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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 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

A further concern with many aggregate fertility studies is the failure to deal with nonstationary

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:

$$\Delta x_t \qquad ct \quad bx_t \qquad {}_j \quad {}_j\Delta x_{t\;\,j} \qquad {}_t \qquad {}_j \quad {}_t \tag{3}$$

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:

Δz_t =1αυ5 24.7Γ_j TΔz_t 0Δ_j (φλ0.0254 Tχ (.5 TΔ (+0 TΔ δB7ψσ ισ τηε)89ρ5 TΔ 0.375 0 0 ργ /Φ0 12 Tφν635 0 TΔ (4) 0.2641 Tχ (Γ) Tφ

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 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 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.

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 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.

Contrary to the information in the cointegrating equations, innovations in relative income do not

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Table 1. Dickey-Fuller Tests for Unit Roots

A. 20-24 year age group

	Null Hypothesis	
variable	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)	-2.3[illegible] (0,t)

Table 3. Tests of Cointegration in Model with Fertility (fr), Female Labor Force Participation Rate (lf), Female Wage (wg) and 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	83.52	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 = [illegible]

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 [illegible]

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	1.04	.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 decomposition [illegible] s: 20-24 age group

Variance Decomposition of LRI24:

Period	S.E.	LRI24	[illegible]	[illegible]	[illegible]
1	0.032943	100.0000	0.000000	0.000000	0.000000
2	0.048732	76.37658	0.468434	2.685956	20.46903
3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	0.061996	60.66826	6.293661	12.63848	20.3996[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

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	0.24691[illegible]4	99.42018	0.000000
2	0.010574	0.606173	16.1139[illegible]3	77.13810	6.141802
3	0.013909	0.855002	21.53608	53.08033	25.03466
4	0.019143	2.25177	22.98729	34.29093	40.47001
5	0.023653	3.513659	32.05152	26.00473	38.43009
6	0.027574	[illegible]	[illegible]	[illegible]	[illegible]
7	0.031273	3.129036	43.77174	21.243[illegible]20	31.85602
8	[illegible]	2.659899	[illegible]	20.93005	[illegible]
9	[illegible]	2.17555	52.95632	20.90050	24.04565
10	0.041643	1.847269	56.58226	20.58358	20.94688
11	0.044530	1.634179	59.16456	20.67781	18.52345
12	0.047031	1.465469	61.55862	20.32151	16.65440
13	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
14	0.050902	1.303491	64.73884	19.69857	14.25910
15	0.052398	1.268546	65.58187	19.53664	13.61295
16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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	0.0570[illegible]06	1.121583	65.94016	19.59173	13.34653

Variance Decomposition of LFR24:

Period	S.E.	LRI24	LWG24	LLF24	LFR24
1	0.025463	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	74.60113
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
6	0.090975	1.350050	39.40274	8.128790	51.11861
7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	0.108063	1.221373	49.60838	10.54191	38.72833
9	0.114887	1.132106	53.22612	11.06123	34.5805[illegible]4
10	0.120549	1.031755	56.21146	11.29797	31.458[illegible]81
11	0.125160	0.961350	58.42825	11.41988	29.190[illegible]52
12	0.128897	0.920660	59.90339	11.53169	27.644[illegible]25
13	0.131961	0.890049	60.74934	11.66585	26.694[illegible]75
14	0.134406	0.860807	61.10671	11.81738	[illegible]
15	0.1[illegible]36579	0.835406	61.13093	11.96604	26.06763
16	0.1[illegible]38246	0.816784	60.97048	12.08607	26.12766
17	0.1[illegible]39532	0.803313	60.73449	12.16692	26.29528
18	0.1[illegible]40496	0.802772	60.48257	12.21364	26.50102
19	0.1[illegible]41207	0.818563	60.24021	12.23959	26.70163
20	0.1[illegible]41734	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

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

LFR34

307367 70.28765 0.804618 20.60037

8.261089 69.73152 0.963946 21.04345

8.130049 68.70301 1.077161 22.08978

23.42786

Variance Decomposition of LLF34:

Period S.E. LRI34 LWG34 LLF34

2 0.165237

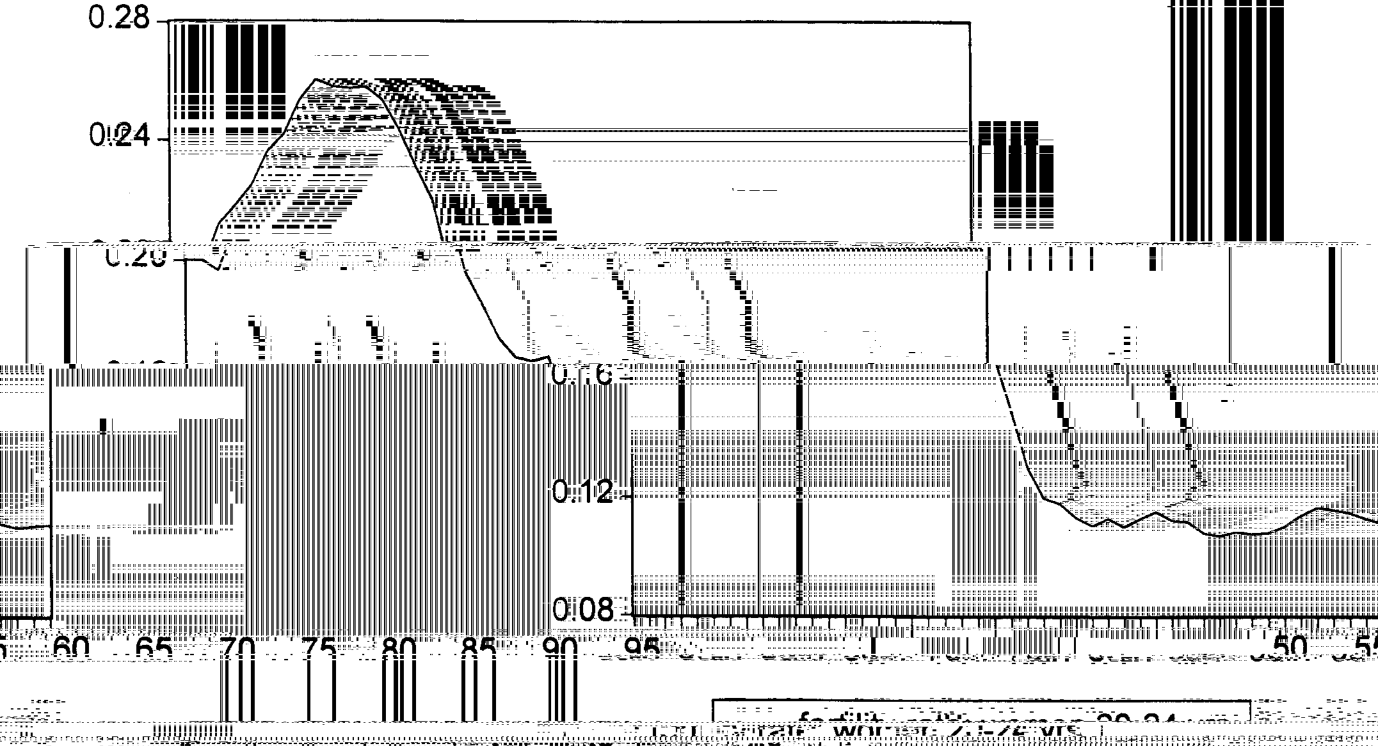
4 0.166314

6 0.168780

7 0.170610 8.000874 68.14099

8 0.173800 7.824079 67.61349 1.134570

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



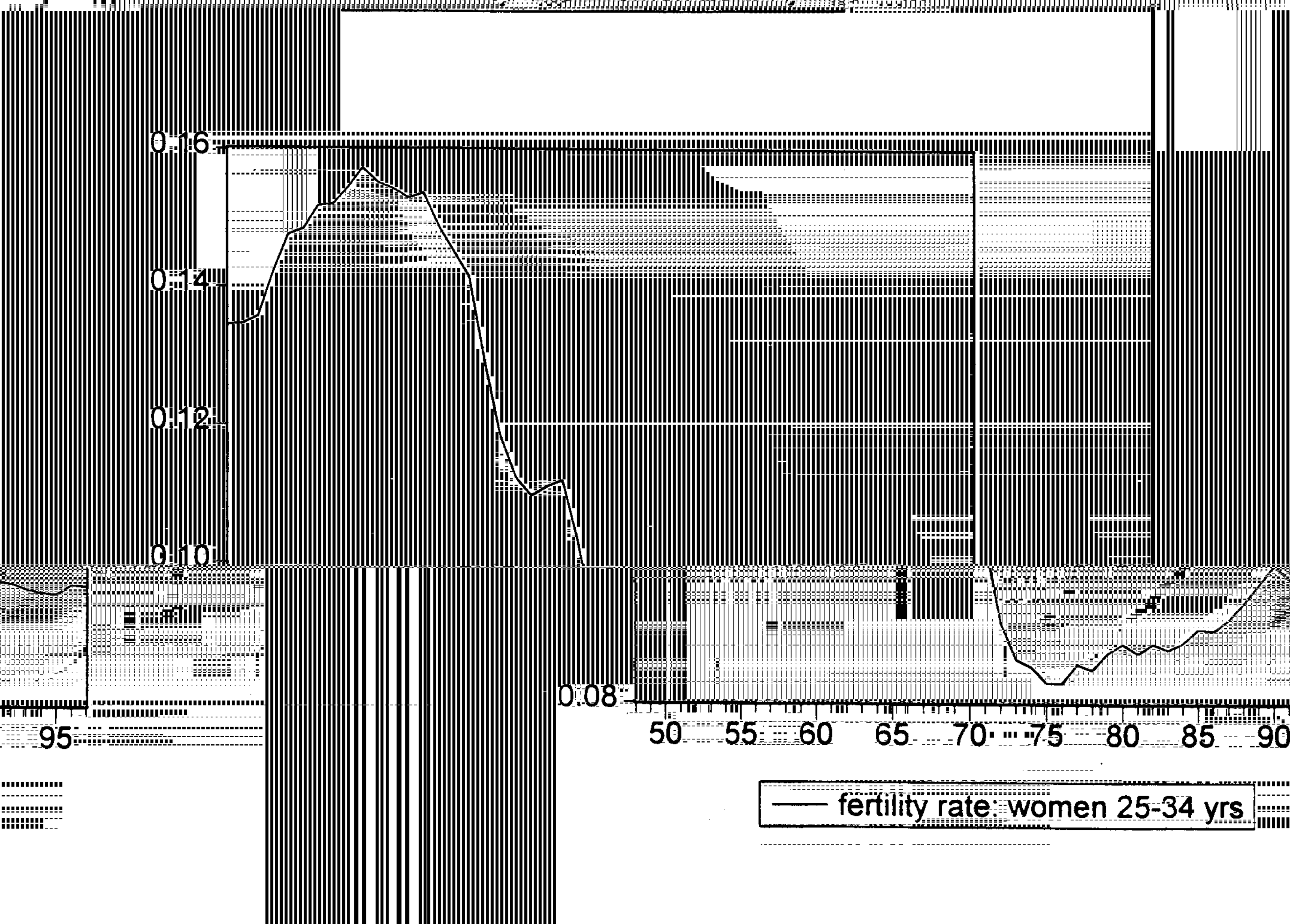


Figure 2: Labor force participation rates of women of ages 20-24 and 25-34.

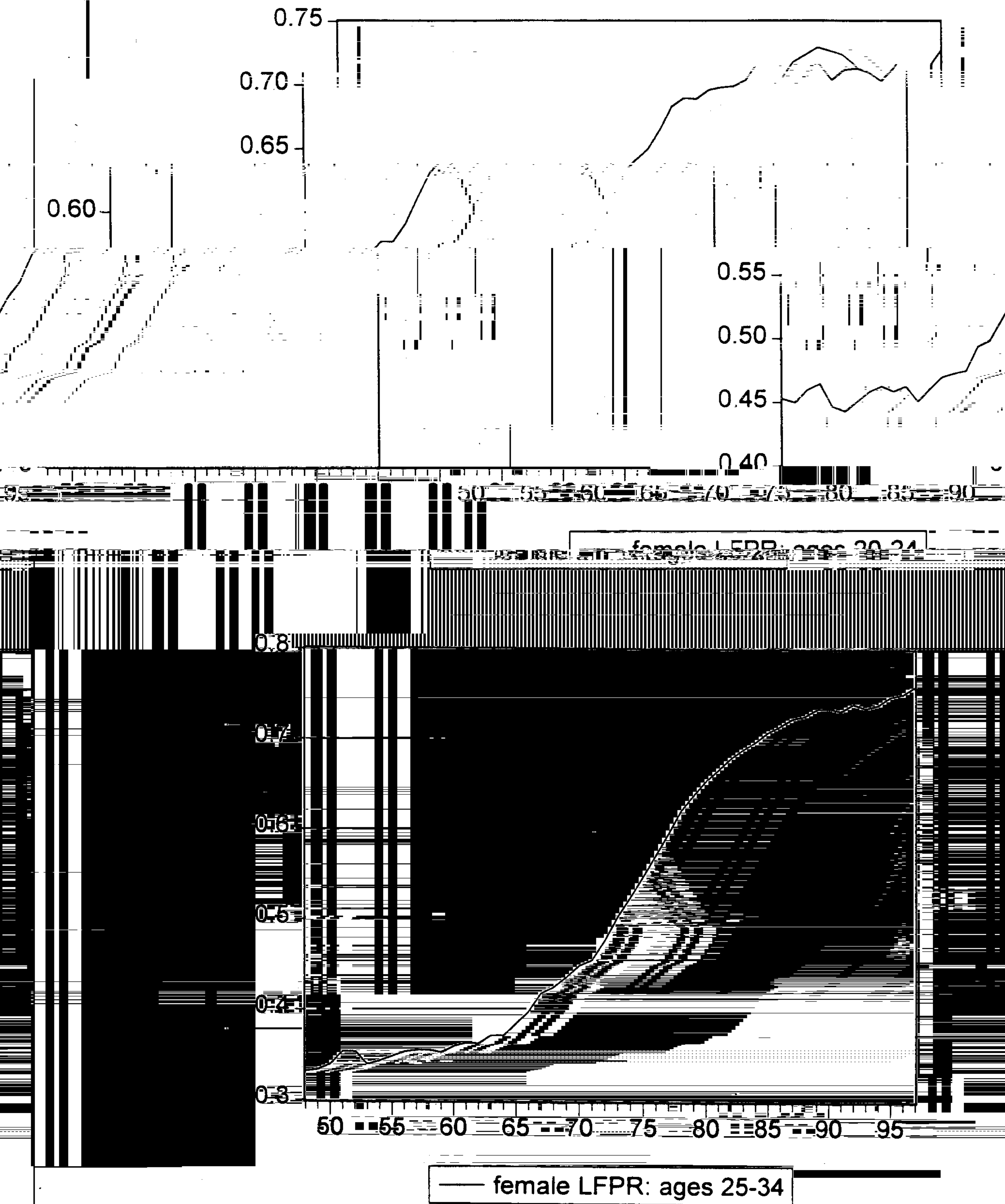


Figure 3: Real wages of women of ages 20-24 and 25-34

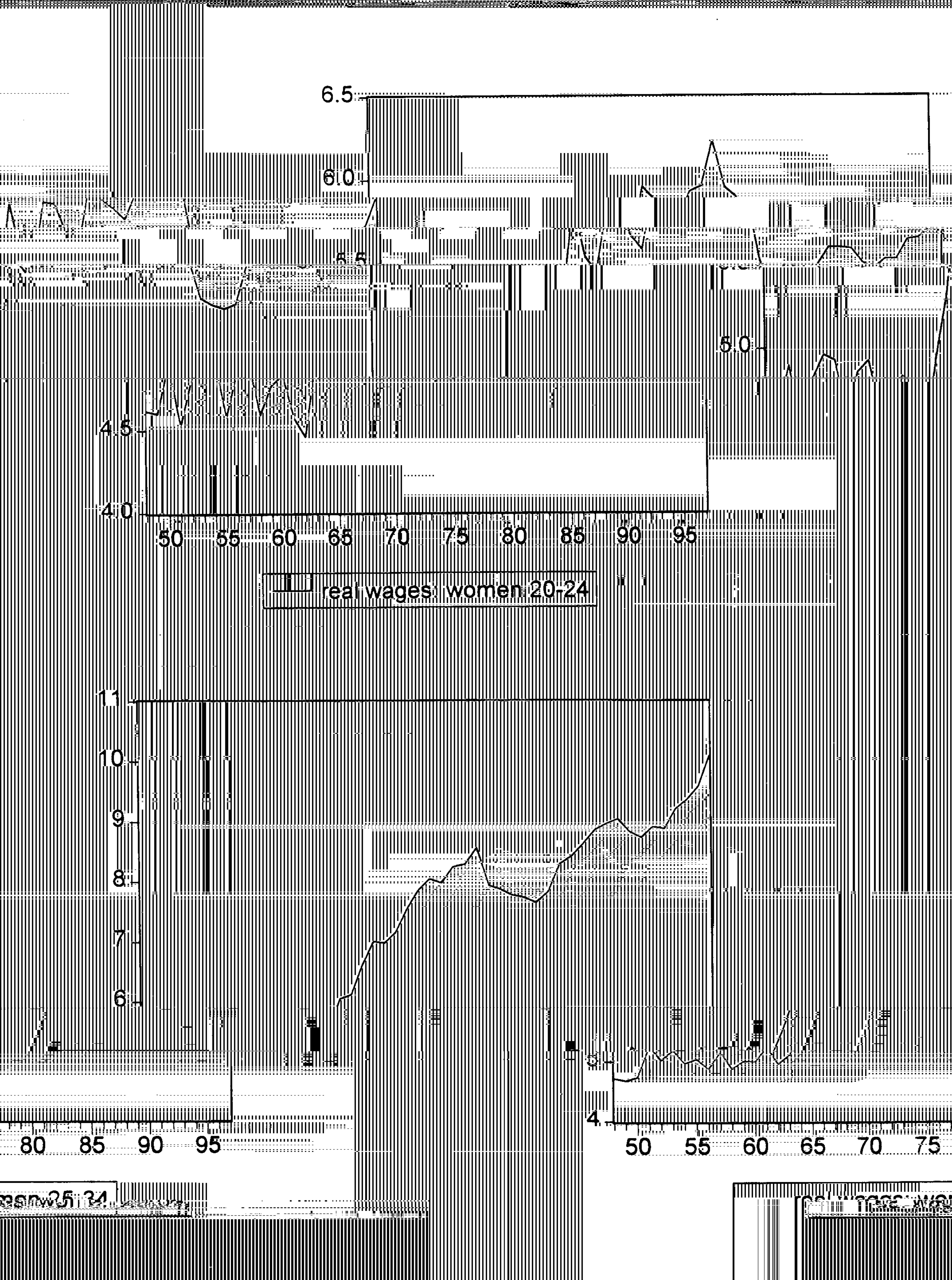
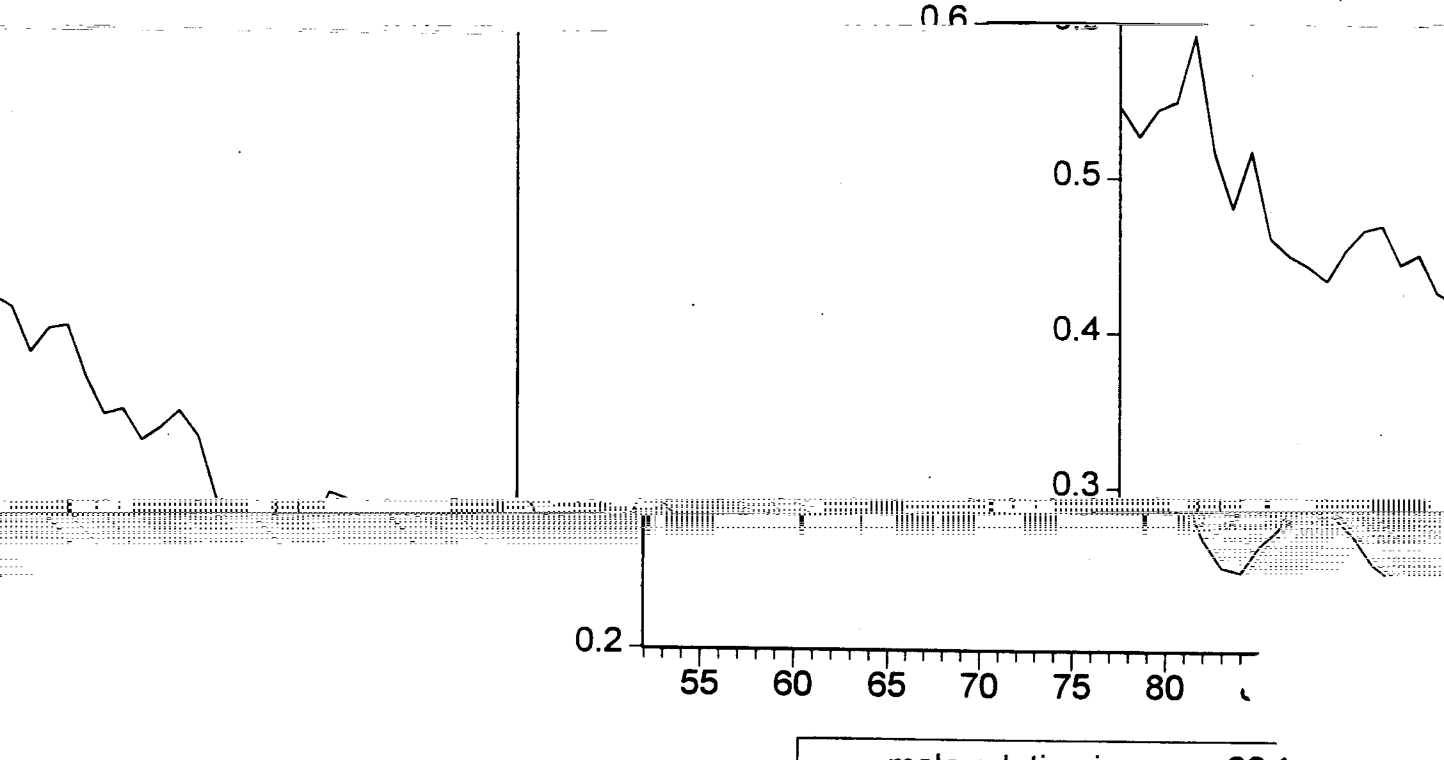
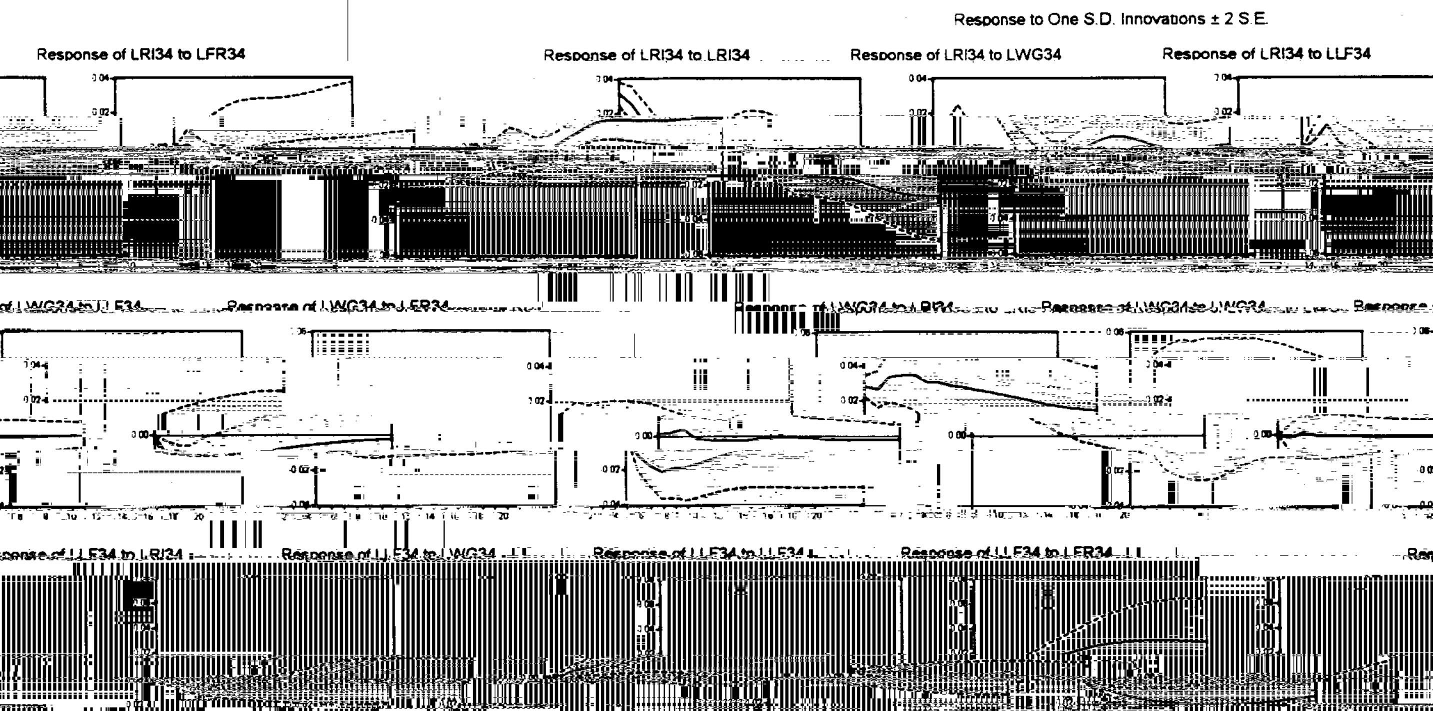


Figure 4. Male relative income: incomes of males aged 20-24 divided by incomes of males aged 35-44 lagged five years, and incomes of males aged 25-34 divided by incomes of males aged 45-54 lagged five years.



[redacted]



Response to One S.D. Innovations ± 2 S.E.
Response of LRI34 to LFR34
Response of LRI34 to LRI34
Response of LRI34 to LWG34
Response of LRI34 to LLF34
Response of LWG34 to LFR34
Response of LLF34 to LRI34
Response of LLF34 to LLF34
Response of LLF34 to LFR34