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

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Abstract

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 business cycle volatility observed in the US and other G7 economies. During the postwar period, these countries have experienced dramatic demographic change, though 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 US business cycle volatility. Through simple quantitative accounting exercises, 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 experienced in the US 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, though 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. 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 US and the rest of the G7.

We establish this relationship between demographics and business cycle volatility in the following manner. To begin, 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) and Gomme et al. (2004) show that in postwar US data, the cyclical volatility of market work is U-shaped as a function of age. The young experience much greater volatility of employment and hours worked relative to the prime-aged over the business cycle; the volatility of those closer to retirement is somewhere in between. Our first contribution is to show that this is an empirical regularity for all G7 countries. In Section 2 we show that for these economies, the business cycle volatility of market work is U-shaped as a function of age. For example, when averaged across countries the standard deviation of cyclical employment fluctuations of 15-19 year olds is nearly 7 times greater than that of 40-49 year olds; as a result, while teenagers on average 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 more than 3 times greater than 40-49 year olds.

Given this observation, a natural conjecture is that the responsiveness of aggregate output to business cycle shocks depends on the age composition of the workforce. For instance, periods in which an economy is characterized by a large share of young workers should be, holding all else constant, periods of greater cyclical volatility in market work and output than otherwise. Our second contribution is to show that this is indeed the case. During the postwar period, the G7 countries have experienced substantial variation in business cycle volatility. Variation in the timing and extent 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. Since demographic 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.

Our final contribution is to relate these findings to the recent literature addressing "The Great Moderation" – the decline in macroeconomic volatility experienced in the US since the early- to mid-1980's.[1] Given our empirical findings, we are able to quantify the importance of the changing workforce composition for this reduction. This is done in Section 4. Through simple quantitative accounting exercises, we find that demographic change accounts for roughly a fifth to a third of the moderation experienced in the US.

This indicates that at a first pass, demographic composition may be an important propagation mechanism in the analysis of business cycle fluctuations. As such, there are strong returns to a theoretical understanding for why differences

[1] See Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) for early papers identifying a break in output growth volatility. Blanchard and Simon (2001) argue that this moderation is part of a longer term decline in volatility starting at least since the 1950's. The term "The Great Moderation" is first used to describe this phenomenon by Stock and Watson (2002), and later by Bernanke (2004).

in the volatility of market work exist across age groups, and how variation in the age composition manifests itself in variation of macroeconomic volatility in a quantitative framework. Further concluding remarks are provided in Section 5.

2. Differences in Market Work Volatility by Age

In this section, we analyze the business cycle responsiveness of market work for data disaggregated by age. We begin with an analysis of the US and Japan, countries for which consistent information on hours worked by age groups is available. We supplement this with an 'episodic' analysis, in which we document the unemployment rate response for various age groups to postwar US recessions. We conclude the section with an analysis of age differences in business cycle volatility of employment for the sample of industrialized economies represented by the G7. See Appendix A for detailed information on data sources used throughout the paper.

2.1. Evidence from the US 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 CPS to construct annual series for per capita hours worked from 1964 to 2004 for 15 to 19 year olds, 20 to 24 year olds, 25 to 29 year olds, proceeding in 5 year age groups to 60 to 64 year olds, and for those aged 65 years and older. We also construct an aggregate series for all individuals 15 years and older. For Japan, we construct annual time series for 1972 to 2004, using data reported in the Annual Report of the Labour Force Survey. The age groups we consider are the same as in the US.

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 8 years), we use a

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	7.578	3.448	2.590	1.944	1.409	1.629	2.649	4.345
R^2	0.72	0.83	0.83	0.93	0.93	0.77	0.32	0.24
cyclical volatility	6.513	3.143	2.357	1.885	1.372	1.442	1.429	2.122
% of hours	3.98	10.89	13.03	25.86	23.19	16.35	4.30	2.39
% of hours volatility	12.58	16.59	14.89	23.64	15.43	11.43	2.98	2.46

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

smoothing parameter of 100 and 1600 for annual and quarterly data, respectively, throughout the paper. While the HP filter yields a very close approximation to the ideal high-pass filter for quarterly data, it performs less well for annual data. To address such concerns, we also conduct our analysis of annual data detrending with the band-pass (BP) filter, as proposed by Baxter and King (1999). Throughout the paper, BP filtered data refer to data with fluctuations less frequent than 8 years removed, unless otherwise stated.

Table 2.1 presents results on the volatility of hours worked in the US for the $15-19$, $20-24$, $25-29$, $30-39$, $40-49$, $50-59$, $60-64$, and 65+ year old age groups. The first row of data presents the percent standard deviation of the age-specific series, where the data are detrended with the HP filter. Since the results using BP filtered data are very similar, we do not discuss them here; see Appendix B for the analogous table. We see a distinct U-shaped pattern in the volatility of hours worked fluctuations by age.

We are not interested in the high frequency fluctuations in these detrended time series per se, but rather in those that are attributable to 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 current and lagged detrended aggregate hours. Our measure of business cycle volatility is the percent standard 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 due to the business cycle. The exceptions are the $60-64$ and 65+ age groups. Here, a significantly larger fraction of fluctuations are potentially due to age-specific, non-cyclical shocks.[2] The third row indicates the business cycle volatility of hours worked for each age group. As a point of reference, the standard deviation for aggregate hours worked is 1.97%.

Compared to Row 1, the largest differences between 'raw' and 'cyclical' volatilities are for those aged 60 years and older, reflecting the discussion of the previous paragraph. Nevertheless, the U-shaped pattern in volatility remains. The young experience much greater cyclical volatility in hours relative to 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 4.5 and 2 times that of $40-49$ year olds, respectively. Relative to $40-49$ year olds, the $25-29$ and 65+ age groups experience more than 50% greater hours worked volatility.[3]

The fourth row indicates the average share of aggregate hours worked during 1964 to 2004 attributable to each age group. The last row indicates the share

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

[3] 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) and Moser (1986) who document differences in cyclical sensitivity across age groups. More broadly, the literature documents business cycle differences as a function of skill; see for instance, Kydland and Prescott (1993) and Hoynes (2000), and the references therein. Note that these 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	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

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

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 the aggregate are disproportionately accounted for by young workers. While those aged 15 to 29 years make up only 28% of aggregate hours worked, they account for 44% of aggregate hours volatility. On the other hand, prime-aged workers in their 40's and 50's account for 40% of hours but only 27% of hours volatility.

Table 2.2 presents the same calculations for Japan. As in the US, there is a distinct U-shaped pattern to both the raw and 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. At the aggregate level, the standard deviation is 0.94% compared to 1.97% in the US. This is mirrored in the cross-country differences for each age group as well.

Second, the age-specific regression R^2's for Japan are intermediate to the large and small values found for the US. Interestingly, the R^2's for those aged 60+ years are larger in Japan, indicating that hours fluctuations for these workers are more largely due to the business cycle.

Third, the magnitude of the volatility differences between age groups is not as pronounced in Japan. The exception is the $60-64$ age group, whose sensitivity to the business cycle is 36% (48%) greater than those aged $40-49$ $(50-59)$; this compares to a value of 3.4% (-0.3%) in the US. Note also that teenagers are 4 or 4.5 times more volatile than prime-aged individuals in Japan, roughly similar to the relative volatility found in the US across these age groups.

Lastly, in Japan individuals over the age of 60 are much more significant contributors to the volatility of aggregate hours as compared to the US. This is due to their larger hours share and their greater age-specific cyclical volatility relative to the aggregate. In fact, leaving teenagers aside, the $60-64$ and 65+ age groups experience greater cyclical volatility in hours worked than any other age group.

To close this subsection, we provide additional evidence on the differences in business cycle sensitivity of market work across age group. In Figure 1, we present the 'average' response of unemployment to a postwar US 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 to isolate periodic fluctuations between 6 and 32 quarters.[4] This method identifies all of the NBER dating committee recessions, plus four additional episodes: 1962:II, 1967:II, 1986:III, and 1994:III.[5] Along the horizontal axis, date 0 represents the last quarter before output falls below trend. The figure tracks the BP filtered age-specific

[4]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.

[5]Moreover, the timing of our recessions and those identified by the NBER are 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 four other recessions, our procedure identifies starting dates that are within one quarter of the NBER dates (indicated in parentheses): 1953:III (1953:II), 1969:III (1969:IV), 1974:II (1974:III), and 2001:II (2001:I).

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 around the average. Unemployment rises quickly in response to a recession, and crosses above trend at date 2 (this is true for all age groups except the 65+, which crosses at date 3). The unemployment response peaks at either date 4 or 5, then slowly returns to trend.

This recessionary response is much stronger for younger aged 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 $16-19$ age group experiences an average trough-to-peak unemployment response of approximately 2.4% about trend; the 20 - 24 year olds experience a similar response. This compares with a trough-to-peak response of only 1% about trend 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.

2.2. Evidence 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 is not available for all countries, we restrict our attention to business cycle volatility in employment. The data we analyze is from published and unpublished national government sources, and the OECD Labour Force Statistics database. The data are at an annual frequency, and time coverage varies across countries. Again, see Appendix A for details.

We identify cyclical fluctuations in the data as in our analysis of hours worked for the US and Japan. For many of the G7 countries, the high frequency fluctuations of those aged 65 years 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 age group is actually negatively correlated with aggregate employment and output. As a result, for all countries except Japan, we omit those aged 65 years and older, and define aggregate employment as employment among those aged 15 to 64.[6] We retain this age group for Japan since their age-specific employment regression produces an R^2 of 0.7, indicating that employment among the old is highly correlated with the cycle.

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

Again, the age profile of business cycle employment volatility can be roughly characterized as U-shaped, with large differences across age groups. The young and old display greater cyclical sensitivity than prime-aged individuals. In all countries, the 15 to 29 year old age groups are much more volatile than those aged 30 to 49. This is particularly true for the continental European countries. Taking a simple average across all countries, while the young comprise approximately 30% of aggregate employment, they account for 50% of aggregate employment volatility. Large differences between the prime-aged and those older than 60 are also evident in continental Europe and Japan. In each of these countries, this older age group contributes disproportionately to aggregate volatility as well.

To summarize, we find age-specific differences in business cycle responsiveness of market work to be an empirical regularity in our sample of industrialized

[6] This reflects the potential that the labor supply decisions of those aged 65+ are very different from those faced by people of pre-retirement age. Note that since the 65+ share of the labor force and employment is small, our results are unchanged if we include this group in our analysis.

		15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64
US[A]	cyclical volatility	4.438	2.285	1.694	1.328	1.000	1.109	0.990
	% of empl.	6.72	12.30	12.89	24.82	22.27	16.38	4.62
	% of empl. volatility	18.90	17.82	13.85	20.90	14.12	11.51	2.90
Japan[B]	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	4.515	2.250	1.673	1.278	1.000	0.980	1.192
	% of empl.	7.46	12.37	13.53	26.61	22.41	14.34	3.29
	% of empl. volatility	21.25	17.56	14.28	21.42	14.14	8.87	2.47
France	cyclical volatility	15.56	9.172	4.232	2.144	1.000	2.757	6.382
	% of empl.	2.75	10.36	13.70	27.27	25.21	17.49	3.21
	% of empl. volatility	12.28	27.29	16.55	16.79	7.24	13.85	5.89
Germany	cyclical volatility	3.733	3.759	3.045	1.963	1.000	1.427	7.063
	% of empl.	7.82	12.66	11.96	24.57	23.48	16.27	3.25
	% of empl. volatility	12.63	20.59	15.77	20.88	10.16	10.04	9.93
Italy	cyclical volatility	6.591	4.233	3.034	1.418	1.000	3.009	3.114
	% of empl.	7.70	8.41	12.45	28.05	24.43	15.94	3.02
	% of cyclical employment	20.53	14.40	15.28	16.08	9.88	20.03	3.80
UK[A]	cyclical volatility	6.131	3.386	1.909	1.560	1.000	1.239	1.895
	% of empl.	6.54	10.90	12.37	25.28	23.51	17.37	4.03
	% of empl. volatility	20.80	19.15	12.25	20.47	12.20	11.17	3.97

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

economies. Our findings extend the results of Clark and Summers (1981) and Gomme et al. (2004) for the US to the rest of the G7. That these economies differ greatly in terms of industry composition, average labor productivity, 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 business cycle volatility and demographics in the G7 economies. Our identification comes from cross-country differences in the extent and timing of demographic change during the postwar period. As a rough summary of this change, Figure 2 presents birth rates for three of the G7 countries.

In the US, Canada, and (though to a lesser extent) the UK, the postwar baby boom led to an unusually large cohort of "20-something" labor market entrants in the mid to late 1970's, and subsequently a large cohort of prime-aged labor market participants beginning around 1995. In the continental European countries of France, Italy and Germany, the postwar baby boom was much less pronounced. As a result, changes in the age composition have been less dramatic. Instead, gradually declining fertility has resulted in a gradual aging of the labor force. In Japan, a sharp and rapid decline in fertility was experienced after WWII that led to a marked fall in the number of young workers entering the labor force since the early 1970's. In addition, declining fertility has led to population aging and an increasing share of workforce participants over the age of 60; this has been particularly pronounced since 1980.

The effect of these demographic changes on the age composition of the labor force are exemplified in Figure 3, which presents the share of the labor force composed of individuals aged 15 to 29 years old for the same three countries shown in Figure 2. From comparing Figures 2 and 3, it is clear that the dominant force determining labor force composition change since WWII is population change stemming from 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 to determine the impact of changes in the age distribution on changes in aggregate output volatility experienced in specific countries. Given the large literature addressing the moderation of US business cycles in the past 20 years, and the relevance of our results to this issue, we defer that discussion to the next section.

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 across ages documented in Section 2. 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 indicate that the low frequency movements in workforce shares are driven by movements in population age composition. Since population composition is largely determined by fertility decisions made at least 15 years prior, this component of labor force shares is exogenous to current business cycle conditions. This leaves the potential endogeneity of age-specific: (i) labor force participation rates, and (ii) international migration to cyclical volatility unaccounted for. In our analysis (see below), we pursue two formal approaches to address these issues.

It is obviously very difficult to obtain a direct, point-in-time measure of cyclical volatility, or more abstractly, an economy's responsiveness to business cycle shocks. As a result, 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. See Appendix A for data sources. The benchmark filter we adopt is the HP filter. To demonstrate robustness of our results, we also present results for volatility measures constructed with other filters and time windows.

3.1. A First Cut

The benchmark regression we consider is:

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

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 'international volatility shocks' common across countries. This also implies that our identification of γ is through cross-country variation in age composition change that is not shared across countries over time.

Because of limitations in data availability, time coverage differs from country to country, so that 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. See Appendix A for details. Quarterly real GDP data are 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.

The first specification we consider is one where $\mathbf{share}_{it}$ is the share of *volatile-aged* labor force participants. That is, we use our results from Section 2 to identify those age groups for which business cycle hours worked or employment volatility is greatest; to facilitate interpretation of the estimated value of γ, we include groups in descending order of volatility to the point where the share measure comprises approximately one third of each country's $15-64$ year old labor force (15+ in Japan). Hence, $\mathbf{share}_i$ is the labor force share of: $15-29$ year olds in the US, Canada, and the UK; $15-29$ plus $60-64$ year olds in France, Germany, and Italy; and $15-29$ plus 60+ year olds in Japan. We view this specification as a simple and informative first cut to illustrate the effect of the age distribution on business cycle volatility. We present results with a more detailed disaggregation 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 US 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 US, output volatility rose from the early 1960's 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 the baby boomers into the workforce. The evolution of output volatility was very different in Japan. Business cycle volatility fell beginning in 1971, accelerating in the late 1970's. After stabilizing in the early 1980's, volatility has since risen. Again, this pattern is closely tracked by the volatile-aged labor force share.

Figures 6 and 7 present the same series for all G7 countries. In each panel, the vertical axes are identical to facilitate comparison. In six of the seven countries, business cycle volatility and the volatile labor force share clearly covary; though admittedly, in Italy the magnitude of the movements are small, and in Canada there appears to be a slight phase shift. In France, unconditional evidence on this

	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)$^{A,\blacktriangle}$
$\hat{\gamma}$	3.714***	3.714***	4.382***	1.986***	2.046**	2.144***	2.444***
	(0.751)	(1.091)	(1.436)	(0.668)	(0.941)	(0.692)	(0.879)
Nobs	207	207	213	207	213	180	180

A and B: 41 qtr and 21 qtr window used to construct dependent variable, respectively.
★ and ▲: 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.

relationship is clearly weak, though relative to the US, Canada, the UK, Japan, and Germany, there is quantitatively little change in output volatility to explain in the first place.

Table 3.1 presents estimation results on γ, the average effect of the labor force measure on business cycle volatility in the G7. Column 1 displays our benchmark OLS estimate. The share of volatile-aged workforce participants has a positive impact on business cycle volatility. To interpret the magnitude of the coefficient estimate, an increase in this labor force share of 10% increases cyclical volatility by 0.37.[7] This effect is estimated to be significant at the 1% level.

The results in Column 1 suffer from autocorrelated residuals. This is due in part to the construction of our measure of business cycle volatility, which results in overlap of output data in consecutive observations of σ_{it}. To address this issue, we run standard tests on the regression residuals to determine the highest order of serial correlation. For the benchmark specification, we cannot reject a highest order of 2. In Column 2, we report results when heteroskedasticity and autocorrelation robust standard errors are constructed using the Newey-West estimator.

[7] Again, we delay discussion of this result in relation to the Great Moderation in the US to the following section.

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 of the result, Table 3.1 reports coefficient estimates when we change the way cyclical volatility is measured. In Columns 3 and 5 we shrink the window within which observations are used to measure volatility, from 41 to 21 quarters. In Columns 4 and 5, we consider real output detrended by first-differencing;[8] 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 only results for the 41 quarter window in Columns 6 and 7 (results using the 21 quarter window are virtually identical). The estimated effect of the volatile aged labor force share on all measures of cyclical volatility 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, given that the definition of the dependent variable differs.

The results of Table 3.1 are potentially subject to endogeneity problems since 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 when our labor force measure is projected onto measures of the total population. In particular, for each country, the volatile aged labor force share is instrumented by the population age distribution.[9]

[8] This is the detrending method used, for instance, by Blanchard and Simon (2001).

[9] We instrument with the entire distribution (as opposed to simply the population share of the volatile age groups) because we find other age groups' population shares to have predictive

	1	2	3	4	5	6
			endogeneity		*Blanchard - Simon*	
	OLS	IV1	IV2	BP	OLS	IV2
A. annual						
$\hat{\gamma}$	3.714***	3.834***	3.642***	3.884***	4.910***	4.868***
	(1.091)	(1.073)	(1.086)	(1.107)	(1.043)	(1.043)
Nobs	207	207	207	207	203	203
B. 4-year						
$\hat{\gamma}$	4.110***	4.120***	4.078***	4.229***		
	(1.375)	(1.311)	(1.369)	(1.463)	—	—
Nobs	55	55	55	55		

***: significant at 1% level.

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.

The first column of Table 3.2, Panel A repeats our benchmark OLS result of 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 very 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 one step further, to address the possibility that the population age distribution may be endogenous as well. This would result 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 approach is straightforward. Excluding migration, an age group's share of the 15 to 64 year old population is

power in the first stage regressions. This is suggestive of 'cohort crowding' effects in the labor market, or potential complementarity in labor demand across workers of different age groups. Results from instrumenting with the volatile age group's population share are similar and not presented for brevity.

determined by the distribution of births 15 to 64 years prior.[10] Since past fertility is exogenous to current macroeconomic volatility conditions, instrumenting by lagged birth rates allows us to obtain unbiased estimates of the causal impact of labor force composition.

As such, we instrument by projecting the (current) 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 very similar to the original OLS result.

Using population shares and lagged birth rates as instruments is problematic, however, if demographics affect cyclical volatility, independent of their influence on labor force composition. This is a possibility 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. We discard all fluctuations at frequencies greater than 20 years using the BP filter.[11] 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 restricting attention to only low frequency variation in workforce composition due to factors such as demographic change that are orthogonal to cyclical volatility shocks. Column 4 of Table 3.2, Panel A reports the result from using this filtered

[10] This ignores deaths among individuals younger than 64 years of age, which is statistically negligible among G7 countries.

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

measure of the labor force share as a regressor. Again, the coefficient estimate is positive and significant, and very similar to our benchmark result.

In addition, we add to our benchmark specification the regressors considered by Blanchard and Simon (2001). In their paper, Blanchard and Simon conclude that inflation volatility displays a strong, and potentially causal, relationship with output volatility. This conclusion is based upon panel data analysis very 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, the concern with this analysis stems from endogeneity of inflation measures and output volatility. This bias makes inference somewhat 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. Instead, the point is simply to illustrate that our results are robust to concerns of spurious correlation between labor force composition and output volatility.[12] The OLS estimate from this exercise is reported in Column 5 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 statistical significance of the original findings (the results for the IV1 and BP exercises are virtually identical).

Our final experiment concerns the 'spacing' or temporal frequency of observations. The demographic change underlying our inference is a gradual process.

[12] The previous discussion on validity of population measures as instruments raises another possibility for spurious correlation: namely, that demographic change has impacted upon 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 subsection suggest that such spurious correlation is highly unlikely.

Consequently, perhaps the only meaningful variation in our labor force measure obtains 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.[13] Columns 1 through 4 present coefficient estimates for our benchmark OLS, IV, and BP filtered cases, respectively. Notice that this change does not significantly affect our results; in fact, it only serves to strengthen our conclusion of a positive link between the labor force share of volatile aged individuals and business cycle volatility. Results from including inflation measures as regressors are also unchanged, and not presented for brevity.

3.2. Looking at the Entire Age Distribution

The results to this point indicate that labor force composition has causal impact on macroeconomic volatility. Periods exhibiting a larger share of age groups with cyclically sensitive market work tend to be periods of 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 regressors in our volatility regressions. This is motivated by our results of Section 2: namely, that 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 impact 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 implement this by altering our benchmark specification so that the regres-

[13] 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 would result in a disproportionately large drop in the number of observations.

		30 - 39	40 - 49	50 - 59	60 - 64[A]	Nobs
1	OLS	-3.025^{*}	-4.057^{***}	-6.255^{***}	-0.716	207
		(1.617)	(1.488)	(2.085)	(4.370)	
2	IV1	-3.238^{**}	-4.206^{***}	-6.520^{***}	-0.316	207
		(1.673)	(1.487)	(2.212)	(4.494)	
3	IV2	-2.985^{*}	-4.074^{***}	-6.002^{***}	-2.654	207
		(1.816)	(1.555)	(2.057)	(2.810)	
4	BP	-2.822^{**}	-4.273^{**}	-6.461^{***}	0.483	207
		(1.816)	(1.666)	(2.493)	(4.656)	

*, **, 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. A: 60 - 64 age group replaced by 60+ in Japan.

sor, **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 (60+ in Japan). Since labor force shares sum to one, we exclude the 15 – 29 year old age group for the obvious reason.[14] 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 results. Relative to our conjecture, the estimated coefficients have the expected sign and magnitude. A decrease in the share of 15 to 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 reduction in volatility comes from shifting young workforce members into the 60 to 64 age group, though this effect is not significantly different from zero. This is consistent with our results of Section 2 which indicate that both the young and old tend to contribute disproportionately to aggregate market work

[14] This is the same approach taken by Feyrer (2004) to study the impact of demographics on productivity growth in OECD countries.

volatility in G7. On the other hand, shifting labor force shares out of the young and into prime-aged groups results in large and statistically significant reductions in cyclical volatility, with the largest effect from the 50 to 59 age group. Again, this is consistent with the U-shape in market work volatility.

We conducted additional experiments by varying the excluded age group one-by-one 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 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, within Sets 1 and 2, the difference in estimates 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 $50-59$'s and $15-29$'s, respectively, and insignificant for both the $40-49$'s and $60-64$'s.

Though not reported here, we also experimented 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 as a function of age. Finally, we repeated the robustness checks of the previous subsection by considering different definitions of business cycle volatility. Again, the sign and significance of estimated coefficients is not sensitive to the details regarding the detrending of output or the size of window used in computing volatility.

		30 - 39	40 - 49	50 - 59	60 - 64^{A}	Nobs
1	OLS	-3.395	-3.964^{*}	-6.424^{**}	2.730	55
		(2.455)	(2.065)	(2.817)	(6.555)	
2	IV1	-3.325	-3.932^{*}	-6.436^{**}	3.045	55
		(2.467)	(2.065)	(2.915)	(6.615)	
3	IV2	-3.193	-4.086^{*}	-6.147^{**}	2.633	55
		(2.436)	(2.068)	(2.741)	(6.524)	
4	BP	-2.767	-4.386^{*}	-6.515^{*}	4.683	55
		(2.606)	(2.333)	(3.633)	(7.249)	

* 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. A: 60 - 64 age group replaced by 60+ in Japan.

In the remaining rows of Table 3.3 we report robustness checks addressing 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 as instruments (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 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, we find statistically significant effects of the labor force age composition.

Finally, Table 3.4 presents the same regression estimates as Table 3.3, 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. 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 interpret 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. That is, the U-shaped 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 in US Business Cycle Volatility

Since the early- to mid-1980's the US has undergone a substantial decline in business cycle volatility, as evidenced in Figure 4. The reduction in frequency and amplitude of business cycles represented in this change has been sufficiently pronounced as to generate a designation for the phenomenon. 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 (Clarida et al., 2000; Blanchard and Simon, 2001; Stock and Watson, 2002); regulatory changes and financial market innovation related to household borrowing (Campbell and Hercowitz, 2006; Justiniano and Primiceri, 2006), changes that have allowed for a reduction in production volatility relative to sales volatility on the part of firms (McConnell and Perez-Quiros, 2000; Kahn et al., 2002; Ramey and Vine, 2004); and good luck in the form of a reduction in the variance of business cycle shocks (Stock and Watson, 2002 and 2003; Ahmed et al., 2004; Justiniano and Primiceri, 2006).

In this section, we take a first step in quantifying the role played by demographic change in accounting for the moderation of US business cycle volatility.

Our view is that a definitive answer – accounting for sources of fluctuations, equilibrium effects on relative factor prices induced by changing workforce composition, and the like – requires a quantitative theoretical approach. We view the simple accounting exercises conducted below as suggestive of the rough magnitude in change owing to demographic considerations, and indicative of the need to pursue a careful quantitative analysis.

Our first exercise simply involves interpreting the coefficient estimates from our G7 panel regressions. In 1978, our measure of cyclical volatility in the US peaks. This year coincides with the peak in the 15 to 29 year old labor force share at 38.5%, reflecting the influx of baby boomers into labor market participation. Business cycle volatility then fell rapidly during the mid-1980's. Again, this coincides with a fall in the 15 to 29 year old labor force share as baby boomers entered their 40's and 50's. By 1999, the 15 to 29 year old share was only 27.1%, representing a level reduction of 11.4% from 1978.

From our OLS estimates of Subsection 3.2, such a shift in workforce composition from the $15-29$ age group into the $40-49$ age group predicts a volatility reduction of $0.114 \times 4.057 = 0.462$. Given that our measure of cyclical volatility fell from 2.379 to 0.955 between 1978 and 1999, the change in the age composition of the labor force accounts for roughly 32% of the moderation between these two dates.

Finally, we present results from a simple decomposition exercise to determine how much of the change in aggregate employment and hours worked volatility owes to the change in workforce age composition. To do this we use the data analyzed in Section 2, and compare the standard deviation of HP and BP filtered measures between the periods $1967-1984$ and $1985-2004$. Note that the first period exhibited high cyclical volatility, while volatility in the latter period was much lower. The standard deviation of per capita aggregate employment fluctuations fell 26.4 log points across the two periods in HP filtered data, and 64.5 log points in BP filtered data. For hours worked, the standard deviation fell 42.1 and 81.8 log points in HP and BP filtered data, respectively.

To determine the role played by demographic change, we construct a counterfactual series for per capita aggregate employment, e_t, that holds the age structure fixed. To do this, note that:

$$e_t = e_t^{16} p_t^{16} + e_t^{20} p_t^{20} + \ldots + e_t^{65} p_t^{65},$$

where e_t^{16} is per capita employment (or the employment rate) of 16-19 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 rate series, $\{e_t^x\}$, but set the population share values for each age group constant.

Our counterfactual holds the age composition fixed at the 1978 shares, so that counterfactual per capita aggregate employment for date t is:

$$\hat{e}_t^{1978} = e_t^{16} p_{1978}^{16} + e_t^{20} p_{1978}^{20} + \ldots + e_t^{65} p_{1978}^{65}.$$

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 share values observed in 1978, the standard deviation would have fallen by only 12.3 log points in HP filtered data, and 49.5 log points with the BP filter. That is, the change in age composition explains between $(26.4 - 12.3)/26.4 = 53\%$ and $(64.5 - 49.5)/64.5 = 23\%$ of the moderation in aggregate employment volatility. Performing the same counterfactual experiment for HP and BP filtered hours worked, we find that between

52% and 20% of the moderation in aggregate hours volatility is due to demographic change. Note that these estimates are roughly the same magnitude as those attributed 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 played by demographics in understanding the Great Moderation in our on-going theoretical work.

5. Conclusion

Recently, a number of papers have documented the empirical implications of demographic change for macroeconomic analysis. Shimer (1998) and Abraham and Shimer (2002) study the impact of the aging of the baby boom on US unemployment. Feyrer (2004) studies the relationship between the age composition of the workforce and productivity growth in OECD countries. 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 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. Finally, through a series of quantitative accounting exercises, we find that the change in demographic composition accounts for a significant fraction of the moderation in cyclical volatility experienced in the US.

These results indicate that the demographic composition of an economy's workforce constitutes a potentially important propagation mechanism in business cycle analysis. As such, there are strong returns to a theoretical understanding for why differences in cyclical volatility of market work exist across age groups, and how variation in the workforce age composition manifests itself in variation of macroeconomic volatility.[15] In ongoing work we are pursuing these questions within the context of quantitative general equilibrium analysis.

A. Data Sources

US. Hours worked: 1964 – 2004, 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.

[15] Indeed, an interesting question is whether such an explanation can also address the results of Shimer (1998) regarding demographic composition and average unemployment.

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

In this appendix we present tables analagous to those presented in Section 2, except for data detrended with the BP filter. The first table presents information analagous to Table 2.1 for the US.

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	5.764	2.723	1.890	1.555	1.119	1.382	2.026	3.433
R^2	0.78	0.87	0.85	0.93	0.92	0.84	0.17	0.16
cyclical volatility	5.162	2.572	1.742	1.522	1.081	1.289	0.853	1.353
% of hours	3.98	10.89	13.03	25.86	23.19	16.35	4.30	2.39
% of hours volatility	12.56	17.11	13.87	24.05	15.32	12.87	2.24	1.98

The next table is analagous to Table 2.2 for Japan.

	15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64	65+
raw volatility	3.199	1.094	0.908	0.796	0.683	0.660	1.019	1.186
R^2	0.71	0.52	0.72	0.76	0.80	0.85	0.30	0.32
cyclical volatility	2.622	0.704	0.589	0.532	0.517	0.516	0.563	0.653
% of hours	2.21	10.18	11.77	23.34	24.19	18.67	4.92	4.73
% of hours volatility	9.60	11.89	11.50	20.58	20.75	15.96	4.59	5.12

The final table is analagous to Table 2.3 for the G7.

		15 - 19	20 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 64
US	cyclical volatility	4.725	2.583	1.797	1.436	1.000	1.067	0.925
	% of empl.	6.72	12.30	12.89	24.82	22.27	16.38	4.62
	% of empl. volatility	19.09	19.10	13.93	21.42	13.39	10.50	2.57
Japan	cyclical volatility	6.415	1.067	1.048	1.062	1.000	1.000	1.870
	% of empl.	2.91	10.77	11.45	22.75	23.22	17.96	10.93
	% of empl. volatility	14.59	8.98	9.38	18.88	18.15	14.04	15.97
Canada	cyclical volatility	4.139	2.260	1.594	1.252	1.000	0.836	1.029
	% of empl.	7.46	12.37	13.53	26.61	22.41	14.34	3.29
	% of empl. volatility	20.38	18.45	14.24	21.99	14.80	7.91	2.23
France	cyclical volatility	9.316	7.341	3.156	1.805	1.000	2.007	3.947
	% of empl.	2.75	10.36	13.70	27.27	25.21	17.49	3.21
	% of empl. volatility	9.58	28.47	16.19	18.43	9.44	13.15	4.75
Germany	cyclical volatility	3.867	3.905	2.981	1.837	1.000	1.594	8.529
	% of empl.	7.82	12.66	11.96	24.57	23.48	16.27	3.25
	% of empl. volatility	12.72	20.81	15.01	19.01	9.88	10.91	11.66
Italy	cyclical volatility	6.147	3.615	2.252	1.234	1.000	2.724	3.985
	% of empl.	7.70	8.41	12.45	28.05	24.43	15.94	3.02
	% of cyclical employment	21.50	13.80	12.73	15.71	11.09	19.70	5.47
UK	cyclical volatility	5.331	3.324	2.051	1.602	1.000	1.506	2.163
	% of empl.	6.54	10.90	12.37	25.28	23.51	17.37	4.03
	% of empl. volatility	17.84	18.55	12.98	20.74	12.03	13.39	4.46

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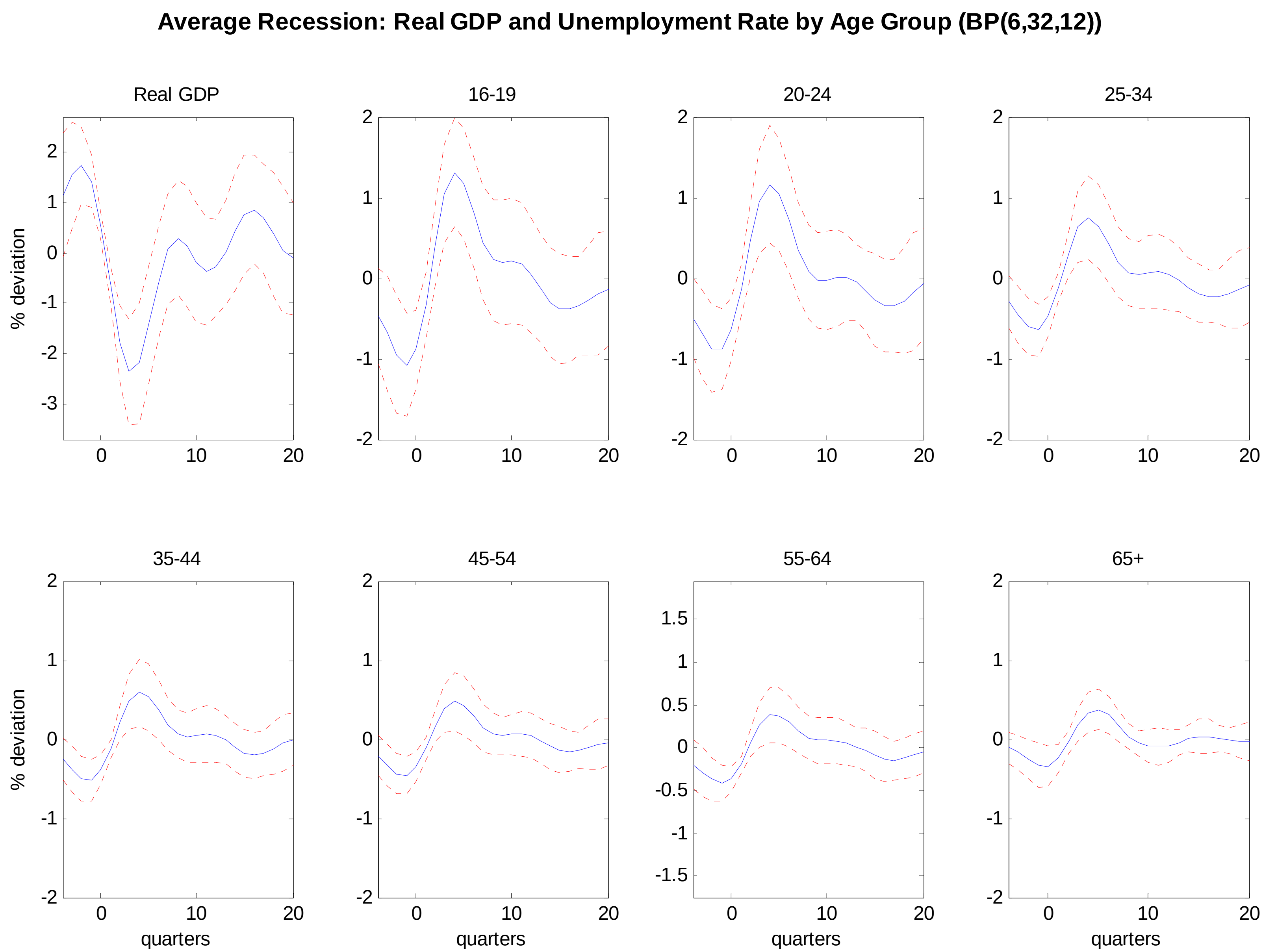

Figure 1. Average Response of Unemployment to Postwar US Recession. Solid line: average response; dashed lines: two standard deviation bands.

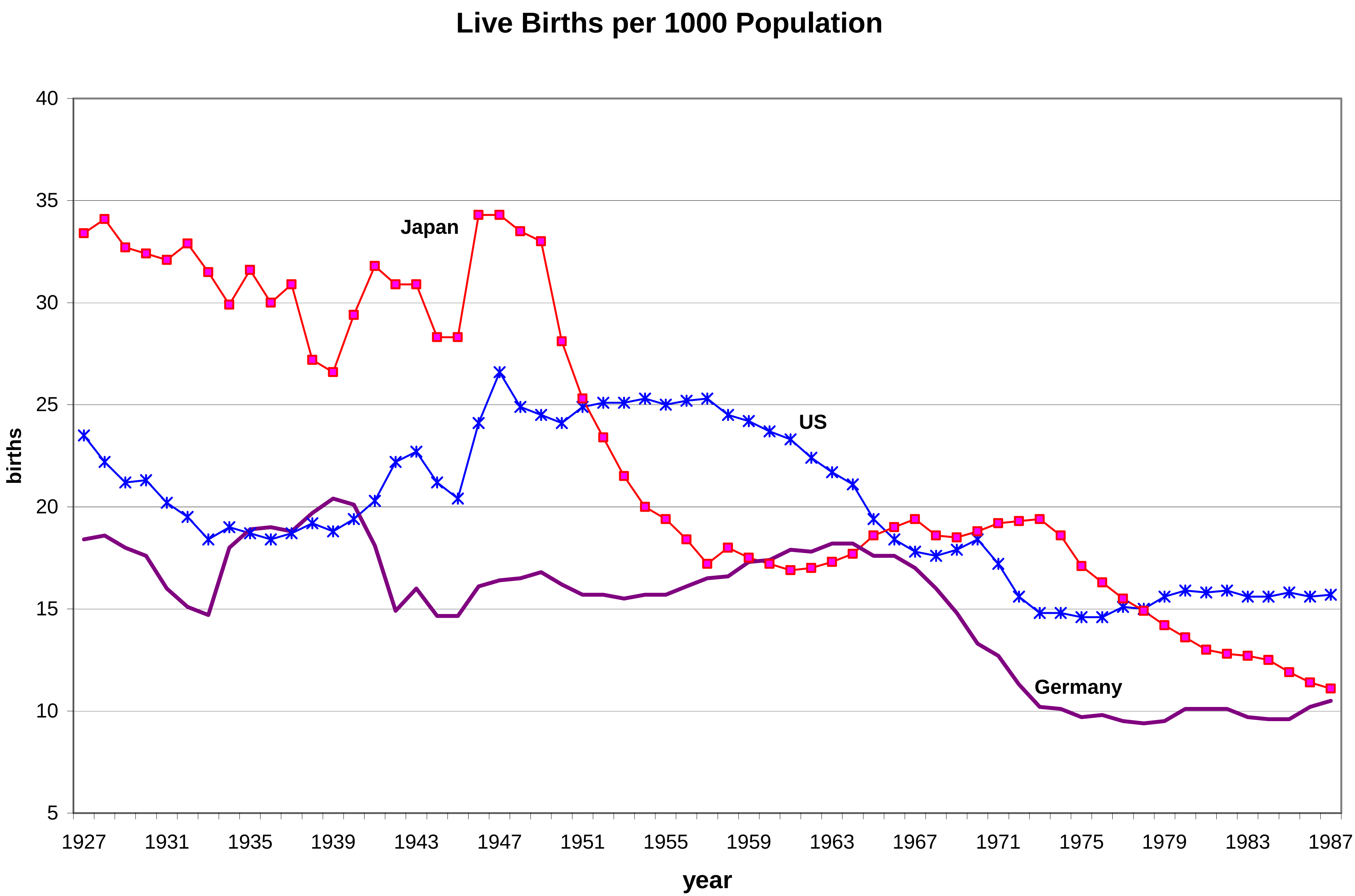

Figure 2. Variation in Demographic Change. Birth rates for three of the G7 economies.

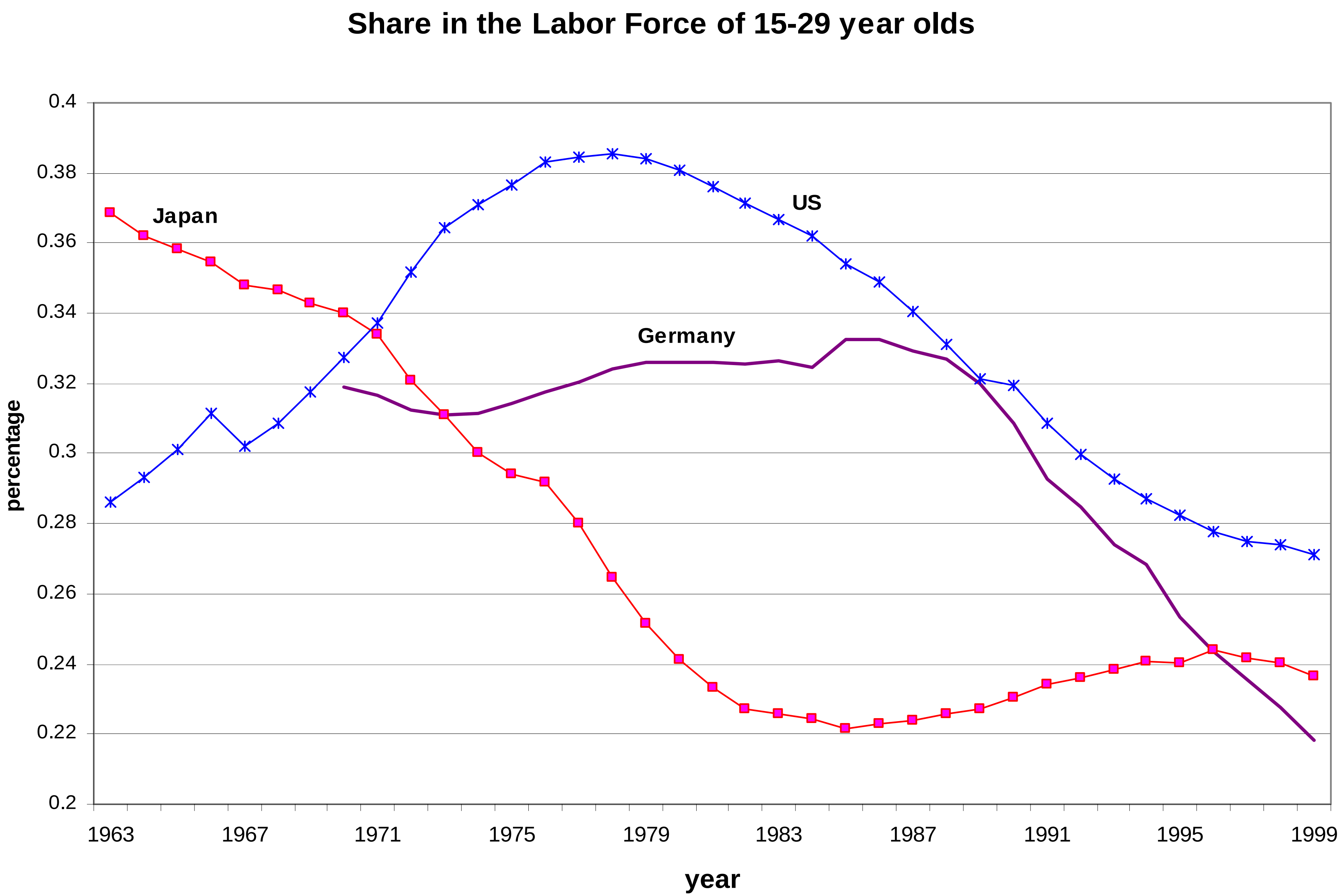

Figure 3. Variation in Demographic Change. Labor force shares of 15 to 29 year olds for three of the G7 economies.

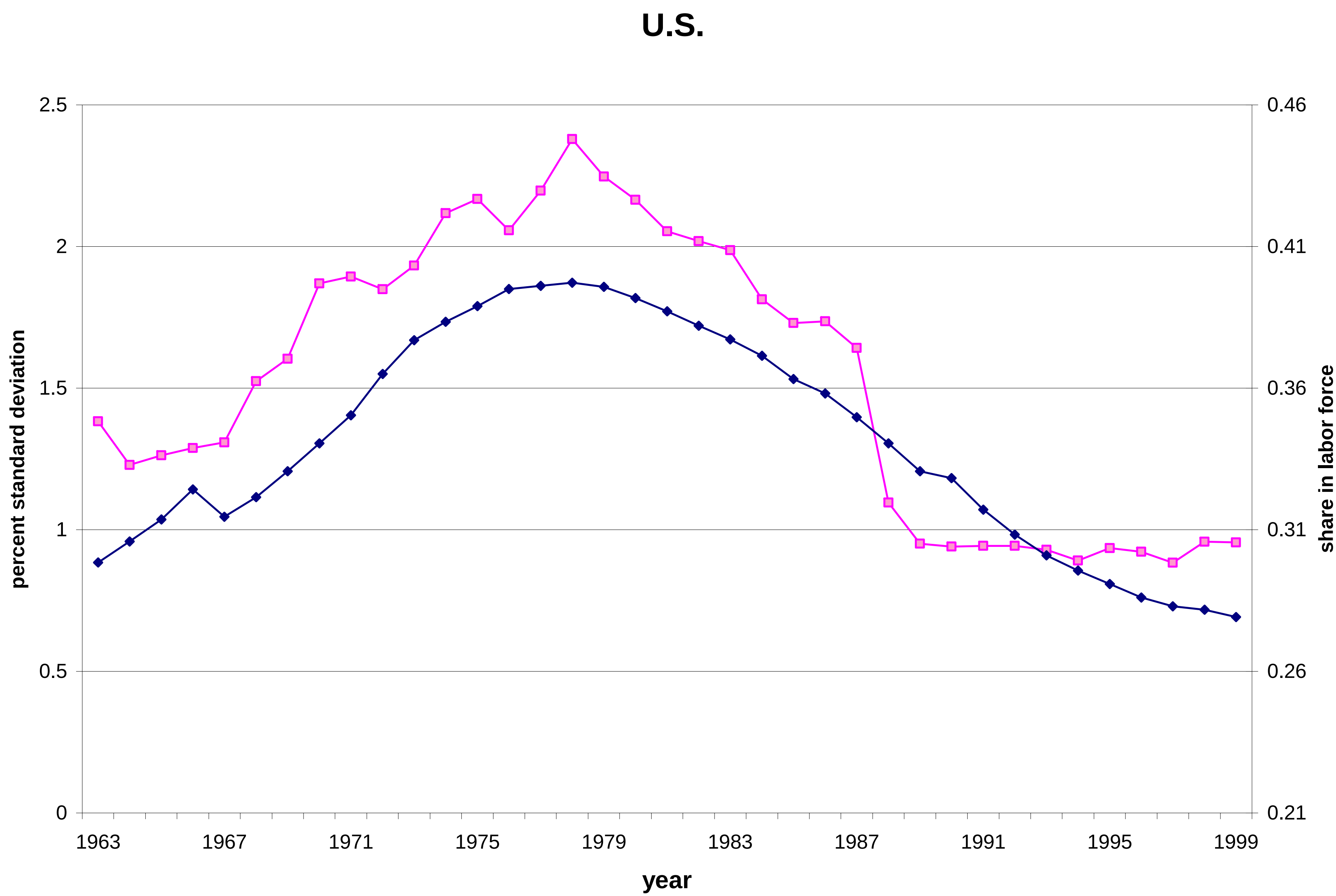

Figure 4. Demographics and Business Cycle Volatility, US. Light, square-hatched line: standard deviation of output fluctuations calculated over 10 year rolling window; dark, diamond-hatched line: labor force share of 'volatile age group'.

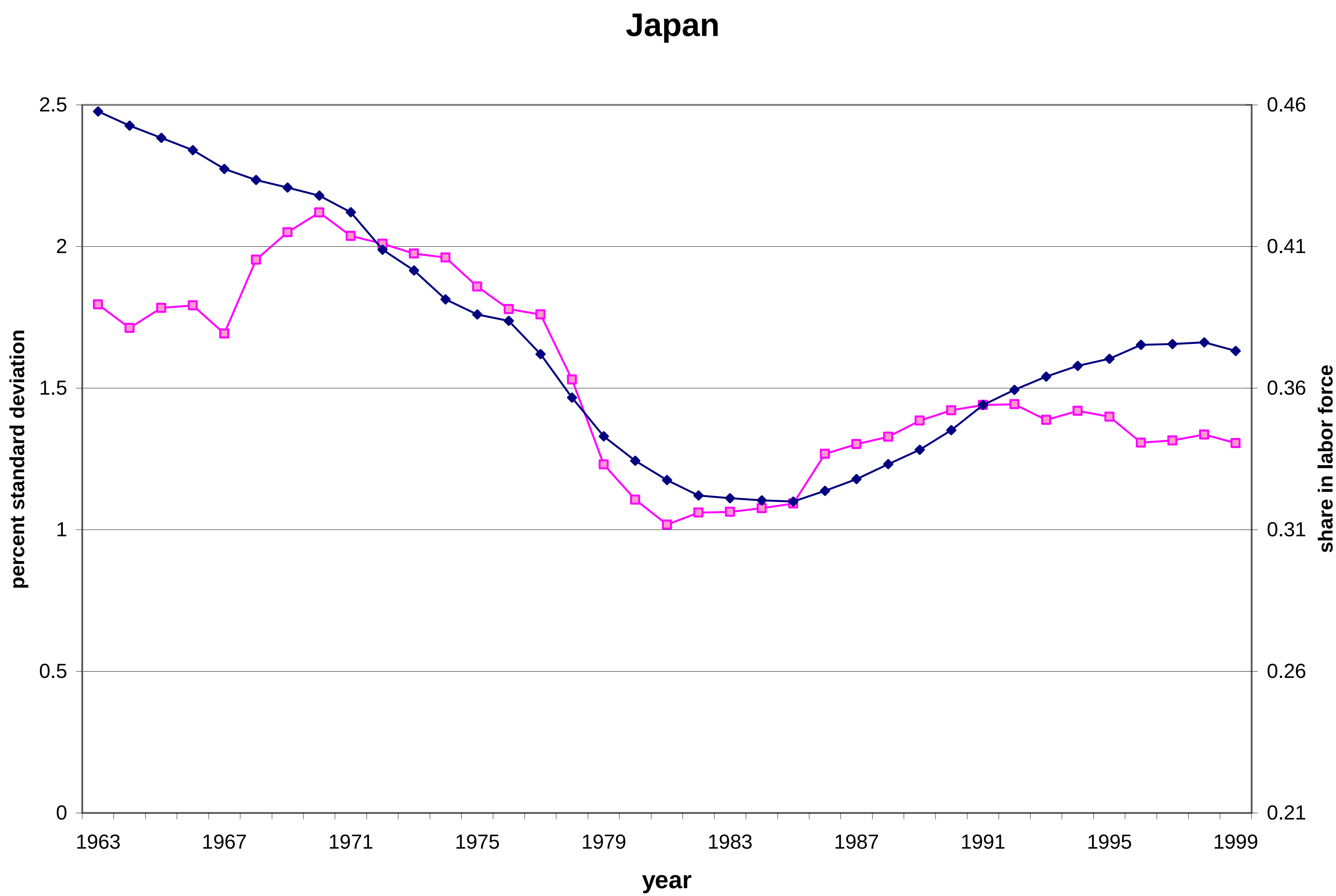

Figure 5. Demographics and Business Cycle Volatility, Japan. Light, square-hatched line: standard deviation of output fluctuations calculated over 10 year rolling window; dark, diamond-hatched line: labor force share of ‘volatile age group’.

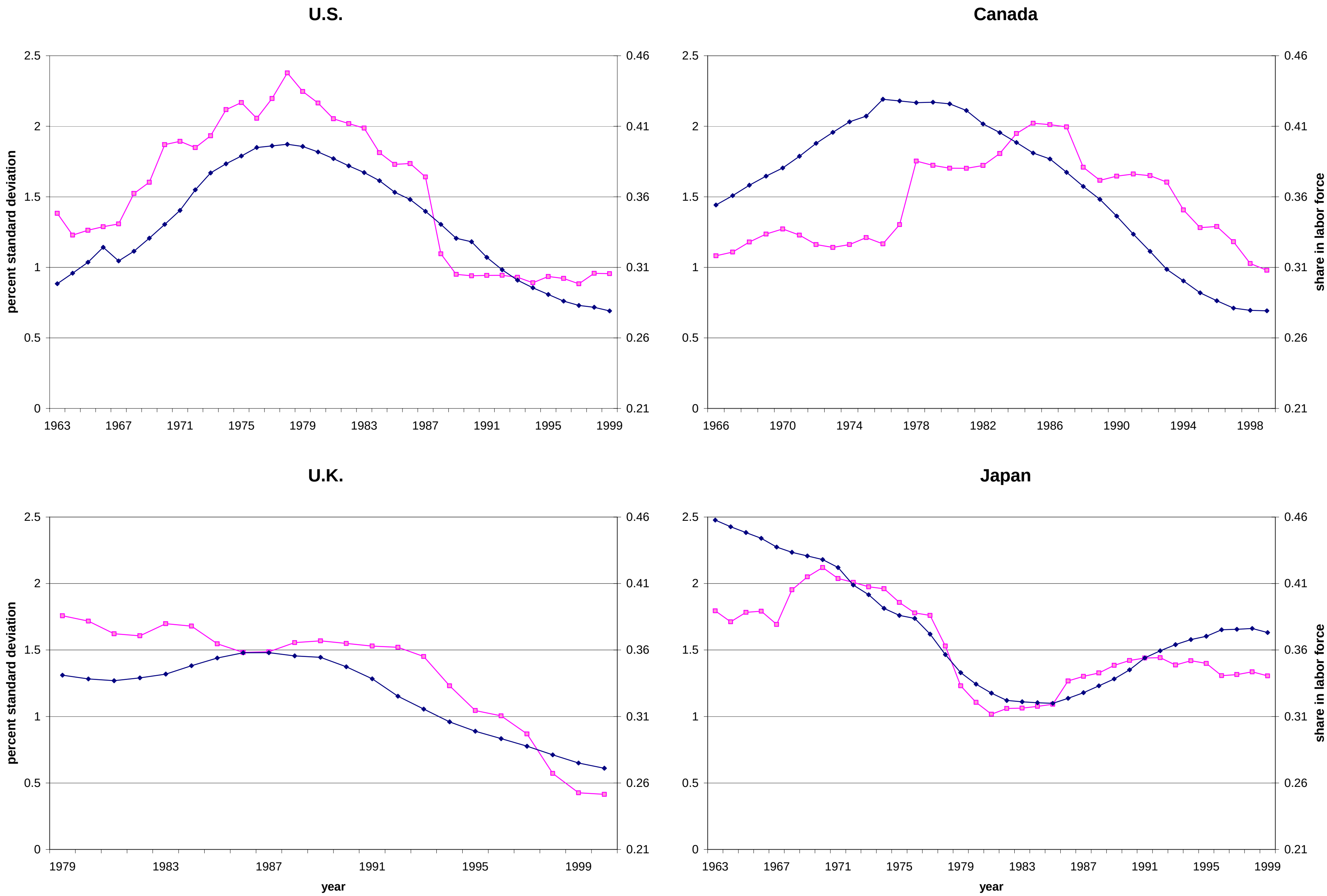

Figure 6. Demographics and Business Cycle Volatility, G7 Economies, Part 1. Light, square-hatched line: business cycle output volatility; dark, diamond-hatched line: ‘volatile aged’ labor force share.

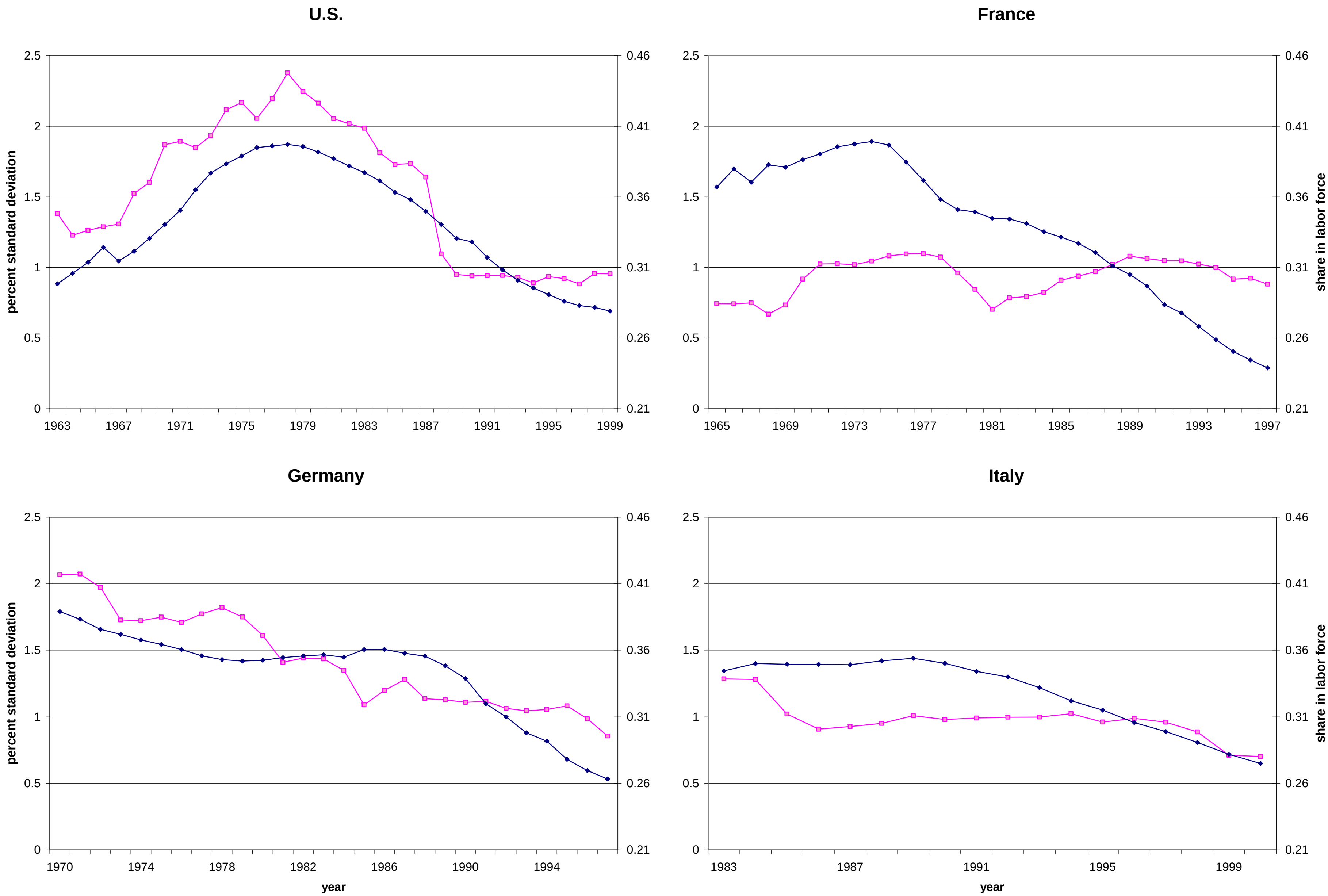

Figure 7. Demographics and Business Cycle Volatility, G7 Economies, Part 2. Light, square-hatched line: business cycle output volatility; dark, diamond-hatched line: 'volatile aged' labor force share.