determine how much of the change in aggregate market work volatility is attributable to the change in workforce age composition. We use the data analyzed in Section 2 and compare the volatility of HP-filtered measures between 1967 - 1984 and 1985 - 2004.

The standard deviation of per capita aggregate employment fluctuations fell 54.7 log points across the two periods. To isolate the effect due purely to the change in composition, we construct a counterfactual series for per capita aggregate employment, e_t, that holds the age structure fixed. Note that:

$$e_t = e_t^{15} p_t^{15} + e_t^{20} p_t^{20} + \ldots + e_t^{65} p_t^{65},$$

where e_t^{15} is per capita employment (or the employment rate) of 15 - 19 year olds, e_t^{20} is the employment rate of 20 - 24 year olds, and so on, progressing in 5 year age groups; e_t^{65} is the employment rate of 65+ year olds at date t, and p_t^x is the population share of age group x. The counterfactual series are constructed using the historically observed age-specific employment rates, $\{e_t^x\}$, but setting the population shares constant. Our exercise holds the age composition fixed at the 1978 shares, so that counterfactual aggregate employment for date t is:

$$\hat{e}_t^{1978} = e_t^{15} p_{1978}^{15} + e_t^{20} p_{1978}^{20} + \ldots + e_t^{65} p_{1978}^{65}.$$

Doing this for every year, 1967-2004, generates a counterfactual time series $\{\hat{e}_t^{1978}\}$.

We compare the standard deviation of filtered counterfactual employment across the pre- and post-moderation periods. Had the age composition stayed constant at the level observed in 1978, the standard deviation would have fallen by only 40.2 log points. That is, the change in age composition explains $(54.7 - 40.2) \div 54.7$ or 26% of the moderation in aggregate employment volatility. Performing the same experiment for hours worked, we find that 21% of its moderation is due to demographic change.

Is this exercise informative? Note that the decomposition assumes that the volatility of age-specific employment and hours worked are independent of the age composition. That is, it assumes the absence of indirect effects of changing age structure on aggregate volatility via changes in the volatility of age-specific employment and hours worked.

To determine whether this is reasonable, we test for the presence of such effects using cross-country regression analysis similar to that considered in Section 3. For example, we regress the volatility of employment of 15 - 29 year olds on the 15 - 29 year old labor force share, controlling for country fixed effects and factors affecting business cycle volatility common across countries. We find that a 10% increase in the share of 15 - 29 year olds decreases the standard deviation of their employment by 0.0007%; this is not estimated to be different from zero at conventional significance levels. For brevity, we do not report results for other age groups since, again, the effects are estimated to be small in magnitude and statistically insignificant. Hence, we find no strong evidence for these indirect effects in the G7 sample.

To conclude, note that the results of the decomposition exercise on aggregate market work volatility are similar in magnitude to the role of demographic change in the moderation of output volatility derived from our panel regression analysis. We take this as evidence for an important role for demographics in explaining the Great Moderation.

5. Modeling the Great Moderation

The first challenge in quantifying the role of demographic change in the Great Moderation is developing a framework that generates age-group differences in the cyclical volatility of hours worked. For comparability with the literature, we present a model that represents a minimal deviation from the standard real business cycle (RBC) model. Within the RBC framework, differences across age groups can arise from differences in preferences (or succinctly, differences in labor supply), factors relating to technology (labor demand), or both.[18]

In this section we present a simple model that abstracts from differences in labor supply characteristics. Rather, we show that focusing on differences in labor demand faced by age groups captures differences in hours fluctuations in U.S. data surprisingly well.[19] Moreover, in Jaimovich, Pruitt, and Siu (2007) (hereafter JPS), we show that labor demand differences are crucial for matching differences in the cyclicality of age-specific wages. We document that while all wages are procyclical, wages of young workers are more volatile over the cycle than those of others; a model with differences in labor supply alone would have difficulty replicating this.[20] For brevity, we keep the presentation to a minimum and refer the reader to JPS for further discussion.

[18] Note that most RBC models are not conducive to addressing cyclical variation in hours worked due to variation in labor force participation. In Jaimovich, Pruitt and Siu (2007), we conduct the standard decomposition of the variance of age-specific hours into components owing to fluctuations in hours per worker (intensive margin), workers per labor force member (extensive margin), and labor force members per age group member (participation margin). We find that the participation margin is the primary source of the total variance in hours for only those aged 60+. This age group's hours account for only a small fraction of the aggregate, and their hours fluctuations are not highly correlated with the cycle. Given this, we view abstracting from variation in participation as a reasonable first step in modeling age-group differences in the volatility of hours worked.

[19] See Ríos-Rull (1996) and Gomme et al. (2004) for models highlighting differences in labor supply due to life-cycle considerations. They show that life-cycle mechanisms successfully explain volatility differences between prime-aged and old workers; however, such considerations cannot fully account for the volatility of young workers. See Castro and Coen-Pirani (2006) who also emphasize the role of labor demand factors for differences in the cyclical volatility of hours by education levels; see also Gomme et al. (2004) for discussion on the potential role of labor demand differences. Finally, see Nagypál (2004) for an alternative approach highlighting the interaction between age and worker-occupation match quality.

[20] In particular, consider a model with just young and old agents. If hours are perfectly substitutable and wages are competitive, it is obvious that both young and old wages share identical cyclical properties. Now, suppose young and old hours are distinct factor inputs. The observed procyclicality of hours and wages of both young and old implies a cycle driven by shocks to labor demand. Matching the relative volatility of hours requires a greater elasticity of labor supply (or a smaller income effect) to wage changes for young agents. However, without differences in the magnitude of cyclical shocks to labor demand, this implies counterfactually smaller fluctuations in young wages.

For simplicity, we assume that there are only two types of workers, young and old; we abstract from differences between the prime-aged and retirement-aged by combining them in the "old" group.[21] We posit that an individual's age directly determines his or her labor market experience, so that all young workers are "inexperienced" while all old workers are "experienced". Production exhibits *capital-experience complementarity.* With this technology, differences in the cyclical demand for experienced and inexperienced labor arise naturally. The intuition for this is straightforward. As an extreme case, suppose that capital and old / experienced labor are perfect complements, while capital and young / inexperienced labor display some substitutability. If capital services are a state variable and firms are profit maximizing and price-taking, then any shock generating a change in inputs results only in variation in the quantity of young labor.

The primary challenge is matching observed differences in hours volatility. As will be clear, it is trivial to parameterize the model explicitly to do so. To discipline our analysis, we estimate the key parameters governing the degree of capital-experience complementarity in a manner that does not target differences in the cyclical volatility of hours. Performing counterfactuals, we find that even in this simple framework, demographic composition plays an important role in determining macroeconomic volatility.

5.1. The Model

5.1.1. Firms

Final goods are produced by perfectly competitive firms according to the CES production function:

$$Y_t = \left[\mu \left(A_t H_{Yt}\right)^{\sigma} + (1-\mu)\left[\lambda K_t^{\rho} + (1-\lambda)\left(A_t H_{Ot}\right)^{\rho}\right]^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}}.$$

[21] In Section 2, we found that while 65+ year olds display greater hours volatility, their contribution to aggregate hours volatility is small.

Here H_{Yt} is labor input of young or inexperienced workers, H_{Ot} is labor input of old or experienced workers, and K_t is capital services hired at date t. Labor-augmenting technology follows a deterministic growth path with persistent transitory shocks:

$$A_t = \exp(gt + z_t),$$

$$z_t = \phi z_{t-1} + \varepsilon_t, \quad 0 < \phi < 1,$$

where $E(\varepsilon) = 0$, $0 \leq var(\varepsilon) = \sigma_\varepsilon^2 < \infty$, and $g > 0$ is the trend growth rate of technology.

The elasticity of substitution between experienced workers and capital is given by $(1-\rho)^{-1}$, while the elasticity of substitution between inexperienced workers and the H_O-K composite is $(1-\sigma)^{-1}$. Following Krusell et al. (2000), we define production as exhibiting capital-experience complementarity when $\sigma > \rho$.[22]

Firms rent capital, and young and old workers' time, from perfectly competitive factor markets to maximize profits:

$$\Pi_t \equiv Y_t - r_t K_t - W_{Yt} H_{Yt} - W_{Ot} H_{Ot}.$$

Here r_t is the capital rental rate, W_{Yt} is the wage rate of young workers, and W_{Ot} is the wage rate of old workers. Optimality entails equating factor prices with marginal revenue products:

$$r_t = Y_t^{1-\sigma}(1-\mu)\left[\lambda K_t^\rho + (1-\lambda)(A_t H_{Ot})^\rho\right]^{\frac{\sigma-\rho}{\rho}} \lambda K_t^{\rho-1},$$

$$W_{Ot} = Y_t^{1-\sigma}(1-\mu)\left[\lambda K_t^\rho + (1-\lambda)(A_t H_{Ot})^\rho\right]^{\frac{\sigma-\rho}{\rho}} (1-\lambda) A_t^\rho H_{Ot}^{\rho-1},$$

$$W_{Yt} = Y_t^{1-\sigma} \mu A_t^\sigma H_{Yt}^{\sigma-1}.$$

[22] The large body of literature on capital-skill complementarity has concentrated on education as a proxy for skill (see Krusell et al., 2000, and the references therein). In this model we concentrate on the other significant dimension of skill emphasized in Mincerian wage regressions, namely labor market experience.

5.1.2. Households

The economy is populated by a large number of identical, infinitely-lived households. Each household is composed of a unit mass of family members; s_Y denotes the share of family members that are young. Young family members derive utility from consumption, C_Y, and disutility from hours spent working, N_Y. Old family members have similar preferences defined over consumption, C_O, and working hours, N_O.

The representative household's date t problem is to maximize:

$$E_t \sum_{j=t}^{\infty} \beta^{j-t} s_Y \left[\log C_{Yj} - \psi_Y N_{Yj}^{1+\theta_Y} / (1+\theta_Y) \right] + \\ (1-s_Y) \left[\log C_{Oj} - \psi_O N_{Oj}^{1+\theta_O} / (1+\theta_O) \right],$$

subject to

$$s_Y C_{Yj} + (1-s_Y) C_{Oj} + \tilde{K}_{j+1} = (1-\delta)\tilde{K}_j + r_j \tilde{K}_j + \\ s_Y W_{Yj} N_{Yj} + (1-s_Y) W_{Oj} N_{Oj},\ \forall j \geq t.$$

We normalize the time endowment of all family members to unity, so that $0 \leq N_{Yt} \leq 1$ and $0 \leq N_{Ot} \leq 1$. The household takes all prices as given.

Because of additive separability in preferences, optimality entails equating consumption across all family members:

$$C_{Yt} = C_{Ot} = C_t. \tag{5.1}$$

The first-order condition for capital holdings is given by:

$$C_t^{-1} = \beta E_t \left[C_{t+1}^{-1} (r_{t+1} + 1 - \delta) \right].$$

The first-order conditions for hours worked are given by:

$$W_{Yt} = \psi_Y C_t N_{Yt}^{\theta_Y},$$

$$W_{Ot} = \psi_O C_t N_{Ot}^{\theta_Y}.$$

Condition (5.1) implies that the income effect of a consumption change on labor supply is equal across young and old workers. In our benchmark calibration, we set $\theta_Y = \theta_O$ so that the substitution effect of wage changes on labor supply are equated across workers. Adopting identical income and substitution effects allows us to isolate the role of capital-experience complementarity in generating volatility differences across young and old workers.

5.1.3. Equilibrium

Equilibrium is defined as follows. Given $\tilde{K}_0 > 0$ and the stochastic process, $\{z_t\}$, a *competitive equilibrium* is an allocation, $\{C_t,\ N_{Yt},\ N_{Ot},\ \tilde{K}_{t+1},\ Y_t,\ H_{Yt},\ H_{Ot},\ K_t\}$, and a price system, $\{W_{Yt},\ W_{Ot},\ r_t\}$, such that: given prices, the allocation solves both the representative household's problem and the representative firm's problem; and factor markets clear for all t:

$$K_t = \tilde{K}_t; \quad H_{Yt} = s_Y N_{Yt}; \quad H_{Ot} = (1 - s_Y) N_{Ot}.$$

Walras' law ensures clearing in the final goods market:

$$C_t + K_{t+1} = Y_t + (1 - \delta) K_t, \quad \forall t.$$

Finally, for the purposes of model evaluation, we define aggregate hours worked as $H_t = s_Y H_{Yt} + (1 - s_Y) H_{Ot}$.

5.2. Quantitative Specification

For comparability with the RBC literature, we adopt a standard calibration procedure as closely as possible. However, the model's parameters governing elasticities of substitution in production, σ and ρ, cannot be calibrated to match standard first-moments in the U.S. data. Instead, we adopt a structural estimation procedure to identify these values using NIPA and CPS data. After discussing the procedure, we discuss calibration of the remaining parameters in Subsection 5.2.2.

5.2.1. Structural Estimation

Our strategy entails estimating σ from the model's aggregate labor demand equation.[23] Consider the firm's first-order condition with respect to the demand for H_{Yt} rewritten in logged, first-differenced form:

$$\Delta \log W_{Yt} = a_0 + (\sigma - 1)\Delta \log \left(H_{Yt}/Y_t\right) + \sigma u_t, \tag{5.2}$$

where a_0 is a constant, and u_t is a function of current and lagged shocks:

$$u_t = \varepsilon_t - (1 - \phi)\left(\varepsilon_{t-1} + \phi\varepsilon_{t-2} + \phi^2\varepsilon_{t-3} + ...\right).$$

Hence, σ is determined from the response of W_Y to exogenous changes in H_Y and Y.

Because the basic monthly CPS does not include information on hourly wages until 1982, we estimate a variant of condition (5.2) for which data is available for the entire period of interest. This is obtained by multiplying both sides of the first-order condition by H_{Yt}:

$$\Delta \log LI_{Yt} = a_1 + \sigma\Delta \log H_{Yt} + (1 - \sigma)\,\Delta \log Y_t + \sigma u_t,$$

where $LI_{Yt} \equiv W_{Yt}H_{Yt}$ denotes labor income earned by young workers. Annual observations on respondents' total labor income are available from the CPS March supplement. Abstracting from endogeneity issues (see below), σ can be estimated from a simple restricted least-squares regression. To estimate ρ, we proceed in a

[23] A similar approach is used in Burnside, Eichenbaum and Rebelo (1995) and the references therein.

similar manner. Combining the firm's first-order conditions with respect to H_{Ot} and K_t and performing similar manipulations obtains:

$$\Delta \log \left(Q_{Ot}/Q_{Kt}\right) = a_2 + \rho \Delta \log \left(H_{Ot}/K_t\right) + \rho u_t, \tag{5.3}$$

where Q_{Ot} denotes the share of national income earned by old labor and Q_{Kt} the share of national income earned by capital.

This procedure does not require imposing any restrictions from the model's specification of household behavior.[24] The only assumptions required to pin down σ and ρ are: (i) profit maximization on the part of firms, and (ii) that factor prices reflect marginal revenue products. No aspect of our approach imposes $\sigma > \rho$; whether this condition is satisfied depends on the relationship between aggregate prices and quantities observed in the data.

The data used in estimation come from standard sources. Briefly, Y_t, K_t, and Q_{Kt} come from the BEA's NIPA and Fixed Asset Tables. H_{Yt}, H_{Ot}, LI_{Yt}, and Q_{Ot} are constructed using March CPS data. Because of this, our data comprise annual observations for the period 1968 - 2005. Given the results of Section 2, we classify agents aged 15 - 29 as young and agents aged 30+ as old. Finally, H_{Yt} is measured as effective hours worked by 15 - 29 year olds and is derived by weighting respondents' raw hours using wages as relative weights; the same is done for H_{Ot}. Our weighting procedure follows that of Krusell et al. (2000). See JPS for a detailed discussion of the data.

To obtain unbiased estimates, we instrument our regressors in (5.2) and (5.3) by variables unrelated to shocks shifting firms' input demand, be them technology shocks, u_t, or other omitted factors. Specifically, we use lagged birth rates and the Ramey-Shapiro dates (Ramey and Shapiro, 1998; Ramey, 2006) as instruments. The Ramey-Shapiro dates correspond to dummy variables indicating the onset of

[24] We see this as a virtue, since our goal is to abstract from labor supply differences, and isolate the quantitative role of differences in the cyclical demand for young and old labor.

government spending increases due to war and military build-ups. Given Ramey and Shapiro's narrative approach in identification, these dates are exogenous to shocks to technology. Using lagged birth rates allows us to identify changes in current labor supply caused by changes in past fertility that also are exogenous to shifts in labor demand. Using this procedure, we obtain IV estimates of $\hat{\sigma} = 0.619$ and $\hat{\rho} = 0.119$ with standard errors of 0.207 and 0.313, respectively.[25] Hence, we use values of $\sigma = 0.62$ and $\rho = 0.12$ in our analysis.

5.2.2. Calibration

Given values for σ and ρ, we calibrate the remaining parameters in the standard way. We set $\beta = 0.995$ so that each period corresponds to a quarter; $\theta_Y = \theta_O = 0$ so that all household members have Rogerson-Hansen preferences. We set $\delta = 0.023$ to obtain an (annual) steady-state capital-to-output ratio of 3.

Our maintained hypothesis is that the Great Moderation is due to two factors: a fall in the volatility of technology shocks, and a fall in the share of aggregate hours worked by young agents.[26] Therefore, we proceed as follows. We set μ and λ to match the $1968 - 1984$ national income shares of $Q_K = 0.37$ and $Q_O = 0.47$. With values for $\{\sigma, \rho, \mu, \lambda\}$ and data on output and factor inputs, we back out the implied technology series, $\{A_t\}$.[27]

We find that the standard deviation of the technology shock falls by 73% across the 1968 - 1984 and 1985 - 2004 periods, with very little change in persistence.

[25] See JPS for further discussion regarding validity of our instruments and robustness of our IV estimates, and comparison with un-instrumented least squares results.

[26] See Arias, Hansen, and Ohanian (2006) who investigate the role of decreased Solow residual volatility in the standard RBC model.

[27] Unfortunately, quarterly data on hours worked disaggregated by age are not available from the CPS before 1976. As a result, we derive a semi-annual measure for technology using semi-annual data on output, capital, and hours. Age-specific hours worked are constructed using data from the March and October CPS. It can be verified easily that second-moment properties of the business cycle component of output, aggregate hours, and the Solow residual are essentially identical at quarterly and semi-annual frequencies.

As such, we set $\phi = 0.93$ in both periods and vary σ_ε from 0.0087 to 0.0050 across periods to match the observed volatility in $\{A_t\}$. In the pre-moderation period, $s_Y = 0.35$ is set to match the average population share of young individuals in 1968 - 1984. N_{Yss} and N_{Oss} are set to jointly match: the observed ratio of young-to-old hours worked in 1968 - 1984, and a steady-state value for aggregate hours of $H_{ss} = s_Y N_{Yss} + (1 - s_Y) N_{Oss} = 0.3$. To match the change in the share of aggregate hours by young and old agents, we set $s_Y = 0.27$ and increase N_{Oss} by 12% in the post-moderation period to match the average values observed in 1985 - 2004.

5.3. Results

To evaluate the model's predictions, we separately simulate data for the pre- and post-moderation periods according to the calibration just described. Aside from the changes to the shock process and demographics across periods, all other parameters are held fixed.

Table 5.1 presents second-moment statistics for HP-filtered output and hours worked for the U.S.; the first column covers the 1968 - 1984 period, the second column covers 1985 - 2004, and the third column presents the log difference. The volatility of output and aggregate hours both exhibit drastic moderation, on the order of a 75-log-point fall across the two periods. Interestingly, the fall in the volatility of hours worked by young individuals has been smaller (only 47 log points) so that, relative to output, the standard deviation of H_Y has actually risen by 27 log points.

Panel B of Table 5.1 presents the same statistics for model simulated data. For the benchmark calibration, the model generates volatility of young and old hours relative to output that matches the average values (of approximately 1.6 and 0.75, respectively) found in the U.S. for the 1968 - 2004 period. Hence, in con-

	A. US data			*B. benchmark model*			*C. counterfactual*	
	PRE	POST	CHANGE	PRE	POST	CHANGE	POST	CHANGE
std(Y)	1.99	0.95	-0.74	1.85	1.00	-0.62	1.06	-0.55
std(H)	1.90	0.90	-0.75	1.90	0.99	-0.66	1.09	-0.55
std(H) /std(Y)	0.95	0.94	-0.01	1.03	0.99	-0.04	1.03	0
std(H_Y) /std(Y)	1.38	1.79	$+0.27$	1.58	1.65	$+0.04$	1.58	0
std(H_O) /std(Y)	0.78	0.74	-0.04	0.76	0.80	$+0.04$	0.76	0
std(H_Y) /std(H_O)	1.76	2.40	$+0.31$	2.07	2.08	$+0.00$	2.07	0

Table 5.1: Second Moment Statistics. A: US data, 1968-1984 and 1985-2004. B and C: model generated values from the benchmark and conterfactual calibrations.

trast to almost all other RBC models, this model has no difficulty in matching the fact that aggregate hours are nearly as volatile as output.[28] The key difference is the estimated elasticity of substitution between young hours and the K-H_O composite; this is greater than the value of one implied by the usual Cobb-Douglas specification between aggregate hours and capital. This suggests that heterogeneity of labor input in production has the potential to resolve the "hours volatility puzzle" in the RBC literature (see, for instance, King and Rebelo, 1999; Gomme et al., 2004; and JPS). Finally, note that the model does a good job of replicating the Great Moderation driven solely by changes in the volatility of shocks and the share of young and old; specifically, the model generates moderation in the volatility of aggregate output and hours that is 84% and 88% as large as those found in the data.

To assess the role of demographic change in accounting for the model-generated moderation, we perform a counterfactual experiment similar to that of Section 4 where we found that demographic change accounts for 21% of the reduction in aggregate hours volatility. We re-simulate data for the post-1985 period holding

[28] In addition, when calibrated to the entire 1968 - 2004 period, the model generates volatility in aggregate output and hours, and age-specific hours similar to the U.S. data. See JPS for details, as well as details on the model's implications for the cyclicality of age-specific wages.

demographic factors fixed at their pre-1984 values, allowing only the shock volatility to fall. The results are reported in Panel C of Table 5.1. Had demographics stayed constant across periods, aggregate volatility would have fallen by only 55 log points. Hence, demographic change accounts for approximately 10% of the moderation in output, and 15% of the moderation in aggregate hours.[29]

Note that the benchmark model does not capture the increase in the relative volatility of young workers' hours since 1984.[30] As a result, the benchmark counterfactual likely understates the role of demographic change. Not only did the post-moderation period see a fall in the share of young, volatile workers, but also those workers became more volatile. In this case, holding shares constant at pre-moderation values would entail larger demographic effects.[31] Because the model cannot account for this, we propose two simple, reduced-form modifications to gauge its quantitative importance.

The first modification involves varying the labor supply elasticities across periods. Specifically, we set the pre-moderation values of θ_Y and θ_O to match the relative volatilities of young and old hours to output in 1968 - 1984; we set the post-moderation values of θ_Y and θ_O to match the relative volatilities in 1985 - 2004. This modification alone does not allow us to match $std\left(H_Y\right)/std\left(Y\right) = 1.79$ in the post-moderation period. This is not surprising since the benchmark calibration (which set $\theta_Y = 0$) considerably underpredicts this statistic. Given this, we

[29] We also performed the counterfactual in which the post-1985 period is re-simulated with the shock process of the pre-1984 period, allowing only demographics to change. In this experiment, demographic change accounts for virtually the same fraction of the moderation in hours and output as discussed above.

[30] Recall that in Section 4, we found no evidence for an effect of age composition on age-specific employment volatility in the G7. Hence, an open question is whether the increase in the relative volatility of young hours in the U.S. is related to demographic change, or is due to some other factor. In on-going work, we investigate the potential relationship between the age structure and age-group volatility in the U.S., exploiting state level variation in demographic change.

[31] The same is true for old workers, as their hours became slightly more stable (see Panel A, Table 5.1); quantitatively, this effect is likely much weaker.

also modify the specification of preferences. Specifically, we assume that family members have momentary utility functions of the form considered in Greenwood, Hercowitz, and Huffman (1988):

$$U_i = \log\left[C_i - \psi_i N_i^{1+\theta_i} / (1+\theta_i)\right], \quad i = \{Y, O\}.$$

As is well known, this specification induces greater hours volatility due to the lack of income effects on labor supply.

We first repeat the counterfactual with equalized labor supply elasticities ($\theta_Y = \theta_O$), and find that demographic change accounts for essentially the same share of the moderation in volatility as in the benchmark experiment with Rogerson-Hansen preferences. We take this as evidence that the change in preference specification per se does not affect the counterfactual results. We then consider the case in which we match $std\,(H_Y)\,/std\,(Y)$ and $std\,(H_O)\,/std\,(Y)$ in both periods. Performing the same counterfactual as described above, we find that demographic change now accounts for 15% of the moderation in output volatility, and 25% of the moderation in aggregate hours volatility, in the modified model.

In summary, this simple variant of the RBC model with capital-experience complementarity attributes a similar role to demographic change in the moderation of macroeconomic volatility to what is predicted in our experiments in Section 4. Hence, a structural model that is capable of replicating the observed changes in the relative volatility of hours worked by young and old agents would potentially attribute a similar role to demographics. Finally, note that the current model has only two groups of workers. Thus, our counterfactuals ignore important composition changes within the 15 - 29 and 30+ year old age groups. Specifically, the counterfactuals understate the fall in the share of 15 - 19 year olds, and the increase in the share of 40 - 49 year olds observed in the post-moderation period. Because these are the most volatile and most stable age groups, respectively, a more disaggregated treatment of the age composition would suggest an even greater role for demographics. In JPS, we show how a richer environment with more than two demographic groups confirms this conjecture.[32]

6. Conclusion

Recently, a number of papers have documented the empirical implications of demographic change for macroeconomic analysis.[33] In this paper, we investigate the consequences of demographic change for business cycle analysis. We find that changes in the age composition of the labor force account for a significant fraction of the variation in postwar business cycle volatility in G7 economies.

Our identification comes from the variation in the extent and timing of demographic change experienced across countries during the postwar period. Using panel data methods, we show that the age composition of the workforce has a quantitatively large and statistically significant effect on cyclical volatility. Moreover, the estimated effect is found to be U-shaped as a function of age. We supplement this by documenting a U-shaped pattern in the cyclical volatility of employment and hours worked across age groups in the same sample of countries. Taken together, these findings indicate that the crucial channel of influence of demographic composition on business cycle volatility operates through differences in the sensitivity of market work across age groups.

We articulate this idea within the context of a quantitative macroeconomic model featuring capital-experience complementarity in production. We show that the model generates significant differences in the volatility of hours worked across age groups, and we demonstrate that variation in the age composition of aggregate

[32] Including more age groups implies that elasticity parameters can no longer be estimated with linear, least-squares methods. Such issues make inclusion of the richer model beyond the scope of this paper.

[33] See, for instance, Shimer (1998) and Abraham and Shimer (2002) who study the impact of the aging of the baby boom on U.S. unemployment.

hours accounts for a significant fraction of the moderation in U.S. business cycle volatility. These results corroborate estimates of the role of demographics in the Great Moderation that are derived from simple quantitative accounting exercises performed on U.S. data. In summary, we find that demographic composition constitutes an important propagation mechanism in business cycle analysis.

A. Data Sources

US. Hours worked: 1963 - 2005, March CPS, Bureau of Labor Statistics and US Census Bureau. Employment, labor force, and population: 1963 - 2004, OECD Labour Force Statistics database (hereafter OECD LFS). Birth rates: 1900 - 1989, *Historical Statistics of the United States, Colonial Times to 1970*, and Mini Historical Statistics, US Census Bureau. Real GDP: 1958 - 2004, FRED database, Federal Reserve Bank of St. Louis.

Japan. Hours worked: 1972 - 2004, *Annual Report of the Labour Force Survey* (hereafter ARLFS), Statistics Bureau of Japan. Employment: 1967 - 1971, OECD LFS; 1972 - 2004, ARLFS. Labor force and population: 1963 - 1971, OECD LFS; 1972 - 2004, ARLFS. Birth rates: 1900 - 1989, *Historical Statistics of Japan*, Statistics Bureau of Japan. Real GDP: 1958 - 2004, Economic and Social Research Institute, Cabinet Office, Government of Japan.

Canada: Employment: 1976 - 2004, OECD LFS. Labor force and population: 1966 - 1975, special tabulation of Labour Force Survey provided by Statistics Canada; 1976 - 2004, OECD LFS. Birth rates: 1900 - 1989, B.R. Mitchell (2003), *International Historical Statistics: the Americas, 1750-2000*, New York : Palgrave Macmillan. Real GDP: 1961 - 2004, CANSIM database.

France: Employment: 1968 - 2004, OECD LFS. Labor force and population: 1965

- 2004, OECD LFS. Birth rates: 1900 - 1989, B.R. Mitchell (2003), *International Historical Statistics: Europe, 1750-2000*, New York : Palgrave Macmillan (hereafter MITCHELL E). Real GDP: 1960 - 2002, Stock and Watson (2003), which has been modified to account for 1968 strikes.

Germany: Employment, labor force and population: 1970 - 2004, OECD LFS. Birth rates: 1900 - 1955, MITCHELL E; 1956 - 1989, Federal Statistics Office, Germany. Real GDP: 1965 - 2002, Stock and Watson (2003), which has been modified to account for 1991 reunification.

Italy: Employment and labor force: 1983 - 2004, Eurostat database and OECD LFS. Population: 1983 - 2004, *World Population Prospects*, United Nations. Birth rates: 1900 - 1989, MITCHELL E. Real GDP: 1978 - 2004, Stock and Watson (2003), and Eurostat database.

UK: Employment: 1983, special tabulation of Labour Force Survey provided by Office for National Statistics, UK; 1984 - 2004, OECD LFS. Labor force and population: 1979 - 1983, special tabulation of Labour Force Survey provided by Office for National Statistics, UK; 1984 - 2004, OECD LFS. Birth rates: 1900 - 1989, MITCHELL E. Real GDP: 1974 - 2004, Office for National Statistics, UK.

For all countries, inflation rates constructed from GDP deflator data obtained from the Datastream database, Thomson Financial.

B. Additional Tables

B.1. Alternative Filtering

Here we present the tables of Section 2, except HP filtering with smoothing parameter 100. The first table is analogous to Table 2.1 for the US.

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	6.858	3.283	2.510	1.729	1.391	1.399	2.248	4.324
R^2	0.77	0.78	0.89	0.92	0.92	0.70	0.44	0.40
cyclical volatility	5.995	2.874	2.231	1.617	1.317	1.150	1.336	2.695
% of hours	3.24	10.33	12.86	25.38	23.29	17.20	4.82	2.88
% of hours volatility	10.58	16.18	15.63	22.37	16.71	10.78	3.51	4.23

The next table is analogous to Table 2.2 for Japan.

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	4.270	1.469	1.222	1.123	0.977	0.830	1.516	1.986
R^2	0.74	0.68	0.80	0.78	0.76	0.88	0.57	0.39
cyclical volatility	3.475	1.115	1.055	0.970	0.850	0.782	1.156	1.161
% of hours	2.21	10.18	11.77	23.34	24.19	18.67	4.92	4.73
% of hours volatility	7.65	11.30	12.37	22.55	20.47	14.53	5.66	5.47

B.2. Alternative Demographic Splits

Here we presents results on the volatility of hours worked in the US by age and education. Because of the relatively small fraction of 15 - 19 year olds with postsecondary education, we omit them in the analysis; because of relatively small sample sizes, we combine the 60 - 64 and 65+ age groups.

	15+	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60+
raw vol.							
HS and less	1.607	2.636	2.181	1.761	1.215	1.291	2.001
more than HS	0.849	2.459	1.422	0.755	0.824	0.861	1.949
cyclical vol.							
HS and less	1.569	2.374	1.967	1.657	1.071	1.004	1.169
more than HS	0.794	1.888	1.177	0.590	0.595	0.364	0.750

The next table presents the volatility of hours worked in the US by age and gender. Again, because of small sample sizes, we combine the 60 - 64 and 65+ age groups.

	15+	15-19	20-24	25-29	30-39	40-49	50-59	60+
raw vol.								
female	1.240	5.384	2.279	1.789	1.282	1.091	1.110	2.299
male	1.331	5.117	3.057	1.860	1.394	0.953	0.980	1.774
cyclical vol.								
female	1.220	4.628	1.965	1.352	1.003	0.916	0.794	0.969
male	1.310	4.270	2.480	1.673	1.286	0.863	0.778	0.990

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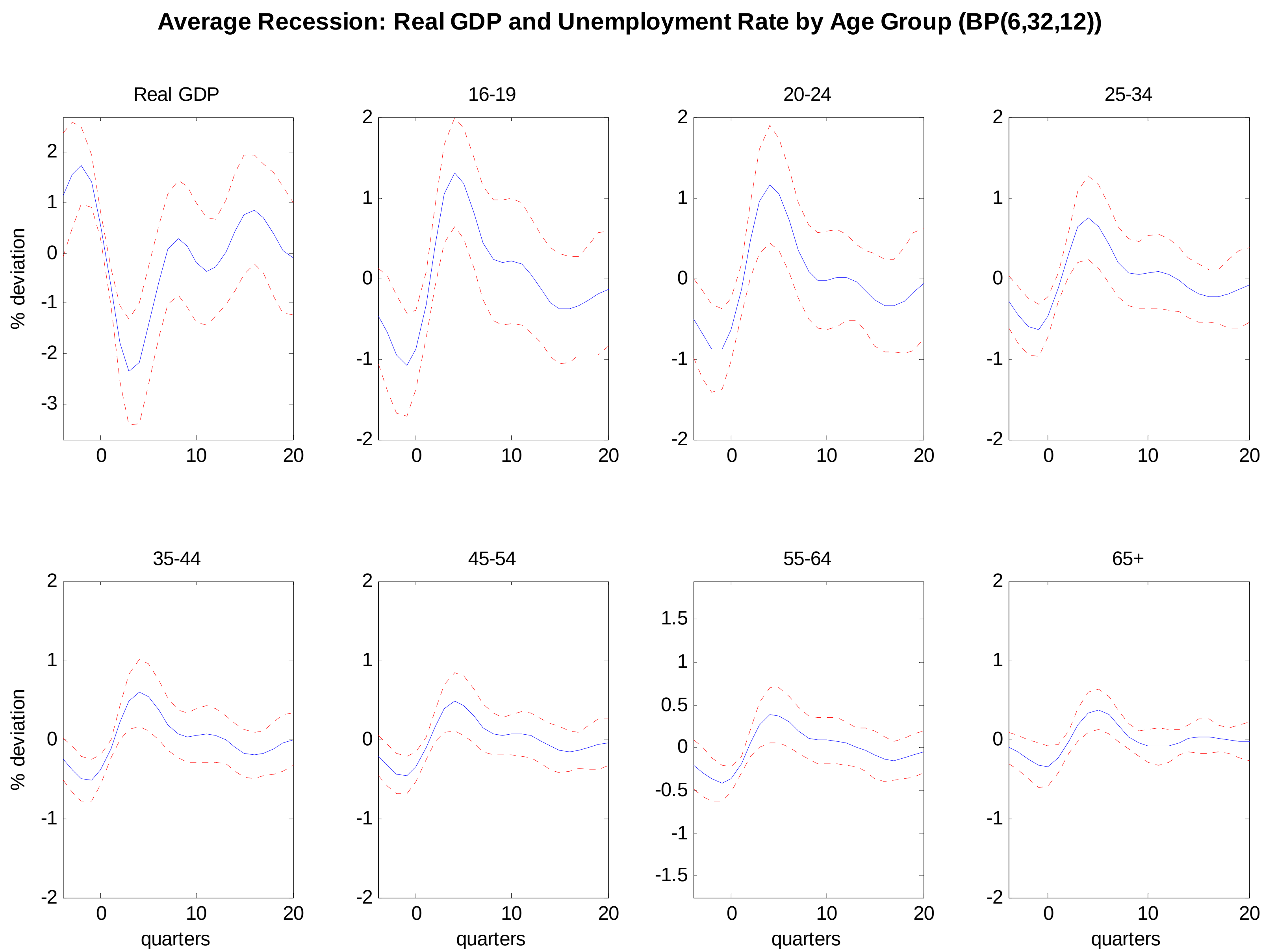

Figure 1. Average Response of Unemployment to Postwar US Recession. Solid line: average response; dashed lines: two standard deviation bands.

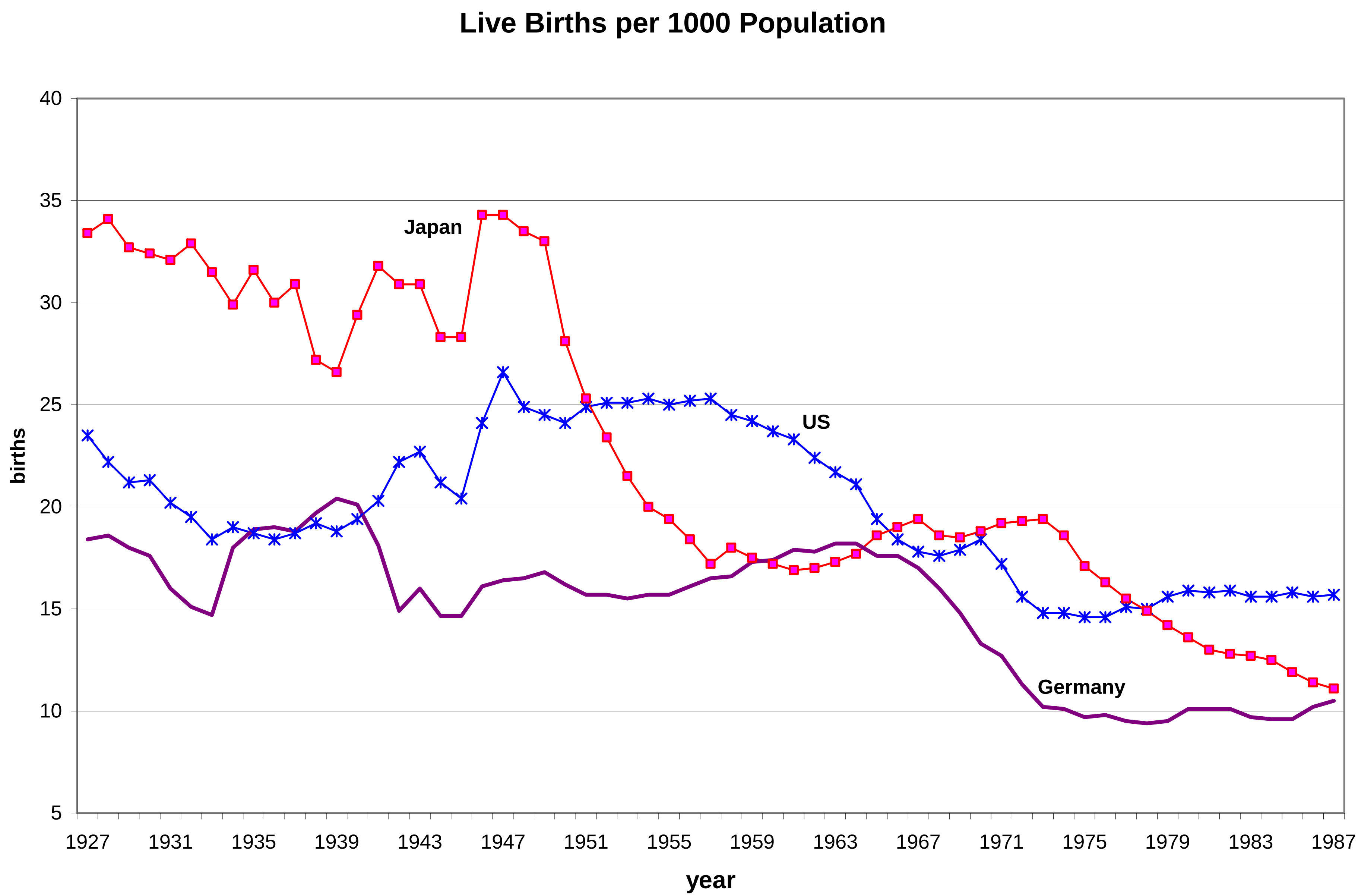

Figure 2. Variation in Demographic Change. Birth rates for three of the G7 economies.

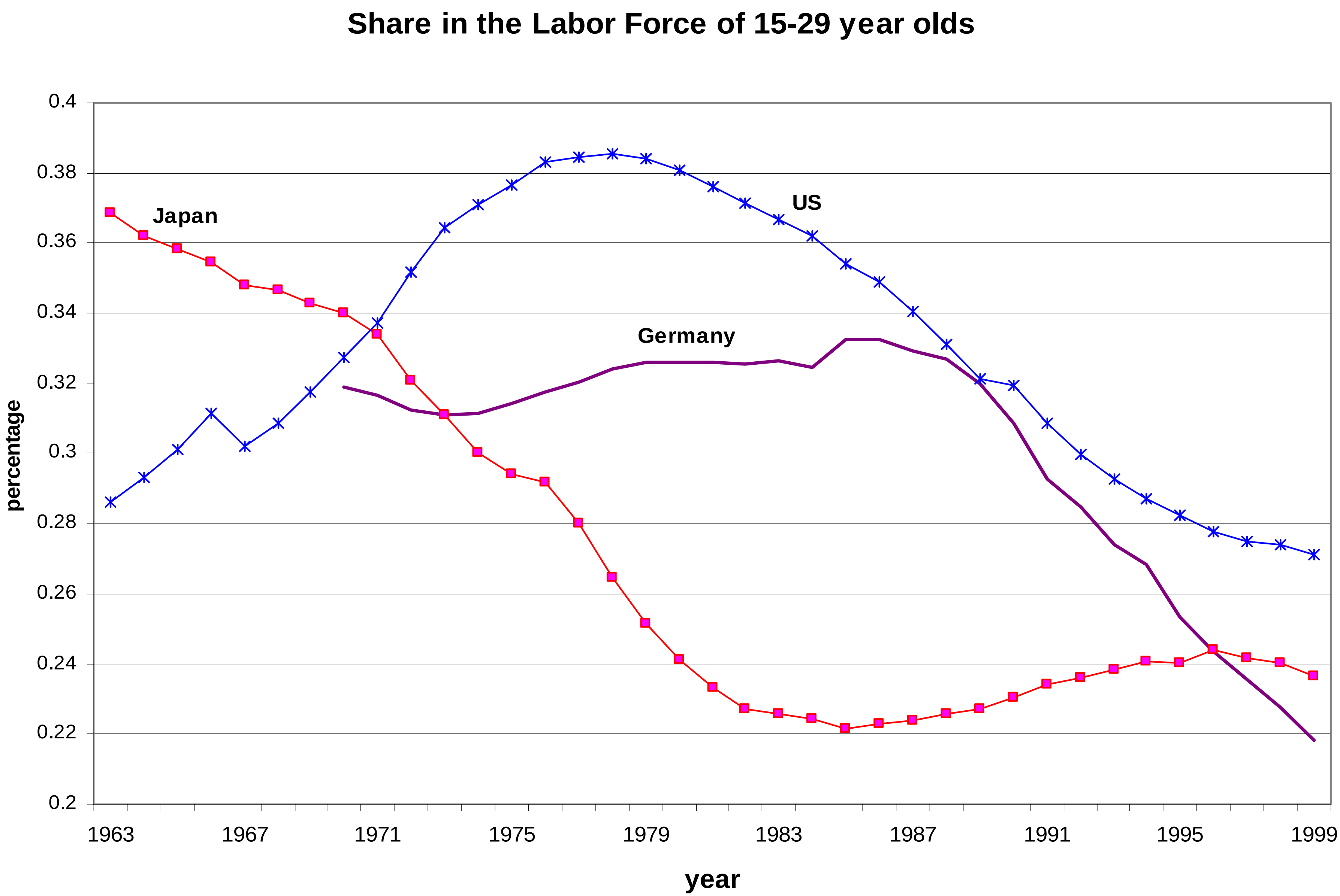

Figure 3. Variation in Demographic Change. Labor force shares of 15 to 29 year olds for three of the G7 economies.

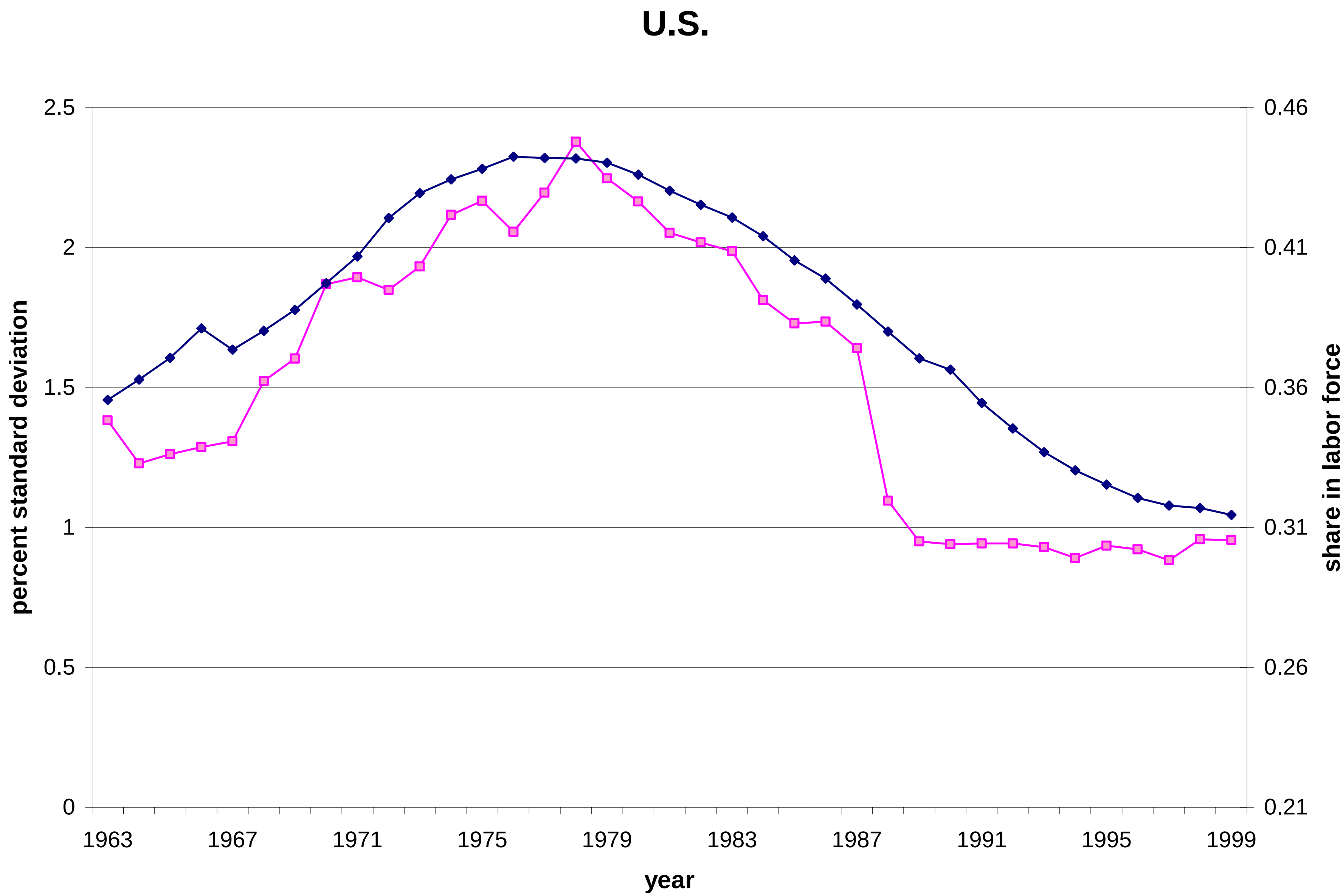

Figure 4. Demographics and Business Cycle Volatility, US. Light, square-hatched line: standard deviation of output fluctuations calculated over 10 year rolling window; dark, diamond-hatched line: labor force share of ‘volatile age group’.

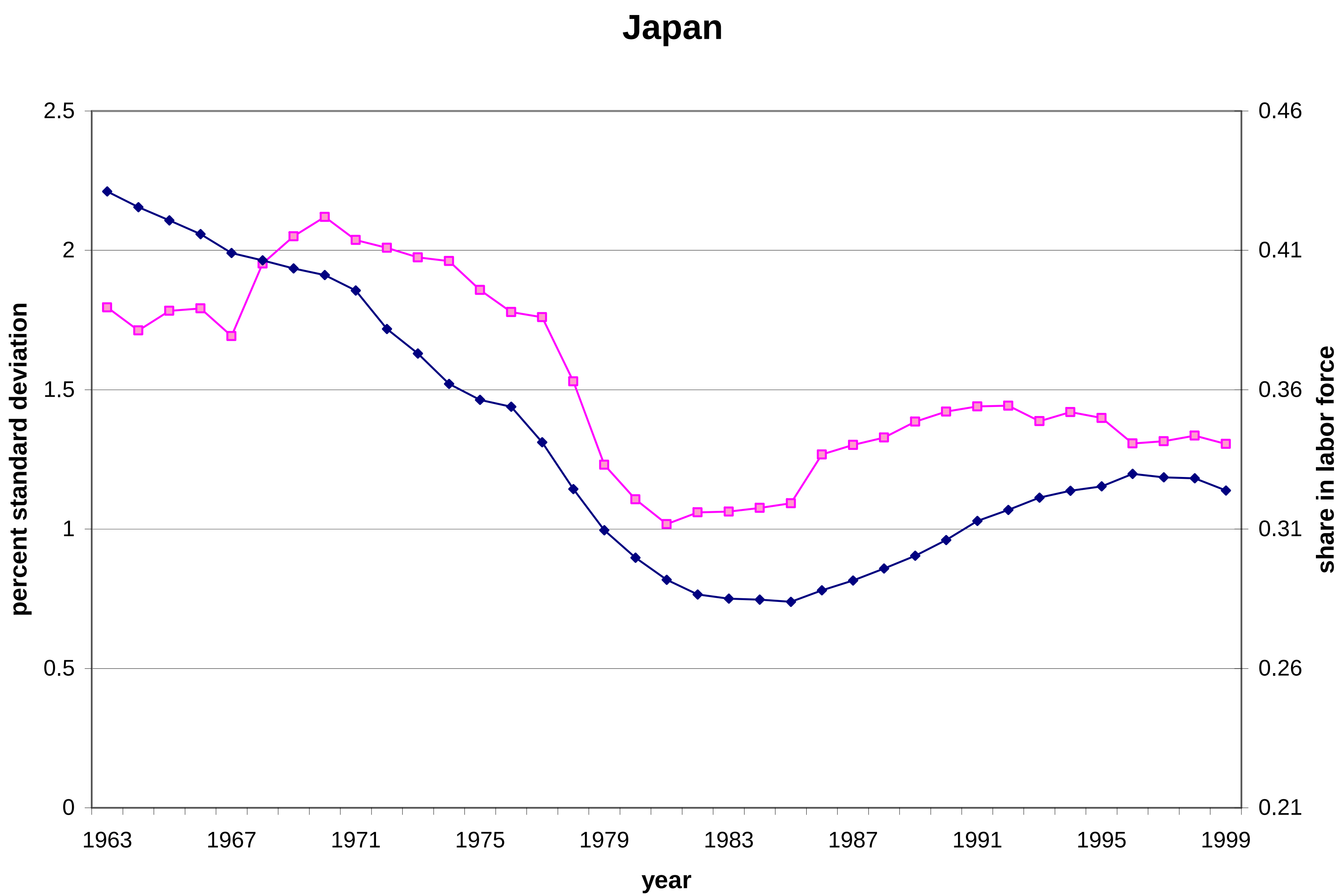

Figure 5. Demographics and Business Cycle Volatility, Japan. Light, square-hatched line: standard deviation of output fluctuations calculated over 10 year rolling window; dark, diamond-hatched line: labor force share of 'volatile age group'.

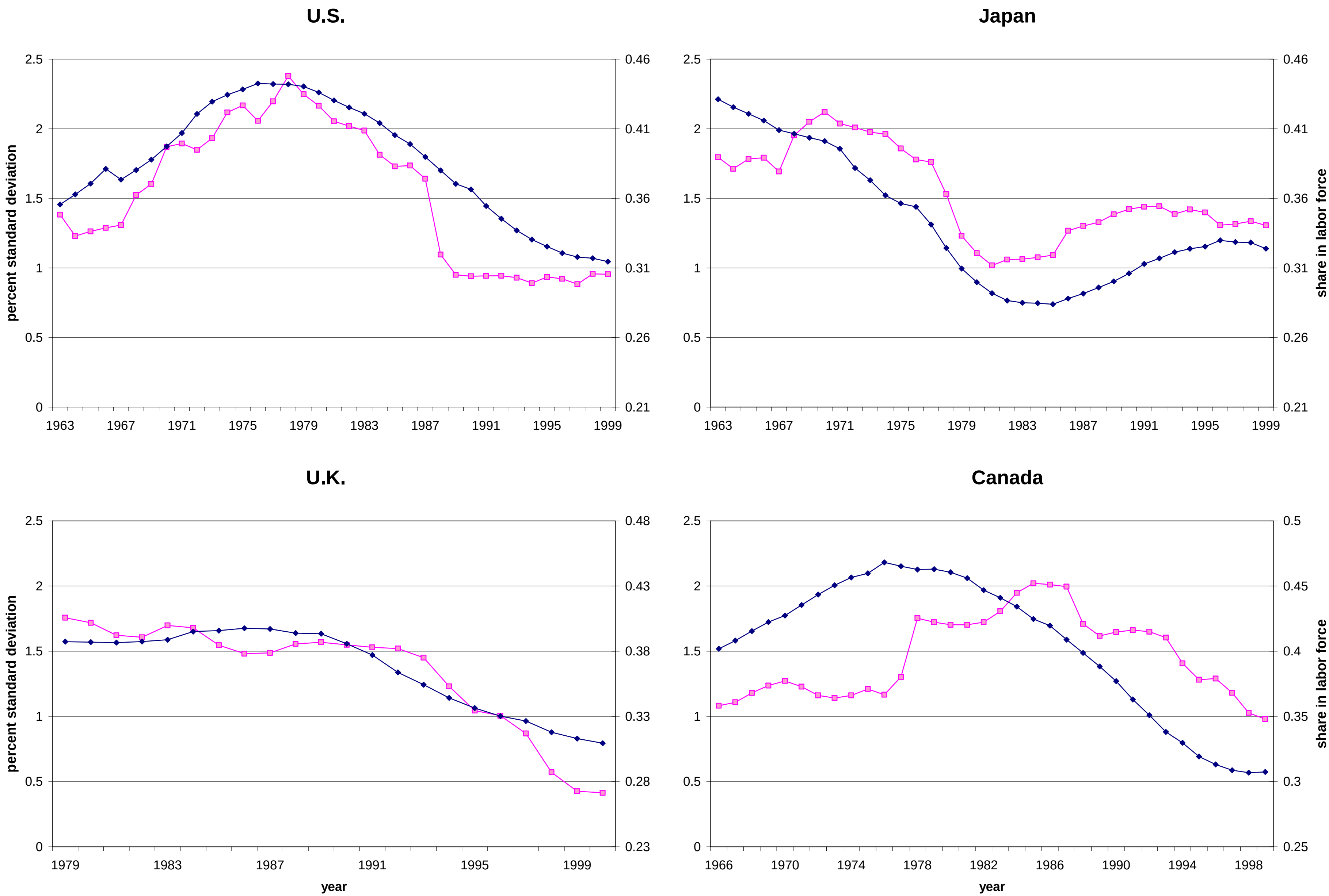

Figure 6. Demographics and Business Cycle Volatility, G7 Economies, Part 1. Light, square-hatched line: business cycle output volatility; dark, diamond-hatched line: 'volatile aged' labor force share.

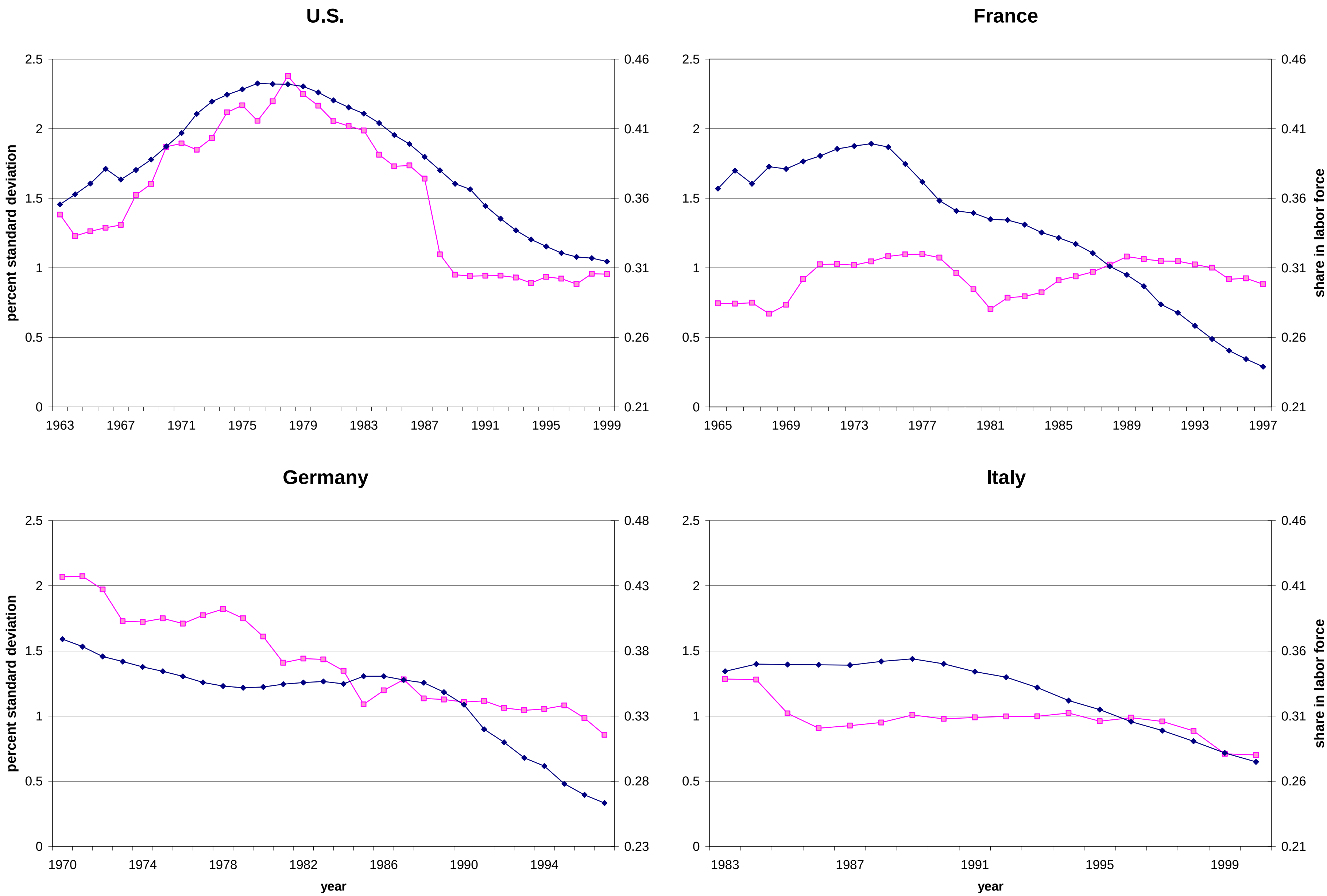

Figure 7. Demographics and Business Cycle Volatility, G7 Economies, Part 2. Light, square-hatched line: business cycle output volatility; dark, diamond-hatched line: ‘volatile aged’ labor force share.