The Spatial Diffusion of Female Labor Force Participation: Evidence from US Counties

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Abstract

Many theories have been proposed to explain the dramatic rise of women' labor force participation over the last century in US. However, few authors have explicitly incorporated the role of spatial diffusion in the analysis. Using data for about 3100 counties over the period 1930-2000, this paper shows that the rise of female labor force participation in US has a strong spatial component. In particular, drawing on techniques developed by geographers for measuring the spatial dependence of social phenomena, we show that the inter-county variation in labor force participation is well explained by a spatial effect term that captures the potential impact of all geographic units on all other units, even after controlling for several demographic and economic factors. Moreover, with the use of thematic maps, we illustrate the dynamic spatial evolution of labor force participation over time and document the spreading of high level of female participation across US. Lastly, we estimate a dynamic model of spatial diffusion which includes lagged values of the variables of interest and quantify the effect of spatial diffusion on female labor force participation growth. Our results suggest that the evolution of women's labor force participation has a strong spatial component and brings empirical support to those theories for which geographic proximity matters.

Key words: Female labor force participation, spatial diffusion, contagion, geography, counties.

JEL Nos.: J21, N32, R12, Z13.

1 Introduction

In this paper we document the spatial diffusion of women's labor force participation (or LFP) over the last century. Using data for about 3100 counties over the period 1940-1990, this paper shows that the rise of female LFP in US has a strong spatial component.

We use this newly constructed dataset to answer questions like: Where did women first start working in large numbers? Why did women start working in some regions and not in others? What factors can explain the geographic diffusion? Are demand driven explanations, based on the increased availability of jobs enough to account for the observed phenomenon?

We quantify the effect of geographic proximity by constructing a measure of labor force potential. This is defined as the weighted average of the labor force participation of all other counties with weights given by the inverse of the geographical distance. We find this variable to be an important determinant of female labor force participation and to explain up to 30% of the overall intra-county variation.

We explore several potential explanations for this finding. We consider many demographic characteristics which are likely to be spatially correlated and may be driving the results. Factors like race, nativity, and sex ratio are likely to be similar in contiguous counties and are likely to affect the female labor force. Similarly, measures of income and education as well as the urban concentration of a county can affect the decision of women to participate and tend to be more similar across counties that are geographically close to each other. We find that, after controlling for all these factors, our measure of labor force potential is still significant at the 1% level. Moreover, the demographic and income variables alone explain up to 75% of the total intercounty variation. We also explore the contribution coming from the industrial and occupational structure of the county: geographically close counties are also likely to share a similar industrial structure which in turn can affect the level of female labor force. Interestingly, the coefficient that captures the effect of geographic proximity increases when we control for industrial structure. As expected, introducing measures of occupational composition decreases the coefficient of the labor force potential variable that remains significant at the 1% level. Our final specification includes the percentage of households owning a radio. This term is meant to capture the role of information diffusion in explaining labor force participation differential. We show that the interaction term constructed using the geographic index and the information variable is positive and strongly significant. This suggests that not only geography matters above and beyond the industrial composition, but also that its effect is magnified through the spreading of information. Next, we restrict the sample to those variables that are available for the entire period 1940-90 and explore the evolution of female labor force over time. We analyze how the change in labor force participation at the county level is affected by a measure that captures the similarity of each county with its neighbors. We expect that counties for which there is higher dissimilarity are the ones that would display larger changes. Moreover, we document the reduction in the dispersion across counties and show the convergence in labor force rates over time.

2 Main Idea of the Model

Culture has two essential elements. First, it is a set of beliefs. Beliefs are probability distributions over outcomes. Beliefs can be communicated from one person to another and one person's beliefs can be used to update another person's beliefs, using Bayes' law. Second, a common culture is desirable because it facilitates coordination. Coordination may be embedded in our preferences as a deep desire to be like others. Or, it could have a practical payoff. For example, if we all drive on the same side of the road, we avoid accidents. Similarly, if we all communicate in a particular way, we avoid misunderstandings. This is a model built to capture these two features that could be used to think about how culture spreads spatially and evolves over time. This still isn't a good motivating question. Perhaps the question would be: Is culture an aspect of preferences (which we can't predict because we don't know how to think about preference choice) or is it an aspect of beliefs, which we can analyze and predict using Bayes' law? Standard view, I think, is that it's preferences. We might be controversial if we can argue it's not.

3 A Simple Static Model

There is a continuum of agents, indexed by i, located on the interval $[0, 1]$. Each agent chooses an action a_i to maximize his utility, which depends on the distance of his action from an unknown true state θ and on the distance of his action from the average of other agents' actions $\bar{a}$:[1]

$$U = -(1-r)(a^i - \theta)^2 - r(a^i - \bar{a})^2. \tag{1}$$

The parameter r measures the degree of preference for coordination.[2]

The true state θ is drawn from a standard normal distribution $\theta \sim N(0,1)$. Agents also observe a public signal $z \sim N(\theta, \tau_z^{-1})$ and a private signal $x^i \sim N(\theta, \tau_x^{-1})$. They form beliefs about θ that define their culture. These beliefs are characterize by their mean $\hat{\mu}$ and variance $\hat{\Sigma}$:

$$\hat{\mu}^i = \frac{\tau_z z + \tau_x x^i}{1 + \tau_z + \tau_x} \tag{2}$$

$$\hat{\Sigma} = \frac{1}{1 + \tau_z + \tau_x}. \tag{3}$$

From the first order condition, an agent's optimal action is

$$a^i = (1-r)\hat{\mu}^i + rE[\bar{a}|\hat{\mu}^i] \tag{4}$$

To derive the expectation of the optimal action, we postulate an action rule for an agent based on his signals, take the expectation over all agent's actions given that rule, substitute the expectation into the first-order condition and match coefficients. Morris and Shin (2002) show that the equilibrium delivered by the procedure is a unique equilibrium. Each agent chooses an action $a^i = \alpha x^i + \gamma z$. If all agents follow such a rule, the average action is $\bar{a} = \alpha\theta + \gamma z$.

[1] Question: Maybe this would be simpler and easier to match to our LFP data if the action were discrete: $a^i \in \{0,1\}$.

[2] Note to me: This utility function has the property that the private and social benefit of coordination are identical. There is no coordination externality. Is this what we want?

Individual i's expectation about this average action is $E[\bar{a}|\hat{\mu}^i] = \alpha\hat{\mu}^i + \gamma z$. Substituting this into (4) gives $a^i = (1 - r - \alpha r)\hat{\mu}^i + \gamma z$. Substituting in for $\hat{\mu}^i$ and matching coefficients to solve for α and γ yields the equilibrium action rule:

$$a^i = \frac{(1-r)\tau_x x^i + \tau_z z}{1 + \tau_z + (1-r)\tau_x} \tag{5}$$

3.0.0.1 Where do the signals come from? Each agent observes the beliefs of one other agent j. The index j is chosen randomly, with a uniform distribution on the neighborhood around i: $j \sim unif[i-\delta, i+\delta]$. δ is a measure of how localized interactions are. If δ is small, agents learn only from very nearby agents, and changes in culture will be slow. If $\delta = 1$, then an agent's location does not matter. The spatial component of learning disappears.

4 A Dynamic Model

5 Results we might prove

- S-shaped spatial diffusion. The more people know about a change in θ, the higher the likelihood you learn. Eventually, you converge to knowing the truth.
- Cultural conservatism - The coordination component of the model makes the average action move more slowly than people's beliefs about the state. You don't want to change actions too suddenly because you don't believe others will move their actions suddenly and don't want to be too far from the average action. Is there some data evidence of this? Do survey responses precede changes in actions?

- Celebrities have undo influence - Most people's actions will be like private signals. They will be shared with only one other person. Let's call a celebrity someone who has the opportunity to make their beliefs public knowledge. Then, they will shift the average action a lot. Also, they benefit from being a leader because it ensures that they will be very close to the average action.

  The reason celebrities matter so much is that agents react enormously to public signals because they know that everyone else sees them and reacts to them too. Even if our private information is more precise, we might still put more weight on public signals. (You can see this in (5). The weight on z is greater in the action than it is in beliefs (2).)

- Larger localities (cities) will adopt cultural change faster. If there are more people that you can learn from and who have learned from a diversity of other people, information will be aggregated faster.

6 Evidence of Spatial Diffusion

Drawing on techniques developed by geographers for measuring the spatial dependence of social phenomena, we show that the inter-county variation in labor force participation is well explained by a spatial effect term (the potential labor force index) that captures the potential impact of all geographic units on all other units, even after controlling for several demographic and economic factors.

6.1 Data and Variable Definitions

For this analysis we use labor force data from "Historical, Demographic, Economic, and Social Data: The United States, 1790-2000", Inter-university Consortium for Political and Social Research, ICPSR 2896. For all years, counties are identified by the FIPS code. Our sample consists of 3092 counties. Our dependent variable is female civilian labor force. Our variable of interest, meant to capture the degree of spatial diffusion, is the potential labor force index, defined as:

$$\sum_{i=1}^{3091} \frac{LFP_j}{distance_{ij}} \; \forall j = 1, ..., 3091, j \neq i \tag{6}$$

where the geographic distances of each county from all the others are based on the highway distance among their centroids, and are from the "CTA Transportation Networks" website [3]. Summary statistics for our 1940 variables are in Table 1.

The highest percentage of female LFP (above 30%) can be observed in the Eastern states of the U.S.: some examples are Virginia, New York, Massachusetts, and Georgia. Some of this is probably related to the vicinity of the Piedmont Region [4], where the textile plants are concentrated. Those are also the states where the ratio females - males is the highest. Not surprisingly, those areas are characterized by the lowest median years of school of females. As regards the median family income distribution of 1950 (data not available for 1940), the richest areas are on the Western part of the country, where the median years of school for females is above 9 and the percentage of white

[3] http://www-cta.ornl.gov/transnet/SkimTree.htm.

[4] See Holmes et al. [2].

population is higher than 88%. This is also a reflection of the immigration pattern characterizing the Eastern part of the country. Counties of Tennessee and Kentucky are instead characterized by the lowest (below 5%) female LFP rate. This can also be explained by the high presence in that area of coal mines.

6.2 Results

In this section we describe the results presented in Table 2, Panel A. In the first column we regress the county-level female labor force participation on our measure of spatial diffusion and on a set of state fixed effects. We find that the coefficient is significant and positive in explaining the labor force participation of women. This implies that counties that are contiguous to other counties characterized by higher labor force participation, are themselves more likely to have a high labor force participation. The effect is sizable since a one standard deviation increase in the spatial diffusion index implies an increase in labor force participation of 0.5. This is equivalent to 3 percent of average level of labor force and about 9 percent of the total variation across counties.

In the second column we add controls for the demographic characteristics: percentage of white population, percentage of native population and sex ratio. These measures have been shown in the literature to be significant in explaining female labor force. Our results have all the expected signs: counties with smaller white population, larger immigrant pool and more women are those characterized by higher female labor force. The coefficient of the labor force potential remains positive and statistically significant at the 1% level. In the third column we also add controls for degree of urbanization, median family income, median years of school of males and females as well as average number of children born alive and marriages in a year. The coefficient on the labor force potential is reduced, but it is still sizable, positive and significant. With this specification we are able to explain 75% of the total intra-county variation. In the following columns we add controls for the industrial as well as the occupational structure. Specifically, we add 8 variables capturing the percentage of total employment in each sector and 13 variables capturing the percentage of total employment in each occupation. The excluded variables are construction for the sectoral variables and professional for the occupational ones. Some of these variables appear to have a strong effect on the level of female labor force. Nevertheless, the labor force potential remains positive and significant, meaning that the industrial composition is not the sole responsible for the observed spatial diffusion.

Lastly, we add the percentage of dwellings with a radio and we construct an interaction term between the labor force potential and this measure of information spreading. The interaction term is positive and strongly significant, suggesting that the effect of the geographic component is reinforced by the presence of information diffusion.

7 Spatial Diffusion Over Time

In this section we make use of thematic maps to document the spatial diffusion of women's labor force participation.

Figure 1 shows the labor force participation rate of women at the county level for US in each decade from 1940 to 1990.

Starting in 1940 the District of Columbia and the New York counties displayed the highest labor force participation rates with respectively, 38.2% and 36.6%. Already in the 1940s we can distinguish the area known as "Piedmont region", characterized by a heavy presence of the textile industry associated to high labor force participation. Next to this region, an area of high concentration of coal mines is characterized by a very low participation rate.

EVIDENCE: reduction in the dispersion across counties and show the convergence in labor force rates over time.

8 Related Literature

- A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades Sushil Bikhchandani; David Hirshleifer; Ivo Welch The Journal of Political Economy, Vol. 100, No. 5. (Oct., 1992), pp. 992-1026.

  In this model, all agents want to take an action close to a true state, but they have no coordination motive. They end up taking similar actions because of an informational cascade (also called herding): They observe others' actions sequentially, which they regard as informative signals about the true state. People start following the first movers because they think their actions tell them more than their own signal does. Fads end when a fashion leader (someone with a more precise signal than everyone else) does something different than the prevailing fad.

  Some of the theoretical and empirical results would have to distinguish the information with coordination motive story from the herding story.

- Global Games: Theory and Applications Stephen Morris and Hyun Song Shin, in Advances in Economics and Econometrics, the Eighth World Congress (edited by M. Dewatripont, L. Hansen and S. Turnovsky), Cambridge University Press, (2003).

http://hyunsongshin.org/www/seattle.pdf

This book chapter is a great reference to global games. The related models, starting on p.76, talk a little bit about this kind of local interaction game. Has some other useful references that I haven't tracked down.

- Amador and Weill - this is now closer to their model because it has the decentralized exchange of information. You need that to get the spatial predicitions.

9 Questions

- How might predictions of this model be matched to the data?
- What are some of the features of the geographic data that would be important for the model to capture?
- Do we have data on beliefs across localities, or only participation?
- Is this different enough from Bikchandani et al?
- Are there other similar papers? Do a citation search for BikchandaniHW and a google search on learning and culture.
- This model will require keeping track of the whole distribution of beliefs across the population. Can we keep this analytically tractable enough to derive some results? I think so, but I'm not sure. Looking at what tricks the local interactions papers cited in the Morris and Shin chapter use to keep their models tractable is the next step.

References

[1] Bowles, Gladys K. 1976. "Potential Change in Labor Force in the 1970-80 Decade for Metropolitan and Nonmetropolitan Counties in the United States." *Phylon*, Vol.37, No.3, pp.263-269.

[2] Holmes, Thomas J. and Stevens, John J. 2004. "Spatial Distribution of Economics Activities in North America" in *Handbook of Regional and Urban Economics*, edited by J. V. Henderson and J. F. Thisse, chapter 63, pp.2797-2843.

[3] Tolnay, Stewart E. 1995. "The Spatial Diffusion of Fertility: A Cross-Sectional Analysis of Counties in the American South, 1940." *American Sociological Review*, Vol.60, No. 2, pp.299-308.

[4] Tolnay, Stewart E. and Glynn, Patricia J. 1994. "The Persistence of High Fertility in the American South on the Eve of the Baby Boom." *Demography*, Vol.31, No. 4, pp.615-630.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Obs	Min	Max
Female labor force participation rate	13.631	5.306	3092	3.0401	37.3905
Potential Labor Force Index	82.588	21.563	3093	10.6814	166.8427
Dwelling with radio %	69.36935	19.91309	3091	13.2	98.5
Interaction	5622.223	2060.576	3091		
Demographics:					
White population %	0.886	0.179	3089	.1444	1
Native white population %	0.961	0.047	3089	.6575	1
Females %	0.487	0.02	3093	.1957	.5494
Marriages %	0.014	0.038	3015	0	.7999
Fertility %	0.026	0.008	3089	0	.1135
Urban population %	232.946	254.987	3089	0	1
Median family income 1950	2289.303	814.101	3032	0	5489
Fertility	1135.71	3629.666	3089	0	.1135
Median years of school / males 25+	7.741	2.023	3093	0	12.3
Median years of school / females 25+	8.303	2.063	3093	0	12.2
Industrial sectors:					
Constructions %	0.042	0.024	3089		
Mining %	0.03	0.076	3089		
Farm %	0.417	0.212	3089		
Manufacturing %	0.123	0.121	3089		
Transport %	0.049	0.035	3089		
Retail %	0.12	0.047	3089		
Business %	0.124	0.049	3089		
Other %	0.094	0.052	3089		
Occupations:					
Professionals %	0.173	0.068	3092		
Semiprofessionals %	0.005	0.007	3092		
Farmers %	0.045	0.042	3092		
Managers %	0.056	0.034	3092		
Clerks %	0.193	0.081	3092		
Crafts %	0.005	0.005	3092		
Operatives %	0.102	0.114	3092		
Domestics %	0.217	0.083	3092		
Non-domestic services %	0.116	0.052	3092		
Wage farm laborers %	0.017	0.041	3092		
Family farm laborers %	0.045	0.084	3092		
Non-farm laborers %	0.008	0.012	3092		
Other %	0.017	0.012	3092		

Table 2 - Panel A: ***Dep = Female Labor Force Participation Rate 1940***

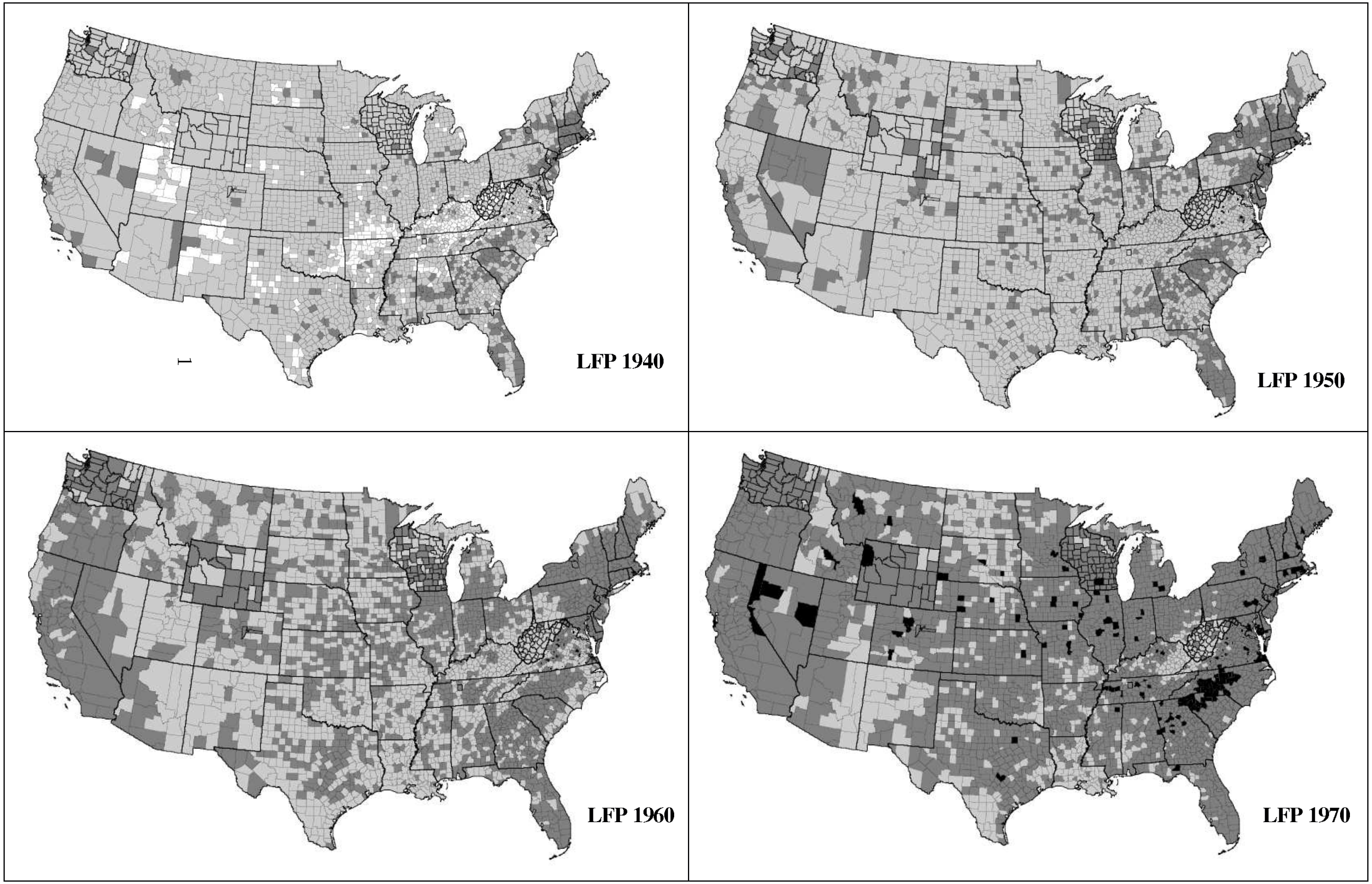
Variable	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**
Potential Labor Force Index	.0466**	.0383**	.0162*	.0273**	.0167**	-.0524**
	(.0123)	(.0109)	(.0082)	(.0078)	(.0065)	(.0129)
Dwellings with radio %						-.0269*
						(.0157)
Interaction						.0009**
						(.0001)
Demographics:						
White population %		-7.4673**	-11.2575**	-11.6387**	-7.8058**	-8.8244*
		(.6011)	(.47822)	(.4549)	(.4347)	(.4468)
Native white population %		-38.5121**	-4.5236*	-4.7392**	-4.7508**	-5.1999**
		(2.4687)	(1.9622)	(1.8192)	(1.4842)	(1.4601)
Females %		121.5833**	38.1814**	24.4100**	20.2475**	18.6605**
		(4.5077)	(3.9835)	(4.2392)	(3.5554)	(3.5005)
Urban population %			.0093**	.0051**	.0038**	.0038**
			(.0003)	(.0003)	(.0003)	(.0003)
Median family income 1950			.0026**	.0017**	.0018**	.0013**
			(.0001)	(.0001)	(.0001)	(.0001)
Median years of school / males 25+			-.2472†	.3410*	.0522	-.1405
			(.1649)	(.1571)	(.1267)	(.1280)
Median years of school / females 25+			.2866**	-.3355*	-.0137	.1621
			(.1666)	(.1561)	(.1259)	(.1276)
Fertility			-44.4448**	-45.2258**	-47.7152	-34.7002**
			(8.3097)	(7.6259)	(6.0991)	(6.1506)
Marriages %			-.0134	-.6694	-.6455	-.5820
			(1.5297)	(1.4121)	(1.1168)	(1.0982)
Industrial sectors				X	X	X
Occupations					X	X
Intercept	9.7793**	-5.0858**	.8091*	.9035	-10.2062	-5.1880†
	(1.0211)	(3.2402)	(2.4237)	(3.5032)	(3.2037)	(3.2684)
Number of obs	3092	3088	2957	2957	2957	2957
Adjusted R-squared	0.2788	0.4872	0.7452	0.7870	0.8673	0.8717

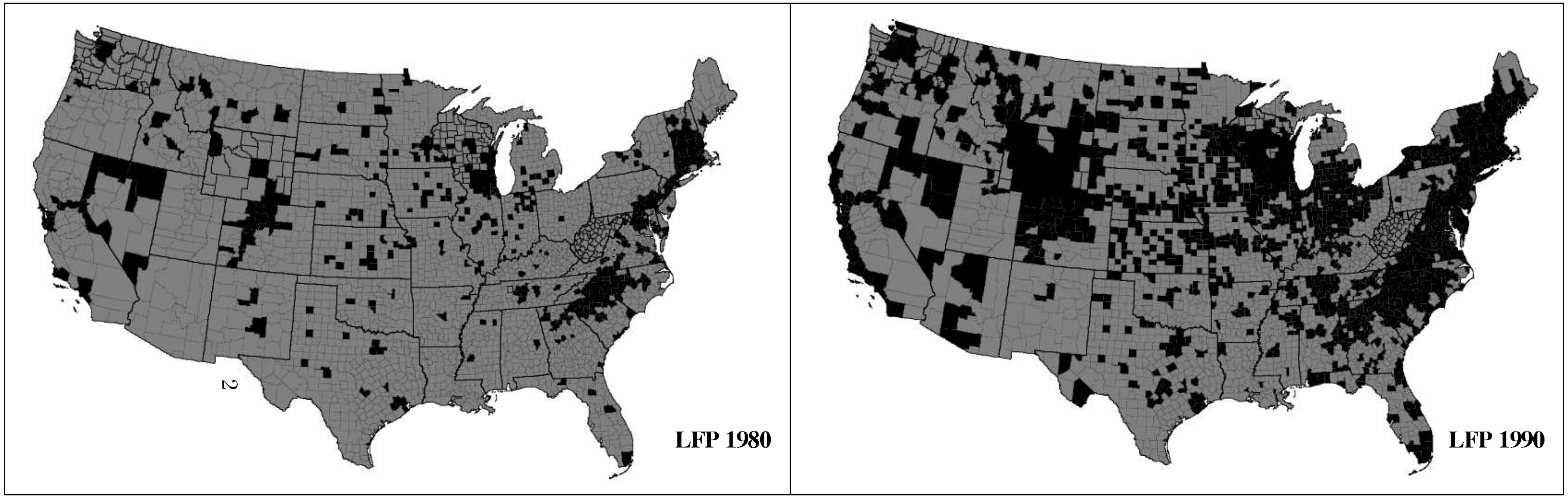
Note: ** significant at 1%; * significant at 5%; † significant at 10%. State fixed effects in all specifications.

Table 2 - Panel B: ***Coefficients for Industrial and Occupational variables from Panel A***

Variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Industrial sectors:						
Mining %				-.6619	1.6364	2.9676†
				(2.5588)	(2.0719)	(2.0456)
Farm %				3.6761†	2.9362†	3.7539*
				(2.5033)	(2.0802)	(2.0500)
Manufacturing %				12.2040**	6.8841**	7.8753**
				(2.5497)	(2.0851)	(2.0533)
Transport %				-5.985*	-2.6008	-.9098
				(3.1008)	(2.4937)	(2.4597)
Retail %				25.6424**	26.3566**	25.4993**
				(3.6378)	(2.9889)	(2.9729)
Business %				21.0182**	36.3078**	35.9806**
				(3.4221)	(2.8887)	(2.8414)
Other %				12.0862**	16.0428**	17.0936**
				(2.9046)	(2.3967)	(2.3588)
Occupations:						
Semiprofessionals %					-5.8710	.5709
					(6.2621)	(6.1888)
Farmers %					13.9470**	15.5650**
					(1.6857)	(1.6648)
Managers %					19.5327**	20.1449**
					(2.2408)	(2.2121)
Clerks %					1.7165	.2218
					(1.5909)	(1.5709)
Crafts %					12.7231	8.9091
					(10.0314)	(9.8693)
Operatives %					23.0788**	22.0980**
					(1.0978)	(1.0838)
Domestics %					10.7960**	10.5440**
					(1.3123)	(1.2917)
Non-domestic services %					3.6951*	3.0513†
					(1.7477)	(1.7193)
Wage farm laborers %					23.0434**	22.6875**
					(1.5497)	(1.5282)
Family farm laborers %					22.1111**	22.2811 **
					(1.1601)	(1.1411)
Non-farm laborers %					4.3034	4.0326
					(3.6240)	(3.5626)
Other %					-3.5489	-3.3343
					(3.4302)	(3.3771)

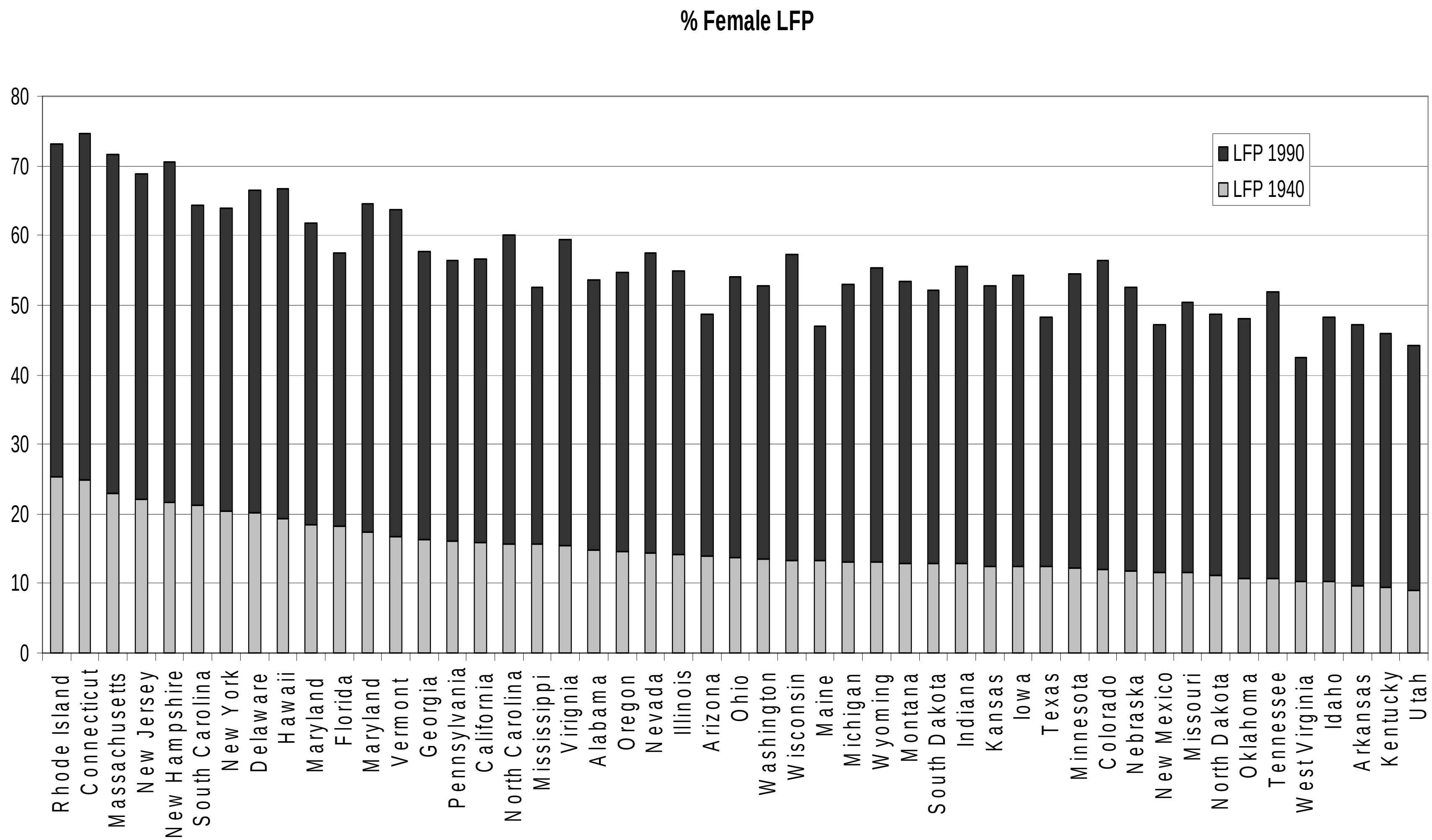
Note: ** significant at 1%; * significant at 5%; † significant at 10%. State fixed effects in all specifications.


LFP 1940
LFP 1950
LFP 1960
LFP 1970



Legend:

0% ≤ LFP ≤ 8%	
8% < LFP ≤ 20%	
20% < LFP ≤ 40%	
LFP > 40%	


% Female LFP
LFP 1990
LFP 1940
0
10
20
30
40
50
60
70
80
Rhode Island
Connecticut
Massachusetts
New Jersey
New Hampshire
South Carolina
New York
Delaware
Hawaii
Maryland
Florida
Maryland
Vermont
Georgia
Pennsylvania
California
North Carolina
Mississippi
Virignia
Alabama
Oregon
Nevada
Illinois
Arizona
Ohio
Washington
Wisconsin
Maine
Michigan
Wyoming
Montana
South Dakota
Indiana
Kansas
Iowa
Texas
Minnesota
Colorado
Nebraska
New Mexico
Missouri
North Dakota
Oklahoma
Tennessee
West Virginia
Idaho
Arkansas
Kentucky
Utah