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Federal Reserve Bank of Chicago

**Simultaneity in Binary Outcome Models
with an Application to Employment
for Couples**

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Kyriazidou, and Martin Weidner*

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Simultaneity in Binary Outcome Models with an Application to Employment for Couples*

Bo E. Honoré[†] Luojia Hu[‡] Ekaterini Kyriazidou[§] Martin Weidner[¶]

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Abstract

Two of Peter Schmidt’s many contributions to econometrics have been to introduce a simultaneous logit model for bivariate binary outcomes and to study estimation of dynamic linear fixed effects panel data models using short panels. In this paper, we study a dynamic panel data version of the bivariate model introduced in [Schmidt and Strauss \(1975\)](#) that allows for lagged dependent variables and fixed effects as in [Ahn and Schmidt \(1995\)](#). We combine a conditional likelihood approach with a method of moments approach to obtain an estimation strategy for the resulting model. We apply this estimation strategy to a simple model for the intra-household relationship in employment. Our main conclusion is that the within-household “correlation” in employment differs significantly by the ethnicity composition of the couple even after one allows for unobserved household specific heterogeneity.

Keywords: Simultaneity, Binary Response, Fixed Effects, Moment Conditions, Employment.

JEL Code: C01, C33, C35, E24.

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1 Introduction

A large recent literature has been concerned with estimation of models with binary outcomes that interact with each other. The papers by [Bresnahan and Reiss \(1991\)](#) and [Tamer \(2003\)](#) are early examples of this. This literature was predated by [Schmidt and Strauss \(1975\)](#) which proposed a statistical model that has the feature that the conditional distribution of each binary variable depends on the outcome of the other.

At the same time, a large econometric literature has been concerned with estimation of linear panel data models with fixed effects and lagged dependent variables. [Ahn and Schmidt \(1995\)](#) is a prominent example of this literature.

This paper combines insights from these literatures by illustrating how the simultaneous binary outcome model in [Schmidt and Strauss \(1975\)](#) can be modified to allow for panel data with individual specific fixed effects and lagged dependent variables. The main contribution of the paper is to develop a toolbox of estimation procedures that can be used to estimate the resulting models.

Methodologically, the paper fits into the literature that is concerned with estimation of standard nonlinear panel data models with fixed effects using short panels. This literature has a long history in econometrics. For example, [Rasch \(1960\)](#) considered conditional likelihood estimation of a static binary logit model with fixed effects, while [Manski \(1987\)](#) proposed a maximum score estimator a semiparametric version of the models. Other classical nonlinear models that have been studied include the censored and truncated regression models ([Honoré \(1992\)](#)), the sample selection model ([Kyriazidou \(1997\)](#)), and the Poisson regression model ([Hausman, Hall, and Griliches \(1984\)](#)). Dynamic versions of the same models were studied by [Honoré and Kyriazidou \(2000\)](#), [Hu \(2002\)](#), [Kyriazidou \(2001\)](#), and [Wooldridge \(1997\)](#). More recently, [Kitazawa \(2013\)](#), [Honoré and Weidner \(2020\)](#) and [Honoré, Muris, and Weidner \(2021\)](#) derived moment conditions for logit-type models with fixed effects and lagged dependent variables. The approach to constructing moment conditions in the paper is in the same spirit as that work.

We illustrate the proposed methods in the context of husband's and wife's employment. In this context, it is natural to allow for the possibility that the outcome for each spouse is related to the outcome of the other's, which makes it natural to consider the Schmidt-Strauss framework. At the same time it is also important to allow for dynamics and heterogeneity in this application given the panel structure of our data. This makes the models studied in this paper relevant. The specific empirical question is how the parameter that captures the dependence between outcomes

for husbands and wives differs by the ethnicity of the couple and varies over time.

The paper is organized as follows: In Section 2, we present the [Schmidt and Strauss \(1975\)](#) model. In Section 3, we discuss the data. Section 4 presents simple evidence for the intra-household dependence in couples' employment by ethnicity. Section 5 discusses the conditional likelihood approach for estimating the Schmidt and Strauss model incorporating the lagged dependent variables and fixed effects. Section 6 discusses the method of moments approach of [Honoré and Weidner \(2020\)](#) which allows for estimating the main parameter of interest. Section 7 concludes. The Appendix provides moment conditions for a special case of the model.

2 The Schmidt-Strauss Model

[Schmidt and Strauss \(1975\)](#) proposed a cross sectional simultaneous equations logit model in which two binary variables for an individual i are each distributed according to a logit model conditional on the other and on a set of explanatory variables

$$\begin{aligned} P(y_{1,i} = 1 | y_{2,i}, x_{1,i}, x_{2,i}) &= \Lambda(x'_{1,i}\beta_1 + \rho y_{2,i}), \\ P(y_{2,i} = 1 | y_{1,i}, x_{1,i}, x_{2,i}) &= \Lambda(x'_{2,i}\beta_2 + \rho y_{1,i}), \end{aligned} \tag{1}$$

where $x_{1,i}$ and $x_{2,i}$ are vectors of explanatory variables, β and ρ are parameters to be estimated, and $\Lambda(\cdot)$ is the logistic cumulative distribution function¹. When ρ is positive (negative), the probability that $y_{1,i}$ equals one is higher (lower) conditional on $y_{2,i}$ being one than conditional on being zero. The same holds for the probability that $y_{2,i}$ is one conditional on $y_{1,i}$. A positive (negative) ρ therefore corresponds to a positive (negative) statistical relationship between $y_{1,i}$ and $y_{2,i}$.

The conditional probabilities in (1) emerge from a statistical model in which $y_{1,i}$ and $y_{2,i}$ have the joint probability distribution

$$\begin{aligned} P(y_{1,i} = c_1, y_{2,i} = c_2 | x_{1,i}, x_{2,i}) \\ = \frac{\exp(c_1 x'_{1,i}\beta_1 + c_2 x'_{2,i}\beta_2 + c_1 c_2 \rho)}{1 + \exp(x'_{1,i}\beta_1) + \exp(x'_{2,i}\beta_2) + \exp(x'_{1,i}\beta_1 + x'_{2,i}\beta_2 + \rho)}. \end{aligned} \tag{2}$$

¹[Schmidt and Strauss \(1975\)](#) show that this model cannot be generalized to allow for different values for ρ in the distribution of $y_{1,i}$ given $y_{2,i}$ and in the distribution of $y_{2,i}$ given $y_{1,i}$.

To see that ρ measures the dependence between $y_{1,i}$ and $y_{2,i}$ in (2) note that

$$\begin{aligned} \rho = & \log(P(y_{1,i} = 1, y_{2,i} = 1 | x_{1,i}, x_{2,i})) + \log(P(y_{1,i} = 0, y_{2,i} = 0 | x_{1,i}, x_{2,i})) \\ & - \log(P(y_{1,i} = 0, y_{2,i} = 1 | x_{1,i}, x_{2,i})) - \log(P(y_{1,i} = 1, y_{2,i} = 0 | x_{1,i}, x_{2,i})). \end{aligned} \quad (3)$$

Therefore, $\log(P(y_{1,i} = c_1, y_{2,i} = c_2 | x_{1,i}, x_{2,i}))$ is supermodular or submodular depending on whether $\rho > 0$ or $\rho < 0$.

The simultaneous logit model of [Schmidt and Strauss \(1975\)](#) has been applied in a variety of cross sectional studies and in various fields such as labor economics (see, for example, [Lehrer and Stokes \(1985\)](#)), urban economics ([Boehm \(1981\)](#)), health economics ([Akin, Guilkey, and Popkin \(1981\)](#) and [WANG and ROSENMAN \(2007\)](#)), transportation ([Ye, Pendyala, and Gottardi \(2007\)](#)), political science ([Kau, Keenan, and Rubin \(1982\)](#)), finance ([Chen, Firth, and Xu \(2009\)](#)), demography ([Koo and Janowitz \(1983\)](#)), and marketing ([Chen and Hitt \(2000\)](#)).

Below, we apply the model of [Schmidt and Strauss \(1975\)](#) (and its panel data extensions) to an empirical study of husbands' and wives' employment status. In this context, i denotes the identity of the household. The next section introduces the data.

3 Data

For the analysis in this paper, we use the Current Population Survey (CPS) Basic Monthly micro data from the 40 years between January of 1982 and December of 2021. The data is sourced from <https://www.ipums.org/> ([Flood, King, Rodgers, Ruggles, Warren, and Westberry \(2021\)](#)). The monthly CPS has a panel design. Households are interviewed for four consecutive months, then not interviewed for eight months, and finally interviewed for four more consecutive months. We identify households with one head of household and one married or unmarried partner (of the head). The data consists of these heads and partners provided that they are of different sex and are both between the age of 25 and 65 (inclusive).² Below, we sometimes refer to the partners as husbands and wives or as spouses although they are not always legally married. Since our ultimate goal is to investigate the dynamics of the employment status and a number of missing observations are missing in the last four months, we restrict the sample to the first four interview months, and we

²We further clean the data by eliminating individuals with missing or logically inconsistent age increases or inconsistent sex or race.

only use households who are in the sample in all of those four months.

We define four race/ethnicity groups: White, Black, Hispanic, and Other. Below we interchangeably refer to these groups as “race”, “ethnicity” or “race/ethnicity”. The couples are then grouped into five groups based on the race/ethnicity of the two partners: White-White, Black-Black, Hispanic-Hispanic, Other-Other, and Mixed Race. We refer to these groups as the “ethnicity mix” (or sometimes just the “ethnicity”) of the couple.

Table 1 presents summary statistics for the variables used in this paper. The first is a dummy variable for working defined as the employment status being “At work”. The remaining variables are age in years, a dummy variable for children under the age of 5, a dummy variable for any children, and dummy variables for three education levels: high school or less, some college and college degree or more. Note that we report the number of individuals. Since this is a balanced panel with four time periods, the number of observations is larger by a factor of four.

Table 1: Summary Statistics By Household Ethnicity

	Women					
	All	Whites	Blacks	Hispanics	Other	Mixed
Working	0.64	0.65	0.67	0.52	0.62	0.67
Age	43.35	43.80	43.41	40.61	41.92	41.26
Kids < 5	0.19	0.18	0.18	0.28	0.25	0.23
Kids	0.65	0.63	0.69	0.81	0.77	0.65
HS or Less	0.50	0.49	0.53	0.73	0.41	0.39
Some College	0.23	0.24	0.26	0.16	0.18	0.28
College+	0.27	0.28	0.21	0.10	0.42	0.33
No. Individuals	1,002,489	783,312	54,342	63,999	39,765	61,071

	Men					
	All	Whites	Blacks	Hispanics	Other	Mixed
Working	0.83	0.84	0.76	0.83	0.82	0.84
Age	45.53	45.93	45.88	42.81	44.76	43.52
Kids < 5	0.19	0.18	0.18	0.28	0.25	0.23
Kids	0.65	0.63	0.69	0.81	0.77	0.65
HS or Less	0.50	0.48	0.60	0.75	0.38	0.39
Some College	0.22	0.22	0.23	0.15	0.17	0.28
College+	0.29	0.30	0.17	0.10	0.44	0.33
No. Individuals	1,002,489	783,312	54,342	63,999	39,765	61,071

The table shows averages by the ethnicity of the couple for the variables used in this paper. The data is from IPUMS CPS and covers a balanced panel of couples where each individual’s age is between 25 and 65. The data covers the period between 1982 and 2021.

4 Simple Evidence

4.1 Summary Statistics

We start by presenting summary statistics for the joint probability of working by ethnicity. The first panel of Table 2 is for the whole sample, while the next two panels are for the subsamples of couples without children and with children. Our main takeaway from this table is that there is a large difference in these probabilities across the ethnicities, with Hispanic-Hispanic couples looking quite different from the others.

Table 2: Joint Probability of Employment by Ethnicity of the Couple

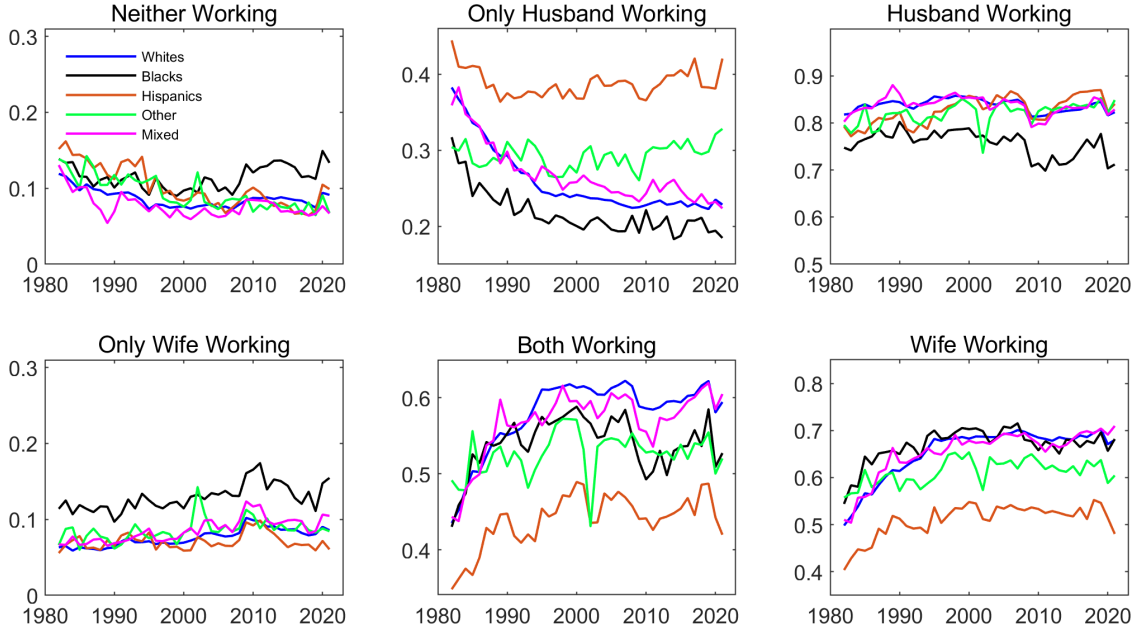
All											
		White/White		Black/Black		Hisp./Hisp.		Other/Other		Mixed	
		Husband		Husband		Husband		Husband		Husband	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Wife	No	0.087	0.260	0.114	0.217	0.096	0.388	0.088	0.294	0.074	0.258
	Yes	0.076	0.578	0.129	0.540	0.071	0.444	0.087	0.531	0.091	0.577
Without Children											
		White/White		Black/Black		Hisp./Hisp.		Other/Other		Mixed	
		Husband		Husband		Husband		Husband		Husband	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Wife	No	0.096	0.231	0.124	0.202	0.106	0.342	0.093	0.255	0.081	0.226
	Yes	0.084	0.589	0.138	0.537	0.080	0.471	0.096	0.557	0.100	0.593
With Children											
		White/White		Black/Black		Hisp./Hisp.		Other/Other		Mixed	
		Husband		Husband		Husband		Husband		Husband	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Wife	No	0.044	0.389	0.072	0.283	0.071	0.508	0.073	0.412	0.053	0.364
	Yes	0.039	0.528	0.090	0.555	0.048	0.373	0.062	0.453	0.059	0.523

The table shows the fraction of couples in each group that report each combination of working and not working. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021.

Table 2 aggregates the data for all years. In Figure 1 we plot the joint probability of working over time for each ethnicity. These are depicted in the four left most plots. The two plots to the right are the marginal probabilities of working for the husbands and wives. Again, that main takeaway is that there are interesting differences across ethnicities, with Hispanics and, to a lesser extent, Blacks standing out. In terms of the evolution of the probabilities over time, the most

distinct feature is the increase in the employment of women in the first part of the sample. This is seen in the marginal probabilities as well and the joint probabilities. It is also interesting that the 2008 recession had a large impact on the employment of men, but almost no effect for the women.

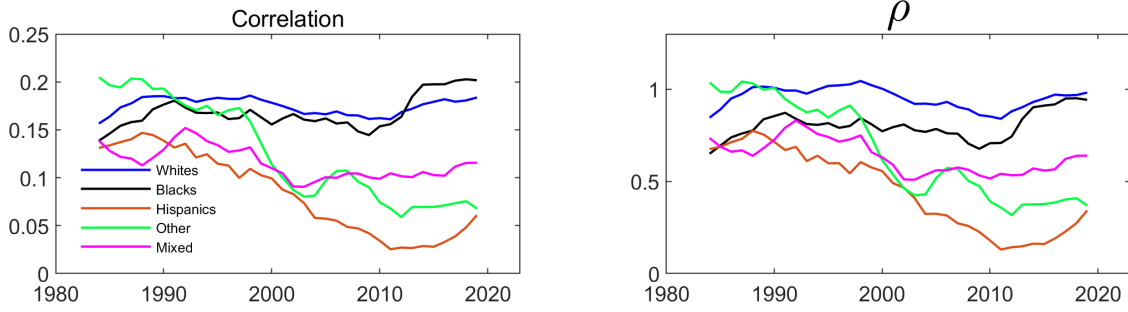
Figure 1: Probability Distribution of Employment Over Time By Ethnicity



The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021.

The left panel of Figure 2 displays the correlation between the spouses' employment over time. The reported correlation is a five year centered moving average. The correlation is always positive for all of the ethnicities. For Blacks and Whites, it remained more or less stable over time, while it decreased dramatically for the other groups, especially for Hispanics and for Others. It is difficult to compare correlations of different pairs of binary variables when the marginal probabilities differ across the pairs. In the right panel of Figure 2, we therefore present the five year centered moving average of the estimate of the parameter ρ in a Schmidt-Strauss model with no explanatory variables. Here $\hat{\rho}$ is calculated by the sample analog of equation (3). The estimated trend for ρ is similar to that for the correlation, although ρ shows a larger difference between Whites and Blacks.

Figure 2: Within Household Correlations In Employment Over Time By Ethnicity



The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021.

4.2 Static Cross Sectional Logit Models

It is clear from the evidence in Section 4.1 that there is a strong relationship between employment of husbands and of wives. In this section, we document that this persists after controlling for a set of observable characteristics. Specifically, in the first four columns of Table 3, we present the results from estimating separate logit models for employment for husbands and for wives as well as the results from maximum likelihood estimation of the Schmidt-Strauss model in equation (2). The explanatory variables are dummy variables for the presence of children younger than 5, for any children, for the person's own ethnicity, for the education categories "some college" and "college and above," and dummy variables for the ethnicity of the couple. The estimation also controls for year dummies, the age and the age-squared of both the husband and the wife, as well as the interaction of the ages. The last four columns present the results from estimating the same models after also including the ethnicity and the education variables of the spouse as explanatory variables.

The estimates of ρ in Table 3 clearly suggest that there is positive association between the employment of husbands and wives after controlling for observed characteristics. In order to investigate whether this association varies systematically across ethnicities, we re-estimate the model in the last two columns of Table 3 separately for each ethnicity. In Table 4, we report the estimated ρ 's. The most striking finding is that the estimated ρ for Whites is much larger than for other ethnicities, while the estimate for Hispanics is the lowest. This ordering is consistent with that found in Figure 2.

Figure 2 above suggested a dramatic fall in the association between the employment of wives

Table 3: Estimation Of Static Cross Sectional Models Of Employment

	Logit		Schmidt-Strauss		Logit		Schmidt-Strauss	
	Women	Men	Women	Men	Women	Men	Women	Men
Kids < 5	-0.808*** (0.006)	0.015* (0.008)	-0.814*** (0.006)	0.146*** (0.009)	-0.801*** (0.006)	0.009 (0.009)	-0.804*** (0.006)	0.143*** (0.009)
Kids	-0.183*** (0.005)	0.218*** (0.006)	-0.209*** (0.005)	0.253*** (0.006)	-0.180*** (0.005)	0.220*** (0.006)	-0.206*** (0.005)	0.254*** (0.006)
Black (Woman)	-0.041 (0.045)		-0.055 (0.045)		-0.055 (0.052)	-0.114* (0.063)	-0.045 (0.053)	-0.107* (0.064)
Hispanic (Woman)	-0.095*** (0.020)		-0.111*** (0.020)		-0.132*** (0.039)	-0.003 (0.047)	-0.134*** (0.039)	0.019 (0.048)
Other (Woman)	-0.156*** (0.020)		-0.171*** (0.020)		-0.199*** (0.038)	-0.078* (0.046)	-0.195*** (0.039)	-0.047 (0.047)
Some College (Woman)	0.381*** (0.005)		0.365*** (0.005)		0.395*** (0.005)	0.188*** (0.007)	0.381*** (0.005)	0.124*** (0.007)
College+ (Woman)	0.571*** (0.005)		0.537*** (0.005)		0.699*** (0.006)	0.228*** (0.008)	0.687*** (0.006)	0.116*** (0.008)
Black (Man)		-0.376*** (0.033)		-0.392*** (0.033)	0.109*** (0.039)	-0.409*** (0.046)	0.153*** (0.040)	-0.433*** (0.047)
Hispanic (Man)		0.003 (0.025)		-0.018 (0.026)	-0.062 (0.039)	-0.039 (0.048)	-0.060 (0.040)	-0.030 (0.049)
Other (Man)		-0.192*** (0.028)		-0.214*** (0.028)	-0.109*** (0.040)	-0.239*** (0.048)	-0.086** (0.041)	-0.225*** (0.049)
Some College (Man)		0.318*** (0.006)		0.298*** (0.006)	0.104*** (0.005)	0.259*** (0.007)	0.079*** (0.005)	0.247*** (0.007)
College+ (Man)		0.742*** (0.006)		0.699*** (0.006)	-0.219*** (0.006)	0.631*** (0.007)	-0.281*** (0.006)	0.676*** (0.007)
Black-Black Couple	0.141*** (0.045)	-0.134*** (0.035)	0.220*** (0.046)	-0.144*** (0.035)	0.028 (0.077)	0.013 (0.093)	0.033 (0.078)	0.007 (0.095)
Hispanic-Hispanic Couple	-0.419*** (0.021)	-0.147*** (0.027)	-0.392*** (0.022)	-0.028 (0.028)	-0.331*** (0.075)	-0.065 (0.091)	-0.332*** (0.076)	-0.006 (0.093)
Other-Other Couple	-0.092*** (0.022)	-0.147*** (0.030)	-0.051** (0.022)	-0.086*** (0.031)	0.079 (0.074)	-0.016 (0.090)	0.080 (0.076)	-0.027 (0.091)
Mixed Couple	0.002 (0.012)	-0.153*** (0.015)	0.029** (0.012)	-0.134*** (0.015)	0.042 (0.038)	-0.105** (0.046)	0.052 (0.039)	-0.113** (0.047)
ρ				0.718*** (0.005)				0.730*** (0.005)

*** p<0.01, ** p<0.05, * p<0.1

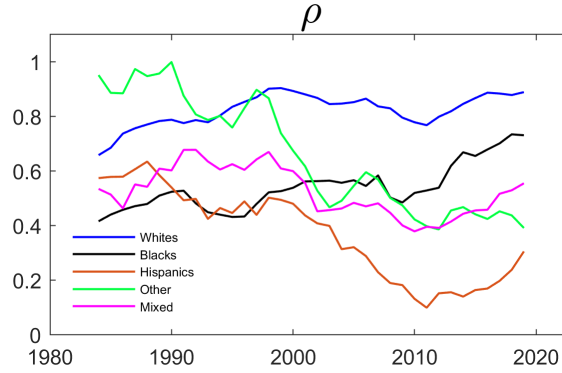
The dependent variable is working and the parameters are estimated by maximum likelihood. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021. Coefficients on year dummies, husband's and wife's age, their interaction and their squares are not reported. Standard errors are clustered at the household level.

Table 4: Estimation Of Static Cross Sectional Models Of Employment By Ethnicity

ρ	Estimates for each ethnicity				
	Whites	Blacks	Hispanics	Other	Mixed
	Schmidt-Strauss	Schmidt-Strauss	Schmidt-Strauss	Schmidt-Strauss	Schmidt-Strauss
	0.814***	0.540***	0.356***	0.604***	0.506***
	(0.006)	(0.019)	(0.019)	(0.025)	(0.020)
*** p<0.01, ** p<0.05, * p<0.1					

The dependent variable is working and the parameters are estimated by maximum likelihood using the same specification as in Table 3. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021. Standard errors are clustered at the household level.

Figure 3: Evolution Of Cross Sectional ρ Over Time By Ethnicity



The dependent variable is working and the parameters are estimated by maximum likelihood using the same specification as in Table 3. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021 and the estimation is done over five year centered rolling windows.

and husbands for Hispanic households and for households composed of “other ethnicities”. To investigate whether this holds after controlling for observable covariates, we estimate the model in Table 3 for each ethnicity and for rolling 5-year time-spans. The estimated coefficients are presented in Figure 3. Qualitatively, the pattern in Figure 3 is similar to that in Figure 2: The association between the employment of wives and husbands has been falling for Hispanics and for Others, while it has been relatively stable for White, Black and Mixed couples.

4.3 Simultaneous Logit Models With Lagged Dependent Variables

In the Schmidt-Strauss model estimated in Table 3, Figure 2 and Figure 3, the only avenue for interdependence between the employment of wives and husbands (conditional on the observed characteristics) is through the parameter, ρ . If the employment of a partner depends on the lagged employment of both partners, then this will be captured by ρ .

In order to investigate the role of dynamics, we first estimate the Schmidt-Strauss model in Table 3 after including an individual's own lagged employment as well as the partner's as explanatory variables. Specifically, we estimate the model

$$P(y_{1,it} = c_1, y_{2,it} = c_2 | \{y_{1,is}, y_{2,is}\}_{s < t}, \{x_{1,is}\}_{s=1}^t, \{x_{2,is}\}_{s=1}^t) \\ = \frac{\exp(c_1(z_{1,it}) + c_2(z_{2,it}) + c_1 c_2 \rho)}{1 + \exp(z_{1,it}) + \exp(z_{2,it}) + \exp(z_{1,it} + z_{2,it} + \rho)}$$

for $c_1, c_2 \in \{0, 1\}$ where

$$z_{1,it} = x'_{1,it}\beta_1 + y_{1,it-1}\gamma_{11} + y_{2,it-1}\gamma_{12} \\ z_{2,it} = x'_{2,it}\beta_2 + y_{1,it-1}\gamma_{21} + y_{2,it-1}\gamma_{22}$$

and $x_{1,it}$ and $x_{2,it}$ are the explanatory variables used above. The results are presented in Table 5. The results in Table 5 suggest that each partner's employment depends strongly and positively on her or his own lagged employment, and that it depends negatively on the partner's lagged employment (after controlling for the observed covariates). In combination, these will introduce a negative correlation in the contemporaneous employment status, which - in turn - would lead to a downward bias in the estimate of ρ when these dynamic interactions are not controlled for in the model. This is reflected in the higher estimate of ρ in the model that allows for lagged employment of both partners as explanatory variables.

Controlling for the lagged employment status of both partners dramatically changed the estimate of ρ . We also estimate the Schmidt-Strauss model in Table 5 separately for each ethnicity group. Table 6 reports the estimated coefficients on the lagged employment variables as well as the estimated ρ . In this specification, Hispanics and Blacks are quite similar to each other in terms of the contemporaneous interdependence between the employment status of the two partners (measured by ρ) as well as in terms of the dynamic interdependence (measured by the γ 's).

The evolution of parameters that govern the dynamics and the interdependence are shown in

Table 5: Estimation Of Dynamic Models Of Employment

	Schmidt-Strauss	
	Women	Men
Lagged Employment (Woman)	4.684*** (0.005)	-1.668*** (0.008)
Lagged Employment (Man)	-1.668*** (0.008)	4.343*** (0.006)
Kids < 5	-0.425*** (0.006)	0.067*** (0.007)
Kids	-0.110*** (0.004)	0.162*** (0.005)
Black (Woman)	-0.049 (0.047)	-0.028 (0.052)
Hispanic (Woman)	-0.097*** (0.035)	0.037 (0.040)
Other (Woman)	-0.115*** (0.034)	-0.004 (0.038)
Some College (Woman)	0.213*** (0.005)	0.077*** (0.006)
College+ (Woman)	0.382*** (0.006)	0.077*** (0.006)
Black (Man)	0.055 (0.035)	-0.223*** (0.039)
Hispanic (Man)	-0.041 (0.035)	0.011 (0.040)
Other (Man)	-0.054 (0.036)	-0.111*** (0.041)
Some College (Man)	0.036*** (0.005)	0.151*** (0.006)
College+ (Man)	-0.159*** (0.005)	0.393*** (0.006)
Black-Black Couple	0.076 (0.069)	-0.077 (0.077)
Hispanic-Hispanic Couple	-0.160** (0.067)	-0.068 (0.076)
Other-Other Couple	0.079 (0.066)	-0.066 (0.075)
Mixed Couple	0.059* (0.034)	-0.102*** (0.039)
ρ		2.040*** (0.008)

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is working and the parameters are estimated by maximum likelihood. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021. Coefficients on year dummies, husband's and wife's age, their interaction and their squares are not reported. Standard errors are clustered at the household level.

Table 6: Estimation Of Dynamic Models Of Employment By Ethnicity

	All	Whites	Blacks	Hispanics	Other	Mixed
γ_{11}	4.684*** (0.005)	4.678*** (0.006)	4.481*** (0.023)	4.716*** (0.021)	4.976*** (0.029)	4.678*** (0.022)
γ_{12}	-1.668*** (0.008)	-1.759*** (0.009)	-1.041*** (0.037)	-1.096*** (0.037)	-1.475*** (0.050)	-1.629*** (0.034)
γ_{21}	-1.668*** (0.008)	-1.759*** (0.009)	-1.061*** (0.037)	-1.082*** (0.036)	-1.460*** (0.050)	-1.638*** (0.034)
γ_{22}	4.343*** (0.006)	4.363*** (0.007)	4.344*** (0.024)	4.019*** (0.023)	4.470*** (0.032)	4.359*** (0.025)
ρ	2.040*** (0.008)	2.170*** (0.009)	1.357*** (0.037)	1.262*** (0.037)	1.764*** (0.050)	1.868*** (0.033)

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is working and the parameters are estimated by maximum likelihood using the same specification as in Table 5. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021. Standard errors are clustered at the household level.

Figures 4 and 5. Specifically, we estimated the Schmidt-Strauss model in Table 5 for each ethnicity over rolling 5-year time-spans and plotted the estimated of the γ 's and of ρ against time.

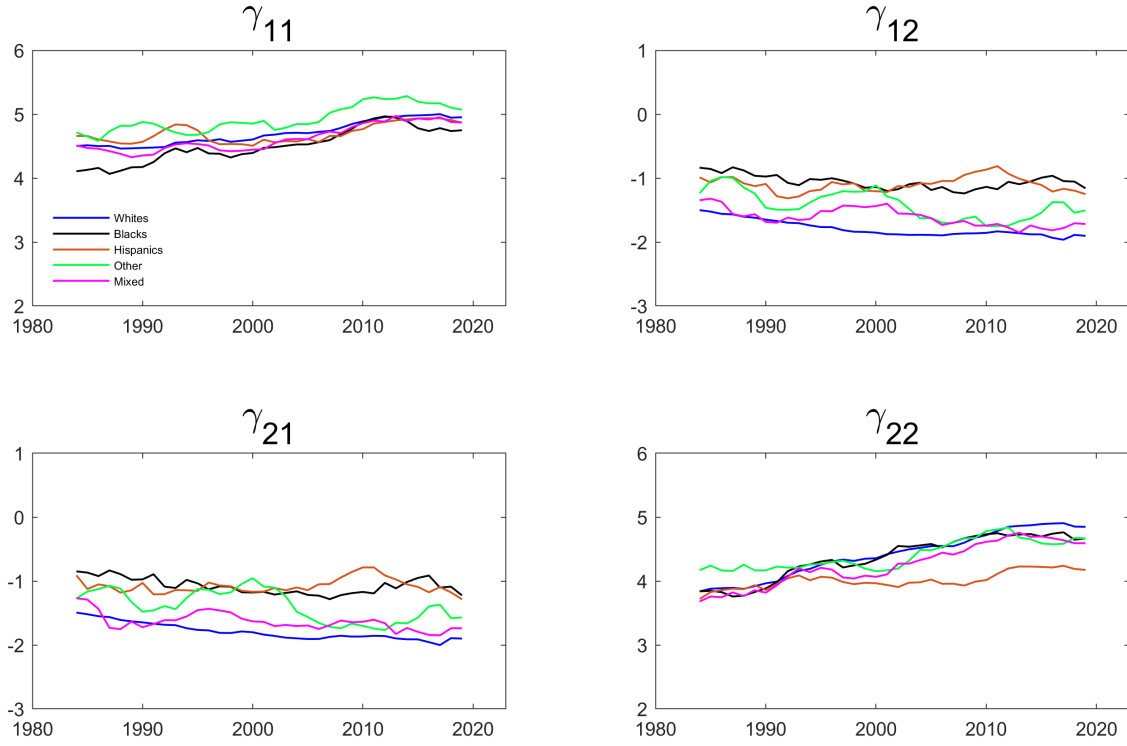
Comparing the patterns in Figure 5 to the patterns in Figure 3, we see that Black and Hispanic couples are more similar. This is consistent with the finding in Table 6. Interestingly, the estimated ρ 's for Hispanics and for Others are now much more stable over time, while the ρ for Whites is now trending up.

It is well-understood that it can be difficult to disentangle state dependence (the causal dependence of a variable at one point in time from its value in the previous period) from unobserved heterogeneity. In the next section, we therefore investigate whether it is possible to allow for fixed effects in the dynamic Schmidt-Strauss framework.

5 Simultaneous Logit Models With Lagged Dependent Variables And Fixed Effects

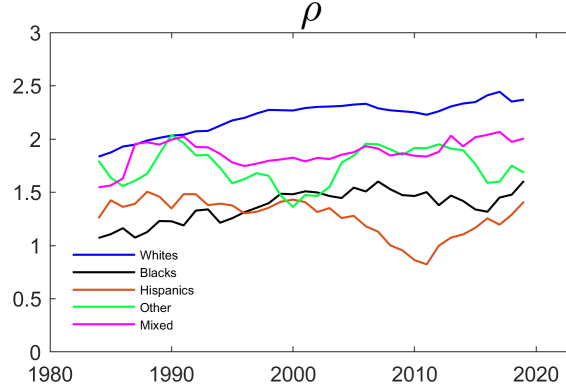
Honoré and Kyriazidou (2019) adapts the Schmidt-Strauss model discussed in Section 2 to a static panel data setting where each outcome can also depend on an individual specific fixed effect.

Figure 4: Evolution Of γ 's Over Time By Ethnicity



The dependent variable is working and the parameters are estimated by maximum likelihood using the same specification as in Table 5. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021 and the estimation is done over five year centered rolling windows.

Figure 5: Evolution Of ρ Over Time By Ethnicity



The dependent variable is working and the parameters are estimated by maximum likelihood using the same specification as in Table 5. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021 and the estimation is done over five year centered rolling windows.

Specifically, assume that

$$\begin{aligned} P\left(y_{1,it} = 1 | y_{2,it}, \{y_{1,is}, y_{2,is}\}_{s < t}, \{x_{1,is}\}_{s=1}^T, \{x_{2,is}\}_{s=1}^T, \alpha_{1,i}, \alpha_{2,i}\right) \\ = \Lambda\left(\alpha_{1,i} + x'_{1,it}\beta_1 + \rho y_{2,it}\right) \end{aligned} \quad (4)$$

and

$$\begin{aligned} P\left(y_{2,it} = 1 | y_{1,it}, \{y_{1,is}, y_{2,is}\}_{s < t}, \{x_{1,is}\}_{s=1}^T, \{x_{2,is}\}_{s=1}^T, \alpha_{1,i}, \alpha_{2,i}\right) \\ = \Lambda\left(\alpha_{2,i} + x'_{2,it}\beta_2 + \rho y_{1,it}\right) \end{aligned} \quad (5)$$

In this model, $\alpha_{1,i}$ and $\alpha_{2,i}$ are the fixed effects, $x_{1,it}$ and $x_{2,it}$ are strictly exogenous explanatory variables, and ρ is the cross-equation dependence parameter, which, as [Schmidt and Strauss \(1975\)](#) show, needs to be the same in the two equations given the structure in (4) and (5).

Following [Schmidt and Strauss \(1975\)](#) it can be shown that

$$\begin{aligned} P\left(y_{1,it} = c_1, y_{2,it} = c_2 | \{y_{1,is}, y_{2,is}\}_{s < t}, \{x_{1,is}\}_{s=1}^T, \{x_{2,is}\}_{s=1}^T, \alpha_{1,i}, \alpha_{2,i}\right) \\ = \frac{\exp\left(c_1\left(\alpha_{1,i} + x'_{1,it}\beta_1\right) + c_2\left(\alpha_{2,i} + x'_{2,it}\beta_2\right) + c_1c_2\rho\right)}{1 + \exp\left(\alpha_{1,i} + x'_{1,it}\beta_1\right) + \exp\left(\alpha_{2,i} + x'_{2,it}\beta_2\right) + \exp\left(\alpha_{1,i} + x'_{1,it}\beta_1 + \alpha_{2,i} + x'_{2,it}\beta_2 + \rho\right)} \end{aligned}$$

for $c_1, c_2 \in \{0, 1\}$. [Honoré and Kyriazidou \(2019\)](#) show that a conditional likelihood argument can be used to identify and estimate β_1 , β_2 , and ρ with as few as $T = 2$ time periods. Indeed, ρ can be allowed to be time dependent in (4) and (5).

[Honoré and Kyriazidou \(2019\)](#) also consider a vector autoregressive simultaneous logit model:

$$\begin{aligned} P(y_{1,it} = 1 | y_{2,it}, y_{1,i}^{t-1}, y_{2,i}^{t-1}, \alpha_{1i}, \alpha_{2i}) &= \Lambda(\alpha_{1i} + y_{1,it-1}\gamma_{11} + y_{2,it-1}\gamma_{12} + \rho y_{2,it}), \\ P(y_{2,it} = 1 | y_{1,it}, y_{1,i}^{t-1}, y_{2,i}^{t-1}, \alpha_{1i}, \alpha_{2i}) &= \Lambda(\alpha_{2i} + y_{1,it-1}\gamma_{21} + y_{2,it-1}\gamma_{22} + \rho y_{1,it}). \end{aligned} \quad (6)$$

This model is arguably the most relevant fixed effects model for the application in this paper. For each individual, we only use data from four months, so with the exception of time-dummies, there is essentially no exogenous variability in the explanatory variables over time. Moreover, we use one time period to provide the initial conditions, and the effect of time variables is probably not important over a three month period.³

[Honoré and Kyriazidou \(2019\)](#) show that $(\gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22})$ is identified in the model given in equation (6) with a total of four time periods (including the one that delivers the initial condition). However, the conditioning argument that leads to the identification eliminates the parameter ρ along with the fixed effects, α_{1i} and α_{2i} . On the positive side, this implies that one can allow the parameter ρ in equation (6) to be individual-specific. On the other hand, ρ may be the parameter of interest in many applications. This makes it problematic that the conditioning argument eliminates it along with α_{1i} and α_{2i} . In the next subsection, we first generalize the results in [Honoré and Kyriazidou \(2019\)](#) to show that using a conditional likelihood approach to eliminate α_{1i} and α_{2i} in equation (6) will also eliminate ρ for all values of T . The conditional likelihood approach is then illustrated empirically by obtaining estimates of the γ 's in equation 6 in the context of husbands' and wives' employment. Since the simultaneity parameter, ρ , is not generally identified from a conditional likelihood approach, we next consider a restricted version of the model, in which the two individual fixed effects are the same, except for an additive constant. In our application, we interpret this as a model with household specific fixed effects. This model is also illustrated empirically.

³The 2008 financial crisis and the onset of the pandemic in 2020 are possible exceptions to this.

5.1 Conditional Likelihood For The AR(1) Schmidt-Strauss Model With Fixed Effects

The traditional approach to estimating nonlinear fixed effects models is to find a sufficient statistic for the fixed effects, and then to construct a conditional likelihood function conditioning on the sufficient statistic. By construction, this conditional likelihood function will not depend on the fixed effects and it may or may not depend on some or all of the parameters of interest. In this subsection, we consider the conditional likelihood approach for the model in equation (6). This extends the analysis in [Honoré and Kyriazidou \(2019\)](#).

We consider a situation in which a pair of outcomes⁴ $(y_{1,t}, y_{2,t})$ from equation (6) are observed for T periods. We also assume that the initial condition, $(y_{1,0}, y_{2,0})$, is observed. We denote the probability distribution of $(y_{1,0}, y_{2,0})$ by $p(y_{1,0}, y_{2,0}, \alpha_1, \alpha_2)$, and we do not assume that it is necessarily generated by the same model. For notational simplicity, we let $z_{1,t} = \gamma_{11}y_{1,t} + \gamma_{12}y_{2,t}$ and $z_{2,t} = \gamma_{21}y_{1,t} + \gamma_{22}y_{2,t}$.

With this, the probability of a particular sequence is

$$\begin{aligned} & \frac{p(y_{1,0}, y_{2,0}, \alpha_1, \alpha_2) \prod_{t=1}^T \exp(y_{1,t}(z_{1,t-1} + \alpha_1)) \exp(y_{2,t}(z_{2,t} + \alpha_2)) \exp(y_{1,t}y_{2,t}\rho)}{\prod_{t=1}^T \{1 + \exp(z_{1,t-1} + \alpha_1) + \exp(z_{2,t-1} + \alpha_2) + \exp(z_{1,t-1} + z_{2,t-1} + \alpha_1 + \alpha_2 + \rho)\}} \\ &= \frac{p(y_{1,0}, y_{2,0}, \alpha_1, \alpha_2)}{1 + \exp(z_{1,0} + \alpha_1) + \exp(z_{2,0} + \alpha_2) + \exp(z_{1,0} + z_{2,0} + \alpha_1 + \alpha_2 + \rho)} \\ & \quad \frac{\prod_{t=1}^T \exp(y_{1,t}(z_{1,t-1} + \alpha_1)) \exp(y_{2,t}(z_{2,t} + \alpha_2)) \exp(y_{1,t}y_{2,t}\rho)}{\prod_{t=1}^{T-1} \{1 + \exp(z_{1,t} + \alpha_1) + \exp(z_{2,t} + \alpha_2) + \exp(z_{1,t} + z_{2,t} + \alpha_1 + \alpha_2 + \rho)\}}. \end{aligned}$$

Now consider two different sequences of $\{(y_{1,t}, y_{2,t})\}_{t=1}^T$ with the same $(y_{1,0}, y_{2,0})$. The probability of one of the sequences conditional on observing one of the two depends on the ratio of the probabilities for the two sequences. The key question is whether the individual-specific effects cancel in that ratio.

In the numerator, the α 's cancel if two sequences have the same $\sum_{t=1}^T y_{1,t}$ and the same $\sum_{t=1}^T y_{2,t}$. In the denominator, each combination of $(y_{1,t}, y_{2,t})$ must appear equally often. The latter is the same

⁴Here we drop the subscript i for simplicity.

as saying that $\sum_{t=1}^{T-1} y_{1,t}$, $\sum_{t=1}^{T-1} y_{2,t}$, $\sum_{t=1}^{T-1} y_{1,t}y_{2,t}$ must be the same⁵. This suggests the sufficient statistic

$$\left(y_{1,0}, y_{2,0}, \sum_{t=1}^{T-1} y_{1,t}, \sum_{t=1}^{T-1} y_{2,t}, \sum_{t=1}^{T-1} y_{1,t}y_{2,t}, y_{1,T}, y_{2,T} \right)$$

and the conditional likelihood function (for a given observation with fixed effects α_1 and α_2) is therefore

$$\mathcal{L} = \frac{\prod_{t=1}^T \exp(y_{1,t}(\gamma_{11}y_{1,t-1} + \gamma_{12}y_{2,t-1})) \exp(y_{2,t}(\gamma_{21}y_{1,t-1} + \gamma_{22}y_{2,t-1}))}{\sum_{\mathcal{B}} \prod_{t=1}^T \exp(c_t(\gamma_{11}c_{t-1} + \gamma_{12}d_{t-1})) \exp(d_t(\gamma_{21}c_{t-1} + \gamma_{22}d_{t-1}))} \quad (7)$$

where \mathcal{B} is the set of all sequences such that

$$c_0 = y_{1,0}, d_0 = y_{2,0}, \sum_{t=1}^{T-1} c_t = \sum_{t=1}^{T-1} y_{1,t}, \sum_{t=1}^{T-1} d_t = \sum_{t=1}^{T-1} y_{2,t},$$

$$\sum_{t=1}^{T-1} c_t d_t = \sum_{t=1}^{T-1} y_{1,t} y_{2,t}, c_T = y_{1,T}, d_T = y_{2,T}.$$

Note that not only does α drop out of the conditional likelihood, but so does ρ . In other words, a conditional likelihood approach does not identify ρ for any T . Also note that the conditional likelihood is constant if $T < 3$, so at least three period are needed in addition to the one providing the initial conditions.

We finally note that the argument above is unchanged if one replaces γ_{11} , γ_{12} , γ_{21} , γ_{22} , and ρ with functions of exogenous covariates as long as the functions do not change over time. For example, in the application some of these parameters could be functions of the level of education or of the presence of children.

5.2 Empirical Illustration

In Table 7, we present the results from estimating γ_{11} , γ_{12} , γ_{21} , and γ_{22} using the conditional likelihood approach discussed above. As expected, the fixed effects estimates are much lower than those reported in Table 6, which did not allow for unobserved heterogeneity. Figure 6 shows the

⁵On the other hand, it seems that the only way to generalize the conditioning argument to a model that also allows for time varying explanatory variables is to condition on equality of the explanatory variables across different time periods. Without such a restriction, the fixed effects in the denominators cannot cancel each other. Chountas and Kyriazidou (2021) pursue such a strategy for the conditional likelihood in a multinomial multivariate model with discrete explanatory variables. In the case of continuous explanatory variables, one may use the kernel weight approach introduced in Honoré and Kyriazidou (2000), although this would lead to an estimator that converges slower than the usual \sqrt{n} .

Table 7: Estimation Of Dynamic Model With Individual Fixed Effects By Ethnicity

	All	Whites	Blacks	Hispanics	Other	Mixed
γ_{11}	1.620*** (0.014)	1.611*** (0.016)	1.640*** (0.061)	1.601*** (0.056)	1.684*** (0.080)	1.761*** (0.062)
γ_{12}	-0.296*** (0.022)	-0.338*** (0.025)	-0.193** (0.085)	-0.078 (0.085)	-0.030 (0.113)	-0.268*** (0.088)
γ_{21}	-0.280*** (0.021)	-0.311*** (0.024)	-0.246*** (0.086)	-0.039 (0.080)	-0.079 (0.112)	-0.302*** (0.085)
γ_{22}	1.357*** (0.017)	1.350*** (0.019)	1.415*** (0.065)	1.324*** (0.058)	1.381*** (0.086)	1.420*** (0.067)

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is working and the parameters are estimated maximizing the conditional likelihood in (7). The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021.

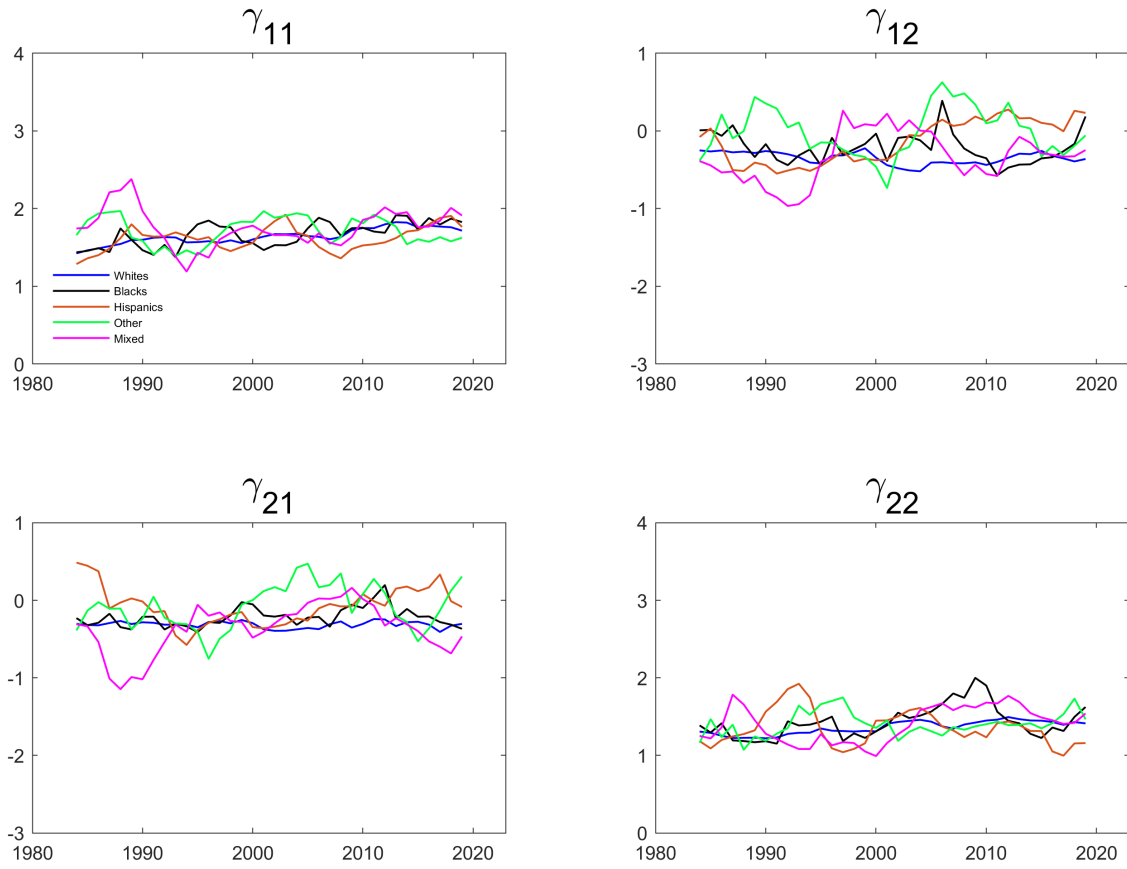
results of estimating the model on rolling 5-year sub-samples for each ethnicity. The estimates are fairly stable over time, and not very different across ethnicities. Overall, there is strong evidence that, after controlling for fixed effects, an individual's own lagged employment has a positive effect. The effect of the spouse's lagged employment tends to be negative and smaller in magnitude. As a comparison, [Chountas and Kyriazidou \(2021\)](#) estimate multinomial fixed effects model of husbands and wives employment. They use quarterly data from the German Socio-Economic panel for the years 2013-15 and four different labor states (full time employment, part time employment, unemployment and out of labor force), and find strong negative effects of the husband's lagged employment on the wife, but mostly positive although statistically insignificant effects of the wife's lagged employment on the husband.

5.3 Conditional Likelihood With Restricted Fixed Effects

In this subsection, we investigate whether additional identification can be obtained by assuming that $\alpha_1 = \alpha$ and $\alpha_2 = \alpha_1 + \kappa$ for some constant κ . Our motivation is to see whether this will allow for identification of ρ . In our application, we interpret this as a model with a family specific fixed effect and a spouse specific level (κ).

As before, we consider a situation in which a pair of outcomes from equation (6) are observed for T periods (in addition to period 0, which delivers the initial condition). Again, we use the notation $z_{1,t} = \gamma_{11}y_{1,t} + \gamma_{12}y_{2,t}$ and $z_{2,t} = \gamma_{21}y_{1,t} + \gamma_{22}y_{2,t}$. With $\alpha_2 = \alpha_1 + \kappa$, the probability of a

Figure 6: Evolution Of γ 's Over Time By Ethnicity Allowing For Individual Fixed Effects



The dependent variable is working and the parameters are estimated maximizing the conditional likelihood in (7). The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021 and the estimation is done over five year centered rolling windows.

particular sequence becomes

$$\begin{aligned}
& \frac{p(y_{1,0}, y_{2,0}, \alpha) \prod_{t=1}^T \exp(y_{1,t}(z_{1,t-1} + \alpha)) \exp(y_{2,t}(z_{2,t} + \alpha + \kappa)) \exp(y_{1,t}y_{2,t}\rho)}{\prod_{t=1}^T \{1 + \exp(z_{1,t-1} + \alpha) + \exp(z_{2,t-1} + \alpha + \kappa) + \exp(z_{1,t-1} + z_{2,t-1} + 2\alpha + \kappa + \rho)\}} \\
&= \frac{p(y_{1,0}, y_{2,0}, \alpha)}{1 + \exp(z_{1,0} + \alpha) + \exp(z_{2,0} + \alpha + \kappa) + \exp(z_{1,0} + z_{2,0} + 2\alpha + \kappa + \rho)} \\
& \quad \frac{\prod_{t=1}^T \exp(y_{1,t}(z_{1,t-1} + \alpha)) \exp(y_{2,t}(z_{2,t} + \alpha + \kappa)) \exp(y_{1,t}y_{2,t}\rho)}{\prod_{t=1}^{T-1} \{1 + \exp(z_{1,t} + \alpha) + \exp(z_{2,t} + \alpha + \kappa) + \exp(z_{1,t} + z_{2,t} + 2\alpha + \kappa + \rho)\}}.
\end{aligned}$$

As above, the key question is whether the individual-specific α 's cancel in the ratio of the probabilities of two different sequences with the same initial conditions. In the numerator, the α 's cancel if the two sequences have the same $\sum_{t=1}^T y_{1,t} + \sum_{t=1}^T y_{2,t}$. In the denominator, each combination of $(y_{1,t}, y_{2,t})$ must appear equally often⁶. The latter is the same as saying that $\sum_{t=1}^{T-1} y_{1,t}$, $\sum_{t=1}^{T-1} y_{2,t}$, $\sum_{t=1}^{T-1} y_{1,t}y_{2,t}$ must be the same. This suggests the sufficient statistic

$$\left(y_{1,0}, y_{2,0}, \sum_{t=1}^{T-1} y_{1,t}, \sum_{t=1}^{T-1} y_{2,t}, \sum_{t=1}^{T-1} y_{1,t}y_{2,t}, y_{1,T} + y_{2,T} \right)$$

The difference from the case where the α 's are unrestricted is that we do not need to condition on $y_{1,T}$ and $y_{2,T}$, but only on the sum. The implication is that a conditional likelihood approach will lead to more sequences being compared to each other.

The conditional likelihood function (for a given individual) is

$$\mathcal{L} = \frac{\prod_{t=1}^T \exp(y_{1,t}(\gamma_{11}y_{1,t-1} + \gamma_{12}y_{2,t-1})) \exp(y_{2,t}(\gamma_{21}y_{1,t-1} + \gamma_{22}y_{2,t-1} + \kappa))}{\sum_{\mathcal{B}} \prod_{t=1}^T \exp(c_t(\gamma_{11}c_{t-1} + \gamma_{12}d_{t-1})) \exp(d_t(\gamma_{21}c_{t-1} + \gamma_{22}d_{t-1} + \kappa))} \quad (8)$$

where \mathcal{B} is the set of all sequences such that

$$c_0 = y_0, d_0 = z_0, \sum_{t=1}^{T-1} c_t = \sum_{t=1}^{T-1} y_{1,t}, \sum_{t=1}^{T-1} d_t = \sum_{t=1}^{T-1} y_{2,t}, \sum_{t=1}^{T-1} c_t d_t = \sum_{t=1}^{T-1} y_{1,t}y_{2,t}, c_T + d_T = y_{1,T} + y_{2,T}$$

⁶As was the case in Section 5.1, it seems that the only way to generalize the conditioning argument to a model that also allows for time varying variables is to condition on equality of the explanatory variables across different time periods.

Table 8: Estimation Of Dynamic Model With Household Fixed Effects By Ethnicity

	All	Whites	Blacks	Hispanics	Other	Mixed
γ_{11}	2.385*** (0.014)	2.374*** (0.016)	2.364*** (0.058)	2.403*** (0.059)	2.436*** (0.078)	2.485*** (0.060)
γ_{12}	-1.511*** (0.015)	-1.542*** (0.018)	-1.409*** (0.063)	-1.318*** (0.060)	-1.298*** (0.081)	-1.505*** (0.065)
γ_{21}	-1.538*** (0.015)	-1.576*** (0.016)	-1.392*** (0.060)	-1.403*** (0.060)	-1.310*** (0.078)	-1.485*** (0.061)
γ_{22}	2.263*** (0.016)	2.285*** (0.018)	2.231*** (0.064)	2.097*** (0.059)	2.206*** (0.083)	2.315*** (0.065)

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is working and the parameters are estimated maximizing the conditional likelihood in (8). The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021.

Note that while α and ρ drop out of this expressions, κ does not. Also note that this argument is unchanged if one replaces κ with some function of predetermined covariates as long as the function does not change over time. The same is true for the parameters γ_{11} , γ_{12} , γ_{21} , and γ_{22} .

5.4 Empirical Illustration

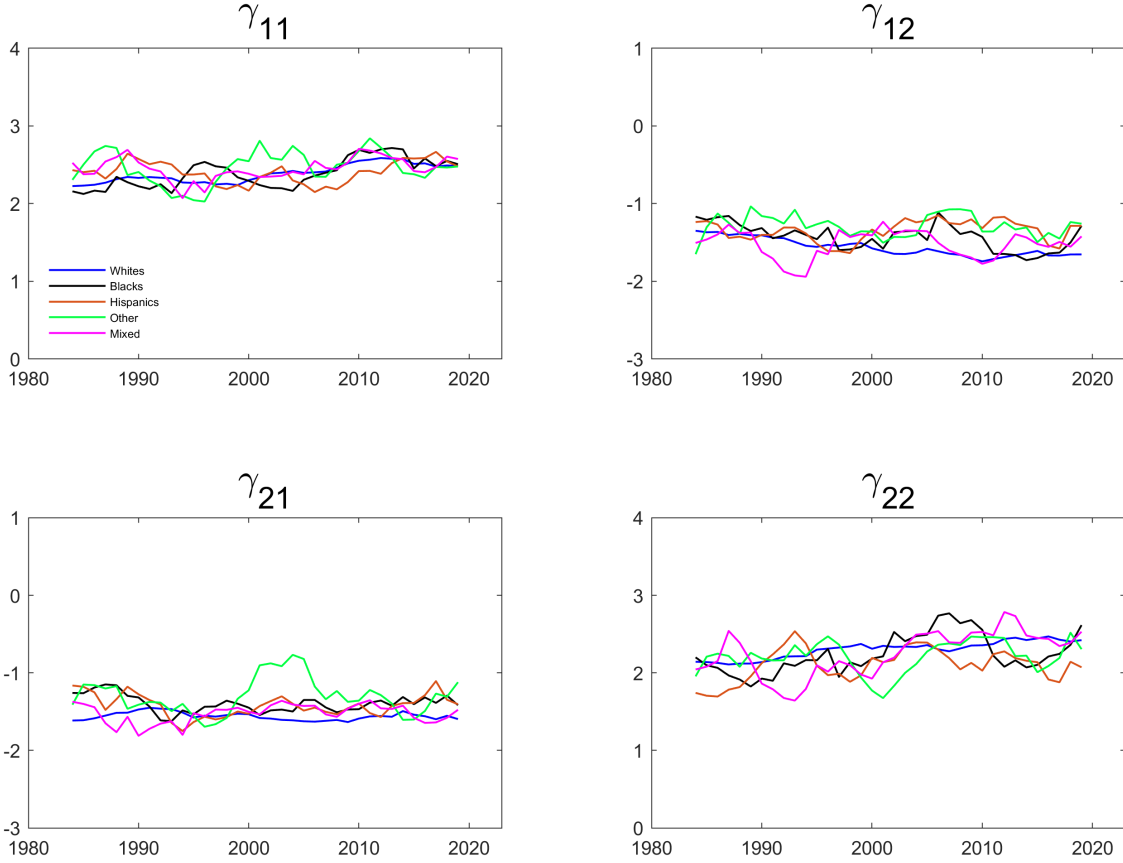
In Table 8, we present the results from estimating γ_{11} , γ_{12} , γ_{21} , and γ_{22} using the conditional likelihood approach discussed above. The fixed effects estimates are again lower than those reported in Table 6, which did not allow for unobserved heterogeneity, but they are larger than the ones that were obtained when we did not restrict the fixed effects for the husbands and the wives. Since the conditional likelihood in equation (8) uses more observations than the one in equation (7), we would expect the estimated standard error to be smaller in Table 8 than in Table 7.

Figure 7 shows the results of estimating the model on rolling 5-year sub-samples for each ethnicity. The estimates are fairly stable over time, and not very different across ethnicities.

6 Moment Conditions For The AR(1) Schmidt-Strauss Model With Fixed Effects

In panel data models with fixed effects, it is sometimes possible to construct moment conditions that do not depend on the fixed effects. When that is the case, one can consider estimating the common parameters of the model by generalized methods of moments. The dynamic linear panel

Figure 7: Evolution Of γ 's Over Time By Ethnicity Allowing For Household Fixed Effects



The dependent variable is working and the parameters are estimated maximizing the conditional likelihood in (8). The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021 and the estimation is done over five year centered rolling windows.

data model is a simple example of this; see, for example [Anderson and Hsiao \(1981\)](#) or [Holtz Eakin, Newey, and Rosen \(1988\)](#). Applications of this idea to nonlinear models include [Honoré \(1992\)](#), [Kyriazidou \(2001\)](#), [Hu \(2002\)](#) and [Kitazawa \(2013\)](#).⁷ [Bonhomme \(2012\)](#) propose a general approach for constructing such moment conditions and [Honoré and Weidner \(2020\)](#) develop a specific numeric strategy for determining whether such moment conditions can be constructed in particular models with discrete outcomes. In this section, we report the results from applying the approach in [Honoré and Weidner \(2020\)](#) to determine whether there are moments that can be used to estimate ρ in a Schmidt-Strauss model with lagged dependent variables and fixed effects.

⁷The maximum score estimator in [Manski \(1987\)](#) can be motivated in terms of moment inequalities.

We consider two versions of the model

$$P \left(y_{1,it} = c_1, y_{2,it} = c_2 \mid \{y_{1,is}, y_{2,is}\}_{s < t}, \{x_{1,is}\}_{s=1}^T, \{x_{2,is}\}_{s=1}^T, \alpha_{1,i}, \alpha_{2,i} \right) \\ = \frac{\exp(c_1(z_{1,it} + \alpha_{1,i}) + c_2(z_{2,it} + \alpha_{2,i}) + c_1 c_2 \rho)}{1 + \exp(z_{1,it} + \alpha_{1,i}) + \exp(z_{2,it} + \alpha_{2,i}) + \exp(z_{1,it} + \alpha_{1,i} + z_{2,it} + \alpha_{2,i} + \rho)}$$

for $t = 1, 2, 3$ and $c_1, c_2 \in \{0, 1\}$ where

$$z_{1,it} = x'_{1,it} \beta_1 + y_{1,it-1} \gamma_{11} + y_{2,it-1} \gamma_{12} \\ z_{2,it} = x'_{2,it} \beta_2 + y_{1,it-1} \gamma_{21} + y_{2,it-1} \gamma_{22}.$$

In one version, $\alpha_{1,i}$ and $\alpha_{2,i}$ are unrestricted, while the other version restricts them to be identical except for an additive constant. Table 9 reports the number of moment conditions for each of the two versions of the dynamic fixed effects Schmidt-Strauss model when one has 3, 4 or 5 time periods of observations in addition to the one that provides the initial conditions.

The data used in this paper has a total of four consecutive time periods, and the results for $T = 3$ are therefore the relevant ones here. In the illustration in Sections 5.2 and 5.4, we have no strictly exogenous time-varying explanatory variables, so according to the calculation reported in Table 9, there will be no moment conditions that depend on ρ when the fixed effects are left unrestricted. On the other hand, there will be six moment conditions for each initial condition when the fixed effects are restricted to be equal except for an additive constant. With more than three time periods (in addition to the one providing the initial conditions), the results suggest that there are moment conditions that depend on ρ even when the fixed effects are unrestricted. While introducing explanatory variables changes the number of moment conditions, it does not change the answer to the questions of whether there exist moment conditions that depend on ρ for a given value of T .

6.1 Moment Conditions For ρ

It is not always easy to derive analytical expressions for the moment conditions. For the empirical application in Sections 5.2 and 5.4 of this paper, T is three and there are no strictly exogenous time-varying explanatory variables. In order to make statements about ρ , we therefore have to limit attention to the model in which the fixed effect is household specific in the sense that $\alpha_{i2} = \alpha_{i1} + \kappa$.

As mentioned above, there will be a total of 45 moment conditions in this case. One can write

Table 9: The Number of Moment Conditions in the Schmidt-Strauss Model

	$T = 3$	$T = 4$	$T = 5$
$x_{k,it} = 0$, unrestricted $(\alpha_{i,1}, \alpha_{i,2})$	24 / 21 / 0	180 / 136 / 4	900 / 534 / 16
$x_{k,it} = 0$, restricted $\alpha_{i,2} = \alpha_{i,1} + \kappa$	45 / 42 / 6	229 / 185 / 18	989 / 623 / 36
$x_{k,it} \neq 0$, unrestricted $(\alpha_{i,1}, \alpha_{i,2})$	4 / 4 / 0	120 / 120 / 64	780 / 780 / 256
$x_{k,it} \neq 0$, restricted $\alpha_{i,2} = \alpha_{i,1} + \kappa$	45 / 45 / 16	229 / 229 / 48	989 / 989 / 96

Results from the numerical counting of moment conditions for the dynamic simultaneous logit are reported. Four different model specifications are considered: additional exogenous regressors are present ($x_{k,it} \neq 0$) or not ($x_{k,it} = 0$), and the fixed effects $(\alpha_{i,1}, \alpha_{i,2})$ are unrestricted or restricted ($\alpha_{i,2} = \alpha_{i,1} + \kappa$). For each of those four specifications and each value of T we report $n_{\text{tot}} / n_{\text{para}} / n_{\rho}$, where n_{tot} is the total number of moment conditions available, n_{para} is the number of moment conditions available that depend on any of the common parameters $(\gamma, \beta, \rho, \kappa)$, and n_{ρ} is the number of moment conditions available that depend on the parameter ρ . All results are for one fixed value of the initial condition $(y_{1,i0}, y_{2,i0})$, but the number of moment conditions is independent from the initial condition. Notice that for $T = 3$ and unrestricted $(\alpha_{i,1}, \alpha_{i,2})$ we have $n_{\rho} = 0$, and in general we believe that the parameter is not identified in that case. However, for either $T > 3$ or restricted $\alpha_{i,2} = \alpha_{i,1} + \kappa$ we find that $n_{\rho} > 0$ and the parameter ρ can be identified and estimated from those moment conditions.

these as six that depend on ρ , 36 that depend on some of the common parameters in the model, but not on ρ , and three that do not depend on any of the parameters in the model. In principle, one may need to use all of these moments to construct an efficient GMM estimator. On the other hand, we can already identify the γ 's and κ from the conditional likelihood approach in Section 5.3, so we only need to use one moment⁸ that depends on ρ in order to (inefficiently) estimate ρ . We therefore focus on finding the six moment linearly independent moment conditions that depend on ρ . Unfortunately, these will not be unique. For example, adding a linear combination of moment conditions that do not depend on ρ to one of the six that do, will leave us with six linearly independent moment conditions that depend on ρ . This also means that some of the moment conditions can be extremely complicated.

Fortunately, it turns out that for the model considered here, one can find six linearly independent moment conditions (for each initial condition) which all depend on ρ , and where each only depends on five of the 64 possible sequences. They are given in the Appendix, and we use those to estimate ρ in the next subsection. These moment conditions are linear in $\exp(\rho)$.

⁸Subject to an identification condition that guarantees that the moment condition has a unique solution for ρ .

Table 10: GMM Estimates Of ρ By Ethnicity Allowing For Household Fixed Effects

	All	Whites	Blacks	Hispanics	Other	Mixed
ρ	1.260*** (0.041)	1.420*** (0.052)	0.360* (0.211)	0.550*** (0.156)	0.730*** (0.207)	0.960*** (0.163)
*** p<0.01, ** p<0.05, * p<0.1						

The dependent variable is working and the parameters are estimated by generalized method of moments using the moment conditions in the Appendix. The data is from IPUMS CPS and covers a balanced panel of couples where each individual’s age is between 25 and 65. The data covers the period between 1982 and 2021. Standard errors are calculated via the bootstrap. Bootstrap estimates of the vector of γ ’s are obtained by bootstrapping their influence function. Bootstrap estimates of ρ are then calculated using GMM after recalculating the weighting matrix.

6.2 Empirical Illustration

In this subsection, we illustrate how the method of moments approach discussed above can be used to estimate ρ . We proceed in two steps. We first estimate the γ ’s and κ using the conditional likelihood approach. We then fix the γ ’s and κ at those estimates and estimate ρ by generalized method of moments using the moment conditions in the appendix. As weighting matrix, we use the inverse of a diagonal matrix that has the variance of the moments evaluated at $\rho = 0$ in the diagonal. This choice is arbitrary and may lead to statistical inefficiency, but $\rho = 0$ is a natural benchmark, and the hope is that using a diagonal matrix will alleviate small sample issues resulting from estimation of an efficient weighting matrix.⁹ Since the moment conditions are linear in $\exp(\rho)$, the GMM objective function will be quadratic in $\exp(\rho)$. This implies that it is numerically well behaved and that ρ is actually identified from it. On the other hand, the solution for $\exp(\rho)$, can sometimes be negative in finite samples. For the estimation below, we search over values of ρ between -2 and 4 .

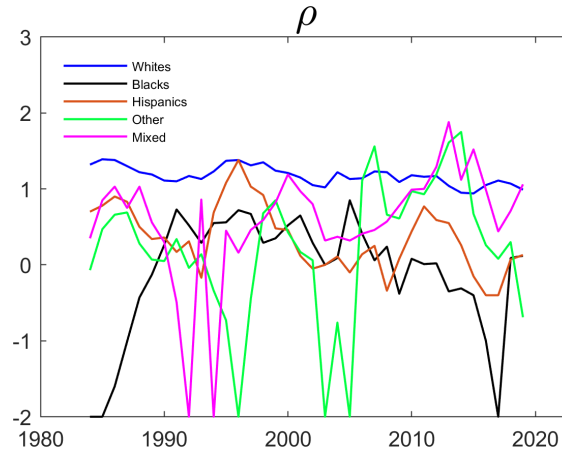
The results of the estimation of ρ are presented in Table 10. Compared to the estimates on ρ presented in Table 6, the fixed effects estimates are much smaller. This suggests that the household specific fixed effect captures much more of the intra-household correlation than the observed characteristics.

Figure 8 presents the results of estimating ρ separately for each ethnicity over rolling 5-year periods. The estimates for Whites seem fairly stable over time and are statistically significantly different from 0 in all time periods.¹⁰ When testing at a 5% level of significance, the estimates for

⁹While the overall sample is large, each of the moment only depends on specific sequences that comprise very small fraction of the observations. In our application, these fractions ranged from less than 0.1% to 3%.

¹⁰The p-value for the test is less than 1% in all cases. All test referred to in this paragraph are based on estimating

Figure 8: Evolution Of ρ By Ethnicity Allowing For Household Fixed Effects



The dependent variable is working and the parameters are estimated by generalized method of moments using the moment conditions in the appendix and the γ 's from Figure 7. The data is from IPUMS CPS and covers a balanced panel of couples where each individual's age is between 25 and 65. The data covers the period between 1982 and 2021 and the estimation is done over five year centered rolling windows.

the other ethnicities are statistically significantly different from 0 in only six of 144 cases (four for Blacks and two for Others).

7 Conclusion

Two of Peter Schmidt's many contributions to econometrics have been to introduce an econometric model for bivariate binary outcomes and to study estimation of dynamic linear fixed effects panel data models using short panels. In this paper, we have combined aspects of this research by studying a version of the model introduced in [Schmidt and Strauss \(1975\)](#) that allows for lagged dependent variables and fixed effects.

We first use the conditional likelihood approach of [Honoré and Kyriazidou \(2019\)](#) to construct a likelihood function that does not depend on the fixed effects of the model. While this conditional likelihood can be used to estimate the other parameters of the model when the total number of time periods is at least four, it turns out that it does depend on the parameter ρ , which in the Schmidt-Strauss model captures the intra-household dependence. Our conditional likelihood approach can

$\exp(\rho)$ without imposing that it is positive, and then testing whether it differs from $\exp(0)$. The reason is that when we estimate ρ , we sometimes obtain a point estimate at the lower bound of the parameter space.

therefore not be used to estimate the simultaneity parameter, ρ .

We next use the approach in [Honoré and Weidner \(2020\)](#) to study whether one can construct moment conditions that can be used to estimate ρ . We find that it is in principle possible to estimate the common parameters of such models when the total number of time periods for each individual is at least five. To construct moment conditions for four time periods, it is necessary to restrict the model. We do this by restricting the fixed effects for the two outcomes to be equal, except for an additive constant.

We apply the estimation strategy developed in this paper to estimate a simple model for the relationship of employment of husbands and wives. Our main conclusion is that the parameter that captures the intra-household “correlation” in employment differs by the ethnicity composition of the couple even after one allows for unobserved household specific heterogeneity.

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Appendix: Moment Conditions

In this Appendix, we explicitly present the six moment conditions discussed in Section 6.1. To simplify the notation, we write $\Gamma_{ij} = \exp(\gamma_{ij})$, $B = \exp(\beta)$, and $P = \exp(\rho)$.

Moment Condition 1

$$E \left[\sum_{k=1}^5 m_k 1 \left\{ \left(\{y_{1,t}\}_{t=0}^3, \{y_{2,t}\}_{t=0}^3 \right) = s_k \right\} \right] = 0$$

where

$$\begin{aligned} s_1 &= (a, 0, 0, 1, b, 0, 1, 0) \\ s_2 &= (a, 0, 0, 1, b, 0, 1, 1) \\ s_3 &= (a, 0, 1, 0, b, 0, 1, 0) \\ s_4 &= (a, 0, 1, 0, b, 1, 1, 0) \\ s_5 &= (a, 0, 1, 1, b, 0, 1, 0) \end{aligned}$$

and

$$\begin{aligned} m_1 = B\Gamma_{11}\Gamma_{22}P & \left[\Gamma_{12} \left(-B\Gamma_{21}\Gamma_{22}^2 + (B+1)\Gamma_{22} + \Gamma_{11}(\Gamma_{21}\Gamma_{22}(B\Gamma_{22} - B - 1) + 1) - 1 \right) \right. \\ & \left. + B(\Gamma_{21} - 1)\Gamma_{22} + \Gamma_{11}(\Gamma_{21} - 1)\Gamma_{22}\Gamma_{12}^2 \right] \end{aligned}$$

$$\begin{aligned} m_2 = \Gamma_{11} & \left[B^2(\Gamma_{21} - 1)\Gamma_{22}^2 + \right. \\ & \Gamma_{12}^2 \left(-B\Gamma_{22}^2P + \Gamma_{11}(B\Gamma_{21}\Gamma_{22}^2P - (B+1)\Gamma_{22} + 1) + (B+1)\Gamma_{22} - 1 \right) \\ & \left. + B\Gamma_{22}\Gamma_{12}(B\Gamma_{22} - \Gamma_{21}((B+1)\Gamma_{22} - 1) + \Gamma_{11}(1 - \Gamma_{21}P) + \Gamma_{22} + P - 2) \right] \end{aligned}$$

$$\begin{aligned} m_3 = -B\Gamma_{11}\Gamma_{12}\Gamma_{22} & \left[\Gamma_{12} \left(-B\Gamma_{21}\Gamma_{22}^2 + (B+1)\Gamma_{22} + \Gamma_{11}(\Gamma_{21}\Gamma_{22}(B\Gamma_{22} - B - 1) + 1) - 1 \right) \right. \\ & \left. + B(\Gamma_{21} - 1)\Gamma_{22} + \Gamma_{11}(\Gamma_{21} - 1)\Gamma_{22}\Gamma_{12}^2 \right] \end{aligned}$$

$$\begin{aligned}
m_4 = & -\Gamma_{11}\Gamma_{12}\Gamma_{21}^{-a}\Gamma_{22}^{1-b}\left[\Gamma_{11}\right. \\
& \left.(B^2(\Gamma_{21}-1)\Gamma_{21}\Gamma_{22}^2 + B\Gamma_{22}\Gamma_{12}(2\Gamma_{21}(P-2) + \Gamma_{21}^2 + 1) - ((\Gamma_{21}-1)\Gamma_{12}^2))\right. \\
& \left. + \Gamma_{12}\Gamma_{11}^2(B\Gamma_{21}\Gamma_{22}(1-\Gamma_{21}P) + \Gamma_{12}(\Gamma_{21}-1)) + B\Gamma_{22}(\Gamma_{12}(\Gamma_{21}-P) - B(\Gamma_{21}-1)\Gamma_{21}\Gamma_{22})\right] \\
m_5 = & B\Gamma_{22}\left[\Gamma_{11}^2\Gamma_{12}^2(-B\Gamma_{21}^2\Gamma_{22}^2P + (B+1)\Gamma_{21}\Gamma_{22}-1)\right. \\
& + \Gamma_{11}\Gamma_{12}(B\Gamma_{22}(\Gamma_{21}(-(B+1)\Gamma_{22}+P-2) + (B+1)\Gamma_{22}\Gamma_{21}^2+1) \\
& + \Gamma_{12}(\Gamma_{21}\Gamma_{22}(B\Gamma_{22}P-B-1)+1)) \\
& \left. + B\Gamma_{22}(\Gamma_{12}(\Gamma_{21}-P) - B(\Gamma_{21}-1)\Gamma_{21}\Gamma_{22})\right]
\end{aligned}$$

Moment Condition 2

$$E\left[\sum_{k=1}^5 m_k 1\left\{\left(\{y_{1,t}\}_{t=0}^3, \{y_{2,t}\}_{t=0}^3\right) = s_k\right\}\right] = 0$$

where

$$\begin{aligned}
s_1 &= (a, 0, 0, 1, b, 1, 0, 0) \\
s_2 &= (a, 0, 0, 1, b, 1, 0, 1) \\
s_3 &= (a, 0, 1, 0, b, 0, 1, 1) \\
s_4 &= (a, 1, 0, 0, b, 1, 0, 0) \\
s_5 &= (a, 1, 0, 0, b, 1, 1, 0)
\end{aligned}$$

and

$$\begin{aligned}
m_1 = & -B\Gamma_{21}P\Gamma_{11}^a\Gamma_{12}^b\left[\Gamma_{12}(-B\Gamma_{21}\Gamma_{22}^2 + (B+1)\Gamma_{22} + \Gamma_{11}(\Gamma_{21}\Gamma_{22}(B\Gamma_{22}-B-1)+1)-1)\right. \\
& \left.+ B(\Gamma_{21}-1)\Gamma_{22} + \Gamma_{11}(\Gamma_{21}-1)\Gamma_{22}\Gamma_{12}^2\right]
\end{aligned}$$

$$\begin{aligned}
m_2 = & \Gamma_{21}(-\Gamma_{11}^a)\Gamma_{12}^b\left[B^2(\Gamma_{21}-1)\Gamma_{22}^2\right. \\
& + \Gamma_{12}^2(-B\Gamma_{22}^2P + \Gamma_{11}(B\Gamma_{21}\Gamma_{22}^2P - (B+1)\Gamma_{22}+1) + (B+1)\Gamma_{22}-1) \\
& \left.+ B\Gamma_{22}\Gamma_{12}(B\Gamma_{22}-\Gamma_{21}((B+1)\Gamma_{22}-1) + \Gamma_{11}(1-\Gamma_{21}P) + \Gamma_{22}+P-2)\right]
\end{aligned}$$

$$\begin{aligned}
m_3 = & \Gamma_{11}^a \Gamma_{21}^a \Gamma_{12}^b \Gamma_{22}^{b-1} [\Gamma_{11}^2 \Gamma_{12}^2 (B \Gamma_{21}^2 \Gamma_{22}^2 P - (B+1) \Gamma_{21} \Gamma_{22} + 1) \\
& - \Gamma_{11} \Gamma_{12} (B \Gamma_{22} (\Gamma_{21} (-(B+1) \Gamma_{22} + P - 2) + (B+1) \Gamma_{22} \Gamma_{21}^2 + 1) \\
& + \Gamma_{12} (\Gamma_{21} \Gamma_{22} (B \Gamma_{22} P - B - 1) + 1)) \\
& + B \Gamma_{22} (B (\Gamma_{21} - 1) \Gamma_{21} \Gamma_{22} + \Gamma_{12} (P - \Gamma_{21}))]
\end{aligned}$$

$$\begin{aligned}
m_4 = & B \Gamma_{21} [\Gamma_{12} (-B \Gamma_{21} \Gamma_{22}^2 + (B+1) \Gamma_{22} + \Gamma_{11} (\Gamma_{21} \Gamma_{22} (B \Gamma_{22} - B - 1) + 1) - 1) \\
& + B (\Gamma_{21} - 1) \Gamma_{22} + \Gamma_{11} (\Gamma_{21} - 1) \Gamma_{22} \Gamma_{12}^2]
\end{aligned}$$

$$\begin{aligned}
m_5 = & \Gamma_{12} [\Gamma_{11} (B^2 (\Gamma_{21} - 1) \Gamma_{21} \Gamma_{22}^2 + B \Gamma_{22} \Gamma_{12} (2 \Gamma_{21} (P - 2) + \Gamma_{21}^2 + 1) - ((\Gamma_{21} - 1) \Gamma_{12}^2)) + \\
& \Gamma_{12} \Gamma_{11}^2 (B \Gamma_{21} \Gamma_{22} (1 - \Gamma_{21} P) + \Gamma_{12} (\Gamma_{21} - 1)) + B \Gamma_{22} (\Gamma_{12} (\Gamma_{21} - P) - B (\Gamma_{21} - 1) \Gamma_{21} \Gamma_{22})]
\end{aligned}$$

Moment Condition 3

$$E \left[\sum_{k=1}^5 m_k 1 \left\{ \left(\{y_{1,t}\}_{t=0}^3, \{y_{2,t}\}_{t=0}^3 \right) = s_k \right\} \right] = 0$$

where

$$\begin{aligned}
s_1 &= (a, 0, 1, 1, b, 1, 0, 1) \\
s_2 &= (a, 0, 1, 1, b, 1, 1, 1) \\
s_3 &= (a, 1, 0, 0, b, 1, 1, 1) \\
s_4 &= (a, 1, 1, 1, b, 0, 1, 0) \\
s_5 &= (a, 1, 1, 1, b, 0, 1, 1)
\end{aligned}$$

and

$$\begin{aligned}
m_1 = & -B \Gamma_{11}^{a+1} \Gamma_{21}^{-a} \Gamma_{12}^b \Gamma_{22}^{1-b} \\
& [\Gamma_{11} (B^2 \Gamma_{21} (\Gamma_{21} - \Gamma_{22}) \Gamma_{22} \\
& + B \Gamma_{12} (2 \Gamma_{22} \Gamma_{21} (P - 2) + \Gamma_{21}^2 + \Gamma_{22}^2) + \Gamma_{12}^2 (\Gamma_{22} - \Gamma_{21})) \\
& + \Gamma_{11}^2 (B \Gamma_{21} (\Gamma_{22} - \Gamma_{21} P) + \Gamma_{12} (\Gamma_{21} - \Gamma_{22})) + B \Gamma_{12} \Gamma_{22} (B \Gamma_{21} (\Gamma_{22} - \Gamma_{21}) + \Gamma_{12} (\Gamma_{21} - \Gamma_{22} P))]
\end{aligned}$$

$$\begin{aligned}
m_2 = & -B\Gamma_{11}^{a+1}\Gamma_{21}^{-a}\Gamma_{12}^b\Gamma_{22}^{-b} \\
& \left[\Gamma_{11} \left((\Gamma_{21} - \Gamma_{22}) \Gamma_{12} (B\Gamma_{21}\Gamma_{22} + 1) - B(\Gamma_{21} - 1) \Gamma_{21}\Gamma_{22} - ((\Gamma_{21} - 1) \Gamma_{22}\Gamma_{12}^2) \right) \right. \\
& \quad \left. + B\Gamma_{12}\Gamma_{21}(\Gamma_{22} - 1) \Gamma_{22} + \Gamma_{12}\Gamma_{21}(\Gamma_{22} - 1) \Gamma_{11}^2 \right]
\end{aligned}$$

$$\begin{aligned}
m_3 = & \Gamma_{11}^2 \Gamma_{12} \Gamma_{21}^{-a} \Gamma_{22}^{-b-1} \\
& \left[\Gamma_{11} (B^2 (\Gamma_{21} - 1) \Gamma_{21} \Gamma_{22}^2 + \Gamma_{12}^2 (\Gamma_{21} (B\Gamma_{22}^2 P - B\Gamma_{22} - 1) + \Gamma_{22})) \right. \\
& \quad + B\Gamma_{22}\Gamma_{12} (\Gamma_{21} (-\Gamma_{22} + P - 2) + \Gamma_{21}^2 + \Gamma_{22}) \\
& \quad + \Gamma_{12}\Gamma_{11}^2 (B\Gamma_{21}\Gamma_{22} (1 - \Gamma_{21}P) + \Gamma_{12} (\Gamma_{21} - \Gamma_{22})) \\
& \quad \left. + B\Gamma_{12}\Gamma_{22} (\Gamma_{12} (\Gamma_{21} - \Gamma_{22}P) - B(\Gamma_{21} - 1) \Gamma_{21}\Gamma_{22}) \right]
\end{aligned}$$

$$\begin{aligned}
m_4 = & B^2\Gamma_{22} [B^2\Gamma_{12}\Gamma_{21}^2 (\Gamma_{22} - 1) \Gamma_{22} + \\
& \Gamma_{11}^2 (\Gamma_{12} (B\Gamma_{22}\Gamma_{21}^2 P + \Gamma_{21} (1 - B\Gamma_{22}) - \Gamma_{22}) + B\Gamma_{21} (\Gamma_{22} - \Gamma_{21}P) + (\Gamma_{22} - \Gamma_{21}) \Gamma_{12}^2) \\
& + B\Gamma_{21}\Gamma_{11} (-B\Gamma_{21} (\Gamma_{22} - 1) \Gamma_{22} + \Gamma_{12}^2 (\Gamma_{22} - \Gamma_{22}^2 P) + \Gamma_{12} (\Gamma_{22} (\Gamma_{22} + P - 2) - \Gamma_{21} (\Gamma_{22} - 1)))]
\end{aligned}$$

$$\begin{aligned}
m_5 = & B^2\Gamma_{11} \left[\Gamma_{11} \left((\Gamma_{21} - \Gamma_{22}) \Gamma_{12} (B\Gamma_{21}\Gamma_{22} + 1) - B(\Gamma_{21} - 1) \Gamma_{21}\Gamma_{22} - ((\Gamma_{21} - 1) \Gamma_{22}\Gamma_{12}^2) \right) \right. \\
& \quad \left. + B\Gamma_{12}\Gamma_{21}(\Gamma_{22} - 1) \Gamma_{22} + \Gamma_{12}\Gamma_{21}(\Gamma_{22} - 1) \Gamma_{11}^2 \right]
\end{aligned}$$

Moment Condition 4

$$E \left[\sum_{k=1}^5 m_k 1 \left\{ \left(\{y_{1,t}\}_{t=0}^3, \{y_{2,t}\}_{t=0}^3 \right) = s_k \right\} \right] = 0$$

where

$$s_1 = (a, 1, 0, 0, b, 1, 0, 1)$$

$$s_2 = (a, 1, 0, 1, b, 0, 0, 1)$$

$$s_3 = (a, 1, 0, 1, b, 1, 0, 1)$$

$$s_4 = (a, 1, 1, 0, b, 1, 0, 0)$$

$$s_5 = (a, 1, 1, 0, b, 1, 0, 1)$$

and

$$m_1 = \Gamma_{12}$$

$$\begin{aligned} & \left[\Gamma_{11} \left(-\Gamma_{21} \left(B^2 + \Gamma_{12} (B - B\Gamma_{22}P) + B\Gamma_{22} - BP + 2B + 1 \right) + B(B+1)\Gamma_{22}\Gamma_{21}^2 + B + 1 \right) \right. \\ & \quad \left. + \Gamma_{12}\Gamma_{11}^2 \left(-B\Gamma_{22}\Gamma_{21}^2P + (B+1)\Gamma_{21} - 1 \right) + B \left(-B\Gamma_{22}\Gamma_{21}^2 + (B+1)\Gamma_{21} - P \right) \right] \end{aligned}$$

$$\begin{aligned} m_2 = & -B\Gamma_{12}\Gamma_{21}^a\Gamma_{22}^b \left[\Gamma_{11} \left(-\Gamma_{21} \left(B^2 - 2BP + 4B + 1 \right) + B(B+1)\Gamma_{21}^2 + B + 1 \right) \right. \\ & \left. + \Gamma_{11}^2 \left(-B\Gamma_{21}^2P + (B+1)\Gamma_{21} - 1 \right) + B \left(-B\Gamma_{21}^2 + (B+1)\Gamma_{21} - P \right) \right] \end{aligned}$$

$$\begin{aligned} m_3 = & -B\Gamma_{12} \left[\Gamma_{11} \left(-B\Gamma_{22}\Gamma_{21}^2 + (B+1)\Gamma_{21} + \Gamma_{12} \left(B\Gamma_{22}\Gamma_{21}^2 - (B+1)\Gamma_{22}\Gamma_{21} + 1 \right) - 1 \right) \right. \\ & \left. + B\Gamma_{21} (\Gamma_{22} - 1) + \Gamma_{12}\Gamma_{21} (\Gamma_{22} - 1) \Gamma_{11}^2 \right] \end{aligned}$$

$$\begin{aligned} m_4 = & B \left[B^2 (\Gamma_{22} - 1) \Gamma_{21}^2 \Gamma_{11}^{-1} \right. \\ & + B\Gamma_{21} \left(-(B+1)\Gamma_{21} (\Gamma_{22} - 1) + \Gamma_{12} (1 - \Gamma_{22}P) + \Gamma_{22} + P - 2 \right) \\ & \left. + \Gamma_{11} \left(-B\Gamma_{21}^2P + \Gamma_{12} \left(B\Gamma_{22}\Gamma_{21}^2P - (B+1)\Gamma_{21} + 1 \right) + (B+1)\Gamma_{21} - 1 \right) \right] \end{aligned}$$

$$\begin{aligned} m_5 = & BP \left[\Gamma_{11} \left(-B\Gamma_{22}\Gamma_{21}^2 + (B+1)\Gamma_{21} + \Gamma_{12} \left(B\Gamma_{22}\Gamma_{21}^2 - (B+1)\Gamma_{22}\Gamma_{21} + 1 \right) - 1 \right) \right. \\ & \left. + B\Gamma_{21} (\Gamma_{22} - 1) + \Gamma_{12}\Gamma_{21} (\Gamma_{22} - 1) \Gamma_{11}^2 \right] \end{aligned}$$

Moment Condition 5

$$E \left[\sum_{k=1}^5 m_k 1 \left\{ \left(\{y_{1,t}\}_{t=0}^3, \{y_{2,t}\}_{t=0}^3 \right) = s_k \right\} \right] = 0$$

where

$$\begin{aligned}
s_1 &= (a, 0, 0, 0, b, 0, 1, 0) \\
s_2 &= (a, 0, 0, 0, b, 0, 1, 1) \\
s_3 &= (a, 0, 1, 0, b, 0, 0, 0) \\
s_4 &= (a, 0, 1, 0, b, 0, 0, 1) \\
s_5 &= (a, 0, 1, 0, b, 1, 0, 0)
\end{aligned}$$

and

$$\begin{aligned}
m_1 = B\Gamma_{12}\Gamma_{21}^a\Gamma_{22}^b [B(\Gamma_{22} - \Gamma_{21}) + \Gamma_{12}(\Gamma_{22}(B\Gamma_{21} - B - 1) + 1) \\
+ \Gamma_{11}(\Gamma_{21}(B(-\Gamma_{22}) + B - \Gamma_{12} + 1) + \Gamma_{12}\Gamma_{22} - 1)]
\end{aligned}$$

$$\begin{aligned}
m_2 = \Gamma_{12}\Gamma_{21}^a\Gamma_{22}^{b-1} \\
[B^2\Gamma_{22}(\Gamma_{22} - \Gamma_{21}) + B\Gamma_{12}(\Gamma_{21}((B+1)\Gamma_{22} - 1) - \Gamma_{22}((B+1)\Gamma_{22} + P - 2)) \\
+ \Gamma_{12}^2(B\Gamma_{22}^2P - (B+1)\Gamma_{22} + 1) \\
+ \Gamma_{11}(B(\Gamma_{21}P - \Gamma_{22}) + \Gamma_{12}(\Gamma_{22}(B\Gamma_{21}(-P) + B + 1) - 1))]
\end{aligned}$$

$$\begin{aligned}
m_3 = -B^2\Gamma_{12}\Gamma_{21}^a\Gamma_{22}^b [B(\Gamma_{22} - \Gamma_{21}) + \Gamma_{12}(\Gamma_{22}(B\Gamma_{21} - B - 1) + 1) \\
+ \Gamma_{11}(\Gamma_{21}(B(-\Gamma_{22}) + B - \Gamma_{12} + 1) + \Gamma_{12}\Gamma_{22} - 1)]
\end{aligned}$$

$$\begin{aligned}
m_4 = -B\Gamma_{12}\Gamma_{21}^{a-1}\Gamma_{22}^b [\Gamma_{11}^2(-B\Gamma_{21}^2P + (B+1)\Gamma_{21} - 1) \\
+ \Gamma_{11}[B(\Gamma_{21}(-(B+1)\Gamma_{22} + P - 2) + (B+1)\Gamma_{21}^2 + \Gamma_{22}) \\
+ \Gamma_{12}(\Gamma_{21}(B\Gamma_{22}P - B - 1) + 1)] \\
+ B(B\Gamma_{21}(\Gamma_{22} - \Gamma_{21}) + \Gamma_{12}(\Gamma_{21} - \Gamma_{22}P))]
\end{aligned}$$

$$m_5 = B [\Gamma_{11} (B^2 \Gamma_{21} (\Gamma_{21} - \Gamma_{22}) \Gamma_{22} + B \Gamma_{12} (2 \Gamma_{22} \Gamma_{21} (P - 2) + \Gamma_{21}^2 + \Gamma_{22}^2) + \Gamma_{12}^2 (\Gamma_{22} - \Gamma_{21})) \\ + \Gamma_{11}^2 (B \Gamma_{21} (\Gamma_{22} - \Gamma_{21} P) + \Gamma_{12} (\Gamma_{21} - \Gamma_{22})) + B \Gamma_{12} \Gamma_{22} (B \Gamma_{21} (\Gamma_{22} - \Gamma_{21}) + \Gamma_{12} (\Gamma_{21} - \Gamma_{22} P))]]$$

Moment Condition 6

$$E \left[\sum_{k=1}^5 m_k 1 \left\{ \left(\{y_{1,t}\}_{t=0}^3, \{y_{2,t}\}_{t=0}^3 \right) = s_k \right\} \right] = 0$$

where

$$\begin{aligned} s_1 &= (a, 0, 0, 0, b, 1, 0, 1) \\ s_2 &= (a, 0, 1, 0, b, 1, 0, 1) \\ s_3 &= (a, 0, 1, 1, b, 0, 0, 0) \\ s_4 &= (a, 0, 1, 1, b, 0, 0, 1) \\ s_5 &= (a, 1, 0, 0, b, 0, 1, 0) \end{aligned}$$

and

$$m_1 = \Gamma_{11}^a \Gamma_{21}^{1-a} \Gamma_{12}^b \Gamma_{22}^{-b} [-\Gamma_{12} (-\Gamma_{22} (B^2 - 2BP + 4B + 1) + B(B + 1)\Gamma_{22}^2 + B + 1) \\ + \Gamma_{12}^2 (B\Gamma_{22}^2 P - (B + 1)\Gamma_{22} + 1) + B (B\Gamma_{22}^2 - (B + 1)\Gamma_{22} + P)]$$

$$m_2 = BP \Gamma_{11}^a \Gamma_{21}^{-a} \Gamma_{12}^b \Gamma_{22}^{1-b} [B (\Gamma_{21} - \Gamma_{22}) + \Gamma_{12} (\Gamma_{22} (B (-\Gamma_{21}) + B + 1) - 1) \\ + \Gamma_{11} (\Gamma_{21} (B\Gamma_{22} - B + \Gamma_{12} - 1) - \Gamma_{12}\Gamma_{22} + 1)]$$

$$m_3 = B^2 \Gamma_{21} \Gamma_{11}^{a-1} \Gamma_{12}^b \\ [\Gamma_{12} (-B^2 \Gamma_{22} + B \Gamma_{22} P + \Gamma_{11} (\Gamma_{22} (B \Gamma_{21} (-P) + B + 1) - 1) \\ - 2B \Gamma_{22} + B \Gamma_{21} ((B + 1)\Gamma_{22} - 1) + B - \Gamma_{22} + 1) \\ + B (\Gamma_{22} (B (-\Gamma_{21}) + B + 1) + \Gamma_{11} (\Gamma_{21} P - \Gamma_{22}) - P)]$$

$$\begin{aligned}
m_4 = & B^2 \Gamma_{11}^{a-1} \Gamma_{12}^b [B (\Gamma_{22} - \Gamma_{21}) + \Gamma_{12} (\Gamma_{22} (B \Gamma_{21} - B - 1) + 1) \\
& + \Gamma_{11} (\Gamma_{21} (B (-\Gamma_{22}) + B - \Gamma_{12} + 1) + \Gamma_{12} \Gamma_{22} - 1)]
\end{aligned}$$

$$\begin{aligned}
m_5 = & B [B^2 (\Gamma_{21} - \Gamma_{22}) \Gamma_{22} + B \Gamma_{12} (\Gamma_{22} ((B + 1) \Gamma_{22} + P - 2) - \Gamma_{21} ((B + 1) \Gamma_{22} - 1)) \\
& + \Gamma_{12}^2 (-B \Gamma_{22}^2 P + (B + 1) \Gamma_{22} - 1) \\
& + \Gamma_{11} (B (\Gamma_{22} - \Gamma_{21} P) + \Gamma_{12} (\Gamma_{22} (B \Gamma_{21} P - B - 1) + 1))]
\end{aligned}$$