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A Cointegration Model of Age-Specific Fertility and Female Labor Supply

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Abstract

Cointegration methods suitable for estimation and testing with nonstationary data are applied to U.S. time series data on age-specific fertility rates, female labor force participation rates, women's wages, and male relative incomes. Likelihood ratio tests indicate the existence of two cointegrating relations that are identified as a fertility equation and a labor supply equation, respectively. Estimated long run relations and short run dynamics are consistent with economic models of fertility and female labor market behavior.

Keywords: Fertility, Cointegration, Time Series Models.

1. Introduction.

Models of fertility based on economic theories of behavior have been subjected to rigorous conceptual and empirical scrutiny (see Olsen, 1994, and Macunovich, 1996a, for surveys and Murphy, 1992, and Smith ,1981, for critical reviews). Advances in survey data sets and statistical methods suitable for microdata analysis have fostered a flowering of household fertility studies (Hotz, Klerman, and Willis, 1997). At the same time, however, most empirical analysis of aggregate fertility patterns has relied on traditional regression methods, with little influence from recent developments in multiple time series methods appropriate for nonstationary variables.

Although important theoretical propositions are testable with individual data, understanding of trends and patterns in fertility behavior at the societal level requires aggregate analysis (Ryder, 1980). Possible determinants of fertility, such as total unemployment rates, may not vary across a sample of individuals, requiring the evaluation of their impacts with aggregate time series data. The aggregation of individual effects to make statements about total fertility is also problematic, as the composition of the population changes over time. Some effects that are measured at the individual level may reflect changes in individuals' positions within a society, and these effects will not be present at the societal level. Alternatively, social contagion may induce behavioral changes across a population that are not reflected in individual differences.

Analysis of aggregate time series data has its own considerable challenges. Aggregates, such as total fertility rates, reflect both the level of age-specific fertility and its timing, whereas the analysis of age-specific rates allows these effects to be disentangled. Fertility and its determinants are most likely nonstationary time series that trend or drift persistently away from their initial values. Such nonstationarity may undermine classical estimation and inference with traditional regression procedures, leading to spurious inferences about relations among variables. Furthermore, the principal determinants of fertility, e.g., women's wages, female labor force participation, husband's incomes, are quite possibly endogenously determined in conjunction with fertility decisions. This problem of endogenous regressors can undermine the identifiability of the fertility model, rendering the relations unestimable. Even if the relations are identified, the problem of endogenous regressors leads to inconsistent least squares estimators of model parameters.

The objective of this paper is to revisit a simple economic model of fertility, employing contemporary time series methods that are suitable for the challenges described. In particular, estimation and testing is performed within the cointegration model of Johansen (1995) that is appropriate for analyzing relations between nonstationary time series. Cointegration exists when there are one or more stationary linear relations among a set of nonstationary variables. Johansen's procedure allows the empirical determination of the number of stationary relations, and produces maximum likelihood estimators of the parameters of these relations. Subject to valid identifying restrictions, these estimators are consistent even in the presence of endogenous explanatory variables. Furthermore, these estimators are governed by asymptotic normal distributions, permitting valid statistical inference with conventional test statistics. Finally, to capture information on both the level and timing of fertility, the analysis is applied to two age-specific fertility rates covering the prime childbearing years of U.S. women.

2. Empirical Economic Studies of Fertility with Aggregate Data.

Economic models of fertility are grounded in either Easterlin's (1980b) relative income hypothesis or the New Home Economics (NHE) of Becker (1981) and Willis (1973). The former theory emphasizes the role of male incomes, relative to economic aspirations, as the driving force behind fertility and female labor force participation. Economic aspirations of young adults are determined by material conditions prevailing in their parental homes during their teenage years, when their parents would be close to their prime in earnings capacity. An increase in relative income shifts preferences in favor of childbearing and away from labor force activity by young adult women.

In the full Easterlin model relative income is determined by the size of the young adult cohort relative to that of prime aged adults, both measured contemporaneously (Easterlin 1980a). An unusually large cohort of young adults faces competition from their peers in education and employment opportunities, with adverse consequences for their earnings. At the same time the earnings of their parents, attached to a smaller birth cohort, may have been unusually high, contributing to the formation of high material aspirations by the younger generation. Therefore, relative cohort size influences both incomes and economic aspirations of each generation as they face decisions concerning fertility and labor market activity in their early adult years. Empirical tests of the Easterlin model have been surveyed by Pampel and Peters (1995) and Macunovich (1998).

The NHE model stresses the role of female wages, representing the opportunity cost of childbearing, as a determinant of fertility. Female wages are seen to have both (positive) income and (negative) substitution effects on fertility, with opposite effects on female labor force participation. Income from sources other than women's wages is expected to have a positive effect on the demand for child services, assuming such services are a normal good. Becker hypothesizes that child services have both quality and a quantity dimensions, so that rising incomes need not necessarily lead to larger desired numbers of children. Surveys of empirical studies of the NHE model are provided by Macunovich (1996a) and Hotz, Klerman, and Willis (1997).

Given the previous surveys of empirical studies of fertility cited above, it is unnecessary to provide another general overview here. The objective of this section is to assess previous aggregate studies of economic models of fertility from the perspective of contemporary time series analysis. This review emphasizes the issues arising from the nonstationarity of variables and considerations of endogenous regressors that are characteristic of empirical studies of fertility with time series data.

Numerous studies of fertility from the NHE or the relative income perspectives employ questionable exogeneity assumptions to “achieve” identification of their models. Female wages are treated as exogenous, for example, in Butz and Ward (1979), Shapiro (1988), Lee and Gan (1989), and Winegarden (1984), often in interaction terms involving other variables. Wage rates depend upon work experience, which is interdependent with fertility. Consequently, the treatment of female wages as exogenous in these regressions raises, at a minimum, the possibility of simultaneity bias, and at worst underidentified models.

Although Mincer (1963) contends that fertility and female labor market activity should be modeled with two separate equations, many researchers include female labor force participation as an argument in their fertility equations. Butz and Ward (1979) and Ermisch (1979, 1980), for example, use this variable to aggregate families with both working and nonworking women, leading to interaction terms involving female labor force participation rate and the other explanatory variables. Although these researchers treat the endogeneity of female labor force participation with instrumental variables procedures, this variable appears as an exogenous regressor in the fertility models of Shields and Tracy (1986) and Pampel (1993).

Other researchers have explicitly dealt with the endogeneity of female labor force, women's wages, and fertility participation with simultaneous equations techniques that produce consistent estimators by use of instrumental variables. Sprague (1988) and Devaney (1983) estimate two-equation systems with fertility and female labor force participation rates as jointly dependent variables, while also treating female wage endogeneity through instrumental variables. In Macunovich's (1996b) model fertility and labor force participation do not appear as regressors in the equation for the other variable, and she handles the problem of wage endogeneity by controlling for education, age and experience differences in the construction of her variables.

Although these latter studies move towards a solution to the problem of endogeneity of explanatory variables in the fertility equation, they may not go far enough. The entire system of variables involved in aggregate fertility models is subject to rampant endogeneity. Labor force participation, women's wages, and fertility are joint outcomes of interdependent decisions made by men and women throughout their young adult years. In addition, male incomes are affected by female wages and labor force participation as a result of possible substitution between male and female workers in labor markets. Even relative cohort size may be endogenous, in so far as immigration responds to labor market conditions to influence the population of young adults. None of the traditional explanatory variables in fertility equations provides the exogeneity that is necessary for traditional econometric identification and estimation of structural models.

A further concern with many aggregate fertility studies is the failure to deal with nonstationary variables. Although both visual inspection (see Figures 1-5) and formal tests (section 4) indicate that fertility and its covariates are nonstationary, most studies have ignored this issue. Notable exceptions in the fertility literature include Abeysinghe (1991, 1993), Cheng (1996), Ermisch (1988), Macunovich and Easterlin (1988), Masih and Masih (1999), Mocan (1990), Wang, Yip, and Scotese (1994), and Wright (1989). All of these studies find that the variables in their models must be differenced to become stationary, a property that undermines the validity of traditional estimation procedures and statistical inferences in regressions involving undifferenced series.

If there is no stationary linear combination of these nonstationary time series, then all variables must be differenced to stationarity prior to estimation and inference. This is the case for the models of Wang, et al. (1994), who investigate the relations among total fertility, total weekly hours of work, and real GNP, Cheng (1996) who considers the bivariate relation between the crude birth rate and the female labor force participation rate, Macunovich and Easterlin (1988) in a bivariate model of age-specific fertility and unemployment rates, and Wright (1989) who looks at bivariate relations between male relative cohort size and total fertility in sixteen European countries. Mocan (1990) finds a stationary linear combination between U.S. birth rates and divorce rates, but not between either of these demographic variables and male or female unemployment rates. To the extent that these models adequately capture the important theoretical determinants of fertility, this failure to find *cointegration* among the variables is a serious indictment of the underlying theories. The absence of a stationary linear combination implies that there is no long run relation among the variables, so that they may drift away from each other over time. There may be short run interactions among the variables, which these studies have modeled as vector autoregressions involving the variables in differenced form. However, an adequate theory of fertility should be able to account for its long run behavior, with common trends among fertility and its determinants.

The remaining studies have employed cointegration models, and their tests have found some evidence for the existence of long run relations between fertility and economic determinants. Abeysinghe (1993) examines relations between alternative measures of Canadian fertility, female wages, and male (relative) incomes, finding mixed evidence of cointegration. Most coefficients, estimated by a method that produces asymptotically normal and consistent estimators, have signs that match theoretical expectations.

Masih and Masih (1999) test a model of total fertility for Thailand that includes rates of contraception usage, the infant mortality rate, girls' secondary school enrollment rate, female labor force participation, and real GNP as determinants. Although they find evidence of more than one long run relation among these variables, they do not attempt to identify these as separate equilibrium equations. Rather a single relation among all six variables is estimated using a nonlinear least squares procedure that produces asymptotically normal coefficient estimators. They also use impulse response functions and variance decompositions to examine the dynamic impact of exogenous shocks in each variable on total fertility. However, without confidence bounds on these functions it is not possible to determine which of these effects are statistically significant. One interesting finding from their variance decompositions is that the economic variables (real GDP and female labor force participation) have only minor influences on fertility, while contraceptive use and infant mortality play much stronger roles in this developing country.

Ermisch (1988) models parity-specific birth rates as determined by relative cohort size, employment propensity, relative female to male wages, men's wages, the proportion of the cohort at risk of another birth, and four additional economic variables. Although he claims to find cointegration across his categories, it is questionable that the reported test statistics are all significant, since critical values rise (in absolute value) with the number of variables included in the model. Significance tests on the coefficients in the cointegrating equations are based on ordinary least squares estimates, which although consistent, lack the asymptotic normality required for valid inference.

Although the three studies by Abeysinghe, Masih and Masih, and Ermisch find some evidence for cointegrating relations between fertility and its determinants, none of this support comes from U.S. data. The other time series analyses of U.S. data show the relevant series to be nonstationary but not cointegrated. However, tests of cointegration are not powerful, often requiring data spanning many decades to obtain significant test results. Inferences may also be sensitive to the choice of cointegration test, the specification of deterministic components (e.g., time trends and constant terms) in the model, and variable definitions. In subsequent sections of this paper the question of cointegration in an economic model of fertility and female labor force participation is reexamined with U.S. data.

3. Methodology.

Traditional regressions with time series data are grounded in the implicit assumption that the variables in the model are stationary. Heuristically, a stationary time series returns quickly and frequently to its mean value (or to a deterministic trend line), a proposition that does not appear to hold for the variables common in fertility models (see Figures 1-5). A time series that must be differenced d times is said to be integrated of order d, or I(d). The order of integration is also equal to the number of unit roots in the stochastic difference equation characterizing the time series:

$$x_t = m + \sum_{j=1}^{p} a_j x_{t-j} + e_t \tag{1}$$

A series' order of integration may be tested with a sequence of Dickey-Fuller (1979) tests, as suggested by Dickey and Pantula (1987). The initial hypothesis of two unit roots is tested from the significance of b in equation (2) using the critical values tabulated by Fuller (1996).

$$\Delta^2 x_t = m + b\Delta x_t + \sum_{j=1}^{p-2} g_j \Delta^2 x_{t-j} + e_t \tag{2}$$

If the null hypothesis of two unit roots is rejected, the null of a single unit root is tested with the standard Dickey-Fuller regression (3), allowing a deterministic linear trend, if appropriate, under the alternative hypothesis:

$$\Delta x_t = m + ct + bx_t + \sum_{j=1}^{p-1} g_j \Delta x_{t-j} + e_t \tag{3}$$

Variables with differing orders of integration possess such dissimilar stochastic properties that they are unlikely to be functionally related to each other. Most cointegration models involve variables with identical orders of integration, and testing for the number of unit roots of each time series is the logical first step in modeling multiple time series. The remainder of this section deals with the case in which all variables entering the model are I(1).

Although each variable is individually nonstationary, there may exist one or more linear combinations of these variables that are stationary. In this case the variables are said to be cointegrated, and these stationary linear combinations are the cointegrating equations. Let z_t be the nx1 vector of time series in the model, and $\beta' z_t$ be the r stationary linear combinations ($0 \le r \le n$). Then the variables in the system are connected by the set of n dynamic equations, called an error correction model:

$$\Delta z_t = m + \sum_{j=1}^{p-1} \Gamma_j \Delta z_{t-j} + d b' z_{t-1} + e_t \tag{4}$$

The Γ_j are nxn coefficient matrices, μ is a vector of constants, ε_t is a nx1 vector of white noise error processes, δ is an nxr matrix of adjustment parameters, and β is the nxr matrix defined above.

Johansen (1991) begins with an unrestricted version of the error correction model,

$$\Delta z_t = m + \sum_{j=1}^{p-1} \Gamma_j \Delta z_{t-j} + \Pi z_{t-1} + e_t \tag{5}$$

where Π is a nxn nonstochastic matrix whose rank, r, is the number of cointegrating equations. If r=0 there is no cointegration; if r=n the individual time series are actually stationary. For intermediate values of r, Π may be factored as $\Pi = \delta \beta'$, where δ and β are nxr matrices defined above.

Johansen presents two alternative tests for cointegrating rank based on maximum likelihood estimation of the error correction model. Beginning with the null hypothesis r=0, the maximum eigenvalue statistic tests against the alternative that r=1, while the trace statistic tests against r$1. If r=0 is rejected, the next level of cointegration is tested: r=1 against the alternative r=2 for the maximum eigenvalue test, and against r$2 for the trace statistic. Testing continues until a given null hypothesis cannot be rejected. Critical values for the test, which depend upon the deterministic components included in the model, are reported in Johansen (1995).

Once the cointegrating rank has been determined, corresponding maximum likelihood estimates of the parameters of the r cointegrating equations are contained in the matrix $. If only one cointegrating relation is found, then the parameters of this equation are unique up to a factor of proportionality. With higher orders of cointegrating rank, identifying restrictions must be imposed to determine the coefficients in the multiple cointegrating equations. As in traditional simultaneous equations models, identifying restrictions follow from underlying theory.

The maximum likelihood estimators of the coefficients in the cointegrating equations are asymptotically normally distributed, allowing conventional tests of hypothesis on these parameters. These estimators are also consistent, despite the possible presence of more than one endogenous variable in each equation. The problem of simultaneity bias does not arise in cointegrating equations because there can be no correlation between the nonstationary regressors and the stationary errors defined by the cointegrating relations.

The long run relations among the variables are embodied in the cointegrating equations. Their short run dynamic responses to exogenous shocks can be examined through innovation analysis, showing how unanticipated shocks to each variable, or innovations, affect each of the other variables in the system through time. For a system of cointegrated time series, the innovation analysis may be based on the error correction model (4), or the unrestricted vector autoregression,

$$z_t = m + \sum_{j=1}^{p} A_j z_{t-j} + e_t \tag{6}$$

Since the individual elements of $,_t$ may be contemporaneously correlated, they cannot be uniquely identified as innovations specific to each particular variable. This correlation between any pair of disturbances represents a common component that affects the two corresponding variables simultaneously. A common strategy in innovation analysis is to transform (6) to a system with orthogonal errors, by identifying this common component as a shock unique to one of the two variables. The assignment of the common components, referred to as the ordering of the variables, should reflect an underlying theory of causal orders among the variables in the system.

The impact of the orthogonal innovations on each variable is represented by the impulse response functions, which show how each variable responds to a one standard deviation innovation at 0, 1, 2, ... periods following the shock. The impulse response functions are analogous to dynamic multipliers in a system with exogenous variables. Confidence intervals can be constructed around these functions based on analytical approximations (Lutkepohl, 1990) to distinguish significant responses from insignificant ones. The magnitudes of these responses are also described through a decomposition of a variable's forecast error variance into relative contributions from each variable's innovation.

4. Variable definitions and characteristics.

In modeling age-specific fertility rates explanatory variables have been defined to correspond with the ages of the women giving birth. Fertility rates were chosen to span the ages of highest childbearing, with age divisions matching the data available on explanatory variables. Consistency across variables was achieved with age categories of 20-24 and 25-34.

In the Easterlin model fertility and female labor market activity are influenced by incomes of young males relative to those of their parents during late adolescence. For the younger age group the income of young adult males is given by the income of all men aged 20-24, and their parental income is defined as the income of males aged 35-44. Relative income for this group is the ratio of income of the younger males relative to income of older males five years earlier, to reflect the formation of economic aspirations during their late teenage years.

For the 25-34 age category the construction of relative income is more problematic. At this age young adults are between seven and sixteen years beyond their late adolescence, but a sixteen year lag on parental incomes would cause a serious loss of sample observations. Consequently, a five year lag on parental incomes, defined as incomes of males 45-54 years of age, is retained for this construction also. Younger males are those aged 25-34. All income data employed in these definitions is from the U.S. Bureau of the Census Internet Site "Table P-7. Age-People by Median Income and Gender: 1947 to 1997."

For male relative cohort size no lagging of the older male population is necessary. In the full Easterlin model economic opportunities are adversely affected by the size of one's cohort, which changes little as cohorts move through middle age. Consequently, relative cohort size is defined as the ratio of the population of males 20-24 over that of males 40-49 for the younger age category, and as the population of males 25-34 divided by the number aged 45-54 for the older group. The older group represents the cohort of the fathers, with the midpoints of these age intervals approximately one generation older than the young males. Age-specific resident populations of males have been tabulated from various numbers of the Current Population Reports, P-25 (U.S. Bureau of the Census, 1954-95) and U.S. Bureau of the Census internet site, “Resident Population of the United States: Estimates by Age and Sex.”

Labor force participation rates for women aged 20-24 and 25-34 are collected from the Handbook of Labor Statistics (U.S. Bureau of Labor Statistics 1989), Employment and Earnings (U.S. Bureau of Labor Statistics 1990-1991, 1997-1998), and the Statistical Abstract of the United States (U.S. Bureau of the Census 1991-1998).

The wage series is constructed from the income in 1997 dollars of year-round, full-time female workers, aged 20-24 and 25-34, reported in the U.S. Bureau of the Census internet site “Table P-7. Age-People by Median Income and Gender: 1947 to 1997.” By using data on year-round full-time workers, these figures are unlikely to be confounded with welfare payments, and young women are not likely to receive large portions of unearned income. Therefore, these data are reasonably accurate measures of female labor income. Dividing by 1750 hours of full time work per year (50 weeks at 35 hours per week of full time work) yields estimates of an hourly wage figure. These constructed wage series closely track those constructed by Macunovich (1995) from the Current Population Survey (CPS). There is one outlier in 1973 for the CPS data for younger women's wages, which does not appear in the income based data. When this observation is removed, the correlations between the CPS and income based wage series are 0.97 for the 20 to 24 year olds and 0.99 for the older group.

Fertility rates are collected for women aged 20-24, 25-29, and 30-34 from Historical Statistics of the US: Colonial Times to 1970 (U.S. Bureau of the Census, 1975), and from Table 4 of the National Vital Statistics Report (National Center for Health Statistics, 2000). The latter two rates are aggregated using the relative populations of women in these two age categories, from the previously cited sources for the male populations.

The use of total, rather than marital, age-specific fertility matches the comprehensive definitions of the other series. Although male relative incomes are generally viewed as playing a role in marital fertility, its influence on economic aspirations may also affect marriage rates (Easterlin, 1980a). Marital fertility could therefore rise or fall as the economic prospects of young adults turn favorable, as both numerator and denominator determining this rate increase by differing amounts. The use of total rather than marital fertility avoids this weakness in the linkage between relative income and fertility rates.

After deleting observations corresponding to the five year lag on relative income, all data series begin in 1952 and end in 1997. Plots of all variables and their first differences are displayed in Figures 1-5. All series show trends or smooth patterns characteristic of integrated time series. Explicit tests for unit roots are presented in Table 1. Following Dickey and Pantula (1987) tests for the highest expected number of unit roots (in this case two) are implemented first. For male relative cohort size in both age categories, the hypothesis of two unit roots cannot be rejected, while this hypothesis is rejected soundly for all other series. This result casts serious doubt on the use of relative cohort size as an indicator of relative incomes. This point is confirmed by a comparison of the plots of the relative income and corresponding cohort size series. For both age categories relative income trends downwards fairly persistently over the entire period, while relative cohort size shows long periods of both rising and falling values.

Others have questioned whether the linkage between relative cohort size and relative incomes has been broken, for example, due to relatively open labor markets where incipient labor shortages or surpluses would be mitigated by migration. Examining Canadian data, Abeysinghe (1991) found that the association between relative cohort size and fertility that existed until 1976 has since been broken. Wright (1989) found evidence of Granger-causality running from relative cohort size to total fertility for only five of the sixteen European countries examined. The results presented in Table 1 confirm for the United States the findings of Abeysinghe for Canada, and the majority of the European countries investigated by Wright. Based on these results relative cohort size is eliminated from the fertility model as a possible explanatory variable.

Continuing with the unit root tests, Table 1 indicates that all remaining series are integrated of order one. Only female wages for the older group is close to being stationary around a trend, with rejection of the unit root hypothesis for this series at the 10% level but not at the 5% level. Concluding that all four variables for each age group are I(1), traditional regression methods that assume stationarity are precluded. There is, however, the possibility of cointegration among these variables that would allow further investigation of long run relations between fertility, female labor force participation, female wages, and male relative incomes.

5. A Cointegration Model of Fertility and Economic Variables.

Cointegration among the four variables is tested within Johansen's (1995) framework, based on an autoregressive specification with three lags and with all variables in logarithmic form. A deterministic trend is included in the cointegrating equations to accommodate the differing trend characteristics of the four series. Residual diagnostics from this specification (Table 2) show no evidence of first order serial correlation or nonnormality in the equations of either age group.

For the 20-24 year age group both the maximum eigenvalue and trace statistics indicate exactly two cointegrating equations (Table 2). In a multiple time series model with four I(1) variables, the existence of two cointegrating relations reduces the total number of unit roots in the system from four to two. The test results are therefore consistent with the pattern of estimated roots of the autoregressive model, two of which are close to one (0.92) with all remaining roots considerably smaller.

The cointegration test results for the older group are more problematic. All hypothesized values of r (the number of cointegrating relations) from zero through three are rejected by both tests, implying that all four series are stationary I(0) processes. This implausible result is in conflict with the plots of the individual time series and the Dickey-Fuller unit root tests, suggesting reliance on other information. The roots of the autoregressive system are quite similar to those of the system for the younger group, with two roots close to one (at 0.97) and the remainder substantially smaller. Based on this evidence the hypothesis of two cointegrating equations is tentatively accepted for this system as well.

With two cointegrating equations at least one identifying restriction (plus the standard normalizing restriction) must be imposed on each equation to uniquely determine the parameters of these equations (Pesaran and Smith, 1998). Consistent with the reasoning of Mincer (1963), one equation is identified as a fertility equation with the female labor force participation rate excluded, and the second equation is a labor supply equation with fertility omitted. With these exactly identifying restrictions imposed, the cointegrating equations for both age groups are reported in Table 3.

For both age groups the coefficients on female wages, male relative income, and the trend term are statistically significant, with signs that are consistent with theoretical expectations. Fertility is inversely related to women's wages and positively associated with male relative income, while the signs on these coefficients in the labor supply equations are reversed. Interpreting these coefficients as long run elasticities, the female wage effect on fertility is substantially larger for the younger age group (-6.0) compared with the older category (-2.8). These estimates may be compared with Ermisch's (1979) total fertility rate elasticities for Great Britain, which range between -2.81 and -3.44 in his logarithmic model specification.

Although these estimated elasticities seem large, they are not unreasonable relative to the historical changes in wages and fertility rates over the sample period. For women aged 20-24 this estimate implies that a five percent rise in real wages (e.g., as occurred over the decade of the 1970s) is associated with a 30 percent decline in the fertility rate of women in this age group. For example, taking 1970 as the base year for this calculation, a 30 percent decline in this rate would be from 0.1678 to 0.1175 children per woman (compared with the 0.1128 rate observed for 1979). The relatively large wage elasticity for the younger group is consistent with behavior in which young families temporarily postpone having children when women face favorable wage offers. For women aged 25-34, further postponement of childbearing becomes less practical for physiological reasons, so that the response of fertility to attractive wage conditions is not as large, although still statistically significant and substantial.

Conversely, the elasticity of fertility with respect to male relative income is substantially larger for the older age category (3.9) compared with the younger (1.9). This outcome reflects the greater uncertainty that younger wives face regarding the stability of their marriages, leading them to discount the future income that may flow to their family from their husbands' current income. The relative magnitudes of the income elasticities for female labor supply can also be interpreted in this light. An increase in husbands' incomes in younger families does not carry the same certainty of long run economic support for their families as does a similar increase to male incomes in well established families. Consequently, younger women reduce their labor force participation only slightly in response to a rise in male incomes (a -1.0 percent elasticity for the 20-24 age group), while the more secure 25-34 year old women curtail their labor supply much more sharply (with a -4.1 percent elasticity) in response to the same percentage change in male incomes.

The innovation analysis confirms the strong wage effects on fertility and female labor force participation. The analysis summarized in Tables 4 and 5 and Figures 6 and 7 reflects an assignment of common contemporaneous components according to the ordering: relative income, female wages, female labor force participation, and fertility. Reversing the ordering of the last three variables did not change the qualitative results discussed here.

Among women aged 20-24 the impulse response function shows a significant negative response of fertility to wage shocks lasting ten years (Figure 6). Over this time horizon wage shocks account for 63 percent in the variation in total fertility rates according to the variance decompositions (Table 4). Wage shocks also show significant positive impacts on female labor force participation. These effects persist for fifteen years and account for 66 percent of the variation in labor supply at this time horizon. Women aged 25-34 display responses in their fertility and labor supply behavior to wage shocks that are similar in magnitude, timing, direction, and statistical significance (Table 5 and Figure 7).

Contrary to the information in the cointegrating equations, innovations in relative income do not significantly affect fertility or female labor force participation for either age group (Figures 6 and 7). As unanticipated changes, relative male income innovations are apparently viewed as temporary, with uncertain implications for the long run economic well-being of their spouses. Consequently, fertility and labor supply responses are weak.

The well-documented inverse relation between fertility and female labor force participation (Lehrer and Nerlove, 1986) also materializes in the innovation analysis. Female labor supply responds significantly to fertility shocks for both age groups, with up to 40 percent (for 20-24 year olds - Table 4) and 26 percent (for 25-24 year olds - Table 5) of the variation in labor supply accounted for by fertility innovations. Conversely, there is no significant response of fertility to labor supply innovations (Figures 6 and 7), despite the assignment of the contemporaneous component common to these two variables to the labor force participation rate.

6. Discussion and Conclusions.

Multiple time series analysis of fertility and its primary economic determinants confirms the major propositions of economic theories of fertility. These conclusions are supported by a statistical methodology that produces consistent estimators with conventional statistical distributions in the presence of endogenous and nonstationary explanatory variables. For each of the two age groups analyzed here, the finding of two cointegrating relations establishes the existence of common trends among these nonstationary time series. Although the four time series individually drift or trend away from their initial values, they are held together in the long run by two equilibrium relations. These two relation are identified as a fertility equation and a labor supply equation, with female wages and male relative incomes carrying significant and plausibly signed coefficients.

Differences in results between the two age groups add further support to the economic models of fertility and female labor market behavior. The younger age group (20-24 year olds) face expectations of greater marital instability, and these women incorporate this uncertainty into their responses to economic changes. Consistent with this reasoning, the cointegrating equations indicate that the long run relations between fertility and male relative incomes are considerably less elastic for the younger age group as compared with 25-34 year olds. Similarly, the long run elasticity of female labor supply with respect to male relative incomes is considerably smaller for the younger women compared with the older age group, again reflecting the greater uncertainty of the long run economic implications of changes in husbands' incomes for other family members in these younger households.

The importance of women's wages in fertility and female labor supply behavior is confirmed in the innovation analysis. Shocks to women's wages have significant negative effects on fertility, accounting for large proportions of variation in fertility for both age groups. In addition, innovations in women's wages positively and significantly affect female labor force participation rates, also explaining large percentages of variation in labor supply for both age categories. Female labor force participation is also found to respond significantly to shocks in the age specific fertility rates. However, the reverse effect of labor supply shocks on fertility is not statistically significant, offering a new piece of evidence on the direction of causal relations between these two variables.

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Table 1. Dickey-Fuller Tests for Unit Roots

A. 20-24 year age group

variable	Null Hypothesis I[2]	I[1]
Fertility	-3.02 (0)	-0.98 (1)
Female Wages	-7.12 (0)	-2.23 (0,t)
Female Labor Force Participation	-4.50 (0)	-1.33 (1,t)
Relative Income, Males	-6.87 (0)	-2.37 (0,t)
Relative Cohort Size, Males	-1.66 (1,2)	-1.50 (1,2)

B. 25-34 year age group

variable	Null Hypothesis I[2]	I[1]
Fertility	-3.17 (0)	-1.19 (1)
Female Wages	-3.23 (1,4)	-3.41 (1-4,t)
Female Labor Force Participation	-3.25 (0)	-2.20 (1,2,t)
Relative Income, Males	-6.88 (0)	-2.33 (0,t)
Relative Cohort Size, Males	-1.09 (1,2)	-3.76 (2-4)

Note: Number of lagged first and second differences for the I[1] and I[2] models, respectively, are shown in parentheses, with t if deterministic trend is included in the test equation. Five and ten percent critical values are -2.93 and -2.60 with no trend, and -3.50 and -3.18when the trend term is included.

Table 2. Tests of Cointegration in Model with Fertility (fr), Female Labor Force Participation Rate (lf), Female Wages (wg), and Male Relative Income (ri): All Variables in Logarithmic Form.

20-24 year age group

H_0: r =	λ-max	10% c.v.	trace	10% c.v.
0	35.87	19.88	79.73	58.96
1	25.28	16.13	43.86	39.08
2	**12.15**	12.39	**18.59**	22.95
3	6.44	10.56	6.44	10.56

Residual Diagnostics

Lagrange multiplier test for autocorrelation: $\chi^2[16] = 13.3$, p-value = 0.65

Error correction equation for:	fr	lf	wg	ri
Normality ($\chi^2[2]$)	3.74	3.72	4.73	2.74

Roots of the Autoregressive System

.9281, .9281, .8839, .8839, .7699, .7061, .7061, .6316, .6316, .4008, .4008, .3154

25-34 year age group

H_0: r =	λ-max	10% c.v.	trace	10% c.v.
0	39.00	19.88	88.02	58.96
1	20.32	16.13	49.03	39.08
2	16.87	12.39	28.71	22.95
3	11.84	10.56	11.84	10.56

Residual Diagnostics

Lagrange multiplier test for autocorrelation: $\chi^2[16] = 13.3$, p-value = 0.65

Error correction equation for:	fr	lf	wg	ri
Normality ($\chi^2[2]$)	3.74	3.72	4.73	2.74

Roots of the Autoregressive System

.9817, .9817, .8521, .8521, .6368, .6342, .6342, .5530, .5530, .5188, .5188, .4842

Notes. Maximum eigenvalue and trace statistics are reported with their 10 percent critical values in the top panels. The first nonrejection is indicated in bold. Reported diagnostics are the Lagrange multiplier test for first order serial correlation, and the Jarque-Bera test for normality.

Table 3. Maximum Likelihood Estimates of the Cointegrating Equations.

20-24 year age group

	fertility	labor supply	wage rate	male income	trend
fertility equation					
coefficient	-1.00		-6.01	1.94	.052
standard error			(.84)	(.71)	(.017)
labor supply equation					
coefficient		-1.00	1.97	-.962	-.018
standard error			(.24)	(.20)	(.005)

25-34 year age group

	fertility	labor supply	wage rate	male income	trend
fertility equation					
coefficient	-1.00		-2.77	3.95	.116
standard error			(.74)	(.69)	(.022)
labor supply equation					
coefficient		-1.00	2.56	-4.11	-.108
standard error			(.74)	(.69)	(.022)

Table 4. Variance decompositions: 20-24 age group.

Variance Decomposition of LRI24:

Period	S.E.	LRI24	LWG24	LLF24	LFR24
1	0.032943	100.0000	0.000000	0.000000	0.000000
2	0.048732	76.37658	0.468434	2.685956	20.46903
3	0.054527	72.41255	5.254925	2.230558	20.10197
4	0.056691	68.78031	7.154048	3.448070	20.61757
5	0.058709	64.51604	6.818517	6.789353	21.87609
6	0.060715	62.26483	6.375808	10.45707	20.90229
7	0.061996	60.66826	6.293661	12.63848	20.39960
8	0.063167	58.44302	7.153811	13.00629	21.39687
9	0.064951	56.00228	8.622660	12.48042	22.89464
10	0.067218	54.06596	10.16507	11.75923	24.00975
11	0.069349	52.28258	12.01543	11.33145	24.37054
12	0.071248	50.01001	14.37625	11.55186	24.06188
13	0.073335	47.20932	17.14153	12.45706	23.19209
14	0.075826	44.28001	20.15066	13.61127	21.95806
15	0.078486	41.54537	23.27853	14.49314	20.68296
16	0.080969	39.13154	26.36938	14.91406	19.58501
17	0.083127	37.12737	29.21311	14.97704	18.68249
18	0.084969	35.58134	31.62563	14.87629	17.91674
19	0.086541	34.41027	33.54421	14.77363	17.27189
20	0.087895	33.44919	35.01343	14.76187	16.77551

Variance Decomposition of LWG24:

Period	S.E.	LRI24	LWG24	LLF24	LFR24
1	0.033130	22.72288	77.27712	0.000000	0.000000
2	0.043781	23.03433	71.48512	2.948874	2.531678
3	0.048482	19.50701	66.79795	6.185368	7.509667
4	0.052271	16.78133	68.53317	5.681054	9.004444
5	0.055415	15.02999	70.98346	5.074972	8.911583
6	0.057442	14.38771	72.25857	4.893472	8.460249
7	0.058935	13.83933	72.99304	4.981028	8.186602
8	0.060245	13.25407	72.86876	5.263227	8.613945
9	0.061465	12.92964	71.95947	5.716598	9.394286
10	0.062552	12.76629	70.79178	6.063509	10.37841
11	0.063335	12.61087	69.83411	6.176324	11.37870
12	0.063797	12.44171	69.17857	6.152315	12.22740
13	0.064106	12.35466	68.61250	6.094814	12.93802
14	0.064388	12.37218	68.01928	6.047164	13.56138
15	0.064655	12.40822	67.47642	6.004531	14.11084
16	0.064886	12.39230	67.07163	5.962680	14.57339
17	0.065069	12.33726	66.81463	5.930360	14.91775
18	0.065200	12.28775	66.67980	5.911543	15.12090
19	0.065280	12.25877	66.63830	5.900997	15.20193
20	0.065322	12.24324	66.65068	5.893964	15.21212

Table 4 (continued). Variance decompositions: 20-24 age group.[1]

Variance Decomposition of LLF24:

Period	S.E.	LRI24	LWG24	LLF24	LFR24
1	0.007680	0.332909	0.246914	99.42018	0.000000
2	0.010574	0.606173	16.11393	77.13810	6.141802
3	0.013909	0.355002	21.53008	53.08023	25.03469
4	0.019143	2.251771	22.98729	34.29093	40.47001
5	0.023653	3.513659	32.05152	26.00473	38.43009
6	0.027571	3.562440	39.02686	22.38803	35.02267
7	0.031273	3.129036	43.77174	21.24320	31.85602
8	0.034903	2.539989	48.62225	20.95005	27.88771
9	0.038413	2.117555	52.93632	20.90050	24.04563
10	0.041648	1.847269	56.32228	20.88358	20.94688
11	0.044530	1.634179	59.16456	20.67781	18.52345
12	0.047024	1.465469	61.55862	20.32151	16.65440
13	0.049131	1.357983	63.41713	19.96835	15.25654
14	0.050902	1.303491	64.73884	19.69857	14.25910
15	0.052398	1.268546	65.58187	19.53664	13.61295
16	0.053670	1.231899	66.02832	19.47787	13.26191
17	0.054752	1.193350	66.18543	19.48938	13.13184
18	0.055661	1.159262	66.16753	19.52905	13.14417
19	0.056407	1.133999	66.06757	19.56714	13.23129
20	0.057006	1.121583	65.94016	19.59173	13.34653

Variance Decomposition of LFR24:

Period	S.E.	LRI24	LWG24	LLF24	LFR24
1	0.026463	0.139545	11.74375	0.272716	87.84399
2	0.045486	1.315553	14.74227	1.445808	82.49637
3	0.059613	2.306917	20.01914	3.072830	74.60112
4	0.070934	2.123655	26.89343	4.497059	66.48585
5	0.081214	1.640147	33.34132	6.249312	58.76922
6	0.090975	1.350050	39.40274	8.128799	51.11841
7	0.100037	1.264186	44.93727	9.594835	44.20371
8	0.108063	1.221373	49.50838	10.54191	38.72833
9	0.114887	1.132106	53.22612	11.06123	34.58054
10	0.120549	1.031755	56.21146	11.29797	31.45881
11	0.125160	0.961350	58.42825	11.41988	29.19052
12	0.128897	0.920660	59.90339	11.53169	27.64425
13	0.131961	0.890049	60.74934	11.66585	26.69475
14	0.134496	0.860802	61.10671	11.81789	26.21460
15	0.136579	0.835406	61.13093	11.96604	26.06763
16	0.138246	0.815784	60.97048	12.08607	26.12766
17	0.139532	0.803313	60.73449	12.16692	26.29528
18	0.140496	0.802772	60.48257	12.21364	26.50102
19	0.141207	0.818563	60.24021	12.23959	26.70163
20	0.141734	0.847876	60.01991	12.25878	26.87344

Ordering: LRI24 LWG24 LLF24 LFR24

[1]Codes for the variable names are RI=relative male income, WG=female wages, LF=female labor force participation rate, and FR=fertility rate. The prefix, L, indicates natural logarithms.

Table 5. Variance decompositions: 25-34 age group.

Variance Decomposition of LRI34:

Period	S.E.	LRI34	LWG34	LLF34	LFR34
1	0.031257	100.0000	0.000000	0.000000	0.000000
2	0.040813	97.25965	1.682937	0.195145	0.862267
3	0.045866	88.14234	10.52570	0.632453	0.699506
4	0.046831	86.81756	10.77423	1.594056	0.814158
5	0.047082	85.91561	10.67563	1.975732	1.433026
6	0.048172	84.47802	11.34807	2.504080	1.669832
7	0.049870	80.68213	14.73589	2.878560	1.703418
8	0.052400	73.37874	20.84786	2.942089	2.831318
9	0.055559	65.36629	25.74051	2.845189	6.048010
10	0.059551	57.69137	28.97918	2.701545	10.62790
11	0.063954	51.30987	30.98361	2.527349	15.17916
12	0.068235	46.03238	32.76918	2.385249	18.81320
13	0.072345	41.36374	34.85459	2.269623	21.51205
14	0.076549	37.03534	37.52937	2.149191	23.28610
15	0.081043	33.04477	40.58388	2.004848	24.36650
16	0.085888	29.42377	43.71540	1.843919	25.01691
17	0.090980	26.22219	46.62240	1.679661	25.47575
18	0.096142	23.48863	49.13146	1.525479	25.85443
19	0.101185	21.23561	51.19347	1.389470	26.18145
20	0.105975	19.41259	52.89211	1.273926	26.42137

Variance Decomposition of LWG34:

Period	S.E.	LRI34	LWG34	LLF34	LFR34
1	0.109755	18.10558	56.07437	1.187669	24.63238
2	0.113623	16.93002	57.78943	1.133917	24.14663
3	0.119931	15.30025	59.78924	1.036336	23.87417
4	0.126744	13.71320	61.16580	0.928353	24.19265
5	0.132932	12.49089	62.61078	0.845964	24.05237
6	0.137902	11.64683	63.35942	0.789142	24.20460
7	0.142339	10.96855	64.24055	0.742054	24.04884
8	0.146028	10.45245	65.03389	0.710379	23.80328
9	0.149155	10.02692	65.83984	0.684948	23.44828
10	0.151846	9.677979	66.57634	0.665375	23.08031
11	0.154229	9.383012	67.28584	0.649573	22.68158
12	0.156275	9.141773	67.90459	0.637735	22.31590
13	0.158041	8.944411	68.44429	0.627717	21.98358
14	0.159544	8.788657	68.89834	0.619547	21.69345
15	0.160818	8.667338	69.28141	0.612405	21.43884
16	0.161892	8.573290	69.60215	0.606006	21.21855
17	0.162809	8.497386	69.87799	0.600049	21.02457
18	0.163603	8.433688	70.11853	0.594553	20.85323
19	0.164308	8.377877	70.33230	0.589503	20.70032
20	0.164947	8.328113	70.52359	0.584967	20.56333

Table 5 (continued). Variance decompositions: 25-34 age group.[1]

Variance Decomposition of LLF34:

Period	S.E.	LRI34	LWG34	LLF34	LFR34
1	0.165075	8.323445	70.41668	0.728504	20.53137
2	0.165237	8.307367	70.28765	0.804618	20.60037
3	0.165630	8.283106	70.06735	0.900982	20.74856
4	0.166314	8.261089	69.73152	0.963946	21.04345
5	0.167341	8.212209	69.27194	1.026058	21.48980
6	0.168780	8.130049	68.70301	1.077161	22.08978
7	0.170610	8.000874	68.14099	1.113543	22.74460
8	0.172800	7.824079	67.61349	1.134570	23.42786
9	0.175375	7.606835	67.16397	1.142260	24.08693
10	0.178318	7.363257	66.80595	1.135224	24.69556
11	0.181568	7.105356	66.54538	1.116438	25.23283
12	0.185042	6.844632	66.36802	1.089294	25.69805
13	0.188642	6.590563	66.27261	1.057132	26.07969
14	0.192263	6.350846	66.25262	1.022827	26.37370
15	0.195815	6.129356	66.30550	0.988715	26.57643
16	0.199229	5.927461	66.42618	0.956248	26.69011
17	0.202460	5.745023	66.60786	0.926285	26.72083
18	0.205481	5.581489	66.83830	0.899271	26.68094
19	0.208275	5.436078	67.10368	0.875361	26.58488
20	0.210833	5.307977	67.38948	0.854533	26.44802

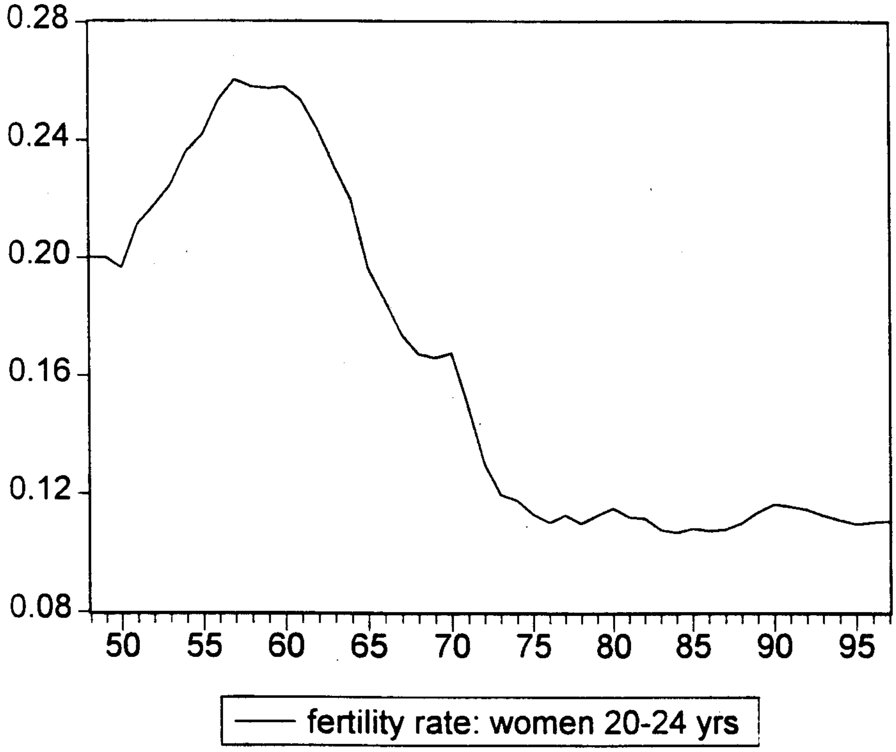
Variance Decomposition of LFR34:

Period	S.E.	LRI34	LWG34	LLF34	LFR34
1	0.211921	5.259147	66.78519	0.923973	27.03169
2	0.215266	5.230917	65.53308	0.961687	28.27431
3	0.219327	5.180603	64.31741	0.955342	29.54664
4	0.223409	5.022491	63.26321	0.950906	30.76339
5	0.227731	4.834444	62.54936	0.939944	31.67625
6	0.232183	4.656409	62.23357	0.913946	32.19607
7	0.236658	4.503989	62.14092	0.882982	32.47211
8	0.241158	4.357900	62.19291	0.851067	32.59812
9	0.245515	4.211294	62.35057	0.821213	32.61692
10	0.249497	4.078309	62.55041	0.796659	32.57462
11	0.252986	3.967290	62.76639	0.777992	32.48832
12	0.255948	3.878388	63.00428	0.765047	32.35228
13	0.258386	3.807435	63.26352	0.757324	32.17172
14	0.260360	3.750410	63.53457	0.753761	31.96126
15	0.261949	3.705056	63.80391	0.753439	31.73759
16	0.263220	3.669588	64.05598	0.755664	31.51877
17	0.264222	3.642068	64.27758	0.759701	31.32065
18	0.264994	3.620904	64.46107	0.764815	31.15321
19	0.265571	3.605334	64.60369	0.770336	31.02064
20	0.265991	3.594922	64.70657	0.775642	30.92286

Ordering: LRI34 LWG34 LLF34 LFR34

[1]Codes for the variable names are RI=relative male income, WG=female wages, LF=female labor force participation rate, and FR=fertility rate. The prefix, L, indicates natural logarithms.

Figure 1. Age specific fertility rates of women aged 20-24 and 25-34.



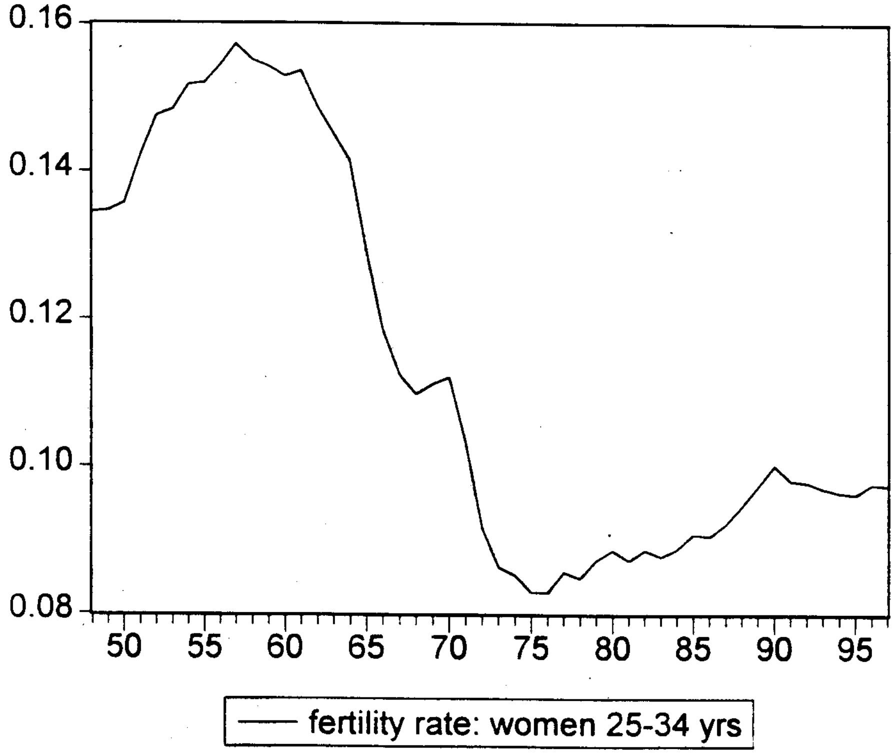
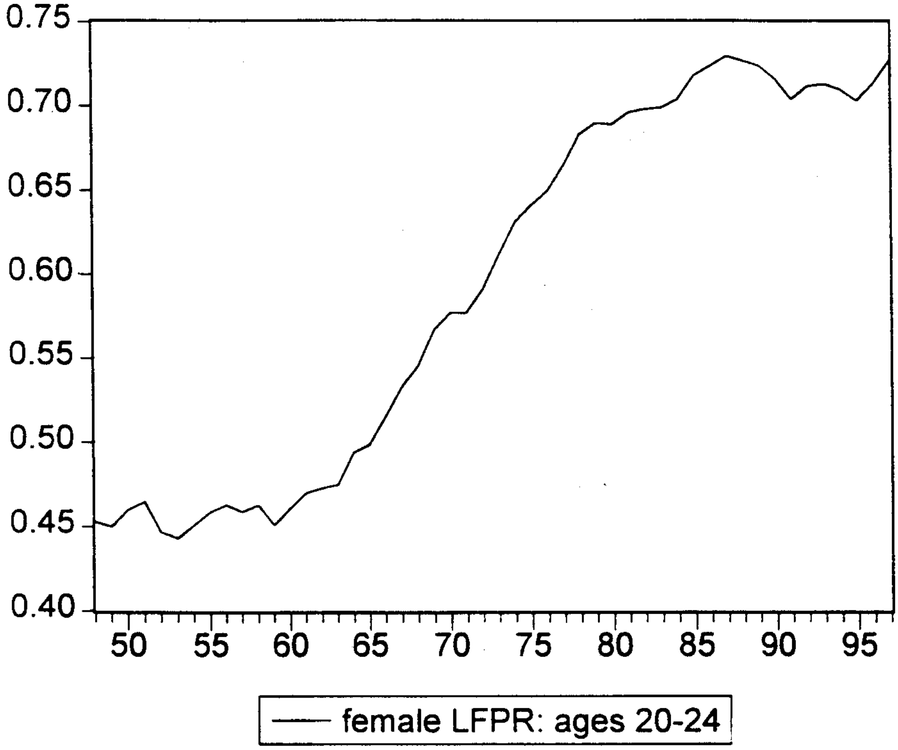


Figure 2. Labor force participation rates of women of ages 20-24 and 25-34.



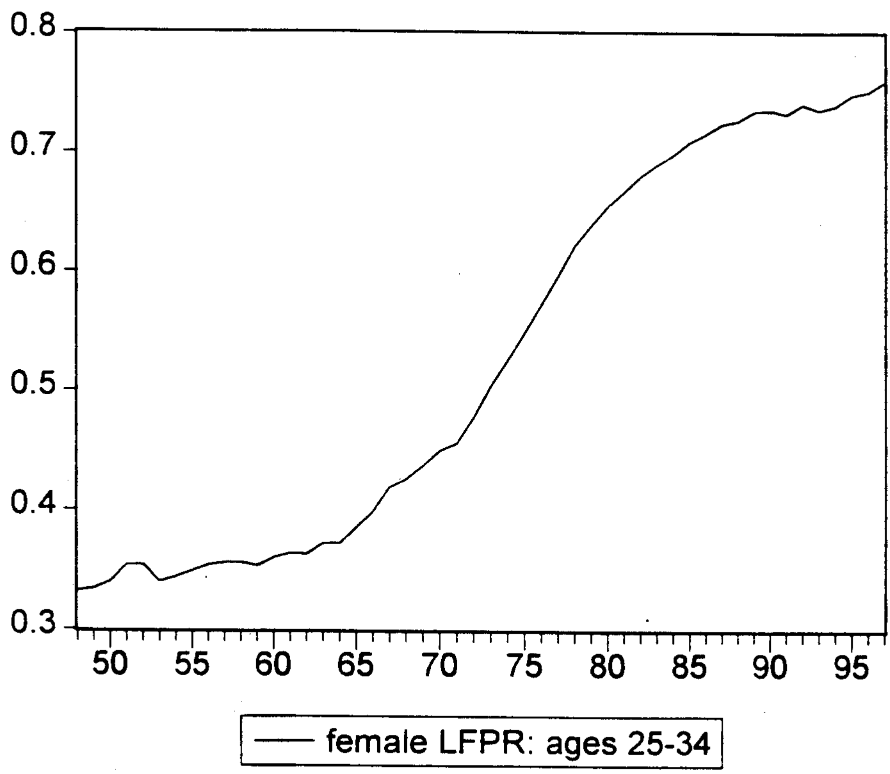
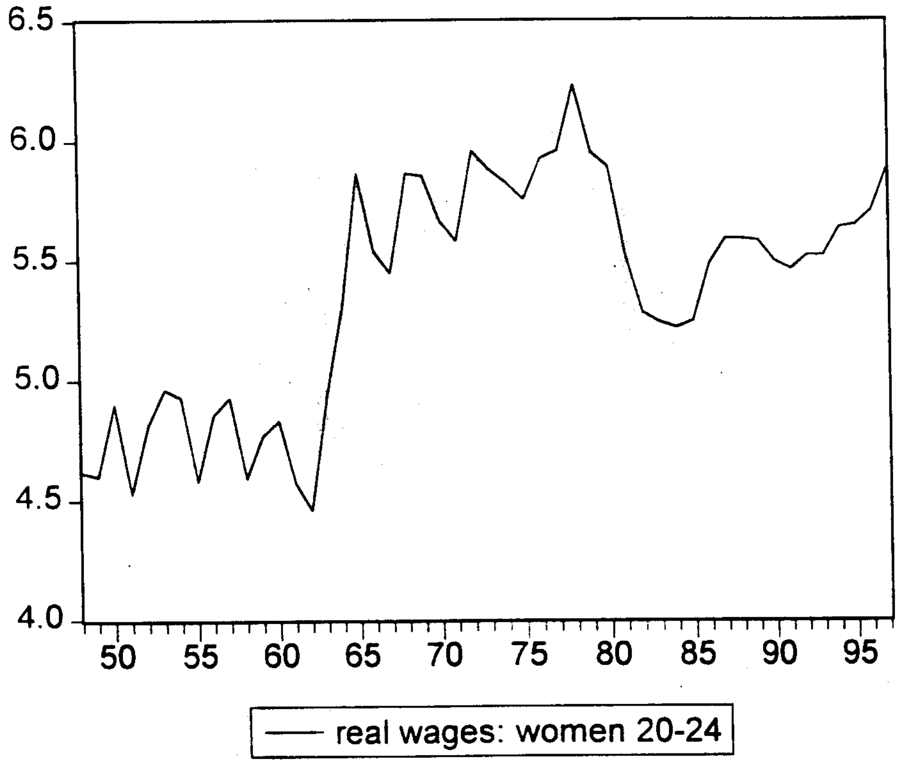


Figure 3. Real wages of women of ages 20-24 and 25-34.



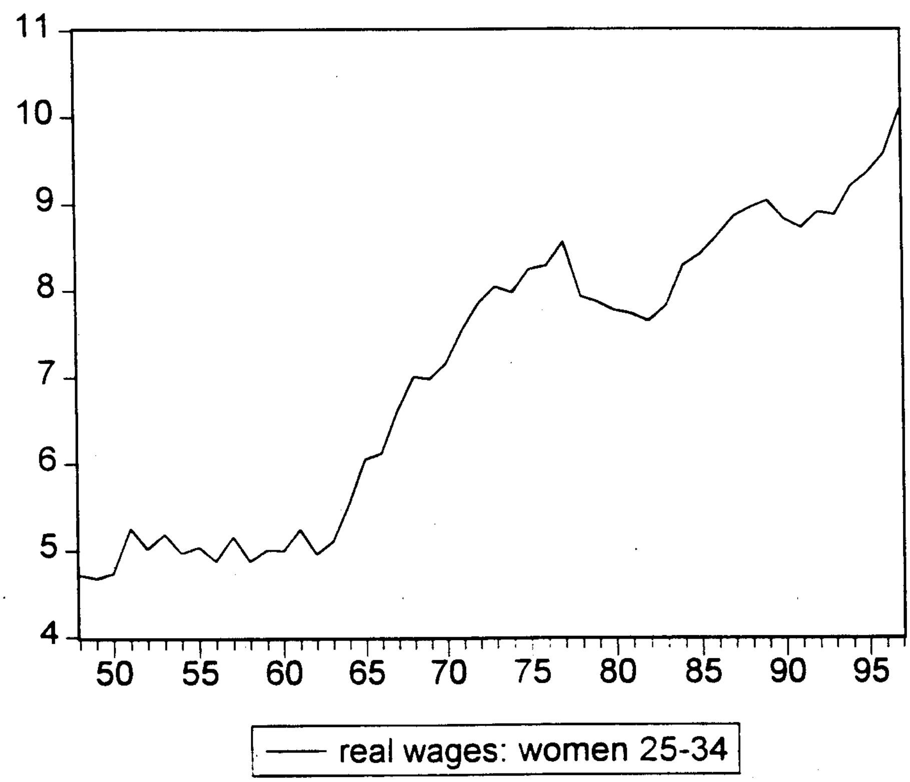
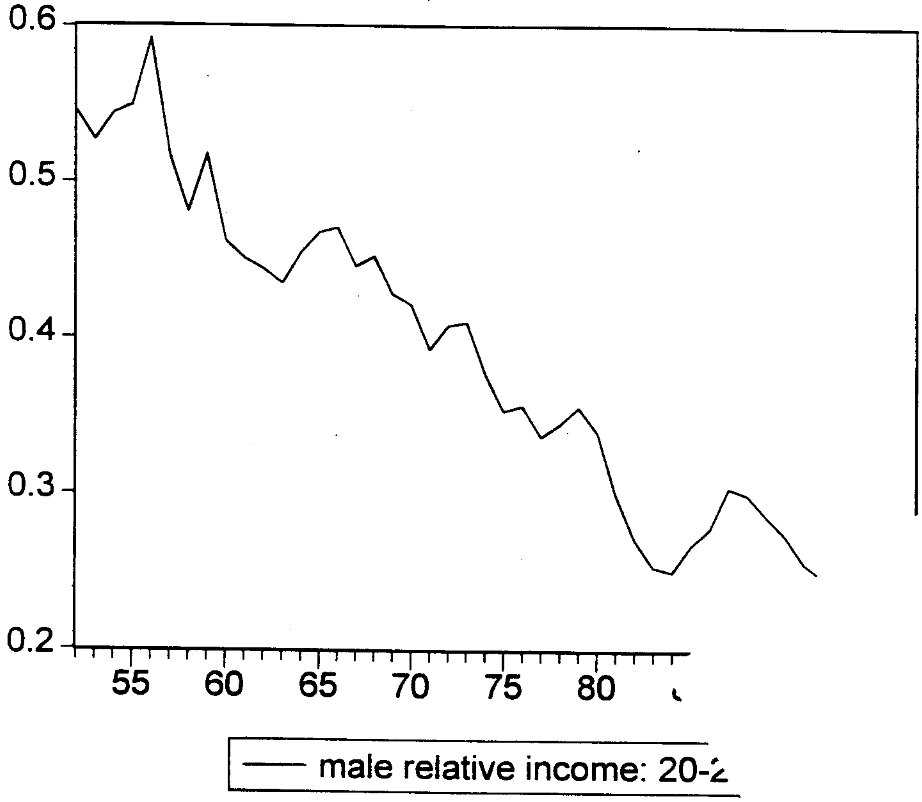


Figure 4. Male relative income: incomes of males aged 20-24 divided by incomes of males aged 35-44 lagged five years, and incomes of males aged 25-34 divided by incomes of males aged 45-54 lagged five years.



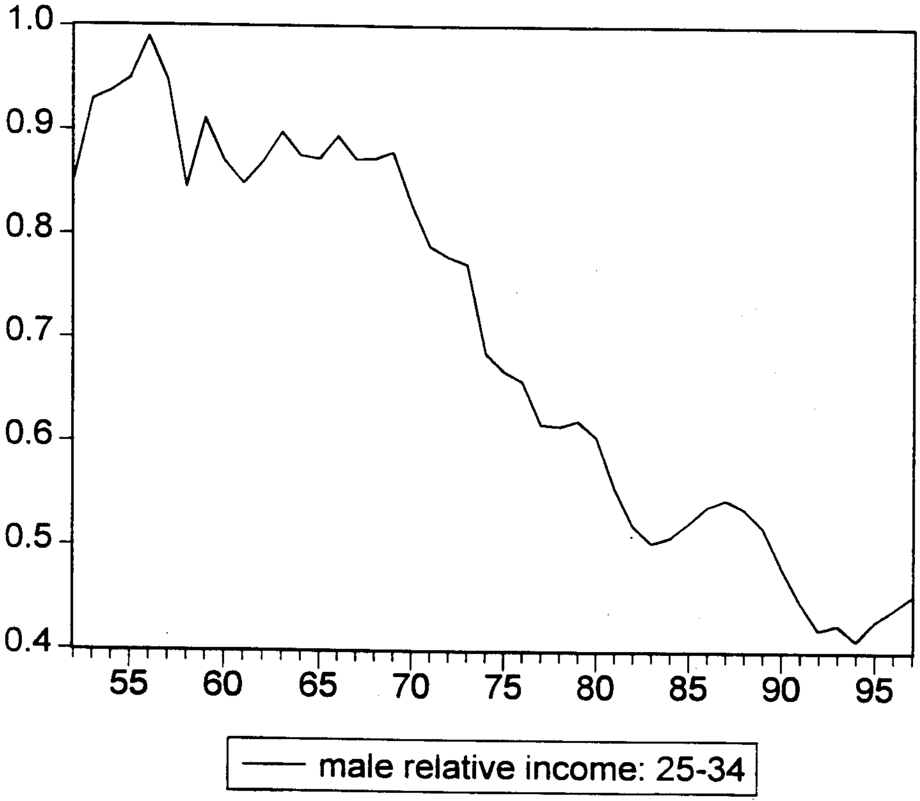


Figure 5. Male relative cohort size: population of men aged 20-24 divided by number of men aged 40-49, and population of men aged 25-34 divided by number of men aged 45-54.

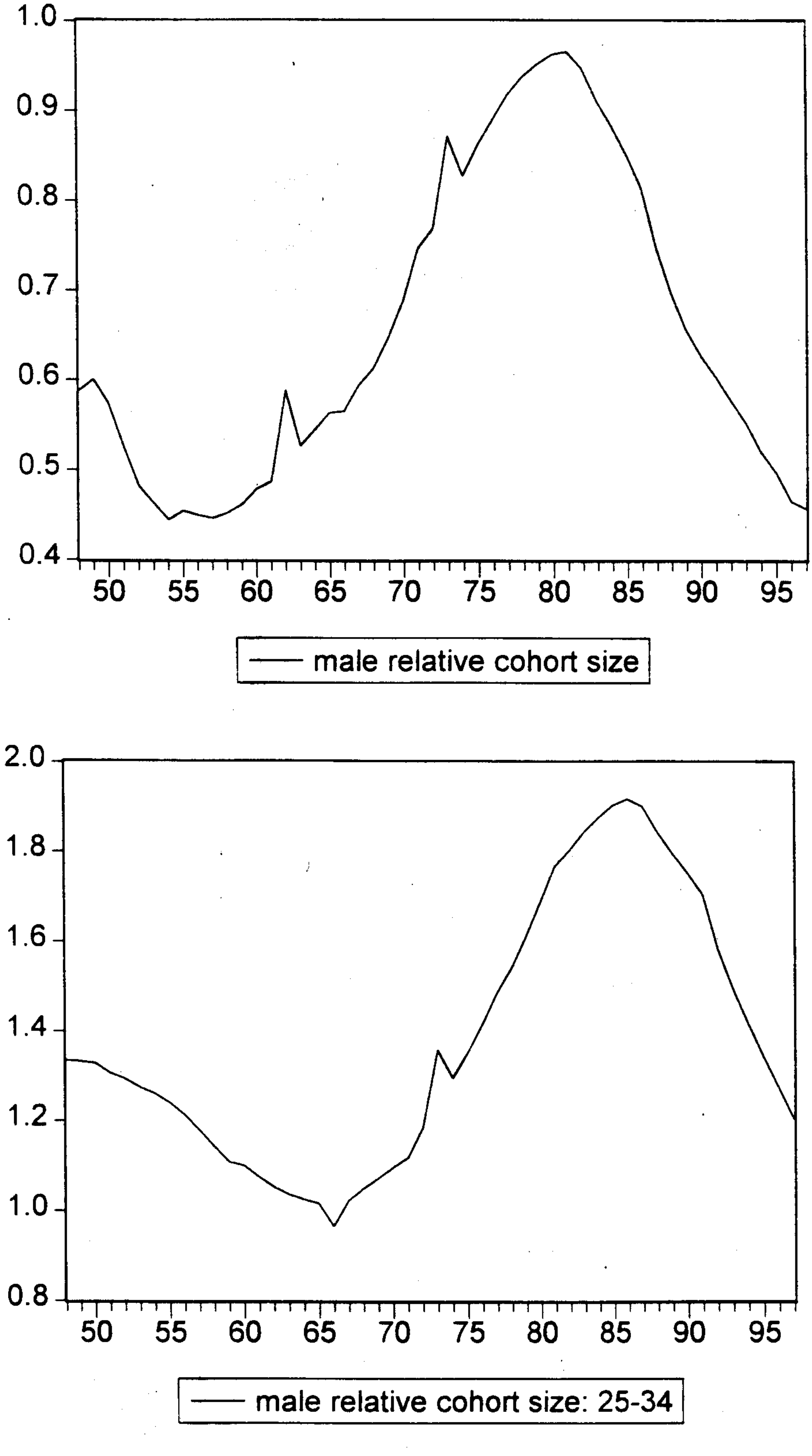
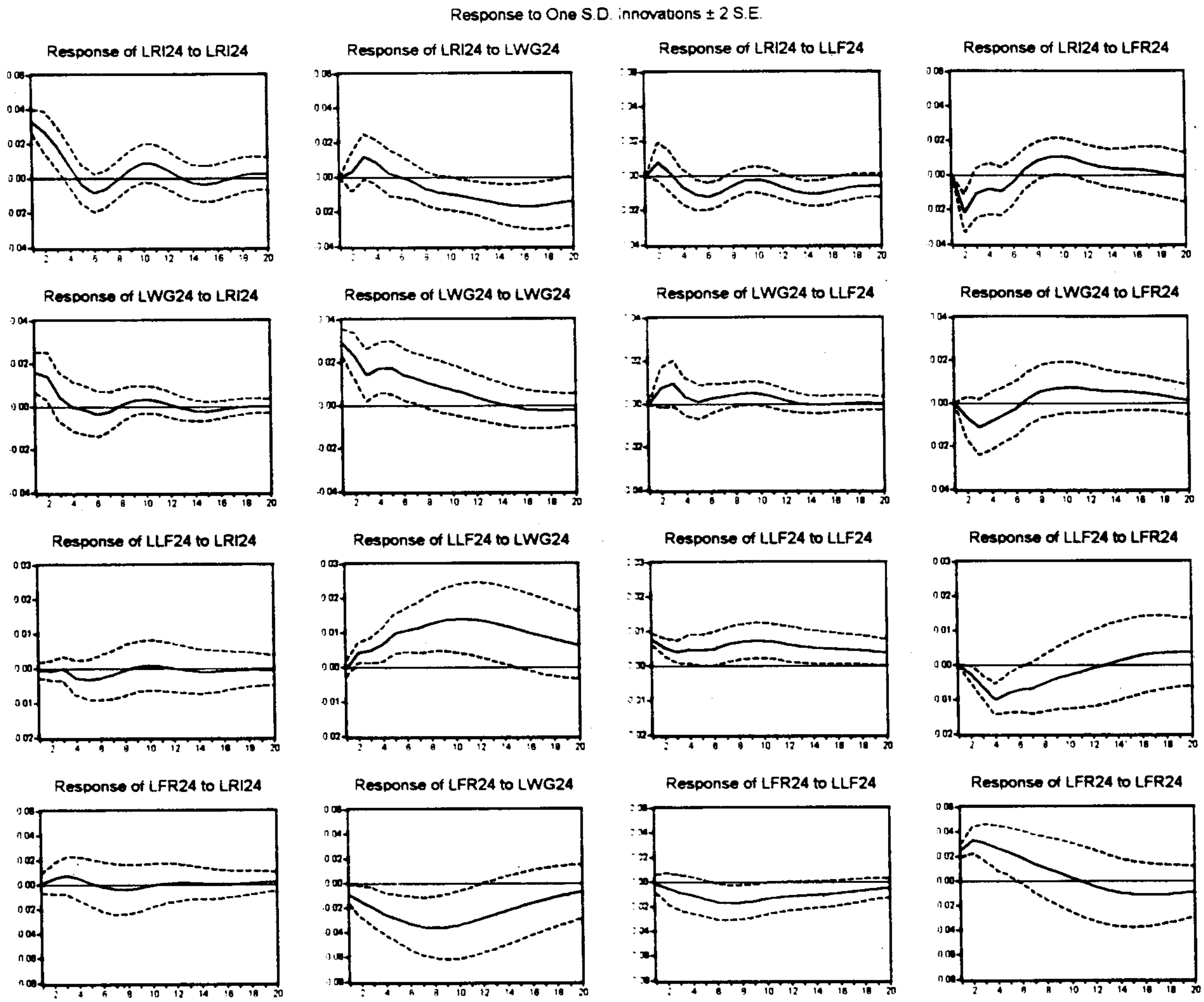
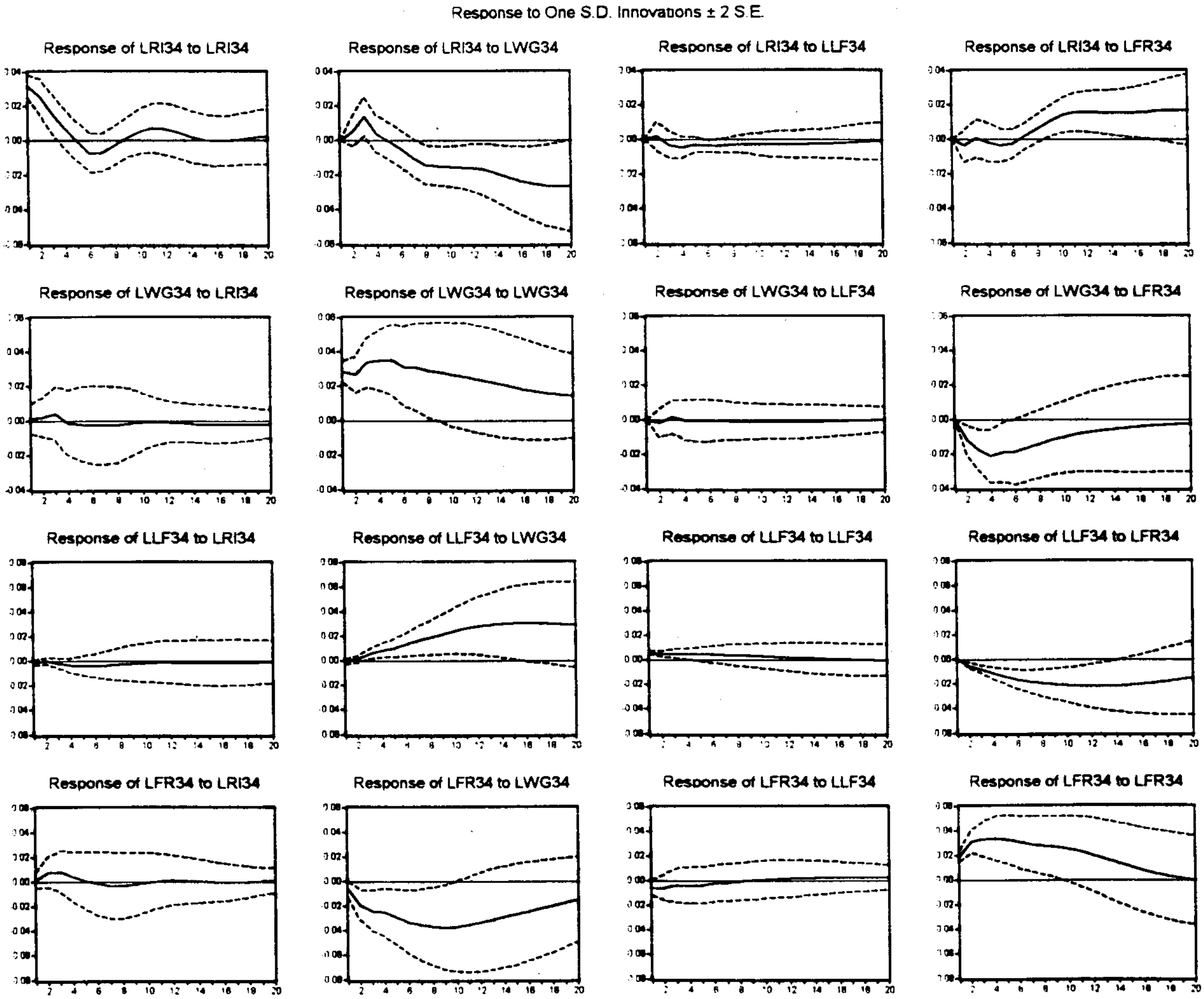


Figure 6. Impulse response functions: 20-24 age group.[1]



[1] Solid lines represent the point estimates of the response; dotted lines indicate bounds that are plus or minus two standard errors from the point estimates. Codes for the variable names are RI=relative male income, WG=female wages, LF=female labor force participation rate, and FR=fertility rate. The prefix, L, indicates natural logarithms.

Figure 7. Impulse response functions: 25-34 age group.[1]



[1] Solid lines represent the point estimates of the response; dotted lines indicate bounds that are plus or minus two standard errors from the point estimates. Codes for the variable names are RI=relative male income, WG=female wages, LF=female labor force participation rate, and FR=fertility rate. The prefix, L, indicates natural logarithms.