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SUPPLEMENT TO "MODELING EARNINGS DYNAMICS"
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APPENDIX B: VARIANCE DECOMPOSITIONS AND WAGE EXPERIENCE PROFILE DECOMPOSITIONS, AND IMPULSE RESPONSE FUNCTIONS, BY EDUCATION LEVEL

TABLE B.I

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN LIFETIME EARNINGS, WAGE, AND HOURS (IN LEVELS). BASELINE MODEL, SAMPLE OF WHITES WITH LOW EDUCATION[a]

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	Contribution to Variance							Breakdown of 'Composite'			
Variable	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC
Lifetime	**6.3**	**2.9**	**2.3**	**42.4**	**−5.0**	**40.8**	**10.3**	**7.5**	**33.0**	**2.6**	**−0.6**
Earnings	(0.4)	(0.2)	(0.5)	(3.8)	(1.9)	(3.8)	(1.0)	(2.2)	(3.7)	(0.6)	(0.3)
Lifetime	**0**	**0**	**5.8**	**66.6**	**−6.6**	**23.1**	**11.2**	**0**	**64.7**	**2.5**	**−0.6**
Wage	(0.0)	(0.0)	(1.2)	(5.7)	(2.8)	(5.8)	(1.5)	(0.0)	(5.7)	(0.8)	(0.5)
Lifetime	**0**	**5.1**	**0.9**	**46.3**	**7.8**	**38.3**	**1.5**	**36.9**	**6.1**	**3.9**	**−0.5**
Hours	(0.0)	(0.2)	(0.2)	(9.5)	(4.8)	(10.8)	(0.6)	(9.5)	(1.5)	(0.8)	(0.2)

[a]Entries in columns I to VII display the contribution of a given type of shock to the variance of lifetime earnings, wage, and hours, and are expressed as a percentage of the lifetime variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of a given shock to zero for all t. We then compute the variance of the appropriate variables. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We normalize columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon^{\omega}_{it}$. Column IV is the combined contribution of the job match wage and hours components, employment and unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII shows the marginal contribution of ξ, IX the marginal contribution of υ with $\mathrm{Var}(\xi)$ set to 0, X the marginal contribution of unemployment spells with $\mathrm{Var}(\xi)$ and $\mathrm{Var}(\upsilon)$ set to 0, and column XI displays the marginal contribution of job changes with $\mathrm{Var}(\xi)$ and $\mathrm{Var}(\upsilon)$ set to 0, and no unemployment. The variance of the levels of lifetime earnings, wages, and hours are 140,540; 30,859; and 249,351,638, respectively. Bootstrap standard errors are in parentheses.

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TABLE B.II

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN EARNINGS, WAGE, AND HOURS IN LEVELS AT DIFFERENT t (POTENTIAL EXPERIENCE). BASELINE MODEL, SAMPLE OF WHITES WITH LOW EDUCATION[a]

Variable/Potential Experience	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
	Contribution to Variance							Breakdown of 'Composite'				
	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC	Variance
Earnings												
$t=1$	**15.3**	**13.8**	**13.3**	**19.6**	**1.5**	**28.7**	**7.8**	**8.8**	**8.8**	**2.0**	**0**	32.35
	(0.4)	(0.6)	(2.8)	(2.7)	(0.7)	(3.5)	(0.7)	(2.4)	(1.4)	(0.3)	(0.0)	
$t=5$	**19.3**	**10.6**	**7.1**	**29.5**	**2.1**	**24.7**	**6.7**	**7.2**	**22.6**	**1.6**	**−1.9**	71.30
	(0.8)	(0.7)	(1.2)	(2.7)	(1.1)	(3.0)	(0.7)	(2.1)	(2.5)	(0.3)	(0.2)	
$t=10$	**19.6**	**10.6**	**4.6**	**33.5**	**−0.7**	**25.8**	**6.4**	**6.7**	**27.4**	**1.6**	**−2.2**	122.74
	(0.9)	(0.8)	(0.8)	(2.9)	(1.2)	(2.8)	(0.7)	(2.0)	(2.8)	(0.4)	(0.2)	
$t=20$	**18.9**	**11.1**	**4.6**	**37.6**	**−4.9**	**26.3**	**6.4**	**6.1**	**30.4**	**2.3**	**−1.3**	193.14
	(0.9)	(0.9)	(0.8)	(3.1)	(1.6)	(2.8)	(0.8)	(2.0)	(3.0)	(0.4)	(0.3)	
$t=30$	**19.4**	**11.7**	**4.9**	**37.3**	**−2.9**	**23.9**	**5.9**	**6.6**	**29.7**	**1.4**	**−0.5**	226.71
	(0.9)	(0.8)	(0.8)	(2.8)	(1.9)	(2.6)	(0.7)	(1.9)	(2.9)	(0.3)	(0.2)	
$t=40$	**18.4**	**12.0**	**4.0**	**38.7**	**−2.3**	**23.0**	**6.2**	**7.1**	**31.3**	**0.6**	**−0.2**	229.89
	(1.0)	(0.7)	(0.8)	(3.1)	(1.3)	(2.9)	(0.7)	(2.1)	(3.1)	(0.3)	(0.1)	
Wage												
$t=1$	**0**	**0**	**41.6**	**27.8**	**0**	**19.8**	**10.7**	**0**	**27.8**	**0**	**0**	5.08
	(0.0)	(0.0)	(7.3)	(4.1)	(0.0)	(6.7)	(1.2)	(0.0)	(4.1)	(0.0)	(0.0)	
$t=5$	**0**	**0**	**19.6**	**54.8**	**0.5**	**16.1**	**9.0**	**0**	**55.0**	**1.2**	**−1.4**	12.25
	(0.0)	(0.0)	(3.0)	(3.6)	(1.1)	(4.8)	(1.0)	(0.0)	(3.6)	(0.3)	(0.4)	
$t=10$	**0**	**0**	**13.5**	**63.4**	**−1.7**	**16.4**	**8.4**	**0**	**62.8**	**1.7**	**−1.1**	20.81
	(0.0)	(0.0)	(2.2)	(4.3)	(1.6)	(4.6)	(1.0)	(0.0)	(4.2)	(0.6)	(0.5)	
$t=20$	**0**	**0**	**11.5**	**68.3**	**−5.3**	**17.4**	**8.1**	**0**	**65.8**	**2.9**	**−0.5**	32.71
	(0.0)	(0.0)	(2.0)	(4.8)	(2.1)	(4.5)	(1.0)	(0.0)	(4.8)	(0.8)	(0.4)	
$t=30$	**0**	**0**	**11.2**	**67.5**	**−1.2**	**15.3**	**7.1**	**0**	**65.3**	**2.4**	**−0.1**	37.93
	(0.0)	(0.0)	(2.0)	(4.5)	(2.1)	(4.5)	(1.0)	(0.0)	(4.5)	(0.7)	(0.3)	
$t=40$	**0**	**0**	**12.0**	**66.3**	**0.3**	**14.1**	**7.3**	**0**	**65.1**	**1.2**	**−0.1**	43.58
	(0.0)	(0.0)	(2.0)	(4.4)	(1.9)	(4.4)	(1.0)	(0.0)	(4.5)	(0.5)	(0.2)	

(*Continues*)

TABLE B.II—*Continued*

Variable/Potential Experience	I ε^e	II ε^h	III ε^ω	IV Composite	V η	VI μ	VII EDUC	VIII ξ	IX υ	X E	XI JC	XII Variance
	Contribution to Variance							Breakdown of 'Composite'				
Hours												
$t = 1$	**0**	**38.8**	**2.2**	**37.1**	**5.1**	**16.0**	**0.6**	**23.9**	**1.3**	**11.9**	**0**	399,956.80
	(0.0)	(1.7)	(0.5)	(6.1)	(1.9)	(4.6)	(0.2)	(6.2)	(0.3)	(0.5)	(0.0)	
$t = 5$	**0**	**40.5**	**1.8**	**36.5**	**3.9**	**16.6**	**0.7**	**26.8**	**3.1**	**6.3**	**0.4**	376,935.68
	(0.0)	(2.1)	(0.3)	(6.5)	(1.7)	(5.1)	(0.3)	(6.7)	(0.8)	(0.9)	(0.1)	
$t = 10$	**0**	**41.5**	**1.2**	**37.0**	**3.8**	**15.8**	**0.6**	**27.5**	**3.3**	**5.6**	**0.5**	397,407.92
	(0.0)	(2.0)	(0.3)	(6.6)	(1.8)	(5.1)	(0.4)	(6.8)	(1.0)	(0.6)	(0.1)	
$t = 20$	**0**	**41.1**	**1.0**	**36.8**	**3.9**	**16.4**	**0.9**	**26.8**	**3.5**	**6.2**	**0.2**	420,268.23
	(0.0)	(2.1)	(0.3)	(6.8)	(1.9)	(5.2)	(0.4)	(6.9)	(1.2)	(0.7)	(0.1)	
$t = 30$	**0**	**42.2**	**1.0**	**35.2**	**5.0**	**16.0**	**0.7**	**28.0**	**3.4**	**3.8**	**−0.1**	408,575.81
	(0.0)	(2.2)	(0.3)	(6.7)	(1.7)	(5.3)	(0.4)	(7.0)	(1.2)	(0.7)	(0.1)	
$t = 40$	**0**	**44.4**	**1.3**	**33.2**	**3.2**	**16.9**	**1.0**	**28.7**	**3.2**	**1.2**	**0.0**	369,827.16
	(0.0)	(2.2)	(0.3)	(7.2)	(2.1)	(5.4)	(0.5)	(7.3)	(1.2)	(0.6)	(0.1)	

[a] Entries in columns I to VII display the contribution of a given type of shock to the variance in earnings, wage, and hours for a cross section of simulated individuals with potential experience t. The contribution is expressed as a percentage of the variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of the given shock to zero for all t. We then compute the variance of the appropriate variables at the specified value of t. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We have normalized columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon_{it}^{\omega}$. Column IV is the combined contribution of the job match wage and hours components, unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII is the marginal contribution of ξ, IX is the marginal contribution of υ with $\mathrm{Var}(\xi)$ set to 0, X is the marginal contribution of eliminating unemployment spells with $\mathrm{Var}(\xi)$ and $\mathrm{Var}(\upsilon)$ set to 0, and column XI is the marginal contribution of job changes with $\mathrm{Var}(\xi)$ and $\mathrm{Var}(\upsilon)$ set to 0, and no unemployment. Column XII is the cross-sectional variance of simulated earnings, wage, and hours, across individuals with potential experience t. Bootstrap standard errors are in parentheses.

TABLE B.III

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN LIFETIME EARNINGS, WAGE, AND HOURS (IN LEVELS). BASELINE MODEL, SAMPLE OF WHITES WITH HIGH EDUCATION[a]

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	Contribution to Variance							Breakdown of 'Composite'			
Variable	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC
Lifetime Earnings	**6.1**	**0.9**	**18.4**	**50.2**	**1.5**	**4.2**	**18.6**	**12.0**	**36.6**	**1.4**	**0.2**
	(0.4)	(0.1)	(1.9)	(4.6)	(2.3)	(7.6)	(2.3)	(1.6)	(3.9)	(0.4)	(0.3)
Lifetime Wage	**0**	**0**	**26.0**	**56.2**	**0.4**	**−2.8**	**20.3**	**0**	**54.5**	**1.2**	**0.4**
	(0.0)	(0.0)	(2.6)	(5.2)	(1.4)	(7.7)	(2.7)	(0.0)	(5.2)	(0.4)	(0.4)
Lifetime Hours	**0**	**2.0**	**0.3**	**79.4**	**2.6**	**14.0**	**1.7**	**76.8**	**0.6**	**2.1**	**−0.1**
	(0.0)	(0.1)	(0.2)	(10.2)	(8.0)	(5.5)	(0.6)	(9.9)	(0.3)	(0.5)	(0.0)

[a]Entries in columns I to VII display the contribution of a given type of shock to the variance of lifetime earnings, wage, and hours, and are expressed as a percentage of the lifetime variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of a given shock to zero for all t. We then compute the variance of the appropriate variables. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We normalize columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon_{it}^{\omega}$. Column IV is the combined contribution of the job match wage and hours components, employment and unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII shows the marginal contribution of ξ, IX the marginal contribution of υ with Var(ξ) set to 0, X the marginal contribution of unemployment spells with Var(ξ) and Var(υ) set to 0, and column XI displays the marginal contribution of job changes with Var(ξ) and Var(υ) set to 0, and no unemployment. The variance of the levels of lifetime earnings, wages, and hours are 990,304; 127,381; and 234,587,187, respectively. Bootstrap standard errors are in parentheses.

TABLE B.IV

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN EARNINGS, WAGE, AND HOURS IN LEVELS AT DIFFERENT t (POTENTIAL EXPERIENCE). BASELINE MODEL, SAMPLE OF WHITES WITH HIGH EDUCATION[a]

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Variable/Potential	Contribution to Variance							Breakdown of 'Composite'				
Experience	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC	Variance
Earnings												
$t=1$	**10.0**	**3.9**	**41.0**	**18.3**	**0.4**	**13.4**	**13.0**	**14.8**	**2.9**	**0.7**	**0**	237.45
	(0.4)	(0.2)	(4.0)	(1.5)	(1.1)	(4.6)	(1.0)	(1.4)	(0.4)	(0.3)	(0.0)	
$t=5$	**15.2**	**3.7**	**29.0**	**27.5**	**2.4**	**10.2**	**11.9**	**11.9**	**15.1**	**0.8**	**−0.3**	499.51
	(0.7)	(0.3)	(2.4)	(2.0)	(1.1)	(3.4)	(1.0)	(1.4)	(2.0)	(0.2)	(0.2)	
$t=10$	**15.5**	**3.7**	**23.9**	**36.9**	**1.7**	**5.7**	**12.6**	**12.4**	**24.3**	**0.7**	**−0.5**	862.00
	(0.9)	(0.4)	(1.9)	(2.5)	(1.2)	(3.8)	(1.1)	(1.6)	(2.6)	(0.3)	(0.3)	
$t=20$	**15.2**	**4.2**	**20.7**	**46.5**	**1.4**	**0.0**	**12.0**	**11.6**	**34.3**	**0.9**	**−0.4**	1440.68
	(1.2)	(0.4)	(2.2)	(4.0)	(1.8)	(6.0)	(1.4)	(1.6)	(3.5)	(0.3)	(0.3)	
$t=30$	**14.9**	**3.4**	**20.2**	**50.2**	**2.6**	**−1.5**	**10.3**	**10.2**	**39.3**	**0.7**	**0.0**	1471.71
	(1.2)	(0.3)	(2.3)	(4.5)	(1.8)	(6.1)	(1.5)	(1.5)	(4.0)	(0.2)	(0.1)	
$t=40$	**15.7**	**4.0**	**18.7**	**51.2**	**4.0**	**−3.7**	**10.0**	**9.7**	**41.3**	**0.3**	**0.0**	1180.55
	(1.6)	(0.4)	(2.2)	(4.3)	(1.9)	(5.7)	(1.3)	(1.5)	(3.8)	(0.2)	(0.0)	

(*Continues*)

TABLE B.IV—*Continued*

Variable/Potential Experience	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
	Contribution to Variance							Breakdown of 'Composite'				
	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC	Variance
Wage												
$t=1$	**0**	**0**	**67.1**	**5.2**	**0**	**10.5**	**17.2**	**0**	**5.2**	**0**	**0**	25.94
	(0.0)	(0.0)	(5.7)	(0.7)	0.0	(5.8)	(1.2)	(0.0)	(0.7)	(0.0)	(0.0)	
$t=5$	**0**	**0**	**48.2**	**26.1**	**2.5**	**7.9**	**15.4**	**0**	**25.9**	**0.3**	**−0.1**	49.43
	(0.0)	(0.0)	(3.5)	(2.8)	(1.3)	(3.8)	(1.3)	(0.0)	(3.0)	(0.3)	(0.4)	
$t=10$	**0**	**0**	**39.4**	**42.1**	**1.5**	**1.6**	**15.4**	**0**	**41.7**	**0.5**	**−0.1**	85.03
	(0.0)	(0.0)	(3.0)	(3.4)	(1.5)	(4.1)	(1.7)	(0.0)	(3.5)	(0.3)	(0.5)	
$t=20$	**0**	**0**	**31.7**	**56.4**	**0.5**	**−3.1**	**14.5**	**0**	**55.3**	**0.8**	**0.2**	146.35
	(0.0)	(0.0)	(3.2)	(5.6)	(1.6)	(6.2)	(1.8)	(0.0)	(5.4)	(0.3)	(0.4)	
$t=30$	**0**	**0**	**29.1**	**59.0**	**2.3**	**−2.7**	**12.3**	**0**	**58.1**	**0.7**	**0.2**	175.25
	(0.0)	(0.0)	(3.1)	(5.2)	(1.5)	(5.2)	(1.6)	(0.0)	(5.1)	(0.3)	(0.2)	
$t=40$	**0**	**0**	**29.8**	**62.3**	**2.4**	**−7.1**	**12.6**	**0**	**61.8**	**0.4**	**0.0**	164.86
	(0.0)	(0.0)	(3.3)	(5.8)	(1.8)	(5.8)	(1.8)	(0.0)	(5.7)	(0.2)	(0.1)	
Hours												
$t=1$	**0**	**20.0**	**0.5**	**68.6**	**2.2**	**8.1**	**0.6**	**58.4**	**0.0**	**10.2**	**0**	323,567.76
	(0.0)	(0.9)	(0.2)	(5.6)	(4.1)	(2.4)	(0.2)	(5.5)	(0.0)	(0.4)	(0.0)	
$t=5$	**0**	**19.2**	**0.4**	**70.6**	**2.1**	**7.4**	**0.4**	**64.3**	**0.2**	**6.1**	**0.0**	315,707.05
	(0.0)	(1.0)	(0.3)	(6.0)	(4.6)	(2.6)	(0.4)	(6.0)	(0.1)	(1.1)	(0.0)	
$t=10$	**0**	**20.2**	**0.3**	**69.4**	**2.7**	**6.7**	**0.7**	**64.1**	**0.2**	**5.1**	**0.0**	335,298.47
	(0.0)	(1.0)	(0.2)	(5.8)	(4.3)	(2.3)	(0.4)	(5.7)	(0.2)	(0.5)	(0.0)	
$t=20$	**0**	**20.2**	**0.1**	**69.3**	**3.2**	**6.2**	**0.9**	**63.3**	**0.4**	**5.6**	**0.0**	333,489.95
	(0.0)	(1.1)	(0.2)	(6.4)	(4.7)	(2.6)	(0.4)	(6.3)	(0.3)	(0.6)	(0.0)	
$t=30$	**0**	**20.2**	**0.5**	**68.4**	**2.6**	**7.5**	**0.8**	**64.3**	**0.5**	**3.6**	**0.0**	297,223.62
	(0.0)	(1.0)	(0.3)	(6.4)	(4.3)	(2.8)	(0.5)	(6.4)	(0.3)	(0.7)	(0.0)	
$t=40$	**0**	**21.9**	**0.2**	**69.5**	**2.1**	**5.4**	**0.7**	**68.3**	**0.3**	**0.9**	**0.0**	242,846.47
	(0.0)	(1.1)	(0.3)	(7.1)	(4.9)	(2.9)	(0.5)	(7.0)	(0.2)	(0.8)	(0.0)	

[a] Entries in columns I to VII display the contribution of a given type of shock to the variance in earnings, wage, and hours for a cross section of simulated individuals with potential experience t. The contribution is expressed as a percentage of the variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of the given shock to zero for all t. We then compute the variance of the appropriate variables at the specified value of t. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We have normalized columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks ε^ω_{it}. Column IV is the combined contribution of the job match wage and hours components, unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII is the marginal contribution of ξ, IX is the marginal contribution of υ with Var(ξ) set to 0, X is the marginal contribution of eliminating unemployment spells with Var(ξ) and Var(υ) set to 0, and column XI is the marginal contribution of job changes with Var(ξ) and Var(υ) set to 0, and no unemployment. Column XII is the cross-sectional variance of simulated earnings, wage, and hours, across individuals with potential experience t. Bootstrap standard errors are in parentheses.

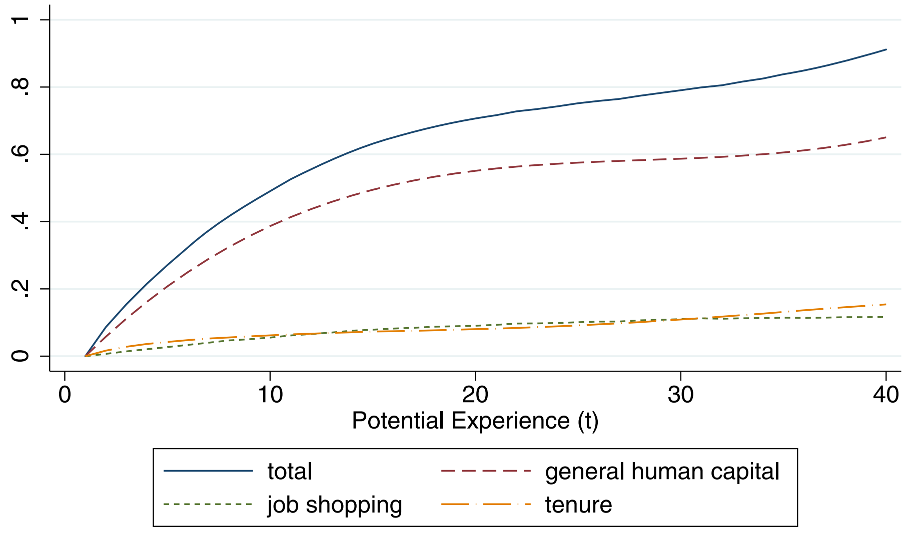


FIGURE B.1.—Decomposing the experience profile of wages. Baseline model, sample of whites with low education. The figure displays the model's decomposition of wage growth over a career (or the experience profile of log wages) into the contributions of job shopping (the mean value of the job-specific wage component υ), the accumulation of tenure (the contribution of the mean value of tenure on the wage experience profile), and the accumulation of general human capital.

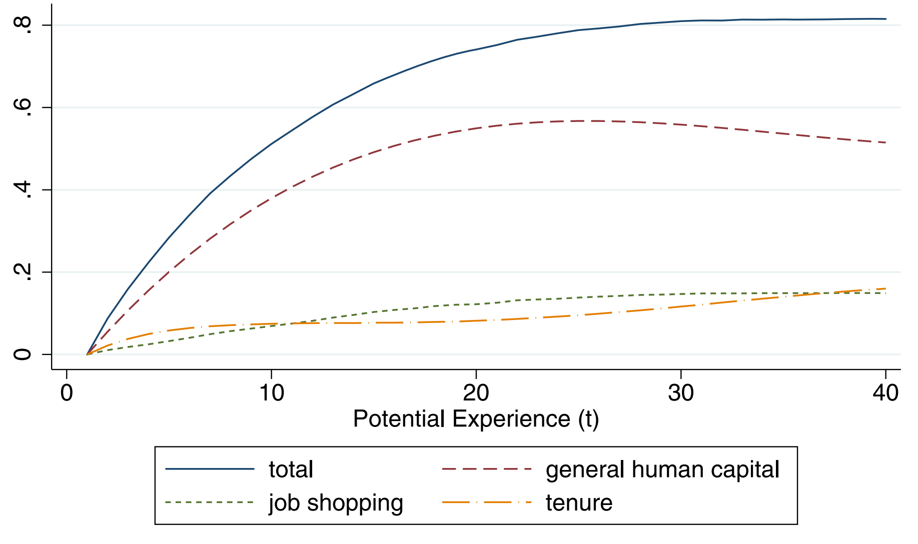


FIGURE B.2.—Decomposing the experience profile of wages. Baseline model, sample of whites with high education. The figure displays the model's decomposition of wage growth over a career (or the experience profile of log wages) into the contributions of job shopping (the mean value of the job-specific wage component υ), the accumulation of tenure (the contribution of the mean value of tenure on the wage experience profile), and the accumulation of general human capital.

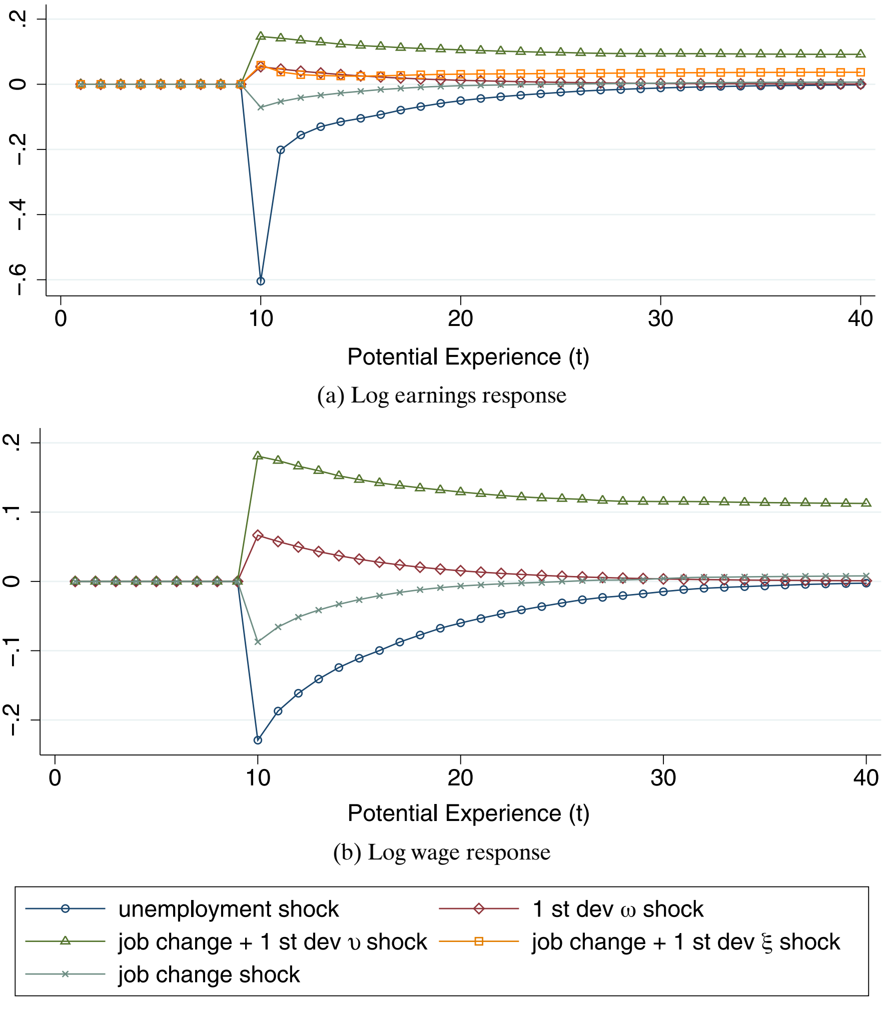
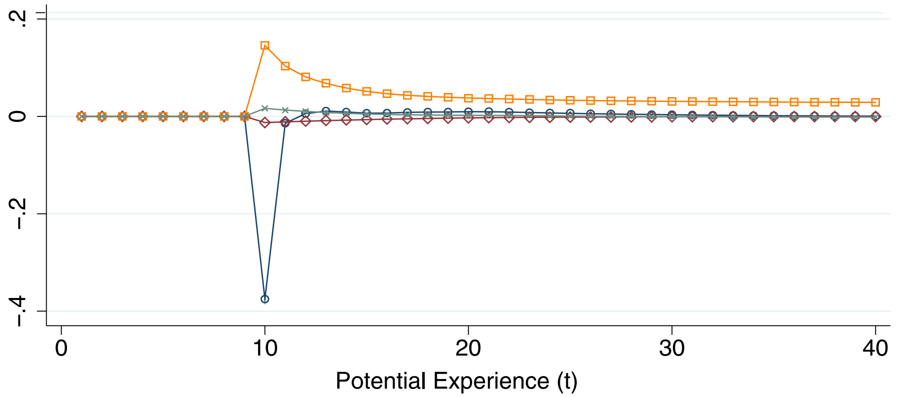


FIGURE B.3.—Mean response of key variables to various shocks at $t = 10$ for sample of whites with low education. The figure displays the response of the mean of log earnings, log wage, and log hours to various shocks that are imposed when potential experience $t = 10$. The shocks are an unemployment shock, a job change shock, a one-standard-deviation shock to the autoregressive component of wages, a job change shock accompanied by a one-standard-deviation shock to the job-specific wage component, and a job change shock accompanied by a one-standard-deviation shock to the job-specific hours component. To construct the point estimates, we first use the model to simulate a large number of individuals through $t = 9$. We then impose the shock indicated in the figures in period 10 on all individuals. After that, we continue the simulation in accordance with the model. The panels in the figure show the mean paths of log earnings, log wages, and log hours relative to the base case. The base case represents the mean of the simulated paths in the absence of the specified intervention in period 10. (*Continues*)



(c) Log hours response

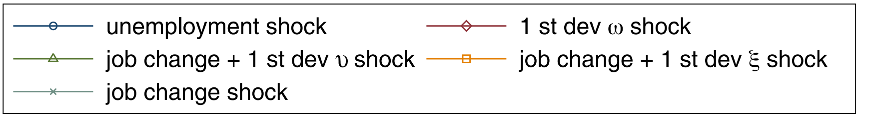
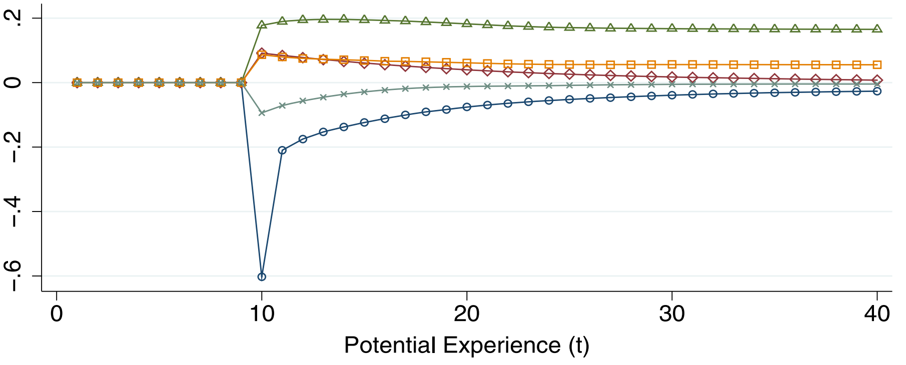


FIGURE B.3.—*Continued*.



(a) Log earnings response

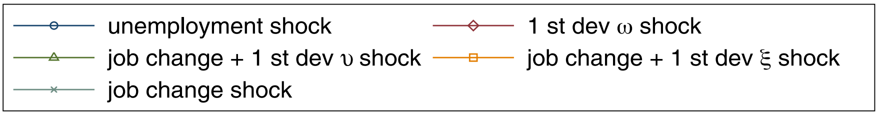
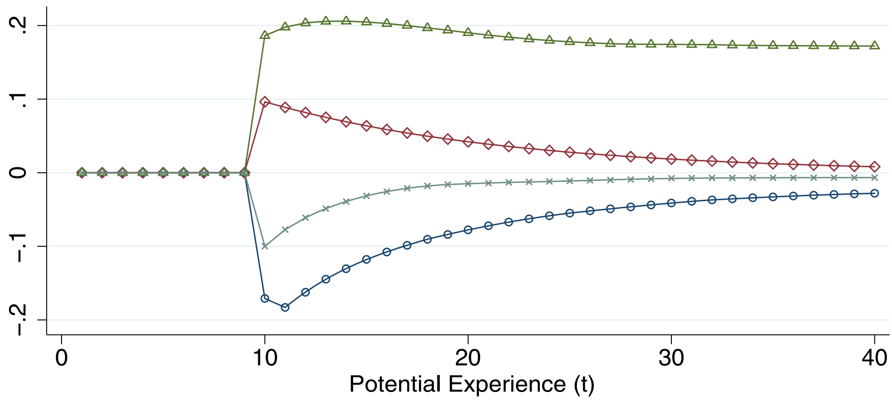
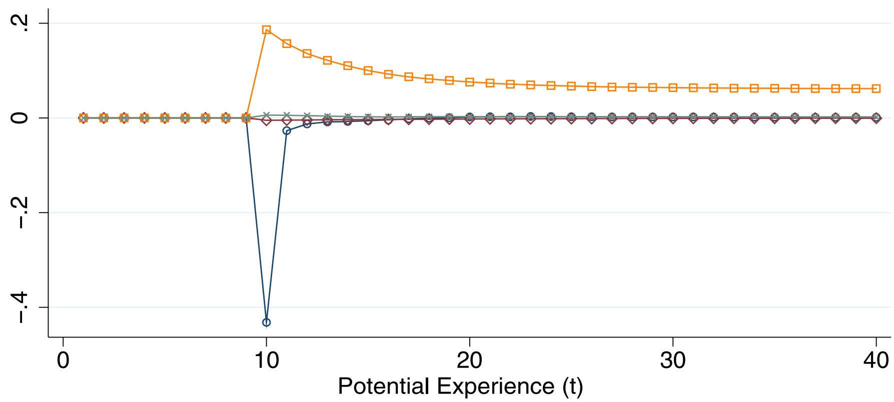


FIGURE B.4.—Mean response of key variables to various shocks at $t = 10$ for sample of whites with high education. The figure displays the response of the mean of log earnings, log wage, and log hours to various shocks that are imposed when potential experience $t = 10$. (*Continues*)



(b) Log wage response



(c) Log hours response

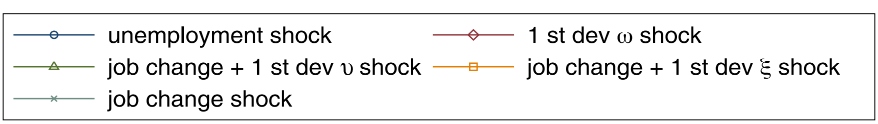
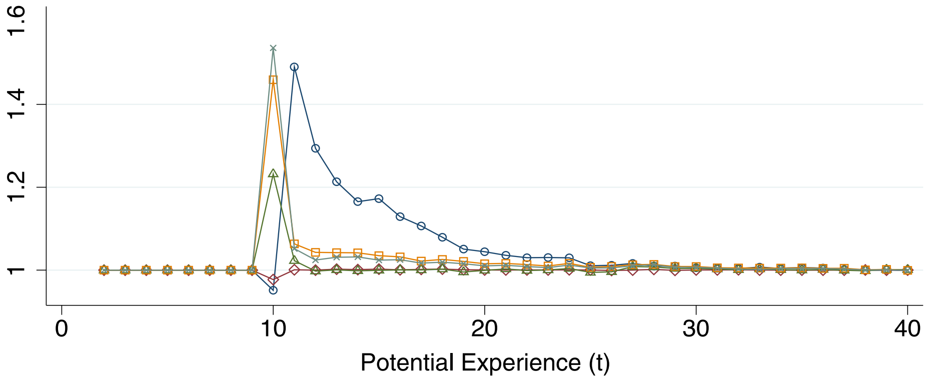
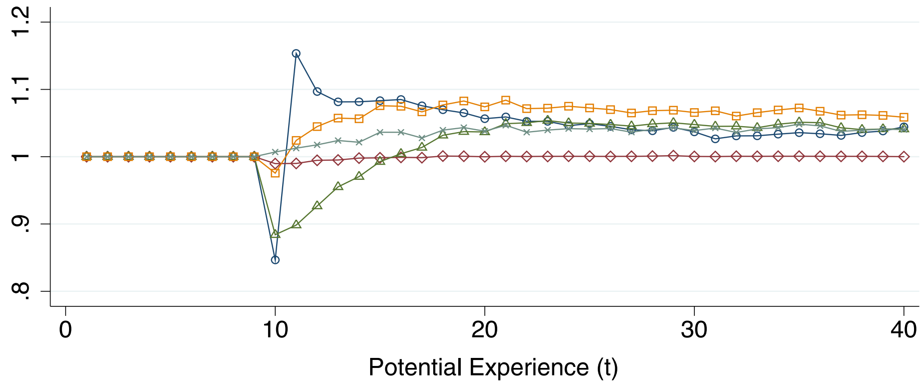


FIGURE B.4.—*Continued*. The shocks are an unemployment shock, a job change shock, a one–standard-deviation shock to the autoregressive component of wages, a job change shock accompanied by a one-standard-deviation shock to the job-specific wage component, and a job change shock accompanied by a one-standard-deviation shock to the job-specific hours component. To construct the point estimates, we first use the model to simulate a large number of individuals through $t = 9$. We then impose the shock indicated in the figures in period 10 on all individuals. After that, we continue the simulation in accordance with the model. The panels in the figure show the mean paths of log earnings, log wages, and log hours relative to the base case. The base case represents the mean of the simulated paths in the absence of the specified intervention in period 10.



(a) Response of cross-sectional variance of the first difference of log earnings to various shocks at $t = 10$



(b) Response of cross-sectional variance of log earnings to various shocks at $t = 10$

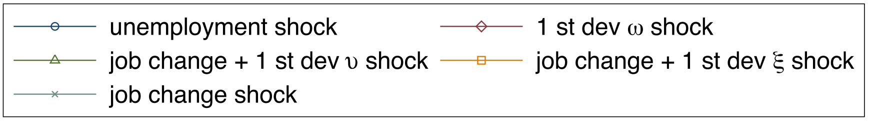
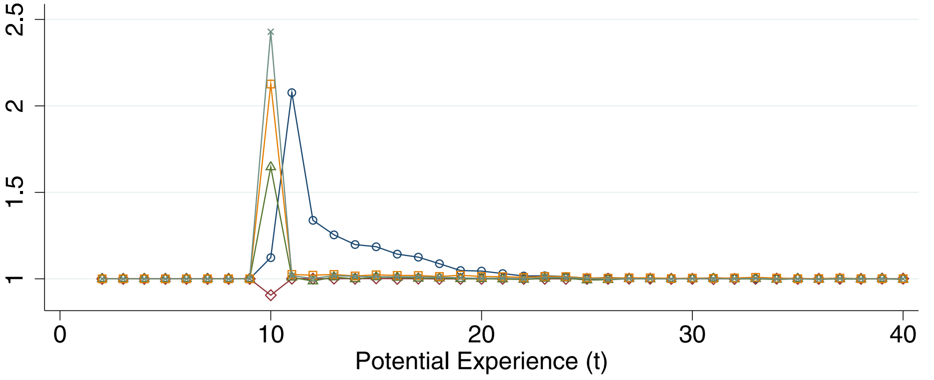
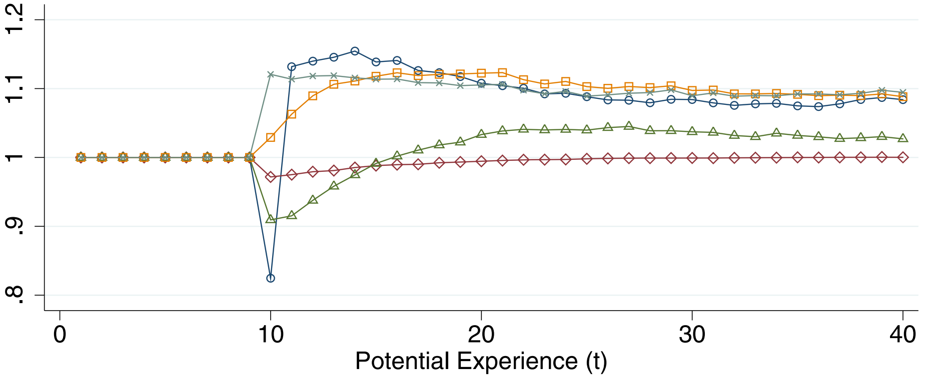


FIGURE B.5.—Sample of whites with low education. Panel (a) in the figure displays the response of the ratio of $\text{Var}(\text{earn}_{it} - \text{earn}_{i,t-1})$ to the baseline variance for the model, to various shocks that are imposed when potential experience $t = 10$. See note in Figure 3. Panel (b) displays the response of the ratio of $\text{Var}(\text{earn}_{it})$ to the baseline variance for the model.



(a) Response of cross-sectional variance of the first difference of log earnings to various shocks at $t = 10$



(b) Response of cross-sectional variance of log earnings to various shocks at $t = 10$

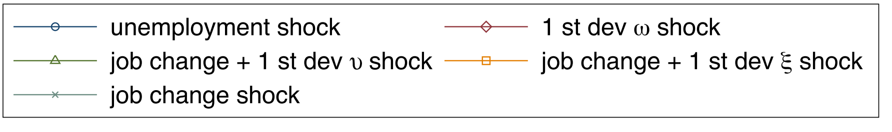


FIGURE B.6.—Sample of whites with high education. Panel (a) in the figure displays the response of the ratio of $\text{Var}(\text{earn}_{it} - \text{earn}_{i,t-1})$ to the baseline variance for the model, to various shocks that are imposed when potential experience $t = 10$. See note in Figure 3. Panel (b) displays the response of the ratio of $\text{Var}(\text{earn}_{it})$ to the baseline variance for the model.

APPENDIX C: RESULTS FOR THE MULTINOMIAL SPECIFICATION OF EMPLOYMENT TRANSITIONS AND JOB CHANGES

C.1. *Model Estimates, Marginal Effects, and Goodness of Fit*

IN THIS SECTION, WE PROVIDE A BRIEF DISCUSSION of the model estimates, presented in Table C.I, focusing on the coefficients in equations (19) and (20) for EE_{it}^{S*} and EE_{it}^{Q*} and the implied estimates of the average marginal effects of the various variables on $\mathrm{Prob}(\mathrm{EE}=1)$, $\mathrm{Prob}(\mathrm{JC}=1)$, and $\mathrm{Prob}(\mathrm{EE}^{Q}=1)$. The marginal effects are computed using simulated data from the model. They depend on the variables and coefficients in both (19) and (20).[51] The coefficients relating EE^{S*} to $t-1$ and $(t-1)^2$ show a mild decline until $t-1$ is 15 and then increase. Since $\min(\mathrm{ED}_{t-1}, 9)$ and TEN_{t-1} both enter with positive coefficients and are rising over the first few years in the labor market, the overall relationship between EE^{S*} and t is weak. The coefficient on $\min(\mathrm{ED}_{t-1}, 9)$ is .097 (.015), indicating modest positive duration dependence in the odds of remaining employed. The marginal effect of one extra year on EE is .0043. TEN_{t-1} also has a modest positive effect on EE. BLACK is negative and significant and EDUC is positive and significant. The job-specific wage component, v_{t-1}, has a positive coefficient of .195 holding wage_t^s constant, and a total effect of .076.

The coefficient on wage_t^s is small and negative: $-.119$ (.088). From the point of view of job mobility, one would expect wage_t^s to be positive, since $\gamma_{w^s}^{\mathrm{EE}^S}$ is also the coefficient on wage_t' in the EE^{Q*} equation (we impose equality of these coefficients). However, all variables that influence $\mathrm{wage}_t' - \mathrm{wage}_t^s$ also have a separate influence on $\mathrm{EE}^{S*} - \mathrm{EE}^{Q*}$. In any event, $\hat{\gamma}_{w^s}^{\mathrm{EE}^S}$ is not statistically significant and the implied average marginal effect of wage_t' on the EE probability is small.

The experience profile of EE^{Q*} shows a mild increase up to about $t-1=12$ and then declines, holding everything else constant. BLACK reduces the value of changing jobs relative to leaving employment, while education raises it. The job-specific wage component v_t' has a large positive effect on EE^{Q*}, .953 (.156).

The heterogeneity term μ raises EE^{S*} and lowers EE^{Q*} by roughly similar amounts, and the component η has a substantial positive effect on EE^{Q*} and essentially no effect on EE^{S*}.

[51]We simulated 27,120 careers (10 for each member of the sample). We then estimated probit models for $\mathrm{EE}=1$, $\mathrm{JC}=1$, and $\mathrm{EE}^{Q}=1$ that include all observed and unobserved variables that appear in (19) and/or (20). The columns of Table C.I of this Supplemental Material labeled "Marginal Effects, Multinomial Model" report average partial derivatives, holding the distributions of the observed variables as well as wage_t', wage_t^s, $v_{j'(t)}'$, $v_{j(t-1)}$, μ, and η constant. These are approximate estimates because the true reduced forms determining EE, JC, and EE^{Q} are not probits with an index that is linear in the underlying variables. The use of the simulated data provides an easy way to condition the distributions of the variables on employment in the previ-

TABLE C.I

MULTINOMIAL MODEL ESTIMATES, SRC SAMPLE[a]

	Multinomial Model Estimates											
Column:	1a	1b	1c	1d	2a	2b	2c	2d	3a	3b	3c	3d
Variable	Parameter	Point Estimate	Bootstrap Mean	Standard Error	Parameter	Point Estimate	Bootstrap Mean	Standard Error	Parameter	Point Estimate	Bootstrap Mean	Standard Error
	EE^{S*} Equation (19)				EE^{Q*} Equation (20)				UE Equation (8)			
(cons)	γ_0^{EES}	**0.655**	0.589	(0.106)	γ_0^{EEQ}	**−0.532**	−0.597	(0.135)	γ_0^{UE}	**1.078**	0.939	(0.301)
$(t-1)$	γ_t^{EES}	**−0.039**	−0.026	(0.012)	γ_t^{EEQ}	**0.017**	0.024	(0.013)	γ_t^{UE}	**−0.104**	−0.082	(0.031)
$(t-1)^2/100$	γ_{t2}^{EES}	**0.128**	0.093	(0.032)	γ_{t2}^{EEQ}	**−0.072**	−0.079	(0.038)	γ_{t2}^{UE}	**0.322**	0.271	(0.111)
$\min(ED_{t-1}, 9)$	γ_{ED}^{EES}	**0.097**	0.099	(0.015)								
TEN_{t-1}	γ_{TEN}^{EES}	**0.056**	0.049	(0.013)	γ_{TEN}^{EEQ}	**−0.054**	−0.049	(0.015)				
BLACK	γ_{BLACK}^{EES}	**−0.220**	−0.206	(0.067)	γ_{BLACK}^{EEQ}	**−0.097**	−0.082	(0.092)	γ_{BLACK}^{UE}	**0.393**	0.336	(0.215)
EDUC	γ_{EDUC}^{EES}	**0.023**	0.019	(0.007)	γ_{EDUC}^{EEQ}	**0.033**	0.030	(0.009)	γ_{EDUC}^{UE}	**0.043**	0.034	(0.021)
$wage_t^s$	γ_{ws}^{EES}	**−0.119**	−0.114	(0.088)								
$wage_t'$					$\gamma_{wage'}^{EEQ}$	**−0.119**	−0.114	(0.088)				
v_{t-1}	δ_{v-1}^{EES}	**0.195**	0.169	(0.145)								
v_t'					$\delta_{v'}^{EEQ}$	**0.953**	0.918	(0.156)				
μ	δ_μ^{EES}	**0.236**	0.261	(0.052)	δ_μ^{EEQ}	**−0.190**	−0.192	(0.074)	δ_μ^{UE}	**0.112**	0.105	(0.140)
η	δ_η^{EES}	**−0.028**	−0.047	(0.052)	δ_η^{EEQ}	**0.368**	0.342	(0.059)	δ_η^{UE}	**0.295**	0.254	(0.138)

(*Continues*)

TABLE C.I—*Continued*

Variable	Marginal Effects, Multinomial Model				Marginal Effects, Baseline Model			
	EE	JC	EE^Q	UE	EE	JC	EE^Q	UE
$(t-1)$	−0.0003	−0.0001	−0.0002	−0.0045	0.0004	−0.0031	−0.0030	−0.0031
$\min(ED_{t-1}, 9)$	0.0043	−0.0081	−0.0071		0.0012		0.0006	
TEN_{t-1}	0.0028	−0.0095	−0.0095			−0.0081	−0.0084	
BLACK	−0.0118	0.0109	0.0078	0.0985	−0.0069	0.0043	0.0020	−0.0074
EDUC	0.0017	0.0011	0.0014	0.0099	0.0023	−0.0027	−0.0021	0.0059
$wage_t^s$	−0.1001	−0.0137	0.0116		0.0032		0.0009	
$wage_t'$	0.0932	0.0119	−0.0145					
v_{t-1}	0.0010	−0.0010	−0.0009			−0.0308	−0.0301	
v_t'	0.0043	0.0227	0.0230			0.0208	0.0203	
μ	0.0071	−0.0375	−0.0357	0.0236	0.0129	−0.0085	−0.0054	0.0767
η	0.0055	0.0365	0.0367	0.0704	−0.0209	0.0652	0.0583	0.0252

TABLE C.I—*Continued*

Column: *Equation*/Variable	4a Parameter	4b Point Estimate	4c Bootstrap Mean	4d Standard Error
Wage Equation (*Eqs.* (1)–(5))				
(cons)		**−0.002**	0.002	(0.052)
$(t-1)$	γ_t^w	**0.069**	0.070	(0.004)
$(t-1)^2/10$	γ_{t2}^w	**−0.022**	−0.022	(0.002)
$(t-1)^3/1000$	γ_{t3}^w	**0.024**	0.024	(0.004)
BLACK	γ_{BLACK}^w	**−0.208**	−0.209	(0.031)
EDUC	γ_{EDUC}^w	**0.105**	0.105	(0.003)
Tenure polynomial		**Yes**		
μ	δ_μ^w	**0.166**	0.170	(0.026)
υ_{t-1}	ρ_υ	**0.575**	0.578	(0.067)
ε^υ	σ_υ	**0.258**	0.267	(0.009)
ε_1^υ	$\sigma_{\upsilon 1}$	**0.077**	0.075	(0.009)
ω_{t-1}	ρ_ω[b]	**0.908**	0.908	(0.026)
$1-E_t$	γ_{1-Et}^ω	**−0.121**	−0.126	(0.012)
$1-E_{t-1}$	γ_{1-Et-1}^ω	**0.038**	0.040	(0.016)
ε^ω	σ_ω	**0.095**	0.090	(0.005)
ε_1^ω (Black, Low Educ)	$\sigma_{\omega 1}$[b]	**0.160**	0.262	(0.055)
ε_1^ω (Black, High Educ)	$\sigma_{\omega 1}$[b]	**0.242**	0.292	(0.050)
ε_1^ω (White, Low Educ)	$\sigma_{\omega 1}$[b]	**0.264**	0.303	(0.022)
ε_1^ω (White, High Educ)	$\sigma_{\omega 1}$[b]	**0.320**	0.329	(0.019)

(*Continues*)

TABLE C.I—*Continued*

Column: *Equation*/Variable	4a Parameter	4b Point Estimate	4c Bootstrap Mean	4d Standard Error
Hours Equation (9)				
(cons)	γ_0^h	**−0.419**	−0.412	(0.013)
$(t-1)$	γ_t^h	**0.007**	0.005	(0.002)
$(t-1)^2/10$	γ_{t2}^h	**−0.002**	−0.002	(0.001)
$(t-1)^3/1000$	γ_{t3}^h	**0.001**	0.001	(0.002)
BLACK	γ_{BLACK}^h	**−0.054**	−0.053	(0.015)
EDUC	γ_{EDUC}^h	**0.010**	0.010	(0.002)
E_t	γ_E^h	**0.438**	0.437	(0.010)
	σ_ξ	**0.150**	0.163	(0.014)
w_t	γ_w^h	**−0.119**	−0.116	(0.016)
μ	δ_μ^h	**0.091**	0.087	(0.013)
η	δ_η^h	**0.067**	0.069	(0.017)
ε^h	σ_h	**0.144**	0.142	(0.002)
Earnings Equation (10)				
(cons)	γ_0^e	**−0.014**	−0.014	(0.001)
w_t	γ_w^e [c]	**1.000**		
h_t	γ_h^e [c]	**1.000**		
	ρ_e	**0.622**	0.622	(0.009)
ε^e	σ_e	**0.170**	0.170	(0.002)

[a]The table presents estimates and standard errors for the multinomial formulation of the model, estimated on the full SRC sample. Estimates were obtained by Indirect Inference, unless indicated otherwise. The second page of the table displays marginal effects on EE, JC, EEQ, and UE. These are computed from simulated data from the multinomial model or the baseline model, as indicated. The parameter estimates for the baseline model are in Table IV. The marginal effects of potential experience account for the quadratic term. The marginal effects of v_{t-1} and v_t' are the effect of a one-standard-deviation change based on the standard deviations for the particular sample. Parametric bootstrap standard errors are in parentheses. Bootstraps are based on 300 replications. As explained in Footnote 24 in the paper, the hours equation includes a second constant that has no effect on earn_{it}^*. The point estimate of that constant is 0.038.

[b]Estimate obtained using additional moment conditions. See discussion in Section 4.

[c]Imposed.

The second page of Table C.I of this Supplemental Material reports the average marginal effect of each variable on Prob(EE = 1), Prob(JC = 1), and Prob($EE^Q = 1$). For comparison, we also report average marginal effects for the baseline model computed from simulated data in the same manner that the marginal effects for the multinomial model are computed. They tend to be about 70 percent as large as the derivatives at the PSID mean of EE and JC that are reported in Table IV.[52] There are some differences in the marginal effects across the two models. Sampling error undoubtedly contributes to the differences, which tend to be largest when the standard errors of the parameters underlying the marginal effects in the case of the baseline model are largest. The separate effects of wage_t' and wage_t^s are poorly identified given the presence of TEN_{t-1}, $v_{j(t-1)}$, and $v'_{j'(t)}$ in the model. However, the effect of a simultaneous increase in both of these variables on EE is very small. This is consistent with the finding that EE is insensitive to wages in the baseline model. The effect of an extra year of employment duration on EE is substantial (relative to the mean of EE). TEN_{t-1} has a substantial negative effect on JC in both models. BLACK has a substantial negative effect on EE (relative to the mean) and a small positive effect on JC. EDUC increases employment but its effect on JC is small and varies in sign across the models. In the multinomial case, the marginal effects of $v_{j(t-1)}$ and $v'_{j'(t)}$ include indirect effects operating through wage_t^s and wage_t'. The job component $v_{j(t-1)}$ reduces JC and the job offer $v'_{j'(t)}$ raises JC in both models. However, the relative magnitude of the effects differs between the two models and the effect of $v_{j(t-1)}$ is small in the multinomial case. The standard deviation of $v'_{j'(t)}$ is .298 in the multinomial case and .350 in the baseline model.

Table C.I, columns 3b and 4b, present estimates for the UE, wage, hours, and earnings equations when they are estimated jointly with (19) and (20). In the UE equation, the effect of BLACK is large and positive, in contrast to the small negative estimate in the baseline case. The results for wage, hours, and earnings are very close to the results using the baseline specification, so we do not discuss them here. However, it is worth highlighting the fact that the coefficient on μ in the wage equation is larger in the multinomial case than in the baseline model: .166 versus .081. This is balanced by the fact that the standard deviation of the initial condition for the job-specific wage component, v_{i1}, is lower in the multinomial case. We would not want to make too much of these differences given standard errors and the fact that we have found that the coefficient on μ is somewhat sensitive to model specification.

ous period. The reported marginal effects for $v'_{j'(t)}$ and $v_{j(t-1)}$ are the sum of the direct effects holding wage_t' and wage_t^s constant and the indirect effects operating through the wage terms.

[52]Part of the difference is because the mean of UE is higher and the mean of JC is lower in the simulated data than in the PSID data. Also, the simulated data are for a 40-year career for each PSID sample member, while the means in the PSID are for the part of the career for which data are available.

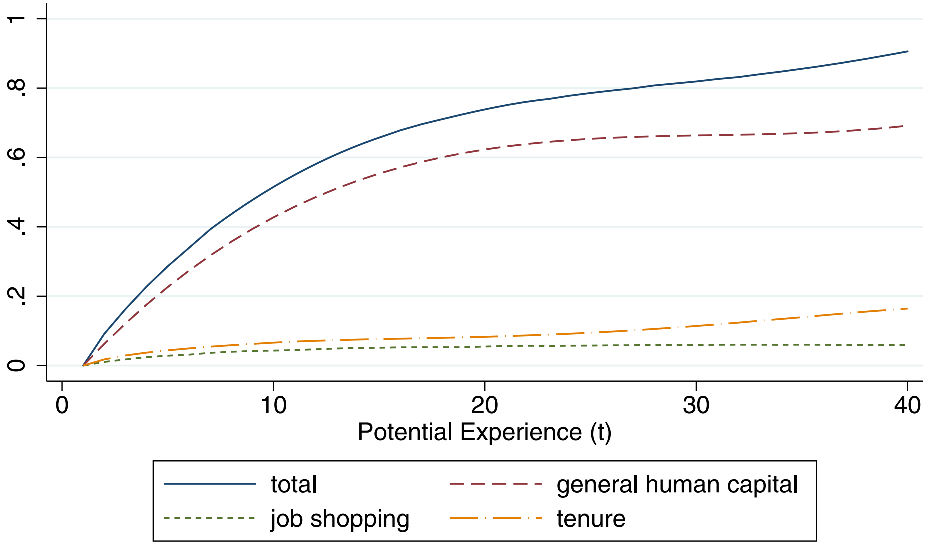


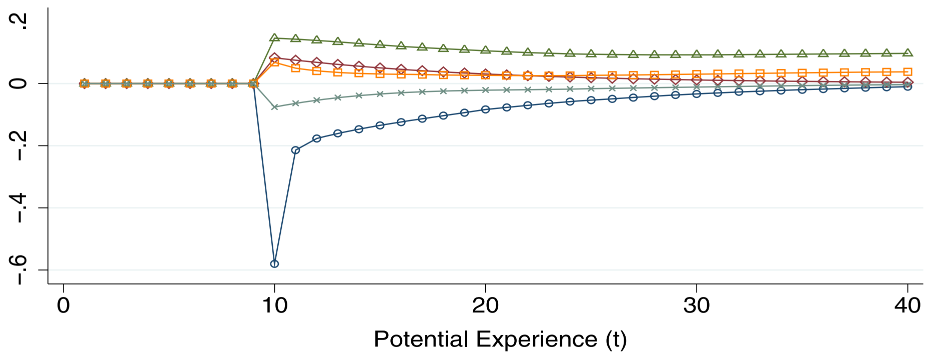
FIGURE C.1.—Decomposing the experience profile of wages. Multinomial model, full sample. The figure displays the model's decomposition of wage growth over a career (or the experience profile of log wages) into the contributions of job shopping (the mean value of the job-specific wage component υ), the accumulation of tenure (the contribution of the mean value of tenure on the wage experience profile), and the accumulation of general human capital.

We have compared the experience profiles of a number of key variables implied by the multinomial model (not reported) to the corresponding prediction of the baseline model and the 95% confidence interval estimates from the PSID that are displayed in Figure 2. The predictions of the two models are similar, and for the most part, the multinomial model fits the data reasonably well. The close correspondence of the point estimates and the bootstrap means reported in Table C.I suggests that there is little bias. However, as we note in the text, we did have more numerical problems estimating the multinomial model.

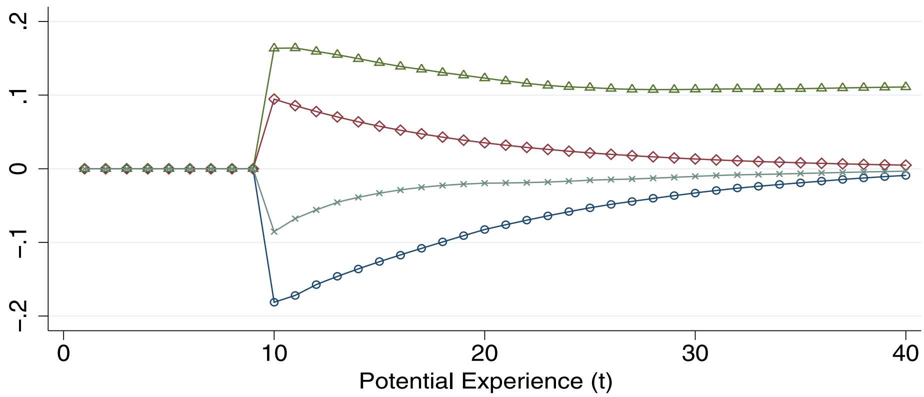
C.2. *Impulse Response Functions and Variance Decompositions*

Figures C.2 and C.3 of this Supplemental Material report the time path of the effects of various shocks on the mean of earnings, wages, and hours, and the variance of the first difference of earnings and the variance of the cross section of earnings. The patterns are remarkably similar to those reported in Figures 3 and 4 for the baseline model. The one notable difference is that the effect of an unemployment shock on the variance of the first difference of earnings is more persistent in the multinomial model.

Table C.II reports the decomposition of the variance of lifetime earnings, wages, and hours. Qualitatively, the results are similar to those for the baseline



(a) Log earnings response



(b) Log wage response

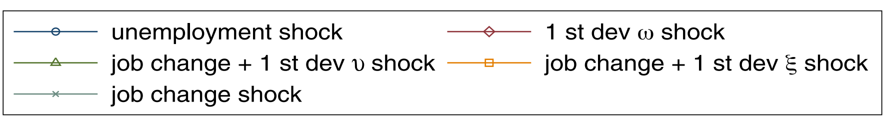
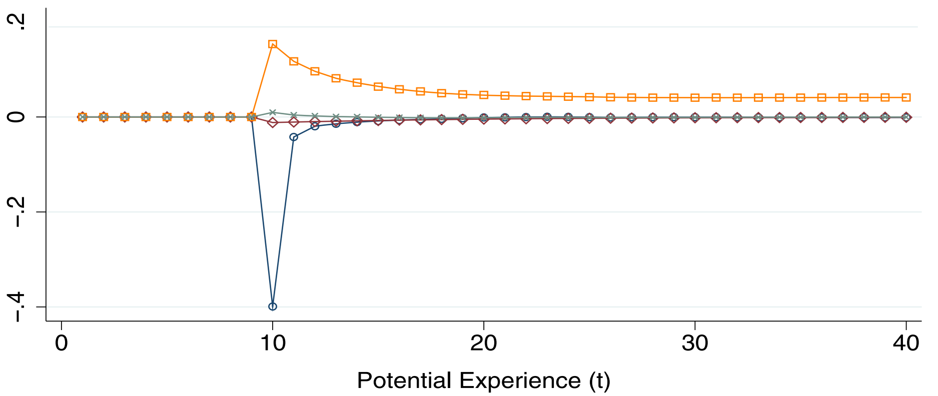


FIGURE C.2.—Mean response of key variables to various shocks at $t = 10$. Multinomial model, full sample. The figure displays the response of the mean of log earnings, log wage, and log hours to various shocks that are imposed when potential experience $t = 10$. The shocks are an unemployment shock, a job change shock, a one-standard-deviation shock to the autoregressive component of wages, a job change shock accompanied by a one-standard-deviation shock to the job-specific wage component, and a job change shock accompanied by a one-standard-deviation shock to the job-specific hours component. To construct the point estimates, we first use the model to simulate a large number of individuals through $t = 9$. We then impose the shock indicated in the figures in period 10 on all individuals. After that, we continue the simulation in accordance with the model. The panels in the figure show the mean paths of log earnings, log wages, and log hours relative to the base case. The base case represents the mean of the simulated paths in the absence of the specified intervention in period 10. (*Continues*)



(c) Log hours response

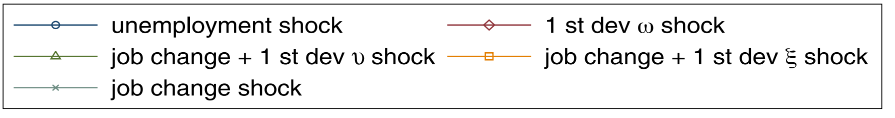
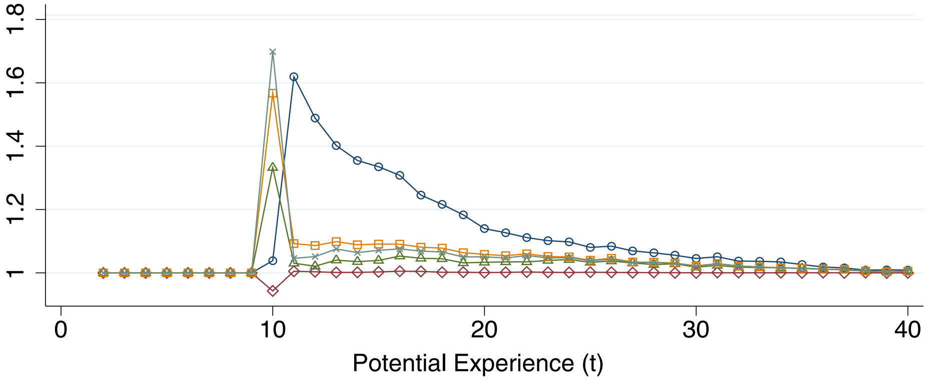


FIGURE C.2.—*Continued*.



(a) Response of cross-sectional variance of the first difference of log earnings to various shocks at $t = 10$

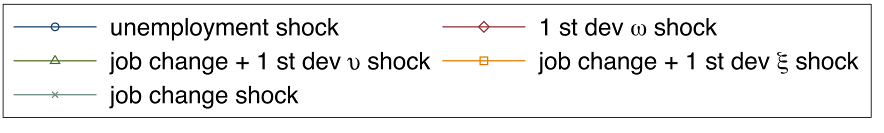
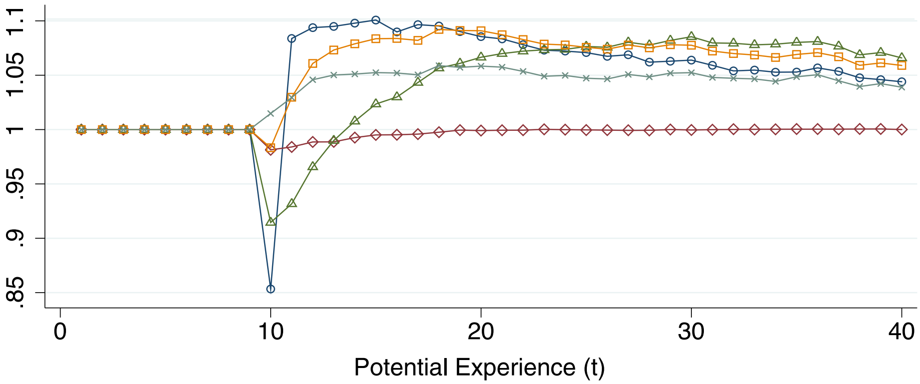


FIGURE C.3.—Multinomial model, full sample. Panel (a) in the figure displays the response of the ratio of $\text{Var}(\text{earn}_{it} - \text{earn}_{i,t-1})$ to the baseline variance for the model, to various shocks that are imposed when potential experience $t = 10$. See note in Figure 3. Panel (b) displays the response of the ratio of $\text{Var}(\text{earn}_{it})$ to the baseline variance for the model. (*Continues*)



(b) Response of cross-sectional variance of log earnings to various shocks at $t = 10$

FIGURE C.3.—*Continued*.

TABLE C.II

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN LIFETIME EARNINGS, WAGE, AND HOURS (IN LEVELS). MULTINOMIAL SPECIFICATION, FULL SRC SAMPLE[a]

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	Contribution to Variance							Breakdown of 'Composite'			
Variable	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC
Lifetime Earnings	**5.2**	**1.8**	**10.1**	**28.1**	**1.4**	**24.5**	**28.9**	**8.0**	**19.8**	**0.7**	**−0.4**
	(0.2)	(0.1)	(0.9)	(2.2)	(1.7)	(3.6)	(1.9)	(1.5)	(1.8)	(0.5)	(0.2)
Lifetime Wage	**0**	**0**	**17.3**	**35.6**	**−2.0**	**14.6**	**34.6**	**0**	**35.0**	**0.7**	**−0.1**
	(0.0)	(0.0)	(1.5)	(2.6)	(0.8)	(4.5)	(3.1)	(0.0)	(2.7)	(0.6)	(0.3)
Lifetime Hours	**0**	**3.6**	**1.2**	**53.6**	**17.0**	**22.4**	**2.1**	**49.4**	**1.6**	**2.4**	**0.2**
	(0.0)	(0.2)	(0.3)	(9.7)	(8.4)	(6.1)	(0.6)	(9.5)	(0.6)	(0.5)	(0.1)

[a]Entries in columns I to VII display the contribution of a given type of shock to the variance of lifetime earnings, wage, and hours, and are expressed as a percentage of the lifetime variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of a given shock to zero for all t. We then compute the variance of the appropriate variables. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We normalize columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon^{\omega}_{it}$. Column IV is the combined contribution of the job match wage and hours components, employment and unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII shows the marginal contribution of ξ, IX the marginal contribution of υ with Var(ξ) set to 0, X the marginal contribution of unemployment spells with Var(ξ) and Var(υ) set to 0, and column XI displays the marginal contribution of job changes with Var(ξ) and Var(υ) set to 0, and no unemployment. The variance of the levels of lifetime earnings, wages, and hours are 579,719; 87,614; and 242,496,503, respectively. Bootstrap standard errors are in parentheses.

TABLE C.III

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN EARNINGS, WAGE, AND HOURS IN LEVELS AT DIFFERENT t (POTENTIAL EXPERIENCE). MULTINOMIAL SPECIFICATION, FULL SRC SAMPLE[a]

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Variable/Potential	Contribution to Variance							Breakdown of 'Composite'				
Experience	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC	Variance
Earnings												
$t=1$	**11.1**	**7.6**	**26.0**	**10.9**	**1.3**	**21.0**	**22.1**	**8.4**	**1.7**	**0.8**	**0**	123.84
	(0.4)	(0.3)	(3.1)	(1.6)	(0.8)	(3.4)	(1.2)	(1.5)	(0.3)	(0.1)	(0.0)	
$t=5$	**14.0**	**6.5**	**18.0**	**21.1**	**2.6**	**16.7**	**21.0**	**7.9**	**14.9**	**−0.3**	**−1.4**	271.60
	(0.5)	(0.3)	(1.7)	(1.7)	(1.1)	(3.0)	(1.2)	(1.4)	(1.3)	(0.6)	(0.2)	
$t=10$	**15.8**	**6.8**	**14.3**	**23.8**	**1.8**	**17.1**	**20.4**	**7.6**	**17.7**	**−0.1**	**−1.4**	468.34
	(0.6)	(0.4)	(1.2)	(1.8)	(1.2)	(2.8)	(1.2)	(1.4)	(1.5)	(0.6)	(0.2)	
$t=20$	**15.1**	**7.4**	**13.4**	**26.1**	**0.8**	**16.6**	**20.5**	**7.8**	**18.6**	**0.3**	**−0.6**	742.39
	(0.8)	(0.4)	(1.1)	(1.8)	(1.2)	(2.8)	(1.2)	(1.4)	(1.6)	(0.4)	(0.2)	
$t=30$	**14.7**	**7.0**	**12.5**	**27.6**	**1.8**	**16.1**	**20.2**	**7.1**	**20.4**	**0.4**	**−0.2**	783.72
	(0.6)	(0.4)	(1.1)	(1.9)	(1.2)	(2.9)	(1.3)	(1.4)	(1.7)	(0.3)	(0.1)	
$t=40$	**15.1**	**6.6**	**12.9**	**28.3**	**1.1**	**15.7**	**20.3**	**7.7**	**20.5**	**0.1**	**−0.1**	778.11
	(0.7)	(0.4)	(1.1)	(2.0)	(1.4)	(2.9)	(1.2)	(1.5)	(1.8)	(0.2)	(0.1)	
Wage												
$t=1$	**0**	**0**	**52.4**	**3.4**	**0**	**16.4**	**27.7**	**0**	**3.4**	**0**	**0**	16.67
	(0.0)	(0.0)	(4.9)	(0.6)	(0.0)	(4.8)	(1.4)	(0.0)	(0.6)	(0.0)	(0.0)	
$t=5$	**0**	**0**	**35.4**	**25.7**	**0.2**	**12.1**	**26.6**	**0**	**28.1**	**−1.1**	**−1.3**	35.08
	(0.0)	(0.0)	(3.0)	(1.8)	(0.5)	(3.6)	(1.6)	(0.0)	(2.1)	(0.7)	(0.3)	
$t=10$	**0**	**0**	**29.0**	**32.8**	**−0.3**	**11.8**	**26.7**	**0**	**34.4**	**−0.5**	**−1.0**	57.49
	(0.0)	(0.0)	(2.3)	(2.2)	(0.6)	(3.5)	(2.0)	(0.0)	(2.3)	(0.7)	(0.4)	
$t=20$	**0**	**0**	**26.0**	**38.1**	**−1.9**	**11.2**	**26.6**	**0**	**37.7**	**0.6**	**−0.1**	89.34
	(0.0)	(0.0)	(2.1)	(2.7)	(0.7)	(3.6)	(2.2)	(0.0)	(2.7)	(0.6)	(0.3)	
$t=30$	**0**	**0**	**24.0**	**40.2**	**−0.3**	**10.1**	**26.1**	**0**	**39.1**	**0.9**	**0.1**	100.29
	(0.0)	(0.0)	(1.9)	(2.7)	(0.6)	(3.6)	(2.1)	(0.0)	(2.7)	(0.4)	(0.2)	
$t=40$	**0**	**0**	**24.9**	**40.5**	**−1.1**	**8.8**	**26.8**	**0**	**40.0**	**0.5**	**0.1**	108.25
	(0.0)	(0.0)	(2.0)	(2.9)	(0.8)	(3.7)	(2.2)	(0.0)	(2.9)	(0.3)	(0.1)	

(*Continues*)

model, in that shocks associated with employment and job mobility play a very large role. They account for 28.1%, 35.6%, and 53.6% of the variance of lifetime earnings, lifetime wage rates, and lifetime hours. These values are large, but are smaller than the baseline estimates. On the other hand, the permanent heterogeneity components η and especially μ play a more important role than in the baseline model, with μ accounting for 24.5% of the variance in earnings and 14.6% of the variance in wages. The larger contributions of μ stem from the fact that the factor loading δ_μ^w is larger in the multinomial model than in the baseline model. The combined variance contribution of η, μ, EDUC, and the initial draw ω_{i1} of ω_{it} and υ_{i1} of υ_{it} are 69.7% for lifetime earnings, 58.4% for lifetime wages, and 42.8% for lifetime hours.

TABLE C.III—*Continued*

Variable/Potential Experience	I ε^e	II ε^h	III ε^ω	IV Composite	V η	VI μ	VII EDUC	VIII ξ	IX υ	X E	XI JC	XII Variance
	Contribution to Variance							Breakdown of 'Composite'				
Hours												
$t = 1$	**0**	**32.8**	**2.0**	**44.7**	**7.0**	**10.6**	**2.9**	**34.2**	**0.1**	**10.5**	**0**	354,084.41
	(0.0)	(1.4)	(0.4)	(5.8)	(3.6)	(2.7)	(0.3)	(5.8)	(0.0)	(0.3)	(0.0)	
$t = 5$	**0**	**33.2**	**1.5**	**46.3**	**9.6**	**8.4**	**0.9**	**35.7**	**0.2**	**10.0**	**0.3**	361,004.01
	(0.0)	(1.5)	(0.4)	(5.8)	(3.8)	(2.8)	(0.3)	(5.9)	(0.3)	(1.0)	(0.1)	
$t = 10$	**0**	**34.1**	**1.7**	**44.8**	**9.5**	**9.5**	**0.5**	**37.0**	**0.5**	**7.0**	**0.4**	373,114.49
	(0.0)	(1.4)	(0.4)	(5.7)	(3.8)	(2.8)	(0.3)	(5.8)	(0.4)	(0.6)	(0.1)	
$t = 20$	**0**	**34.7**	**1.0**	**44.3**	**8.9**	**10.4**	**0.7**	**37.9**	**0.8**	**5.4**	**0.2**	367,520.10
	(0.0)	(1.6)	(0.4)	(6.1)	(4.0)	(3.0)	(0.4)	(6.2)	(0.5)	(0.6)	(0.1)	
$t = 30$	**0**	**35.1**	**1.5**	**42.0**	**9.6**	**10.6**	**1.3**	**38.3**	**1.1**	**2.4**	**0.1**	339,353.11
	(0.0)	(1.7)	(0.4)	(6.2)	(4.0)	(2.9)	(0.4)	(6.3)	(0.5)	(0.6)	(0.1)	
$t = 40$	**0**	**36.6**	**1.3**	**41.8**	**8.9**	**10.7**	**0.7**	**40.5**	**1.0**	**0.3**	**0.0**	304,171.22
	(0.0)	(1.6)	(0.4)	(6.4)	(4.1)	(3.0)	(0.4)	(6.5)	(0.5)	(0.5)	(0.0)	

[a]Entries in columns I to VII display the contribution of a given type of shock to the variance in earnings, wage, and hours for a cross section of simulated individuals with potential experience t. The contribution is expressed as a percentage of the variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of the given shock to zero for all t. We then compute the variance of the appropriate variables at the specified value of t. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We have normalized columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon_{it}^{\omega}$. Column IV is the combined contribution of the job match wage and hours components, unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII is the marginal contribution of ξ, IX is the marginal contribution of υ with Var(ξ) set to 0, X is the marginal contribution of eliminating unemployment spells with Var(ξ) and Var(υ) set to 0, and column XI is the marginal contribution of job changes with Var(ξ) and Var(υ) set to 0, and no unemployment. Column XII is the cross-sectional variance of simulated earnings, wage, and hours, across individuals with potential experience t. Bootstrap standard errors are in parentheses.

APPENDIX D: CHOICE OF VALUES FOR THE VARIANCE OF MEASUREMENT ERROR IN WAGES, HOURS, AND EARNINGS

In this appendix, we discuss our choice of values for σ_{mw}, σ_{mh}, and σ_{me}, the standard deviations of the measurement error (ME) components in wages, hours, and earnings. We begin with σ_{mw}. Using PSID data, Altonji and Devereux (2000) estimated a measurement error model that assumes that people report the true value with probability p and the true value plus a normally distributed measurement error with probability $(1 - p)$.[53] The analysis is restricted to workers who are paid by the hour. They reported results for a sample that includes blacks and whites, union and nonunion members, and men and

[53]Their focus was on whether wages within a job match are subject to downward nominal wage rigidity rather than on the dynamics of earnings, wages, and hours over a career. One could incorporate their alternative specifications of downward nominal wage rigidity within a job into the wage model used in this paper, but we have not pursued this.

women. Using their preferred estimation method, $\sigma_{mw} = 0.045$, which is not sensitive to model specification. This estimate implies that ME accounts for 51% of the variance of wage changes of stayers. In our sample, the variance of wage growth for all observations is 1.32 times the variance for stayers. Consequently, Altonji and Devereux's estimate implies that measurement error accounts for about 38.6% (51.0/1.32) of $\text{Var}(\text{wage}^*_{i,t+1} - \text{wage}^*_{it})$. For a sample of white nonunion men who are paid hourly, their estimate is $\sigma_{mw} = 0.03898$, which accounts for 36% of $\text{Var}(\text{wage}^*_{i,t+1} - \text{wage}^*_{it})$ for job stayers. This would translate into about 27% of $\text{Var}(\text{wage}^*_{i,t+1} - \text{wage}^*_{it})$. The estimates are a little higher when they assume classical measurement error rather than assuming that the responses are a mixture of correct responses and the true values plus measurement error.

However, Altonji and Devereux trimmed their sample by eliminating the bottom and top 1% of wage change observations for stayers. This is more stringent than restricting $\text{wage}^*_{i,t+1} - \text{wage}^*_{it}$ to fall between log(0.2) and log(5), as we do. When they did not trim, their estimate of σ_{mw} rose to .1095, which would account for about 50% of $\text{Var}(\text{wage}^*_{i,t+1} - \text{wage}^*_{it})$. We believe that σ_{mw} and the percentage of the variance accounted for by measurement error would be smaller in our sample given that we do trim.

Bound et al. (2001) surveyed a number of papers on measurement error that used matched data on survey responses and firm or government administrative data. That literature does not provide clear guidance about the measurement error in a reported wage measure such as the one we use. However, Bound, Brown, Duncan, and Rodgers (1994) found that measurement error accounts for 30.2% of the variance in the 4-year first difference in the log of earnings divided by hours. Measurement error in this variable is likely to be larger than measurement error in reported wages. Taken together, the evidence from Altonji and Devereux and Bound et al. (1994) suggests that measurement error accounts for about 35% of $\text{Var}(w^*_{i,t+1} - w^*_{it})$, which is the point estimate we use. The associated value of σ_{mw} is .0843.

We also experimented with alternative estimates based on our own analysis of the PSID. The evidence is based on the equation

$$\text{earn}^*_{it} = \alpha_0 + \alpha_1 \text{wage}^*_{it} + \alpha_2 \text{hours}^*_{it} + \text{error}_{it}.$$

In the full SRC sample, the OLS estimates of α_1 and α_2 are .9418 (.0036) and .7661 (.0073), respectively. If one estimates the above regression by 2SLS using $\text{wage}^*_{i,t-2}$ and $\text{hours}^*_{i,t-2}$ as the instruments for wage^*_{it} and hours^*_{it}, the coefficient estimates are .9980 (.0048) and 1.0059 (.0225), which is fully consistent with imposing the coefficients of 1.0 as well as the presence of measurement error. Using the covariances and variances underlying the OLS regression, we solved for the values of σ_{mw} and σ_{mh} that explain the discrepancy between the OLS regression coefficients and coefficients of 1. The values are $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.121$. An analysis based on the relationship between $[\text{earn}^*_{it} - \text{earn}^*_{i,t-2}]$ and $[\text{wage}^*_{it} - \text{wage}^*_{i,t-2}]$ implies a similar estimate of σ_{mw}.

It is possible that the true coefficient relating earn^*_{it} to wage^*_{it} differs slightly from 1. For this reason, we also estimated σ_{mw} as the amount of measurement error required to explain the difference between the OLS and 2SLS estimates of the regression coefficient relating earn^*_{it} to wage^*_{it}, where we use the lag of wage^*_{it} as the instrument. The OLS and IV coefficient estimates are .9594 (.0043) and 1.019 (.0047), respectively, and the implied estimate of σ_{mw} is .116. We also experiment with this value.

Turning to hours, Bound et al. (1994) found that measurement error contributes about 23% of the variance in the change in log annual hours. We used 25%, which implies that σ_{mh} is .0982. We also experiment with the value implied by the regression of earn^*_{it} on wage^*_{it} and hours^*_{it} discussed above, which is $\sigma_{mh} = 0.121$.

In the case of log earnings, the evidence cited in Bound et al. (2001) suggests that the measurement error accounts for about 25% of $\text{Var}(\text{earn}^*_{it} - \text{earn}^*_{i,t-1})$, which corresponds to $\sigma_{me} = 0.122$. This is the value we use. Changing this value alters the estimate of persistence of the earnings error component and the variance of the innovation in e_{it}, but has little effect on the other parameters in the model.

Results for Alternative Values of σ_{mw} and σ_{mh}

The columns of Table D.I report estimates of the model for alternative values of σ_{mw} and σ_{mh}. The values used in each case are given at the top of each column. To facilitate comparison, we also display the estimates and standard errors for our base case assumptions of $\sigma_{mw} = 0.0843$ and $\sigma_{mh} = 0.0982$ in columns Ia and Ib. We focus our discussion on the case $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.121$, which is the most different from the base case values we use. Relative to the standard errors, the changes in the parameters of the EE, UE, JC, earnings, and hours equations are minor. There are some offsetting differences in the linear and quadratic terms of the potential experience polynomials in the EE, UE, and JC equations. The parameters of the wage equation are also insensitive to the measurement error assumptions, with four important exceptions. The coefficient δ^w_μ on the productivity component μ_i falls from .081 (.035) for the parameter values we chose to .017 when we use the high values of $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.121$. The decline in the importance of the fixed heterogeneity term is accompanied by an increase in ρ_v from .691 (.049) to .782, an increase in σ_{v1} from .165 to .243, a decline in σ_ω from .089 (.005) to .033, and a decline in the values of $\sigma_{\omega 1}$ for the four race-education categories. The net effect of these changes is to reduce the role of the permanent productivity component and the persistent wage component ω_{it} in the variation of wages across people and the persistence over time. Given that we do not find evidence of a unit root in the wage process, a value close to 0 for δ^w_μ is implausible. For example, the substantial correlation across siblings and between parents and children in wage rates conditional on education and race points to a large fixed heterogeneity component that is correlated across siblings and across genera-

TABLE D.I

ESTIMATES OF BASELINE MODEL UNDER ALTERNATIVE MEASUREMENT ERROR ASSUMPTIONS[a]

		Ia	Ib	II	III	IV	V	VI
		Basecase		Point Estimates Under Alternative Measurement Error Assumptions				
Equation/Variable	Parameter	$\sigma_{mw} = 0.0843$, $\sigma_{mh} = 0.0982$		$\sigma_{mw} = 0.1160$, $\sigma_{mh} = 0.0982$	$\sigma_{mw} = 0.1300$, $\sigma_{mh} = 0.0982$	$\sigma_{mw} = 0.0843$, $\sigma_{mh} = 0.1210$	$\sigma_{mw} = 0.1160$, $\sigma_{mh} = 0.1210$	$\sigma_{mw} = 0.1300$, $\sigma_{mh} = 0.1210$
E-E Equation								
constant	γ_0^{EE}	1.389	(0.243)	1.346	1.420	1.402	1.234	1.571
$(t-1)/10$	γ_t^{EE}	−0.252	(0.154)	−0.515	−0.202	−0.259	−0.238	−0.329
$(t-1)^2/100$	γ_{t2}^{EE}	0.108	(0.039)	0.199	0.113	0.111	0.120	0.146
$\min(\text{ED}_{t-1}, 9)$	γ_{ED}^{EE}	0.028	(0.025)	0.036	0.066	0.027	0.046	0.049
BLACK	$\gamma_{\text{BLACK}}^{EE}$	−0.158	(0.115)	−0.239	−0.115	−0.152	−0.194	−0.197
EDUC	$\gamma_{\text{EDUC}}^{EE}$	0.055	(0.015)	0.061	0.017	0.055	0.046	0.022
wage_t^s	$\gamma_{w^s}^{EE}$	0.071	(0.118)	0.123	0.092	0.077	0.172	0.140
μ	δ_μ^{EE}	0.298	(0.121)	0.248	0.292	0.301	0.292	0.233
η	δ_η^{EE}	−0.481	(0.103)	−0.435	−0.307	−0.487	−0.357	−0.372
U-E Equation								
constant	γ_0^{UE}	1.597	(0.487)	0.878	1.472	1.648	1.506	1.631
$(t-1)/10$	γ_t^{UE}	−1.244	(0.564)	−0.378	−1.267	−1.271	−0.956	−1.125
$(t-1)^2/100$	γ_{t2}^{UE}	0.335	(0.176)	0.081	0.342	0.341	0.271	0.449
BLACK	$\gamma_{\text{BLACK}}^{UE}$	−0.046	(0.229)	0.227	0.104	−0.057	−0.024	−0.123
EDUC	$\gamma_{\text{EDUC}}^{UE}$	0.027	(0.030)	0.032	0.044	0.026	0.018	−0.005
μ	δ_μ^{UE}	0.308	(0.176)	0.344	0.354	0.312	0.349	0.349
η	δ_η^{UE}	0.106	(0.176)	0.142	0.083	0.106	0.141	0.041

(*Continues*)

TABLE D.I—*Continued*

		Ia	Ib	II	III	IV	V	VI
		Basecase		Point Estimates Under Alternative Measurement Error Assumptions				
Equation/Variable	Parameter	$\sigma_{mw} = 0.0843$ $\sigma_{mh} = 0.0982$		$\sigma_{mw} = 0.1160$ $\sigma_{mh} = 0.0982$	$\sigma_{mw} = 0.1300$ $\sigma_{mh} = 0.0982$	$\sigma_{mw} = 0.0843$ $\sigma_{mh} = 0.1210$	$\sigma_{mw} = 0.1160$ $\sigma_{mh} = 0.1210$	$\sigma_{mw} = 0.1300$ $\sigma_{mh} = 0.1210$
JC Equation								
constant	γ_0^{JC}	−0.498	(0.218)	−0.587	−0.619	−0.511	−0.377	−0.678
$(t-1)/10$	γ_t^{JC}	−0.058	(0.187)	−0.147	−0.204	−0.010	−0.179	−0.057
$(t-1)^2/100$	γ_{t2}^{JC}	−0.072	(0.050)	−0.024	−0.004	−0.086	−0.013	−0.036
TEN_{t-1}	$\gamma_{\text{TEN}}^{\text{JC}}$	−0.066	(0.023)	−0.089	−0.095	−0.068	−0.097	−0.108
BLACK	$\gamma_{\text{BLACK}}^{\text{JC}}$	0.030	(0.111)	−0.107	−0.243	0.020	−0.051	−0.191
EDUC	$\gamma_{\text{EDUC}}^{\text{JC}}$	−0.022	(0.013)	−0.004	0.002	−0.022	−0.016	0.005
$\upsilon_{j(t-1)}$	$\delta_{\upsilon j(t-1)}^{\text{JC}}$	−0.833	(0.154)	−0.687	−0.720	−0.819	−0.730	−0.689
$\upsilon'_{j'(t)}$	$\delta_{\upsilon' j'(t)}^{\text{JC}}$	0.496	(0.132)	0.442	0.488	0.481	0.507	0.478
μ	δ_{μ}^{JC}	−0.067	(0.127)	0.010	−0.039	−0.058	−0.035	0.009
η	$\delta_{\eta}^{\text{JC}}$	0.539	(0.110)	0.398	0.424	0.523	0.380	0.307

(*Continues*)

TABLE D.I—*Continued*

Equation/Variable		Ia	Ib	II	III	IV	V	VI
		Basecase		Alternative Measurement Error Assumptions				
		$\sigma_{mw} = 0.0843$ $\sigma_{mh} = 0.0982$		$\sigma_{mw} = 0.1160$ $\sigma_{mh} = 0.0982$	$\sigma_{mw} = 0.1300$ $\sigma_{mh} = 0.0982$	$\sigma_{mw} = 0.0843$ $\sigma_{mh} = 0.1210$	$\sigma_{mw} = 0.1160$ $\sigma_{mh} = 0.1210$	$\sigma_{mw} = 0.1300$ $\sigma_{mh} = 0.1210$
Wage Equation								
constant		0.001	(0.055)	0.020	0.002	0.001	0.001	0.001
$(t-1)/10$	γ_t^w	0.642	(0.049)	0.652	0.645	0.645	0.648	0.649
$(t-1)^2/1000$	γ_{t2}^w	−2.071	(0.269)	−2.110	−2.155	−2.084	−2.136	−2.150
$(t-1)^3/100{,}000$	γ_{t3}^w	2.249	(0.438)	2.286	2.452	2.265	2.347	2.393
BLACK	γ_{BLACK}^w	−0.224	(0.029)	−0.212	−0.218	−0.224	−0.215	−0.212
EDUC	γ_{EDUC}^w	0.105	(0.004)	0.104	0.106	0.105	0.106	0.106
μ	δ_μ^w	0.081	(0.035)	0.036	0.039	0.072	0.013	0.017
v_{t-1}	ρ_v	0.691	(0.049)	0.767	0.781	0.697	0.769	0.782
ε^v	σ_v	0.276	(0.009)	0.270	0.265	0.277	0.269	0.267
ε_1^v	σ_{v1}	0.165	(0.016)	0.239	0.252	0.173	0.239	0.243
ω_{t-1}	ρ_ω[b]	0.908	(0.025)	0.908	0.908	0.908	0.908	0.908
$1-E_t$	γ_{1-Et}^ω	−0.134	(0.013)	−0.130	−0.130	−0.134	−0.126	−0.131
$1-E_{t-1}$	γ_{1-Et-1}^ω	0.049	(0.017)	0.033	0.033	0.048	0.029	0.033
ε^ω	σ_ω	0.089	(0.005)	0.055	0.035	0.088	0.054	0.033
ε_1^ω (Black, Low Education)	$\sigma_{\omega 1}$[b,d]	0.160	(0.055)	0.100	0.100	0.156	0.100	0.100
ε_1^ω (Black, High Education)	$\sigma_{\omega 1}$[b]	0.241	(0.050)	0.166	0.130	0.239	0.169	0.152
ε_1^ω (White, Low Education)	$\sigma_{\omega 1}$[b]	0.263	(0.023)	0.196	0.167	0.261	0.199	0.184
ε_1^ω (White, High Education)	$\sigma_{\omega 1}$[b]	0.319	(0.018)	0.267	0.246	0.317	0.269	0.258

(*Continues*)

TABLE D.I—*Continued*

Equation/Variable		Ia	Ib	II	III	IV	V	VI
		Basecase		Alternative Measurement Error Assumptions				
		$\sigma_{mw}=0.0843$ $\sigma_{mh}=0.0982$		$\sigma_{mw}=0.1160$ $\sigma_{mh}=0.0982$	$\sigma_{mw}=0.1300$ $\sigma_{mh}=0.0982$	$\sigma_{mw}=0.0843$ $\sigma_{mh}=0.1210$	$\sigma_{mw}=0.1160$ $\sigma_{mh}=0.1210$	$\sigma_{mw}=0.1300$ $\sigma_{mh}=0.1210$
Hours Equation								
constant	γ_0^h	−0.454	(0.015)	−0.446	−0.449	−0.449	−0.445	−0.447
$(t-1)/10$	γ_t^h	0.091	(0.025)	0.085	0.071	0.089	0.073	0.076
$(t-1)^2/1000$	γ_{t2}^h	−0.303	(0.138)	−0.283	−0.224	−0.294	−0.248	−0.277
$(t-1)^3/100{,}000$	γ_{t3}^h	0.200	(0.225)	0.171	0.086	0.186	0.142	0.191
BLACK	$\gamma_{\mathrm{BLACK}}^h$	−0.054	(0.015)	−0.052	−0.055	−0.054	−0.052	−0.054
EDUC	γ_{EDUC}^h	0.011	(0.002)	0.010	0.011	0.011	0.011	0.011
E_t	γ_E^h	0.430	(0.011)	0.425	0.424	0.426	0.419	0.418
ε^ξ	σ_ξ	0.162	(0.013)	0.176	0.181	0.166	0.180	0.185
$\mathrm{wage}_t^{\mathrm{lat}}$	γ_w^h	−0.084	(0.016)	−0.032	−0.026	−0.070	−0.003	0.013
μ	δ_μ^h	0.098	(0.018)	0.074	0.068	0.092	0.065	0.059
η	δ_η^h	−0.012	(0.024)	−0.018	−0.008	−0.014	−0.009	−0.017
ε^h	σ_h	0.141	(0.003)	0.139	0.138	0.128	0.125	0.123
Earnings Equation								
constant	γ_0^e	−0.018	(0.001)	−0.012	−0.010	−0.007	−0.005	−0.007
$\mathrm{wage}_t^{\mathrm{lat}}$	$\gamma_w^{e\,\mathrm{c}}$	1.000		1.000	1.000	1.000	1.000	1.000
hours_t	$\gamma_h^{e\,\mathrm{c}}$	1.000		1.000	1.000	1.000	1.000	1.000
e_t	ρ_e	0.624	(0.009)	0.637	0.634	0.645	0.661	0.652
ε^e	σ_e	0.169	(0.002)	0.164	0.164	0.161	0.155	0.156

[a]The table presents estimation results for our baseline model estimated on the full SRC sample under alternative measurement error assumptions for wages and hours. Columns Ia and Ib reproduce our basecase estimates from Table IV for comparison (standard errors in parentheses). The alternative assumptions for measurement error are indicated in the corresponding column heading. Estimates were obtained by Indirect Inference, unless indicated otherwise.

[b]Estimate obtained using additional moment conditions. See discussion in Section 4.

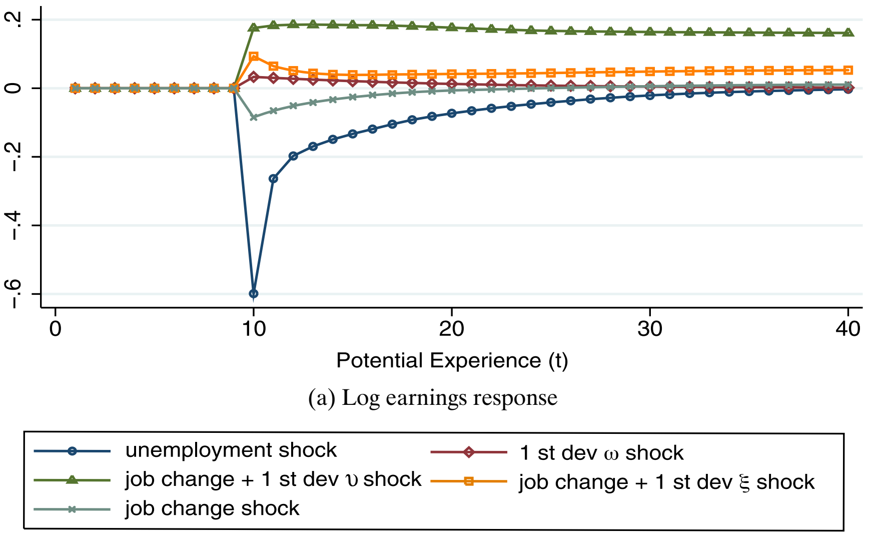
[c]Imposed.

[d]The value $0.10=\mathrm{sqrt}(0.01)$ is the smallest value allowed in the optimization routine that estimates the model parameters.

tions.[54] Furthermore, when $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.121$ are used, the lower bound of $\sigma^2_{\omega 1} \geq .01$ is binding for less educated blacks. For both reasons, we prefer the base case value for σ_{mw}.

A comparison of the estimates using $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.098$ (column III) and $\sigma_{mw} = 0.0843$ and $\sigma_{mh} = 0.121$ (column IV) with the base case establishes that the use of the higher value of σ_{mw} is primarily responsible for differences in the model estimates. This is not surprising given the structure of the model. The higher value for σ_{mh} does lead to a small drop in the standard deviation of the i.i.d. hours shock ε^h_{it}.

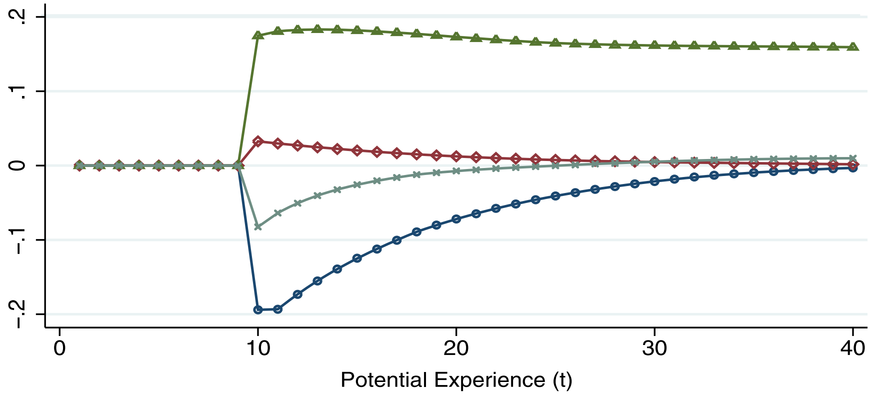
Figure D.1 reports impulse responses of earnings, wages, and hours to various shocks when the high values $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.121$ are used. They



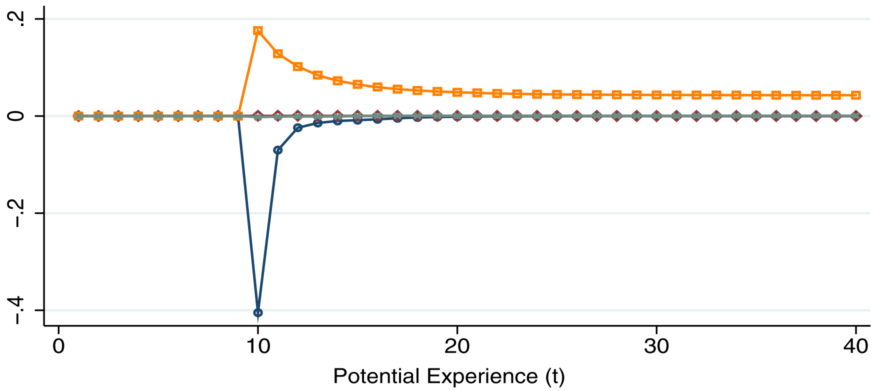
(a) Log earnings response

FIGURE D.1.—Mean response of key variables to various shocks at $t = 10$. Baseline model under alternative measurement error assumptions. The figure displays the response of the mean of log earnings, log wage, and log hours to various shocks that are imposed when potential experience $t = 10$. The shocks are an unemployment shock, a job change shock, a one-standard-deviation shock to the autoregressive component of wages, a job change shock accompanied by a one-standard-deviation shock to the job-specific wage component, and a job change shock accompanied by a one-standard-deviation shock to the job-specific hours component. To construct the point estimates, we first use the model to simulate a large number of individuals through $t = 9$. We then impose the shock indicated in the figures in period 10 on all individuals. After that, we continue the simulation in accordance with the model. The panels in the figure show the mean paths of log earnings, log wages, and log hours relative to the base case. The base case represents the mean of the simulated paths in the absence of the specified intervention in period 10. This figure is based on the alternative measurement error assumptions $\sigma^2_{mw} = 0.1300^2$, $\sigma^2_{mh} = 0.1210^2$. (*Continues*)

[54]Solon (1999) and Black and Devereux (2011) surveyed the literature on family correlations in economic outcomes.



(b) Log wage response



(c) Log hours response

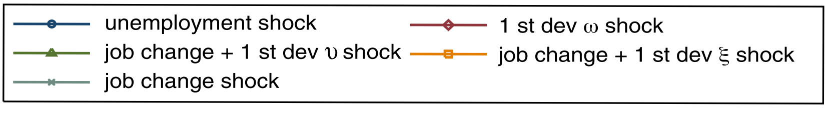


FIGURE D.1.—*Continued*.

are almost indistinguishable from Figure 3, with the exception that the effect of a one-standard-deviation shock to ω_{it} is smaller. This difference is a direct reflection of the larger value for σ_ω in the base case. The response of the cross-sectional variance of earn^*_{it} and $\text{earn}^*_{it} - \text{earn}^*_{i,t-1}$ to various shocks is not very sensitive to the measurement error assumptions (compare Figure D.2 to Figure 4).

Table D.II reports the variance decomposition of lifetime earnings, wages, and hours when $\sigma_{mw} = 0.130$ and $\sigma_{mh} = 0.121$ (Table D.III reports decompositions by t). The main difference with the results using our preferred estimates of σ_{mw} and σ_{mh} (Table VI.A) is that the shocks related to job mobility and em-

TABLE D.II

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN LIFETIME EARNINGS, WAGE, AND HOURS (IN LEVELS). BASELINE MODEL, FULL SRC SAMPLE, UNDER ALTERNATIVE MEASUREMENT ERROR ASSUMPTION ($\sigma^2_{mw} = 0.1300^2$, $\sigma^2_{mh} = 0.1210^2$)[a]

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	Contribution to Variance							Breakdown of 'Composite'			
Variable	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC
Lifetime Earnings	5.5	1.3	2.9	59.3	−2.5	3.9	29.6	10.8	48.5	0.8	−0.8
Lifetime Wage	0	0	4.0	64.7	−2.5	0.4	33.4	0	65.3	0.3	−0.9
Lifetime Hours	0	2.7	0.1	76.3	2.1	15.8	3.0	72.7	0.0	3.6	0.0

[a]Entries in columns I to VII display the contribution of a given type of shock to the variance of lifetime earnings, wage, and hours, and are expressed as a percentage of the lifetime variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of a given shock to zero for all t. We then compute the variance of the appropriate variables. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We normalize columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon^{\omega}_{it}$. Column IV is the combined contribution of the job match wage and hours components, employment and unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII shows the marginal contribution of ξ, IX the marginal contribution of υ with $\mathrm{Var}(\xi)$ set to 0, X the marginal contribution of unemployment spells with $\mathrm{Var}(\xi)$ and $\mathrm{Var}(\upsilon)$ set to 0, and column XI displays the marginal contribution of job changes with $\mathrm{Var}(\xi)$ and $\mathrm{Var}(\upsilon)$ set to 0, and no unemployment.

TABLE D.III

DECOMPOSITION OF CROSS-SECTIONAL VARIANCE IN EARNINGS, WAGE, AND HOURS IN LEVELS AT DIFFERENT t (POTENTIAL EXPERIENCE). BASELINE MODEL, FULL SRC SAMPLE, UNDER ALTERNATIVE MEASUREMENT ERROR ASSUMPTION ($\sigma^2_{mw} = 0.1300^2$, $\sigma^2_{mh} = 0.1210^2$)[a]

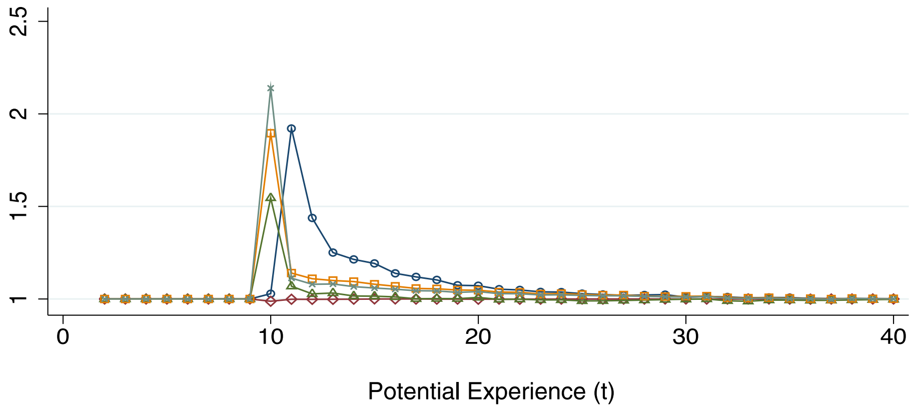
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	Contribution to Variance							Breakdown of 'Composite'			
Variable/Potential Experience	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC
Earnings											
$t = 1$	9.4	5.8	25.6	33.2	0.3	2.5	23.1	12.1	20.3	0.8	0
$t = 5$	14.0	4.8	12.9	43.8	0.2	2.2	22.1	11.7	33.0	0.9	−1.8
$t = 10$	14.6	5.5	6.2	49.1	−0.5	3.2	21.9	10.8	39.1	1.0	−1.8
$t = 20$	14.5	5.4	2.8	54.2	−1.5	2.7	21.8	9.8	44.4	1.0	−0.9
$t = 30$	13.6	5.6	2.0	55.0	−0.1	3.2	20.7	10.9	44.1	0.3	−0.3
$t = 40$	13.8	5.3	1.7	54.6	1.4	2.5	20.7	10.7	44.0	0.0	−0.1
Wage											
$t = 1$	0	0	38.3	33.2	0	0.2	28.3	0	33.2	0	0
$t = 5$	0	0	19.7	52.1	−0.2	−0.2	28.6	0	53.6	0.3	−1.8
$t = 10$	0	0	9.9	61.0	−0.1	0.7	28.6	0	61.9	0.6	−1.5
$t = 20$	0	0	4.3	68.1	−1.2	0.6	28.2	0	67.7	1.1	−0.7
$t = 30$	0	0	3.2	68.5	0.2	0.5	27.6	0	68.2	0.5	−0.3
$t = 40$	0	0	3.2	67.7	1.5	0.7	26.8	0	67.7	0.1	−0.1

(*Continues*)

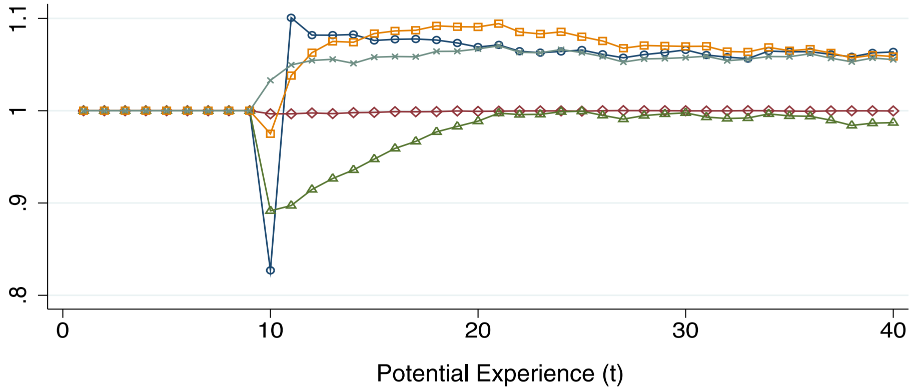
TABLE D.III—*Continued*

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	Contribution to Variance							Breakdown of 'Composite'			
Variable/Potential Experience	ε^e	ε^h	ε^ω	Composite	η	μ	EDUC	ξ	υ	E	JC
Hours											
$t = 1$	0	24.4	0.0	62.1	2.3	7.4	3.8	51.6	0.0	10.5	0
$t = 5$	0	25.4	0.1	63.2	2.1	7.9	1.4	55.7	0.0	7.5	0.0
$t = 10$	0	25.2	0.0	63.2	1.9	8.2	1.4	55.9	0.2	7.1	0.0
$t = 20$	0	26.1	0.0	62.7	1.7	8.1	1.4	56.7	0.0	6.0	0.0
$t = 30$	0	26.9	0.0	61.6	2.7	7.2	1.6	59.4	0.0	2.2	0.0
$t = 40$	0	27.5	0.1	63.2	0.3	7.1	1.8	62.7	0.1	0.4	0.0

[a]Entries in columns I to VII display the contribution of a given type of shock to the variance in earnings, wage, and hours for a cross section of simulated individuals with potential experience t. The contribution is expressed as a percentage of the variance in the basecase. In the basecase, we simulate the full estimated model. To compute the contribution of a particular shock, we simulate the model again, setting the variance of the given shock to zero for all t. We then compute the variance of the appropriate variables at the specified value of t. The difference relative to the basecase is the contribution of the given shock. Since the model is nonlinear, the contributions do not sum up to 100%. We have normalized columns I to VII to sum to 100. Column III is the combined contribution of the initial draw of ω_{i1} and the subsequent shocks $\varepsilon^{\omega}_{it}$. Column IV is the combined contribution of the job match wage and hours components, unemployment shocks, and job change shocks. In columns VIII through XI, we decompose column IV. Column VIII is the marginal contribution of ξ, IX is the marginal contribution of υ with Var(ξ) set to 0, X is the marginal contribution of eliminating unemployment spells with Var(ξ) and Var(υ) set to 0, and column XI is the marginal contribution of job changes with Var(ξ) and Var(υ) set to 0, and no unemployment.



(a) Response of cross-sectional variance of the first difference of log earnings to various shocks at $t = 10$



(b) Response of cross-sectional variance of log earnings to various shocks at $t = 10$

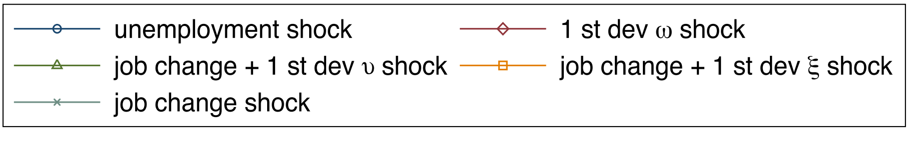


FIGURE D.2.—Baseline model under alternative measurement error assumptions. Panel (a) in the figure displays the response of the ratio of Var($\text{earn}_{it} - \text{earn}_{i,t-1}$) to the baseline variance for the model, to various shocks that are imposed when potential experience $t = 10$. See note in Figure 3. Panel (b) displays the response of the ratio of Var(earn_{it}) to the baseline variance for the model.

ployment transitions account for an even larger share than in our base case: 59.3% versus 43.0% for earnings, 64.7% versus 53.2% for wages, and 76.3% versus 58.9% for hours. This increase is partly due to an increase in the role of v_{it}. However, it also reflects a decline in the importance of μ_i in earnings from 15.9% to 3.9%, and a decline from 9.5% to 2.9% in the combined contribution to the earnings variance of the initial draw of ω_{i1} and the shocks $\varepsilon^{\omega}_{it}$. (Table D.III shows the corresponding decompositions of the variance of earnings, wages, and hours at different values of potential experience.)

In summary, we obtain similar model estimates and impulse response functions when we use larger values for σ_{mw} and σ_{mh} than our base case values. The variance decompositions using the larger values, if anything, reinforce our conclusion that job mobility and employment transitions play a large role in the variance of lifetime earnings, wages, and hours. However, they imply implausibly low values for the combined contribution of the permanent heterogeneity factor μ_i and for the autoregressive component ω_{it} in wage rates.

APPENDIX E: SMOOTHING OF DISCRETE VARIABLES IN THE BASELINE MODEL

This section provides additional details on our strategy for smoothing the discrete variables in our models of earnings dynamics. We focus the discussion on our baseline model, but the smoothing procedure works similarly in the multivariate version of the model.

Recall that in our baseline model presented in Section 2, the discrete (binary) indicators for employment and job changes, E_{it} and JC_{it}, are determined endogenously via equations (6), (8), and (7), and that employment duration, unemployment duration, and tenure (all three also discrete variables) are determined endogenously by

$$\begin{aligned}
&\mathrm{ED}_{it} = E_{it} \cdot (\mathrm{ED}_{i,t-1} + 1), \\
&\mathrm{UD}_{it} = (1 - E_{it}) \cdot (\mathrm{UD}_{i,t-1} + 1), \quad \text{and} \\
&\mathrm{TEN}_{it} = (1 - \mathrm{JC}_{it}) \cdot E_{it} \cdot E_{i,t-1} \cdot (\mathrm{TEN}_{i,t-1} + 1).
\end{aligned}$$

Denote the indexes determining EE_{it}, UE_{it}, and JC_{it} in equations (6), (8), and (7) by

$$\begin{aligned}
\mathrm{index}^{\mathrm{EE}} \equiv{}& X_{i,t-1}\gamma^{\mathrm{EE}}_X + \gamma^{\mathrm{EE}}_{\mathrm{ED}} \min(\mathrm{ED}_{i,t-1}, 9) + \gamma^{\mathrm{EE}}_{\mathrm{TEN}} \mathrm{TEN}_{i,t-1} \\
&+ \gamma^{\mathrm{EE}}_{w^s} \mathrm{wage}^s_{it} + \delta^{\mathrm{EE}}_{\mu} \mu_i + \delta^{\mathrm{EE}}_{\eta} \eta_i + \varepsilon^{\mathrm{EE}}_{it}, \\
\mathrm{index}^{\mathrm{UE}} \equiv{}& X_{i,t-1}\gamma^{\mathrm{UE}}_X + \gamma^{\mathrm{UE}}_{\mathrm{UD}} \mathrm{UD}_{i,t-1} + \delta^{\mathrm{UE}}_{\mu} \mu_i + \delta^{\mathrm{UE}}_{\eta} \eta_i + \varepsilon^{\mathrm{UE}}_{it}, \quad \text{and} \\
\mathrm{index}^{\mathrm{JC}} \equiv{}& X_{i,t-1}\gamma^{\mathrm{JC}}_X + \gamma^{\mathrm{JC}}_{\mathrm{TEN}} \mathrm{TEN}_{i,t-1} + \delta^{\mathrm{JC}}_{v'j'(t)} v'_{ij'(t)} + \delta^{\mathrm{JC}}_{vj(t-1)} v_{ij(t-1)} \\
&+ \delta^{\mathrm{JC}}_{\mu} \mu_i + \delta^{\mathrm{JC}}_{\eta} \eta_i + \varepsilon^{\mathrm{JC}}_{it}.
\end{aligned}$$

Then, equations (6), (8), and (7) can be rewritten as

$$\mathrm{EE}_{it} = I[\mathrm{index}^{\mathrm{EE}} > 0] \quad \text{given} \quad E_{i,t-1} = 1,$$

$$\text{JC}_{it} = I[\text{index}^{\text{JC}} > 0] \quad \text{given} \quad E_{it} = E_{i,t-1} = 1, \quad \text{and}$$

$$\text{UE}_{it} = I[\text{index}^{\text{UE}} > 0] \quad \text{given} \quad E_{i,t-1} = 0.$$

The reason we need to smooth the discrete variables in our model is that, as the "structural" parameters appearing in index^{EE}, index^{UE}, and index^{JC} change continuously (leading to continuous changes in index^{EE}, index^{UE}, and index^{JC}), changes in these indexes can lead to discrete jumps in the indicators E_{it} and JC_{it}. To illustrate this, focus on equation (6). For example, continuous changes in the "structural" parameter γ_X^{EE} can lead to a change in the sign of index^{EE}, which leads to a discrete jump in EE_{it} and thereby in E_{it} (from 0 to 1 or vice versa). These discontinuities in E_{it} (as a function of parameter γ_X^{EE}) then also lead to discontinuities in ED_{it}, UD_{it}, and TEN_{it} (which are functions of E_{it}).

Now, for any given discrete variable V, let $\widetilde{V}$ denote the "smoothed" version of that variable (meaning that it is continuous in the "structural" parameters of the model). Our smoothing strategy essentially replaces the equations for EE_{it}, UE_{it}, E_{it}, and JC_{it} by their following smoothed versions (where λ is set to a small value, as discussed in Section 4):

$$\widetilde{\text{EE}}_{it} = \frac{\exp\left(\dfrac{\text{index}^{\text{EE}}}{\lambda}\right)}{1+\exp\left(\dfrac{\text{index}^{\text{EE}}}{\lambda}\right)} \cdot \widetilde{E}_{i,t-1},$$

$$\widetilde{\text{UE}}_{it} = \frac{\exp\left(\dfrac{\text{index}^{\text{UE}}}{\lambda}\right)}{1+\exp\left(\dfrac{\text{index}^{\text{UE}}}{\lambda}\right)} \cdot \widetilde{E}_{i,t-1},$$

$$\widetilde{E}_{it} = \widetilde{E}_{i,t-1} \cdot \widetilde{\text{EE}}_{it} + (1-\widetilde{E}_{i,t-1}) \cdot \widetilde{\text{UE}}_{it}, \quad \text{and}$$

$$\widetilde{\text{JC}}_{it} = \frac{\exp\left(\dfrac{\text{index}^{\text{JC}}}{\lambda}\right)}{1+\exp\left(\dfrac{\text{index}^{\text{JC}}}{\lambda}\right)} \cdot \widetilde{E}_{it} \cdot \widetilde{E}_{i,t-1}.$$

In the above equations, focus again on $\widetilde{\text{EE}}_{it}$. Note that $\widetilde{\text{EE}}_{it}$ is now a continuous real variable that takes values in the interval $[0, 1]$, and that continuous changes in parameter γ_X^{EE} now lead to continuous changes in $\widetilde{\text{EE}}_{it}$, and thereby to continuous changes in $\widetilde{E}_{it}$.[55] Furthermore, as λ approaches zero, $\widetilde{\text{EE}}_{it}$ approaches a 0/1 binary indicator.

[55]The initial condition of E_{it}, E_{i1}, is smoothed in a similar fashion.

Then, employment duration, unemployment duration, and tenure are determined by

$$\widetilde{\mathrm{ED}}_{it} = \widetilde{E}_{it} \cdot (\widetilde{\mathrm{ED}}_{i,t-1} + 1),$$
$$\widetilde{\mathrm{UD}}_{it} = (1 - \widetilde{E}_{it}) \cdot (\widetilde{\mathrm{UD}}_{i,t-1} + 1), \quad \text{and}$$
$$\widetilde{\mathrm{TEN}}_{it} = (1 - \widetilde{\mathrm{JC}}_{it}) \cdot \widetilde{E}_{it} \cdot \widetilde{E}_{i,t-1} \cdot (\widetilde{\mathrm{TEN}}_{i,t-1} + 1).$$

Since $\widetilde{\mathrm{ED}}_{it}$, $\widetilde{\mathrm{UD}}_{it}$, and $\widetilde{\mathrm{TEN}}_{it}$ are continuous functions of $\widetilde{E}_{it}$, the smoothed version of each of these variables is also continuous in the model's "structural" parameters.

APPENDIX F: PSID ESTIMATES OF THE PARAMETERS OF THE AUXILIARY MODEL

Table F.I shows estimates of the matrices of auxiliary model parameters, Π and Σ, from equation (16), using PSID data from the full SRC sample. Each column in the table corresponds to one of the seven equations in the seemingly unrelated regressions (SUR) system in equation (16).

TABLE F.I

PSID ESTIMATES OF THE PARAMETERS OF THE AUXILIARY MODEL (EQUATION (16))

	I	II	III	IV	V	VI	VII
	$E_t E_{t-1}$	$E_t(1-E_{t-1})$	JC_t	$\widetilde{wage}_t^*$	$\widetilde{hours}_t^*$	$\widetilde{earn}_t^*$	$\ln(1+\widetilde{wage}_t^{*2})$
$(t-1)/10$	0.0017	0.0066*	−0.0653***	0.0065	0.0058	0.0008	0.0323**
	(0.0060)	(0.0030)	(0.0100)	(0.0070)	(0.0090)	(0.0120)	(0.0110)
$(t-1)^2/100$	−0.001	−0.0013*	0.0120***	−0.0014	−0.0027	−0.0038	−0.002
	(0.0010)	(0.0010)	(0.0020)	(0.0010)	(0.0020)	(0.0030)	(0.0020)
ED_{t-1}	0.0009**	−0.0002	0.0013*	0.0014***	0.0013**	0.0017**	0.0012
	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
UD_{t-1}	−0.0009	0.05	0.0029	−0.0933**	−0.1493	−0.1291	0.0357
	(0.0040)	(0.0330)	(0.0060)	(0.0360)	(0.0940)	(0.1000)	(0.0240)
TEN_{t-1}	0.0001	0.0001	−0.0041***	−0.0013***	−0.0011*	0.0005	−0.0032***
	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
$\widetilde{wage}_{t-1}^*$	0.0221	−0.0122***	0.0107	0.4448***	−0.0236	0.1914***	0.0883
	(0.0170)	(0.0030)	(0.0340)	(0.0280)	(0.0250)	(0.0360)	(0.0510)
$\widetilde{wage}_{t-2}^*$	−0.0244***	−0.0136	0.0354**	0.3564***	0.0305	0.2311**	−0.1025***
	(0.0070)	(0.0470)	(0.0110)	(0.0440)	(0.0470)	(0.0800)	(0.0310)
$E_{t-1}E_{t-2}$	0.9178***	−0.8024***	0.1630***	−0.0423	−0.3218***	−0.205	0.0006
	(0.0080)	(0.0380)	(0.0110)	(0.0400)	(0.0970)	(0.1080)	(0.0270)
$E_{t-2}E_{t-3}$	−0.0127	0.1474*	−0.0272	−0.0801	−0.2178	−0.1678	−0.0116
	(0.0110)	(0.0720)	(0.0160)	(0.0690)	(0.1320)	(0.1500)	(0.0400)
$E_{t-1}(1-E_{t-2})$	0.7886***	−0.6507***	0.3290***	−0.1142	−0.5239*	−0.4107	0.034
	(0.0230)	(0.1000)	(0.0290)	(0.1010)	(0.2210)	(0.2420)	(0.0580)
$E_{t-2}(1-E_{t-3})$	−0.0255	0.1417	0.0228	−0.0321	−0.2625*	−0.1652	0.0073
	(0.0140)	(0.0730)	(0.0200)	(0.0710)	(0.1340)	(0.1500)	(0.0390)
$JC_{t-1}E_{t-1}E_{t-2}$	−0.0158***	0.0028***	0.1676***	−0.0073	0.0154*	−0.0068	0.0020
	(0.0050)	(0.0010)	(0.0110)	(0.0060)	(0.0070)	(0.0100)	(0.0060)
$JC_{t-2}E_{t-2}E_{t-3}$	−0.0131**	−0.0008	0.0295***	0.0138*	−0.0108	−0.0017	0.0058
	(0.0040)	(0.0020)	(0.0090)	(0.0050)	(0.0060)	(0.0090)	(0.0040)

(*Continues*)

TABLE F.I—*Continued*

	I	II	III	IV	V	VI	VII
	$E_t E_{t-1}$	$E_t(1-E_{t-1})$	JC_t	$\widetilde{\text{wage}}^*_t$	$\widetilde{\text{hours}}^*_t$	$\widetilde{\text{earn}}^*_t$	$\ln(1+\widetilde{\text{wage}}^{*2}_t)$
$\widetilde{\text{hours}}^*_{t-1}$	0.0453***	0.0147*	−0.0554***	−0.1146***	0.3895***	0.1867***	0.007
	(0.0090)	(0.0060)	(0.0120)	(0.0150)	(0.0170)	(0.0270)	(0.0100)
$\widetilde{\text{hours}}^*_{t-2}$	−0.0093	0.0010	0.0539***	−0.0233*	0.1571***	−0.0531*	0.0215**
	(0.0070)	(0.0060)	(0.0110)	(0.0120)	(0.0140)	(0.0210)	(0.0080)
$\widetilde{\text{earn}}^*_{t-1}$	0.0358***	0.0198***	−0.0645***	0.2064***	0.0567***	0.5602***	−0.0061
	(0.0070)	(0.0040)	(0.0100)	(0.0130)	(0.0100)	(0.0250)	(0.0080)
$\widetilde{\text{earn}}^*_{t-2}$	−0.0078	−0.0032	0.0281**	−0.0096	0.0175	0.1067***	−0.0014
	(0.0050)	(0.0040)	(0.0090)	(0.0090)	(0.0100)	(0.0180)	(0.0080)
$\widetilde{\text{wage}}^*_{t-1}((t-1)/10)$	−0.0154	0.0009	0.0261	0.0818**	−0.0275	−0.0029	−0.0579
	(0.0170)	(0.0010)	(0.0290)	(0.0250)	(0.0250)	(0.0330)	(0.0610)
$\widetilde{\text{wage}}^*_{t-1}((t-1)^2/100)$	0.0015	−0.0003	−0.0037	−0.0145*	0.0062	0.0036	0.0081
	(0.0040)	(0.0000)	(0.0060)	(0.0060)	(0.0060)	(0.0080)	(0.0150)
$\widetilde{\text{wage}}^*_{t-1}\text{JC}_t$	−0.0590***	−0.0025**	−0.4595***	−0.1065***	−0.0565***	−0.1159***	−0.1246***
	(0.0080)	(0.0010)	(0.0630)	(0.0210)	(0.0160)	(0.0250)	(0.0190)
$\widetilde{\text{wage}}^*_{t-2}\text{JC}_{t-1}$	0.0273*	0.0006	0.0598*	−0.0951***	0.0263	−0.03	−0.1087***
	(0.0130)	(0.0010)	(0.0270)	(0.0160)	(0.0160)	(0.0220)	(0.0170)
$\widetilde{\text{wage}}^*_{t-2}E_{t-1}$	0.0089	0.01	−0.0464**	−0.1512**	−0.0395	−0.1286	0.1474***
	(0.0090)	(0.0470)	(0.0160)	(0.0460)	(0.0480)	(0.0790)	(0.0320)
BLACK	−0.0105*	−0.0021	−0.0148*	0.0002	−0.0044	0.0012	−0.0123
	(0.0050)	(0.0030)	(0.0070)	(0.0050)	(0.0090)	(0.0120)	(0.0080)
EDUC	0.0019***	0.0007**	−0.0019*	0.0051***	−0.0006	0.0026*	0.0067***
	(0.0000)	(0.0000)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
constant	0.0425**	0.6392***	0.0448	0.0442	0.5371*	0.3318	0.0003
	(0.0160)	(0.1010)	(0.0250)	(0.1000)	(0.2220)	(0.2430)	(0.0620)
R^2	0.575	0.812	0.142	0.774	0.256	0.674	0.047

*Sig. at 0.05 level.

**Sig. at the 0.01 level.

***Sig. at the 0.001 level.

TABLE F.I—*Continued*

	I	II	III	IV	V	VI	VII
	$E_t E_{t-1}$	$E_t(1-E_{t-1})$	JC_t	$\widetilde{\text{wage}}_t^*$	$\widetilde{\text{hours}}_t^*$	$\widetilde{\text{earn}}_t^*$	$\ln(1+\widetilde{\text{wage}}_t^{*2})$
				Residual Correlation Matrix			
				Correlation Coefficient			
$E_t E_{t-1}$	1.0000						
$E_t(1-E_{t-1})$	−0.0182	1.0000					
JC_t	0.0874	0.0118	1.0000				
$\widetilde{\text{wage}}_t^*$	−0.0903	−0.1210	−0.0335	1.0000			
$\widetilde{\text{hours}}_t^*$	0.2608	0.1015	0.0317	−0.0511	1.0000		
$\widetilde{\text{earn}}_t^*$	0.2705	0.0997	−0.0293	0.1552	0.4978	1.0000	
$\ln(1+\widetilde{\text{wage}}_t^{*2})$	0.1070	0.0804	0.0622	−0.0913	0.0442	0.0175	1.0000
				Standard Deviation			
	0.1323	0.0603	0.2545	0.1820	0.2226	0.2965	0.1606

ADDITIONAL REFERENCES

ALTONJI, J. G., AND P. J. DEVEREUX (2000): "The Extent and Consequences of Downward Nominal Wage Rigidity," in *Research in Labor Economics*, Vol. 19, ed. by S. Polachek. Bingley, U.K.: Emerald Group Publishing Limited, 383–431. [23]

BOUND, J., C. BROWN, G. J. DUNCAN, AND W. L. RODGERS (1994): "Evidence on the Validity of Cross-Sectional and Longitudinal Labor Market Data," *Journal of Labor Economics*, 12 (3), 345–368. [24,25]

SOLON, G. (1999): "Intergenerational Mobility in the Labor Market," in *Handbook of Labor Economics*, Vol. 3A, ed. by O. Ashenfelter and D. Card. Amsterdam: North-Holland, 1761–1800. [30]

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