

## Online Appendix of “Measuring the Effects of Welfare Time Limits”

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### 1 Details on Robustness Analysis

Tables A5 and A6 provide additional evidence for the effects of the time limit and the non-time-limit component of FTP under a variety of model specifications. In Table A5, the main objective of the exercise is to control for work experience. As treatment group individuals may accumulate a higher level of work experience than control group individuals, this may potentially affect the model estimates in a complicated way. Since work-related variables are endogenous, additional instruments are constructed in a similar spirit to moments conditions in equation (12) (see main text) using individual-level employment data. The model and the corresponding instrument matrix are defined formally in the next section on GMM estimator. Columns 1 and 2 report the estimates for the baseline and disadvantaged samples, respectively. In both columns, the baseline model is expanded to include work experience ( $\omega_{it}$ ), as well as contemporaneous and three lagged indicators of employment status ( $x_{it}$ ,  $x_{i,t-1}$ ,  $x_{i,t-2}$ ,  $x_{i,t-3}$ ) as additional regressors.

After controlling for work-related variables, both the stock coefficient  $\beta_S$  and the time horizon coefficient  $\beta_A$  remain similar in size. The treatment group coefficient  $\beta_E$  also remains similar. The estimates reveal interesting relationships between welfare use and labor market outcomes, which are different between baseline and disadvantaged individuals. First, consider baseline individuals (Column 1). All else being equal, welfare use is lower by 0.6 percentage points when an individual accumulates an extra month of work experience. In addition, all else being equal, an individual is 9.9 percentage points less likely to participate in welfare if she works. Both results are consistent with the benefit structure of the welfare program, which provides partial or no payments to workers who have earnings beyond the level designated by the earnings disregard. Next, consider disadvantaged individuals (Column 2). Unlike baseline individuals, neither work experience nor employment status have a significant effect on welfare use. This suggests that the link between welfare use and labor

market outcomes is weak among disadvantaged individuals; attachment to the labor market does not induce them to leave welfare.

Table A6 presents model estimates for the baseline sample under several alternative specifications. The results for the disadvantaged sample are qualitatively similar and are therefore not reported. Column 1 extends the baseline model by allowing for the stock effect to be a piecewise linear function of the remaining stock  $S_{it}$  (e.g., Ribar, Edelhoch and Liu 2008). Under this specification, if the individual has more than six remaining months of welfare eligibility, the marginal effect of the stock on welfare participation is  $\beta_S$ . Otherwise, the marginal effect is  $\beta_S + \beta_{S1}$ , where  $\beta_{S1}$  captures the piecewise linear effect. An extra instrument is required to estimate  $\beta_{S1}$ ; the model and its corresponding instrument matrix are defined formally in the next section on GMM estimator. The results are qualitatively similar to the baseline model. The estimate for  $\beta_S$  is 0.003 with a standard error of 0.004, and the estimate for  $\beta_{S1}$  is 0.041 with a standard error of 0.024. The time horizon coefficient and treatment group coefficient are 0.002 and 0.018, respectively, which are similar to the estimates from the baseline model.

Columns 2 and 3 explore the sensitivity of the model estimates to lagged dependent variables. The specification of lagged dependent variables may affect the estimate for the stock effect in a complicated way. In Column 2, the model is assumed to exhibit first-order state dependence only, and higher-order lags of the dependent variable are excluded from the set of regressors. The stock coefficient  $\beta_S$  becomes slightly larger at 0.008. The coefficient for the first-order autoregressive lag ( $\alpha_1$ ) also becomes larger at 0.728, as it picks up the effects from the omitted second-order lag, which was statistically significant in the baseline model. Both the Sargan-Hansen test and the Arellano-Bond test reject the null hypothesis at the 1 percent level, implying that the model is misspecified. Column 3 considers another end of the spectrum by including six autoregressive lags in the model. Only the first- and second-order autoregressive lags are statistically significant, and the coefficients on the higher-order lags are close to zero. The stock coefficient  $\beta_S$  becomes slightly larger at 0.007, and is statistically significant at the 10 percent level.

The last two columns of the table examine whether the estimation results are sensitive

to the instruments used. In the baseline model, there are 12 lagged dependent variables involved in instrument construction (i.e.,  $y_{i,t-2}, \dots, y_{i,t-1-\bar{m}}$  where  $\bar{m} = 12$ ). Column 4 uses six lagged dependent variables for instrument construction (i.e.,  $\bar{m} = 6$ ), and Column 5 uses 18 lagged dependent variables for instrument construction (i.e.,  $\bar{m} = 18$ ). In both cases, the estimation results are very similar to the baseline model.

Table A7 provides further evidence for state dependence in welfare use. In this exercise, only the control group is used for the estimation of the model in equation (10) (see main text), and the FTP-related parameters ( $\beta_0, \beta_S, \beta_A$ , and  $\beta_E$ ) are set to zero. The analysis then becomes analogous to the existing literature on dynamic panel data models, which focuses on disentangling state dependence from unobserved heterogeneity using existing patterns of behavior in panel data. Columns 1 and 2 report the key estimates for the baseline and disadvantaged control group samples, respectively. The state dependence coefficients are very similar in magnitude to the corresponding estimates in the baseline model. Therefore, the results suggest that individuals exhibit similar state dependence in welfare use even in the absence of time limits.

This issue is further investigated by formally allowing state dependence to differ between control and treatment groups. Three terms are added to equation (10) (see main text):  $\gamma_k E_i y_{i,t-k}$  where  $k = 1, 2, 3$ . If the treatment changes dynamics beyond the stock effect  $\beta_S$ , the coefficients on  $\gamma_k$  should be significantly different from zero.<sup>1 2</sup> The empirical results indicate that the coefficients on  $\gamma_k$  are negative but not statistically significant (see Table A8). Given how the moment conditions are constructed, interactive state dependence considerably reduces the amount of exogenous variations that can be used to identify  $\beta_S$ . However, when more instruments are used, the stock effect is statistically significant at the 10 percent level, while the interactive state dependence coefficients remain not significantly

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<sup>1</sup>One possible explanation for why  $\gamma_k$  can be nonzero is that the non-time limit component may directly affect state dependence in the treatment group, not just the coefficient  $\beta_E$ . The model assumes that the error process is identical between control and treatment group individuals. Therefore,  $\gamma_k$  has no direct behavioral interpretation beyond reflecting potential complicated time-limit dynamics that are not picked up by  $\beta_S$  (or some other effects not picked up by  $\beta_E$ ).

<sup>2</sup>For example, consider substituting out  $S_{it}$  in equation (10) (see main text) using its definition  $\bar{S}_i - \sum_{r=0}^{t-1} y_{ir}$ . Then, the kth-order state dependence in the control group is  $\alpha_k$ . After substituting out  $S_{it}$ , the k-th order state dependence in the treatment group will be smaller at  $\alpha_k - \beta_S$ . However, because we explicitly control for  $S_{it}$  and estimate  $\beta_S$ , the “net” state dependence in the treatment group remains to be  $\alpha_k$  (implying that  $\gamma_k$  should not be significantly different from zero).

different from zero.

## 2 Further Details of the GMM Estimator

**Controlling for Work Experience.** We discuss an extension of the baseline model that controls for work experience and other work-related variables. The model is:

$$y_{it} = \lambda_0 + \sum_{k=1}^{K_1} \alpha_k y_{i,t-k} + \sum_{k=0}^{K_2} \gamma_k x_{i,t-k} + \gamma_w \omega_{it} + \beta_0 E_i \mathbf{1}\{S_{it} < H_{it}\} + \beta_S E_i \mathbf{1}\{S_{it} < H_{it}\} (S_{it} - \bar{S}_i) + \beta_A E_i \mathbf{1}\{S_{it} < H_{it}\} (A_{it} - \bar{A}_i) + \beta_E E_i + \lambda_A A_{it} + \mathbf{X}_{it} \boldsymbol{\lambda} + \mu_i + \epsilon_{it}, \quad (1)$$

where  $x_{it}$  is a employment status indicator for individual  $i$  at month  $t$  ( $=1$  if she works,  $=0$  otherwise), and  $\omega_{it} = \sum_{k=0}^{t-1} x_{ik}$  is her cumulative months of work since random assignment.<sup>3</sup> In general, we should expect that there is a negative relationship between welfare participation and work-related variables, that is, the expected signs of  $\gamma_k$  and  $\gamma_w$  are negative. Similar to equation (11) (see main text), assuming  $S_{it} \neq H_{it} - 1$  and taking first-order difference the above model becomes

$$\begin{aligned} \Delta y_{it} = & \sum_{k=1}^{K_1} \alpha_k \Delta y_{i,t-k} + \sum_{k=0}^{K_2} \gamma_k \Delta x_{i,t-k} + \gamma_w x_{i,t-1} - \beta_S E_i \mathbf{1}\{S_{i,t-1} < H_{i,t-1}\} y_{i,t-1} \\ & + \beta_A E_i \mathbf{1}\{S_{i,t-1} < H_{i,t-1}\} \Delta A_{it} + \lambda_A \Delta A_{it} + \Delta \mathbf{X}_{it} \boldsymbol{\lambda} + \Delta \epsilon_{it}, \end{aligned} \quad (2)$$

where  $\Delta x_{it} = x_{it} - x_{i,t-1}$ . To address the endogeneity of work-related variables  $x_{i,t-k}$  and  $\omega_{it}$ , the following population moments are used:

$$E(x_{i,t-2-m} \Delta \epsilon_{it}) = 0 \quad m = 0, \dots, t-2. \quad (3)$$

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<sup>3</sup>The data on work-related variables comes from (calendar) quarterly administrative records on employment in the FTP public use file. The data is converted to a monthly level for analysis.

Then, similar to equation (21) (see main text), the corresponding instrument submatrix is defined as

$$Z_{iw} = \begin{bmatrix} x_{i2} & x_{i1} & x_{i0} & 0 & \dots & 0 \\ x_{i3} & x_{i2} & x_{i1} & x_{i0} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ x_{i,T-2} & x_{i,T-3} & x_{i,T-4} & x_{i,T-5} & \dots & x_{i,T-1-\bar{m}} \end{bmatrix}_{(T-3) \times \bar{m}}. \quad (4)$$

The full instrument matrix for individual  $i$  is

$$Z_i = \left[ \begin{array}{ccc|c} Z_{iy} & E_i \mathbf{1}\{\bar{S}_i < H_{i0}\} Z_{iy} & Z_{iw} & 0 \\ \hline 0 & 0 & 0 & Z_{ix} \end{array} \right], \quad (5)$$

where the number of columns in  $Z_i$  is  $3\bar{m} + K_x + 3$ , and the number of overidentifying restrictions is  $3\bar{m} + K_x + 3 - [(K_1 + 1) + (K_2 + 2) + (K_x + 3)] = 3\bar{m} - K_1 - K_2 - 3$ .

**Piecewise Linear Effects.** We discuss an extension of the baseline model that allows for piecewise linear stock effects. The model is:

$$y_{it} = \lambda_0 + \sum_{k=1}^K \alpha_k y_{i,t-k} + \beta_0 E_i \mathbf{1}\{S_{it} < H_{it}\} + \beta_S E_i \mathbf{1}\{S_{it} < H_{it}\} (S_{it} - \bar{S}_i) + \beta_{S1} E_i \mathbf{1}\{S_{it} < H_{it}\} \min\{S_{it} - \bar{s}, 0\} + \beta_A E_i \mathbf{1}\{S_{it} < H_{it}\} (A_{it} - \bar{A}_i) + \beta_E E_i + \lambda_A A_{it} + \mathbf{X}_{it} \boldsymbol{\lambda} + \mu_i + \epsilon_{it}. \quad (6)$$

If  $S_{it}$  is larger than  $\bar{s}$ , the marginal effect of  $S_{it}$  will be  $\beta_S$ , otherwise the marginal effect will be  $\beta_S + \beta_{S1}$ . The model is estimated using an expanded instrument matrix:

$$Z_i = \left[ \begin{array}{ccc|c} Z_{iy} & E_i \mathbf{1}\{\bar{S}_i < H_{i0}\} Z_{iy} & E_i \mathbf{1}\{\bar{S}_i < H_{i0}\} \sum_{j=1}^{\bar{m}} Z_{iys}[*j] & 0 \\ \hline 0 & 0 & 0 & Z_{ix} \end{array} \right]. \quad (7)$$

The extra elements are described as follows. Let matrix  $Z_{iys}$  be the entrywise product of  $Z_{iy}$  and  $Z_{is}$  (i.e.,  $Z_{iys} \equiv Z_{iy} \circ Z_{is}$ ), where  $Z_{is}$  is a matrix with the following indicator functions

as entries:

$$Z_{is} = \begin{bmatrix} \mathbf{1}(S_{i2} < \bar{s}) & \mathbf{1}(S_{i1} < \bar{s}) & \mathbf{1}(S_{i0} < \bar{s}) & 0 & \dots & 0 \\ \mathbf{1}(S_{i3} < \bar{s}) & \mathbf{1}(S_{i2} < \bar{s}) & \mathbf{1}(S_{i1} < \bar{s}) & \mathbf{1}(S_{i0} < \bar{s}) & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ \mathbf{1}(S_{i,T-2} < \bar{s}) & \mathbf{1}(S_{i,T-3} < \bar{s}) & \mathbf{1}(S_{i,T-4} < \bar{s}) & \mathbf{1}(S_{i,T-5} < \bar{s}) & \dots & \mathbf{1}(S_{i,T-1-\bar{m}} < \bar{s}) \end{bmatrix}_{(T-3) \times \bar{m}}. \quad (8)$$

The term  $\sum_{j=1}^{\bar{m}} Z_{iys}[*j]$  is a *vector* that is constructed by summing up all columns in  $Z_{iys}$ . In particular, for individual  $i$ , the vector will be nonzero if her stock  $S_{it}$  is smaller than  $\bar{s}$  in at least one time period in the sample. Since the vector represents the extra instrument that is needed for estimating  $\beta_{S1}$ , the number of overidentifying restrictions remains unchanged.

**APPENDIX TABLE A5**  
**CONTROLLING FOR WORK-RELATED VARIABLES USING GMM, KEY ESTIMATES<sup>a</sup>**

Variable (parameter in parentheses)	Baseline Sample (1)	Disadvantaged Sample (2)
$y_{t-1} (\alpha_1)$	0.635 *** (0.020)	0.574 *** (0.026)
$y_{t-2} (\alpha_2)$	0.106 *** (0.012)	0.164 *** (0.017)
$y_{t-3} (\alpha_3)$	-0.002 (0.009)	-0.023 * (0.012)
FTP dummy $\times I\{S<H\}$ ( $\beta_0$ )	0.015 (0.026)	-0.026 (0.032)
FTP dummy $\times I\{S<H\} \times (A-\bar{A})$ ( $\beta_A$ )	0.001 (0.002)	0.004 (0.003)
FTP dummy $\times I\{S<H\} \times (S-\bar{S})$ ( $\beta_S$ )	0.006 ** (0.003)	0.003 * (0.002)
FTP dummy ( $\beta_E$ )	0.023 (0.022)	0.102 *** (0.038)
Work experience ( $\gamma_w$ )	-0.006 ** (0.003)	0.001 (0.005)
Work <sub>t</sub> ( $\gamma_0$ )	-0.099 ** (0.040)	-0.047 (0.041)
Work <sub>t-1</sub> ( $\gamma_1$ )	-0.056 ** (0.028)	0.026 (0.026)
Work <sub>t-2</sub> ( $\gamma_2$ )	0.030 *** (0.011)	0.007 (0.013)
Work <sub>t-3</sub> ( $\gamma_3$ )	-0.013 (0.012)	-0.001 (0.014)
R-squared	0.75	0.73
Sargan-Hansen test for over-identifying restrictions <sup>b</sup>	28.67 (df=27)	30.02 (df=27)
Arellano-Bond test for serial correlation <sup>c</sup>	-0.23	-0.13

a The baseline sample consists of 1445 individuals, and the disadvantaged sample consists of 1130 individuals. Both samples contain 20 months of data (up to month 23 following random assignment). Details of model specification and estimation are given in the Appendix. Other regressors include age, race, years of schooling, number of children, age of the youngest child, a dummy variable that equals one if the youngest child is under age 3, the interaction between the dummy variable above with the FTP dummy, a dummy variable that equals one if the youngest child is over age 18, calendar year indicators, and calendar month indicators. Standard errors are given in parentheses. \*, Significant at the 10 percent level; \*\*, significant at the 5 percent level; \*\*\*, significant at the 1 percent level.

d The reported statistic follows a chi-square distribution with degree of freedom (df) given in parentheses.

e The reported statistic (Arellano and Bond (1991)) follows an asymptotic standard normal distribution.

APPENDIX TABLE A6

ALTERNATIVE SPECIFICATIONS OF THE THEORY-BASED MODEL (BASELINE SAMPLE)<sup>a</sup>

Variable (parameter in parentheses)	Piecewise	Fewer Lags	More Lags	Fewer	More	Keane-
	Linear Stock Effect <sup>b</sup>	of Y	of Y <sup>c</sup>	Instruments <sup>c</sup>	Instruments <sup>c</sup>	Runkle Estimator
	(1)	(2)	(3)	(4)	(5)	(6)
$y_{t-1}$ ( $\alpha_1$ )	0.658 *** (0.018)	0.728 *** (0.015)	0.753 *** (0.026)	0.658 *** (0.019)	0.668 *** (0.017)	0.605 *** (0.039)
$y_{t-2}$ ( $\alpha_2$ )	0.117 *** (0.012)		0.103 *** (0.016)	0.112 *** (0.013)	0.120 *** (0.012)	0.102 *** (0.013)
$y_{t-3}$ ( $\alpha_3$ )			0.006 (0.013)	0.002 (0.010)	0.010 (0.009)	0.003 (0.012)
$y_{t-4}$ ( $\alpha_4$ )			0.002 (0.013)			
$y_{t-5}$ ( $\alpha_5$ )			0.007 (0.012)			
$y_{t-6}$ ( $\alpha_6$ )			-0.001 (0.012)			
FTP dummy $\times$ I{S<H} ( $\beta_0$ )	0.000 (0.023)	0.009 (0.028)	0.026 (0.027)	0.009 (0.023)	0.004 (0.021)	0.032 (0.043)
FTP dummy $\times$ I{S<H} $\times$ (A-16) ( $\beta_A$ )	0.002 (0.002)	0.001 (0.002)	0.000 (0.001)	0.001 (0.002)	0.001 (0.002)	0.002 (0.003)
FTP dummy $\times$ I{S<H} $\times$ (S-24) ( $\beta_S$ )	0.003 (0.004)	0.008 *** (0.002)	0.007 * (0.004)	0.007 ** (0.003)	0.005 ** (0.002)	0.011 ** (0.005)
FTP dummy $\times$ I{S<H} $\times$ min{S-6,0} ( $\beta_{S1}$ )	0.041 * (0.024)					
FTP dummy ( $\beta_E$ )	0.018 (0.018)	0.029 (0.023)	0.010 (0.019)	0.026 (0.018)	0.020 (0.017)	0.031 (0.032)
R-squared	0.74	0.72	0.74	0.74	0.74	0.72
Sargan-Hansen test for over-	25.48 (df=20)	89.12 *** (df=22)	22.24 (df=23)	10.14 (df=8)	37.52 (df=32)	23.17 (df=20)
Arellano-Bond test for serial correlation <sup>e</sup>	-0.03	6.37 ***	-0.41	0.28	0.18	-

a The sample consists of 1445 individuals and 20 months of data (up to month 23 following random assignment). Other regressors include age, race, years of schooling, number of children, age of the youngest child, a dummy variable that equals one if the youngest child is under age 3, the interaction between the dummy variable above with the FTP dummy, a dummy variable that equals one if the youngest child is over age 18, calendar year indicators, and calendar month indicators. Standard errors are given in parentheses. \*, Significant at the 10 percent level; \*\*, significant at the 5 percent level; \*\*\*, significant at the 1 percent level.

b Details of model specification and estimation are given in the Appendix.

c Fifteen, six, and eighteen lagged dependent variables are involved in instrument construction, respectively.

d The reported statistic follows a chi-square distribution with degree of freedom (df) given in parentheses.

e The reported statistic (Arellano and Bond (1991)) follows an asymptotic standard normal distribution.



**APPENDIX TABLE A7**

USING THE CONTROL GROUP SAMPLE ONLY, KEY ESTIMATES<sup>a</sup>

Variable (parameter in parentheses)	Baseline Sample Control Group (1)	Disadvantaged Sample Control Group (2)
$y_{t-1} (\alpha_1)$	0.634 *** (0.028)	0.555 *** (0.039)
$y_{t-2} (\alpha_2)$	0.102 *** (0.018)	0.163 *** (0.024)
$y_{t-3} (\alpha_3)$	0.001 (0.013)	-0.055 *** (0.017)
R-squared	0.75	0.72
Sargan-Hansen test for over-identifying restrictions <sup>b</sup>	17.84 (df=21)	21.70 (df=21)
Arellano-Bond test for serial correlation <sup>c</sup>	1.53	-0.44

a The baseline control group sample consists of 737 individuals, and the disadvantaged control group sample consists of 554 individuals. Both samples contain 20 months of data (up to month 23 following random assignment). Other regressors include age, race, years of schooling, number of children, age of the youngest child, a dummy variable that equals one if the youngest child is under age 3, a dummy variable that equals one if the youngest child is over age 18, calendar year indicators, and calendar month indicators. Standard errors are given in parentheses. \*, Significant at the 10 percent level; \*\*, significant at the 5 percent level; \*\*\*, significant at the 1 percent level.

b The reported statistic follows a chi-square distribution with degree of freedom (df) given in parentheses.

c The reported statistic (Arellano and Bond (1991)) follows an asymptotic standard normal distribution.

**APPENDIX TABLE A8**

ADDITIONAL DYNAMIC SPECIFICATIONS (BASELINE SAMPLE)<sup>a</sup>

Variable (parameter in parentheses)	Linear Stock Effect		Piecewise Linear Stock Effect	
	(1)	(2)	(3)	(4)
$y_{t-1}$ ( $\alpha_1$ )	0.664 *** (0.026)	0.674 *** (0.025)	0.666 *** (0.026)	0.674 *** (0.025)
$y_{t-2}$ ( $\alpha_2$ )	0.120 *** (0.017)	0.127 *** (0.017)	0.121 *** (0.017)	0.127 *** (0.017)
$y_{t-3}$ ( $\alpha_3$ )	0.012 (0.013)	0.017 (0.013)	0.012 (0.013)	0.017 (0.013)
FTP dummy $\times y_{t-1}$	-0.093 (0.105)	-0.120 (0.097)	-0.094 (0.104)	-0.121 (0.094)
FTP dummy $\times y_{t-2}$	-0.024 (0.032)	-0.036 (0.031)	-0.023 (0.032)	-0.035 (0.031)
FTP dummy $\times y_{t-3}$	-0.017 (0.020)	-0.022 (0.020)	-0.018 (0.020)	-0.021 (0.020)
FTP dummy $\times I\{S<H\}$ ( $\beta_0$ )	0.099 (0.087)	0.116 (0.079)	0.091 (0.087)	0.113 (0.078)
FTP dummy $\times I\{S<H\} \times$ (A-16) ( $\beta_A$ )	0.001 (0.003)	0.000 (0.003)	0.001 (0.003)	0.001 (0.003)
FTP dummy $\times I\{S<H\} \times$ (S-24) ( $\beta_S$ )	0.017 (0.012)	0.020 * (0.011)	0.014 (0.012)	0.017 (0.011)
FTP dummy $\times I\{S<H\} \times$ min{S-6,0} ( $\beta_{S1}$ )			0.037 (0.024)	0.029 * (0.017)
FTP dummy ( $\beta_E$ )	0.050 (0.046)	0.060 (0.042)	0.047 (0.046)	0.056 (0.041)
Sargan-Hansen test for over- identifying restrictions <sup>b</sup>	25.84 * (df=17)	36.65 (df=29)	25.94 * (df=17)	34.98 (df=29)
Arellano-Bond test for serial correlation <sup>c</sup>	0.10	0.19	-0.05	0.18
Lag length of instruments used <sup>d</sup>	12	18	12	18

a The sample consists of 1445 individuals and 20 months of data (up to month 23 following random assignment). Other regressors include age, race, years of schooling, number of children, age of the youngest child, a dummy variable that equals one if the youngest child is under age 3, the interaction between the dummy variable above with the FTP dummy, a dummy variable that equals one if the youngest child is over age 18, calendar year indicators, and calendar month indicators. Standard errors are given in parentheses. \*, Significant at the 10 percent level; \*\*, significant at the 5 percent level; \*\*\*, significant at the 1 percent level.

b The reported statistic follows a chi-square distribution with degree of freedom (df) given in parentheses.

c The reported statistic (Arellano and Bond (1991)) follows an asymptotic standard normal distribution.

d Number of lagged dependent variables involved in instrument construction.