Supplement to "The evolution of the earnings distribution in a volatile economy: Evidence from Argentina"

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We present additional data analyses in Appendix A, including a further description of the administrative data (Appendix A.1) and additional figures (Appendix A.2). We provide further details of the statistical model in Appendix B, including a description of the statistical model of total and regular wages (Appendix B.1), details of the model estimation (Appendix B.2), details of the regular-wage construction (Appendix B.3), a comparison with alternative filtering methods (Appendix B.4), the algorithms used to construct regular wages (Appendix B.5), and additional model results (Appendix B.6).

Appendix A: Data appendix

A.1 *Further description of administrative data*

In order to protect the privacy of employees in the data, partial pooling is performed by the Ministry of Labor, Employment, and Social Security of Argentina, which provides the data. According to the methodological documentation provided by the Ministry, partial pooling is done by applying univariate microaggregation to earnings observations above the 98th percentile of the within-industry earnings distribution in each month, following recommendations by the International Household Survey Network

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(Benschop, Machingauta, and Welch (2021)). Specifically, in every month t and industry j, all individuals i with earnings y_{ijt} above the 98th percentile of the within-industry earnings distribution are identified, where industry j is a 2-digit ISIC division. Then every observation in this group is partially pooled by replacing it with a transformation $y_{ijt}^{A} = f^{A}(y_{ijt})$, defined as the average of the three continuous earnings observations, that is, $f^{A}(y_{ijt}) = (1/3)\sum_{k=0}^{k=2} y_{(i-k)jt}$. This is a linear transformation of the original data that does not alter the ordering of observations. Therefore, we could identify which observations have been partially pooled. Note that, while using the group's median or mean to replace all observations within each group would generate bunching at the upper tail of the distribution, the procedure applied to our sample still maintains variation across individual earnings at the very top of the distribution, although decreasing their levels. This arguably gives rise to a downward bias when computing the top 2% *levels* of the earnings distribution. However, since there is no specific time trend in the extent of partial pooling and the same linear transformation is applied each month, we do not have any reason to expect there to be a bias when analyzing *changes* in the log of top earnings over time. In the analysis of earnings dynamics below, we use all observations, including those that have been partially pooled.

A.2 *Further description of household survey data*

A.2.1 *Additional details on variable construction* We first create a data set at the worker-year level by estimating residual annual earnings based on an aggregation of the (one or two) available observations per worker in each year.[1] Therefore, depending on the individual's appearances in a year, two-quarter or only one-quarter information is used to annualize earnings. We create a variable that identifies the quarter-quarter combinations for individuals within a given calendar year. There are nine possible quarter-quarter combinations:

$$[\text{Q1,Q2}], [\text{Q2, Q3}], [\text{Q3,Q4}], [\text{Q1, Q4}], [\text{Q2, Q4}], [\text{Q1,.}], [\text{Q2,.}], [\text{Q3,.}], [\text{Q4,.}], \tag{S1}$$

where "Q1," "Q2," "Q3," and "Q4" represent the four quarters of a year, while "." represents no matching quarter in the current calendar year.

Next, we transform reported nominal earnings in real terms and in multiples of the prevailing minimum wage. In doing so, we drop observations with average earnings below a threshold—namely, half the current minimum wage.[2] We then annualize the individual earnings, keeping in mind that the variable of earnings in the quarter of the data set (*labor_income*) corresponds to monthly earnings. We annualize differently if an individual appears two times or one time in a year. If a given individual appears in two quarters within the same calendar year, then we compute mean real earnings from formal employment as equal to the mean real earnings across quarters multiplied by the number of quarters formally employed times 6. If a given individual appears in only one

[1]We also tried an alternative procedure in which the data is treated at the worker-quarter-year level. Under this alternative procedure, if an individual appears in two quarters in a year, then we treat the observations as two distinct individuals. In this case, a single observation per worker-year is used to annualize earnings.

[2]This accounts for very few observations, as seen in the second-to-last column of Table A.3.

quarter within a given calendar year, then we compute mean real earnings from formal employment as equal to the mean real formal earnings in the quarter times 12.

We collapse the data to the individual-year level data with annualized earnings. Note that this means that all quarter-pair observations for a given individual will be collapsed to one observation per calendar year. Sample weights in the survey for up to two quarters are averaged to yield a yearly individual sample weight. Age is rounded up if it changes during the two quarter observations. The collapsed data contain around 70% of the number of observations compared with before, as shown in the last column of Table A.3.

Finally, we construct earnings residuals by estimating the following earnings equation for all individuals i of gender $G(i) = g$ and age $A(i,t)$ who appeared in a quarter-quarter combination ("season") $S(i,t)$ in year t separately by gender and year, taking into account yearly individual sample weights:

$$\varepsilon_{it} = \log y_{it} - \alpha_{gt} - \sum_{A'} \beta_{gtA'} \mathbf{1}\big[A(i,t) = A'\big] - \sum_{S'} \gamma_{gtS'} \mathbf{1}\big[S(i,t) = S'\big], \tag{S2}$$

where ε_{it} denotes the earnings residual of interest, $\log y_{it}$ is log earnings, α_{gt} is a gender-year-specific intercept, $\beta_{gtA'}$ is a gender-year-age-specific coefficient on the age indicator $\mathbf{1}[A(i,t) = A']$, and $\gamma_{gtS'}$ is a gender-year-season-specific coefficient on the season indicator $\mathbf{1}[S(i,t) = S']$.

A.2.2 *Additional summary statistics* Table A.1 shows the number of observations in each year-quarter in the raw data.

Table A.1. Number of observations by year-quarter combination.

Year	Q1	Q2	Q3	Q4	Total
1996	0	26,498	0	25,288	51,786
1997	0	26,330	0	26,430	52,760
1998	0	25,874	0	24,326	50,200
1999	0	22,264	0	22,333	44,597
2000	0	20,073	0	19,927	40,000
2001	0	19,648	0	19,365	39,013
2002	0	18,467	0	17,184	35,651
2003	0	12,514	11,102	11,440	35,056
2004	10,904	11,888	12,095	11,836	46,723
2005	11,874	12,048	12,473	12,389	48,784
2006	11,874	12,761	16,526	16,256	57,417
2007	15,959	16,078	0	15,761	47,798
2008	16,124	15,953	15,932	16,042	64,051
2009	15,388	15,491	15,746	15,593	62,218
2010	15,167	15,523	15,867	15,375	61,932
2011	14,952	15,554	15,469	15,199	61,174
2012	14,607	15,051	14,883	14,467	59,008
2013	14,195	14,529	14,717	14,716	58,157
2014	15,013	16,102	16,035	15,992	63,142
2015	15,762	16,045	0	0	31,807

Note: This table shows the number of observations in each quarter (Q1–Q4) and year of the EPH household survey data. *Source*: EPH, 1996–2015.

TABLE A.2. Number of observations by panelized year-quarter-quarter combination.

Year	Q1,Q2	Q2,Q3	Q3,Q4	Q2,Q4	Q1,Q4	Q1,.	Q2,.	Q3,.	Q4,.	Total
1996	0	0	0	28,288	0	0	12,354	0	11,144	51,786
1997	0	0	0	29,286	0	0	11,687	0	11,787	52,760
1998	0	0	0	26,658	0	0	12,545	0	10,997	50,200
1999	0	0	0	25,790	0	0	9369	0	9438	44,597
2000	0	0	0	21,996	0	0	9075	0	8929	40,000
2001	0	0	0	20,970	0	0	9163	0	8880	39,013
2002	0	0	0	18,696	0	0	9119	0	7836	35,651
2003	0	0	8678	0	0	0	12,514	6763	7101	35,056
2004	8502	9668	9454	0	3936	4685	2803	2534	5141	46,723
2005	9356	9678	10,104	0	4264	5064	2531	2582	5205	48,784
2006	9692	10,290	13,296	0	4468	4794	2770	4733	7374	57,417
2007	12,660	0	0	0	5718	6770	9748	0	12,902	47,798
2008	12,968	12,250	12,760	0	5748	6766	3344	3427	6788	64,051
2009	12,098	12,046	12,530	0	5688	6495	3419	3458	6484	62,218
2010	11,808	12,346	12,516	0	5384	6571	3446	3436	6425	61,932
2011	11,846	12,426	12,156	0	5410	6324	3418	3178	6416	61,174
2012	11,522	12,232	11,554	0	5556	6068	3174	2990	5912	59,008
2013	11,254	11,674	11,522	0	5208	5964	3065	3119	6351	58,157
2014	12,198	12,500	12,620	0	5558	6135	3753	3475	6903	63,142
2015	12,362	0	0	0	0	9581	9864	0	0	31,807

Note: This table shows the number of observations in each quarter-quarter combination (i.e., each of Q1–Q4 interacted with each of Q1–Q4) and year of the EPH household survey data. There is double counting in the first five columns for quarter pairs—indeed, the number of observations in these columns are all even. *Source*: Authors' calculations based on EPH, 1996–2015.

Table A.2 shows quarter-quarter combinations for the same individual within a given year, based on the rotating panel structure of the EPH household survey data.

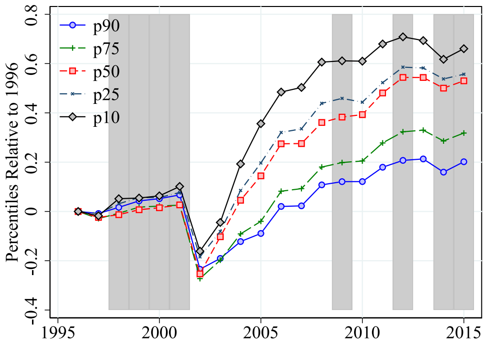
Finally, Table A.3 shows the number of observations as we cumulatively apply our selection criteria starting from the raw data.

TABLE A.3. Number of observations subject to cumulative selection criteria.

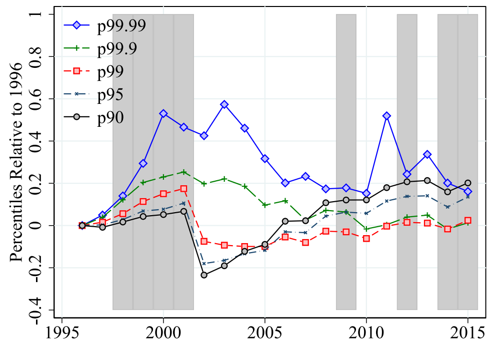
		Quarterly employment in formal private private sector job											
Year	Raw data	Q1,Q2	Q2,Q3	Q3,Q4	Q2,Q4	Q1,Q4	Q1,.	Q2,.	Q3,.	Q4,.	Formal	Threshold	Collapsed
1996	51,786	0	0	0	9038	0	0	3096	0	2602	14,736	14,687	10,180
1997	52,760	0	0	0	9272	0	0	2855	0	2766	14,893	14,869	10,241
1998	50,200	0	0	0	8940	0	0	2979	0	2624	14,543	14,502	10,046
1999	44,597	0	0	0	8512	0	0	2282	0	2168	12,962	12,933	8684
2000	40,000	0	0	0	7202	0	0	2165	0	2102	11,469	11,445	7849
2001	39,013	0	0	0	6880	0	0	2213	0	2056	11,149	11,081	7661
2002	35,651	0	0	0	5788	0	0	2026	0	1479	9293	9250	6367
2003	35,056	0	0	2868	0	0	0	2878	1728	1816	9290	9020	7630
2004	46,723	2916	3332	3232	0	1310	1170	651	553	1395	14,559	14,138	8873
2005	48,784	3300	3418	3596	0	1614	1375	548	632	1389	15,872	15,345	9559
2006	57,417	3682	3876	5136	0	1756	1419	702	1278	2166	20,015	19,345	12,345
2007	47,798	4980	0	0	0	2284	2102	3137	0	4259	16,762	16,147	12,633
2008	64,051	5262	4974	5116	0	2286	2227	1004	954	2248	24,071	23,120	14,624
2009	62,218	4846	4920	5084	0	2308	2105	963	1007	2098	23,331	22,284	14,058
2010	61,932	4626	4974	5168	0	2288	2179	1019	1067	2195	23,516	22,567	14,346
2011	61,174	4876	5210	5154	0	2320	2150	1081	960	2165	23,916	23,002	14,527
2012	59,008	4780	5024	4894	0	2256	2150	943	943	1992	22,982	22,182	13,984
2013	58,157	4836	4660	4770	0	2230	2051	913	982	2211	22,653	21,909	13,905
2014	63,142	5004	5138	5132	0	2362	2101	1138	1100	2358	24,333	23,460	14,943
2015	31,807	5268	0	0	0	0	3375	3432	0	0	12,075	11,707	9142

Note: This table shows the number of observations of the EPH household survey data satisfying cumulative sample selection criteria, starting with the raw data and ending with the collapsed sample. *Source*: Authors' calculations based on EPH, 1996–2015.

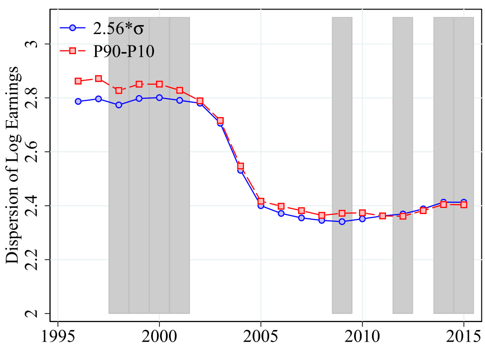
A.3 *Additional figures*



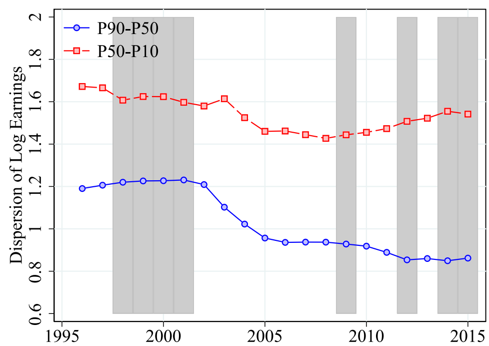
(a) Percentiles



(b) Top percentiles

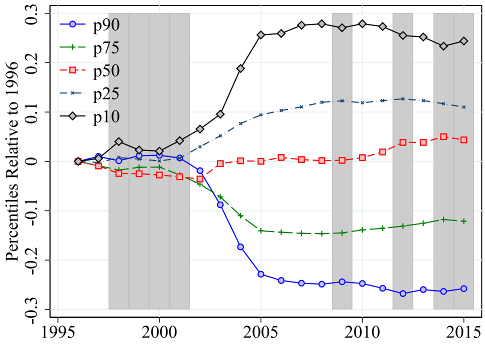


(c) Dispersion

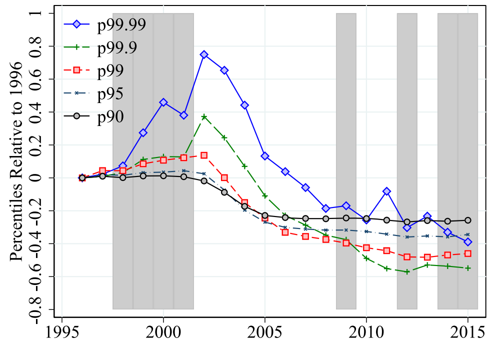


(d) Right- and left-tail dispersion

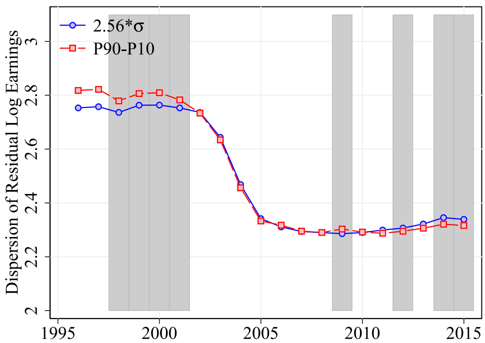
FIGURE A.1. Distribution of earnings in the population. *Notes*: Using raw log earnings and the *CS* sample, Figure A.1 plots the following variables against time for the overall population: (a) P10, P25, P50, P75, P90; (b) P90, P95, P99, P99.9, P99.99; (c) P90-10 and 2.56*SD of log income; (d) P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. Shaded areas indicate recessions. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. *Source*: Authors' calculations based on the RELS, 1997–2015.



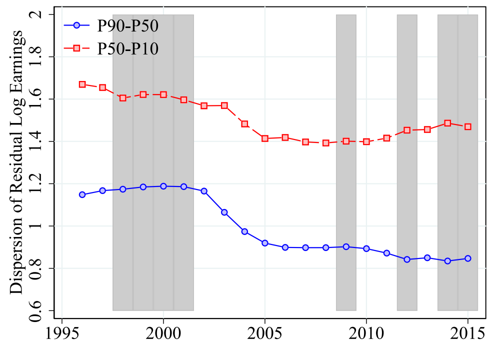
(a) Percentiles



(b) Top percentiles

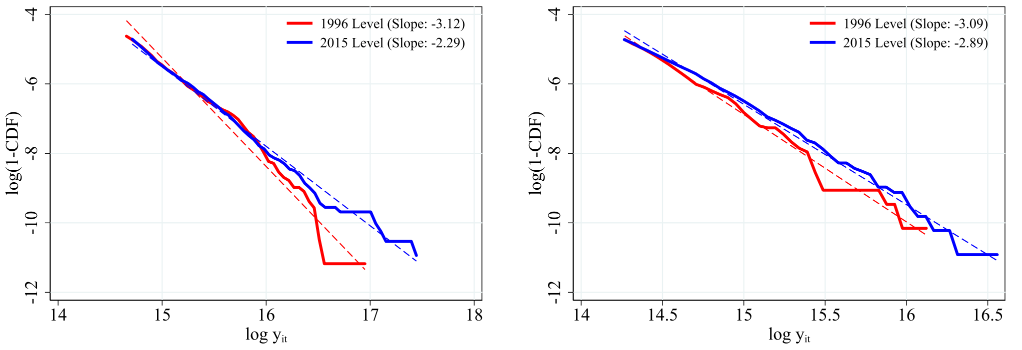


(c) Dispersion



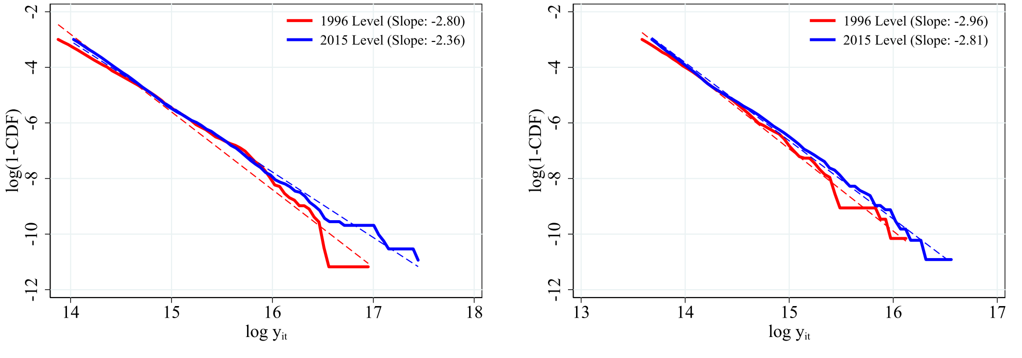
(d) Right- and left-tail dispersion

FIGURE A.2. Distribution of residual earnings in the population after controlling for age. *Notes*: Using residual log earnings and the *CS* sample, Figure A.2 plots the following variables against time for the overall population: (a) P10, P25, P50, P75, P90; (b) P90, P95, P99, P99.9, P99.99; (c) P90-10 and 2.56*SD of residual log earnings; (d) P90-50 and P50-10. All percentiles are normalized to 0 in the first available year. Residual log earnings are computed as the residual from a regression of log real earnings on a full set of age dummies, separately for each year and gender. Shaded areas indicate recessions. 2.56*SD corresponds to P90-10 differential for a Gaussian distribution. *Source*: Authors' calculations based on the RELS, 1996–2015.



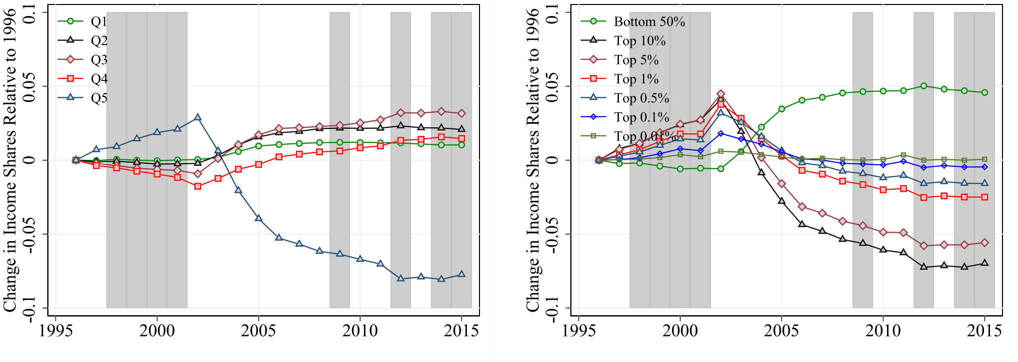
(a) Men (b) Women

Figure A.3. Top income inequality: Pareto tail at top 1%. *Notes*: Using raw log earnings and the top 1% of the *CS* sample, Figure A.3 shows the log of the complementary cumulative distribution function $(\log(1 - CDF))$ of log earnings and the linear fit in 1996 and 2015. This is a log-log plot, and the slope of the regression line gives the Pareto tail index of the earnings distribution. *Source*: Authors' calculations based on the RELS, 1996–2015.



(a) Men (b) Women

Figure A.4. Top income inequality: Pareto tail at top 5%. *Notes*: Using raw log earnings and the top 5% of the *CS* sample, Figure A.4 shows the log of the complementary cumulative distribution function $(\log(1 - CDF))$ of log earnings and the linear fit in 1996 and 2015. This is a log-log plot, and the slope of the regression line gives the Pareto tail index of the earnings distribution. *Source*: Authors' calculations based on the RELS, 1996–2015.



(a) Income shares of quintiles (b) Selected income shares

FIGURE A.5. Changes in income shares relative to 1996. *Notes*: Using raw earnings in levels and the *CS* sample, Figure A.5 plots the following variables against time for the overall population: (a) the share of aggregate income going to each quintile, (b) the share of aggregate income going to the bottom 50%, and top 10%, 5%, 1%, 0.5%, 0.1%, 0.01%. All income shares are normalized to 0 in the first available year. Shaded areas indicate recessions. *Source*: Authors' calculations based on the RELS, 1997–2015.

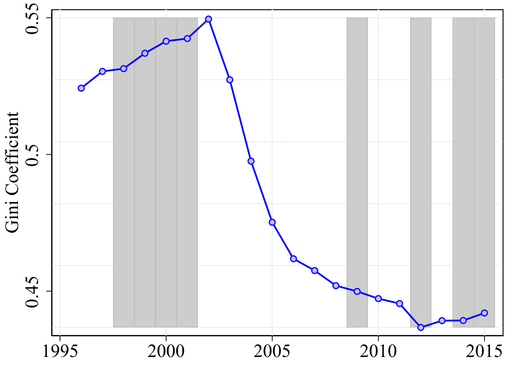
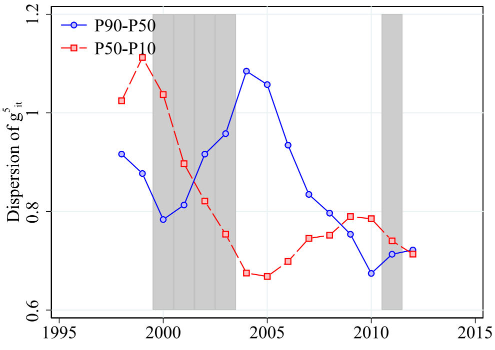
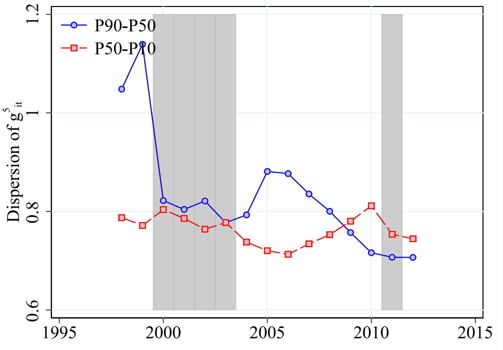


FIGURE A.6. Gini coefficient. *Notes*: Using raw earnings in levels and the *CS* sample, Figure A.6 plots the Gini coefficient against time. Shaded areas indicate recessions. *Source*: Authors' calculations based on the RELS, 1996–2015.

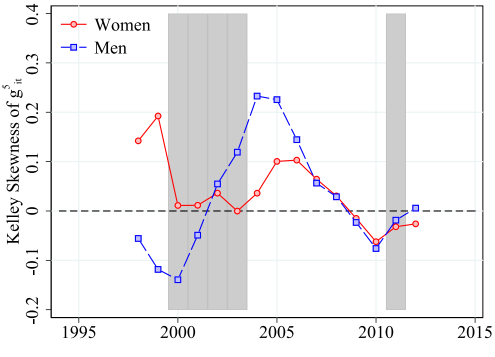


(a) Men

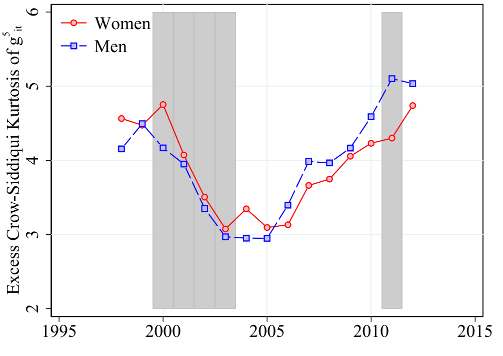


(b) Women

FIGURE A.7. Dispersion of 5-year log earnings changes. *Notes*: Using residual 5-year earnings changes and the *LS* sample, Figure A.7 plots the following variables against time: (a) Men: P90-10 differential; (b) Women: P90-10 differential. Shaded areas indicate recessions. *Source*: Authors' calculations based on the RELS, 1996–2015.

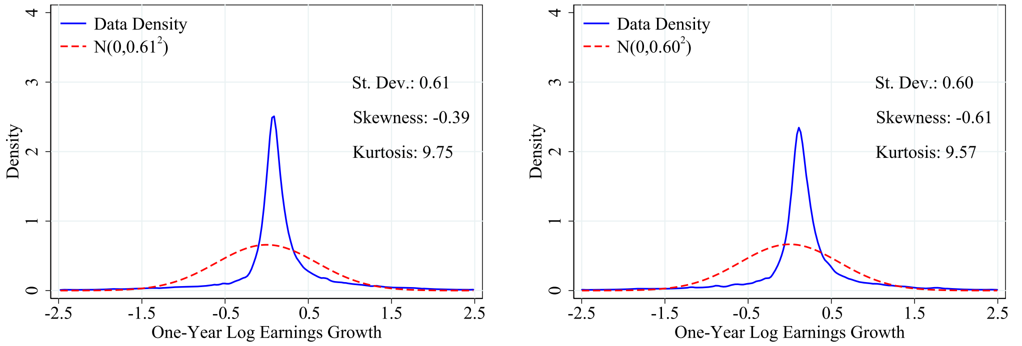


(a) Kelley skewness



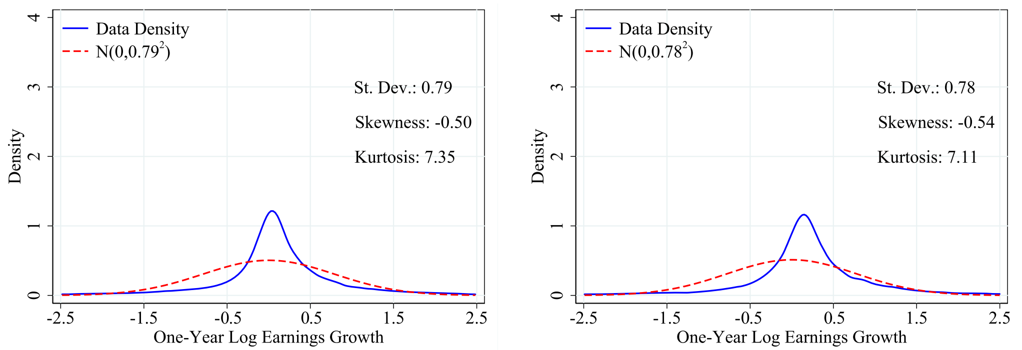
(b) Excess Crow–Siddiqui kurtosis

FIGURE A.8. Kelley skewness and excess Crow–Siddiqui kurtosis of 5-year log earnings changes. *Notes*: Using residual 5-year earnings changes and the *LS* sample, Figure A.8 plots the following variables against time: (a) Men and Women: Kelly skewness; (b) Men and Women: Excess Crow–Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow–Siddiqui measure of kurtosis and 2.91 corresponds to the value of this measure for the Normal distribution. Shaded areas indicate recessions. *Source*: Authors' calculations based on the RELS, 1996–2015.



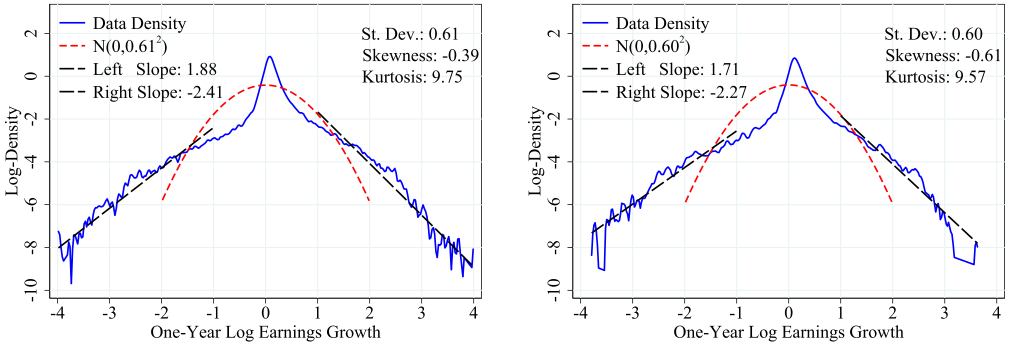
(a) Men (b) Women

FIGURE A.9. Empirical densities of 1-year earnings growth. *Notes*: Figure A.9 shows the density of 1-year log residual earnings growth for men and women for 2005. *Source*: Authors' calculations based on the RELS, 1996–2015.



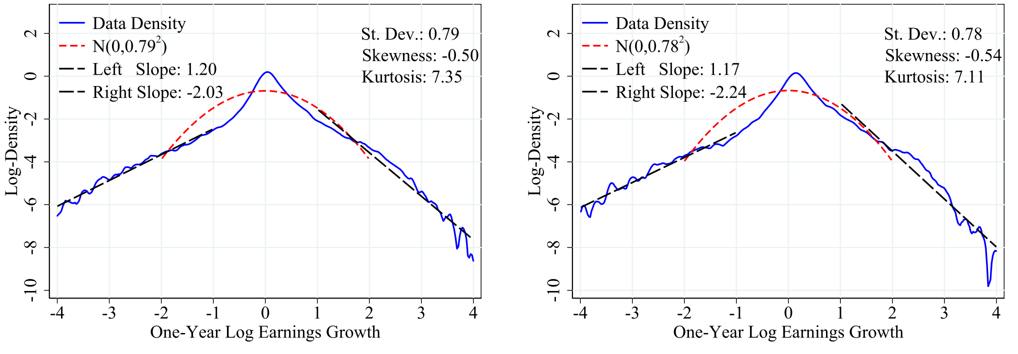
(a) Men (b) Women

FIGURE A.10. Empirical densities of 5-year earnings growth. *Notes*: Figure A.10 shows the density of 5-year log residual earnings growth for men and women for 2005. *Source*: Authors' calculations based on the RELS, 1996–2015.



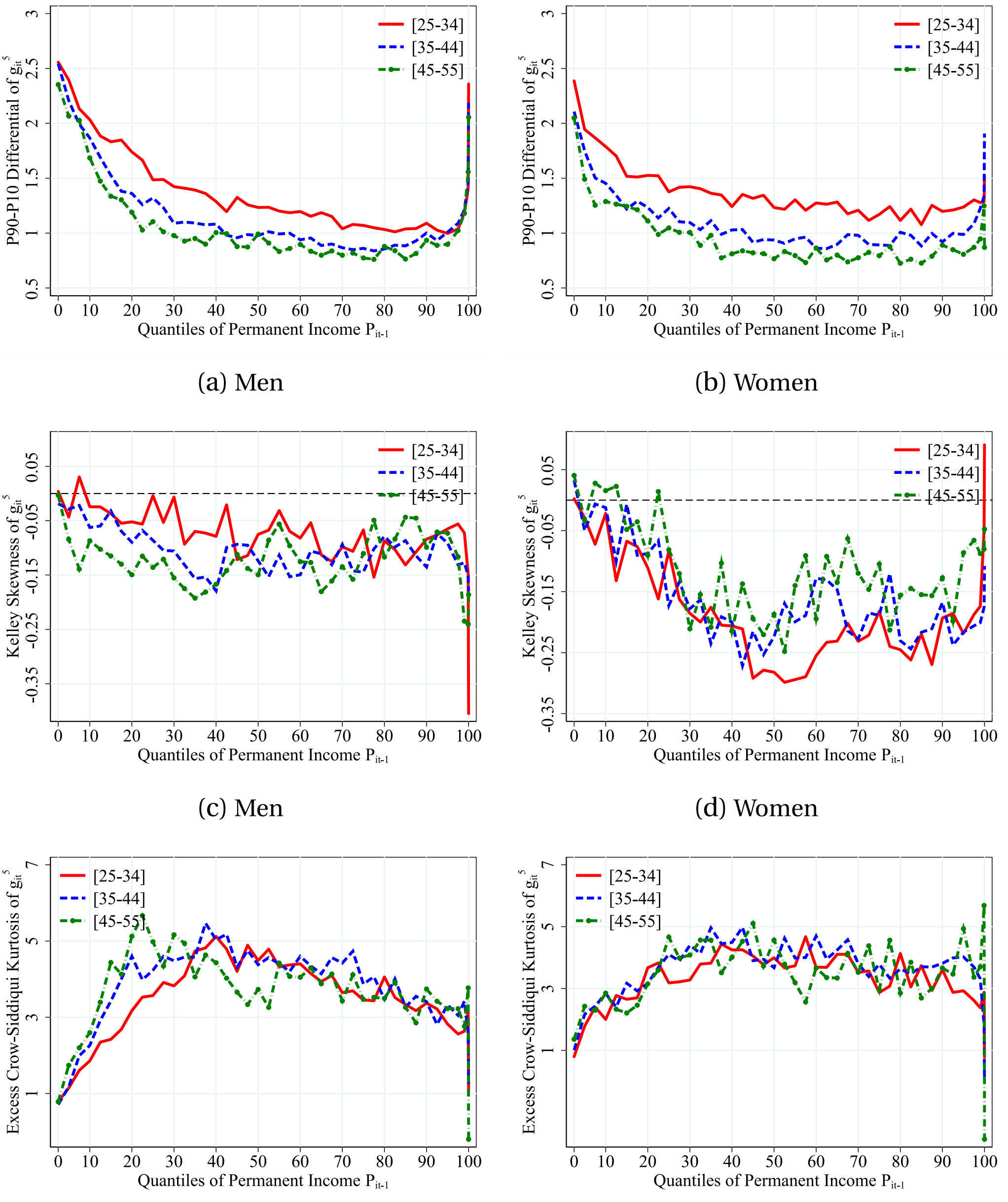
(a) Men (b) Women

FIGURE A.11. Empirical log-densities of 1-year earnings growth. *Notes*: Figure A.11 shows the log-density of 1-year log residual earnings growth for men and women for 2005. *Source*: Authors' calculations based on the RELS, 1996–2015.



(a) Men (b) Women

FIGURE A.12. Empirical log-densities of 5-year earnings growth. *Notes*: Figure A.12 shows the log-density of 5-year log residual earnings growth for men and women for 2005. *Source*: Authors' calculations based on the RELS, 1996–2015.

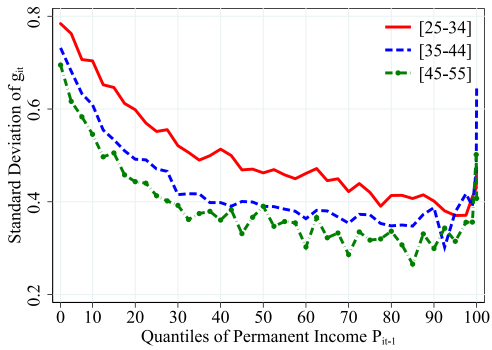


(a) Men (b) Women

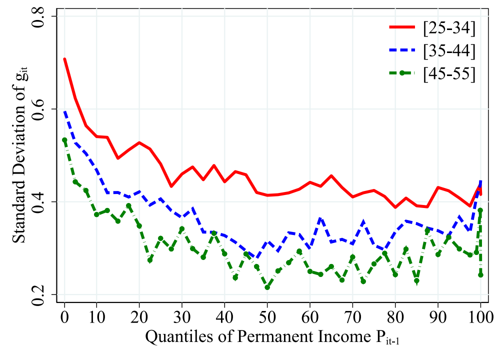
(c) Men (d) Women

(e) Men (f) Women

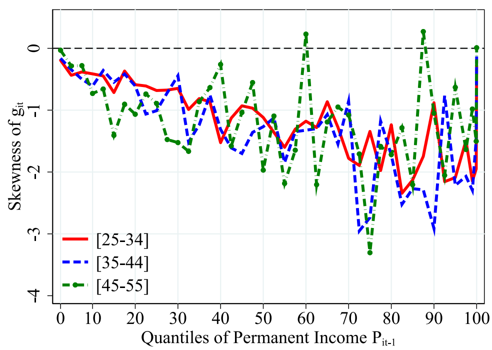
FIGURE A.13. Dispersion, Kelley skewness and excess Crow–Siddiqui kurtosis of 5-year log earnings changes. *Notes*: Using residual 5-year earnings changes and the LS^+ sample, Figure A.13 plots the following variables against permanent income quantile groups for the three age groups: (a) Men: P90-10; (b) Women: P90-10; (c) Men: Kelley Skewness; (d) Women: Kelley Skewness; (e) Men: Excess Crow–Siddiqui kurtosis; (f) Women: Excess Crow–Siddiqui kurtosis. Excess Crow–Siddiqui kurtosis calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$ where the first term is the Crow–Siddiqui measure of kurtosis and 2.91 corresponds to the value of this measure for the Normal distribution. *Source*: Authors' calculations based on the RELS, 1996–2015.



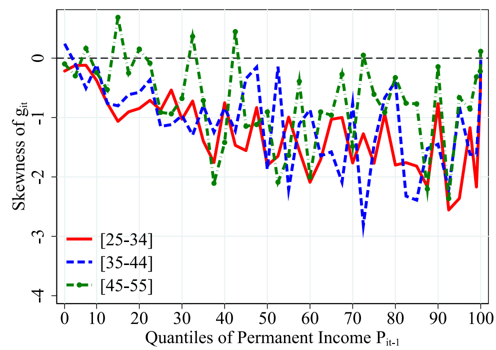
(a) Men



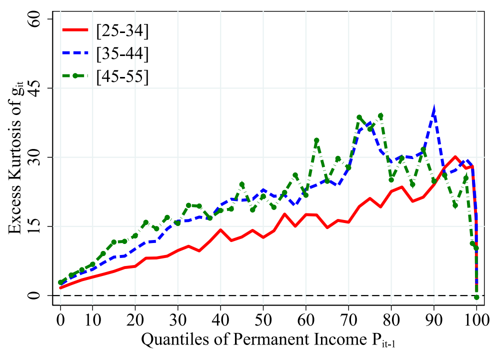
(b) Women



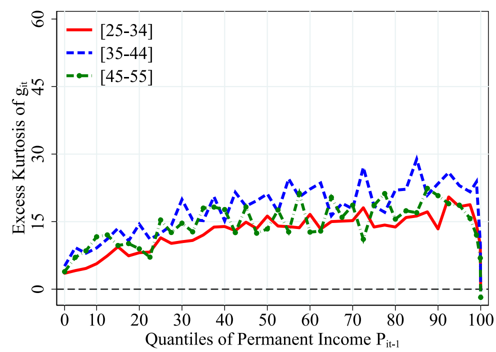
(c) Men



(d) Women

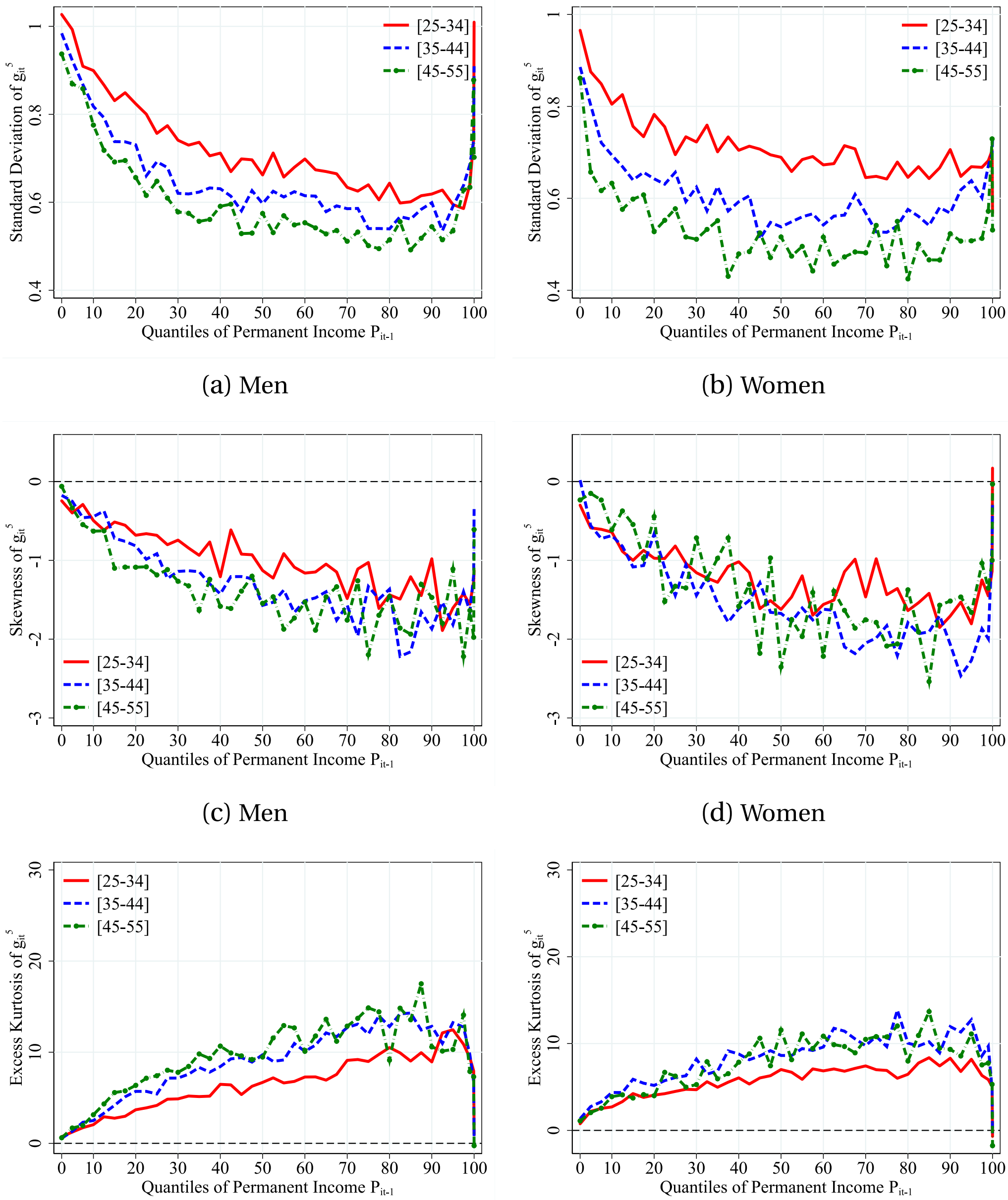


(e) Men



(f) Women

FIGURE A.14. Standardized moments of 1-year log earnings changes. *Notes*: Using residual 1-year earnings changes and the LS^+ sample, Figure A.14 plots the following variables against permanent income quantile groups for the three age groups: (a) Men: Standard deviation; (b) Women: Standard deviation; (c) Men: Skewness; (d) Women: Skewness; (e) Men: Excess kurtosis; (f) Women: Excess kurtosis. *Source*: Authors' calculations based on the RELS, 1996–2015.

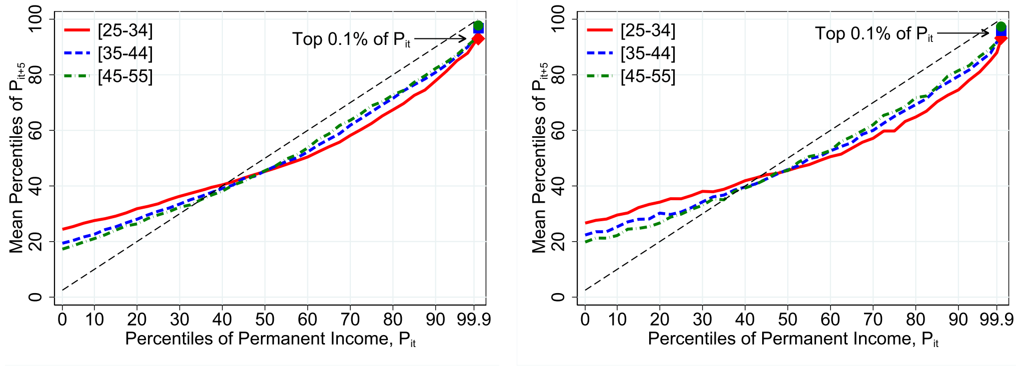


(a) Men (b) Women

(c) Men (d) Women

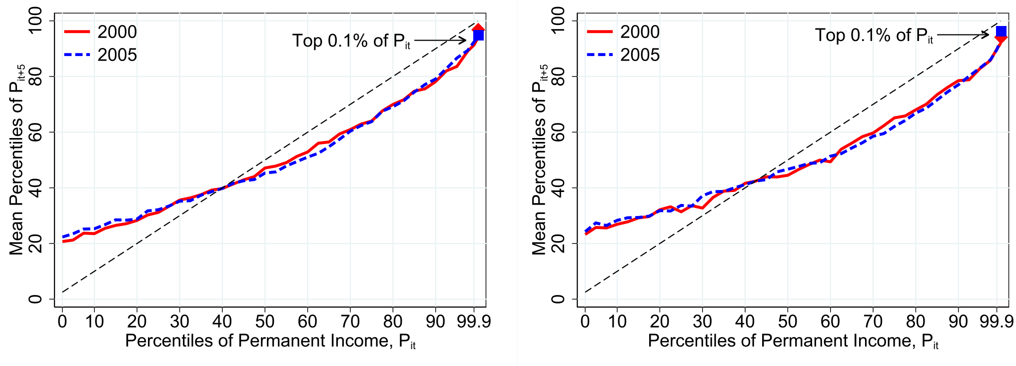
(e) Men (f) Women

FIGURE A.15. Standardized moments of 5-year log earnings changes. *Notes*: Using residual 5-year earnings changes and the LS^{+} sample, Figure A.15 plots the following variables against permanent income quantile groups for the three age groups: (a) Men: Standard deviation; (b) Women: Standard deviation; (c) Men: Skewness; (d) Women: Skewness; (e) Men: Excess kurtosis; (f) Women: Excess kurtosis. *Source*: Authors' calculations based on the RELS, 1996–2015.



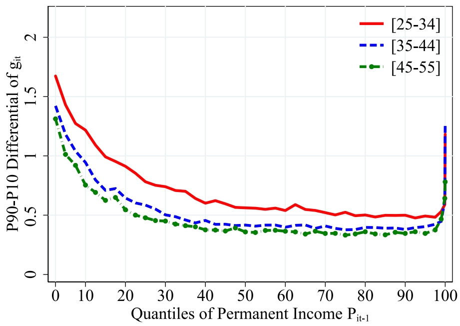
(a) Men (b) Women

FIGURE A.16. Evolution of 5-year mobility over the life cycle. *Notes*: Figure A.16 plots average rank-rank mobility over a 5-year period by showing average rank of permanent income in $t+5$ as a function of the permanent income rank in t. Results are reported as the average mobility during the period of analysis (i.e., 1996–2015) and for three age groups defined in period t (25–34, 35–44, and 45–55). *Source*: Authors' calculations based on the RELS, 1996–2015.

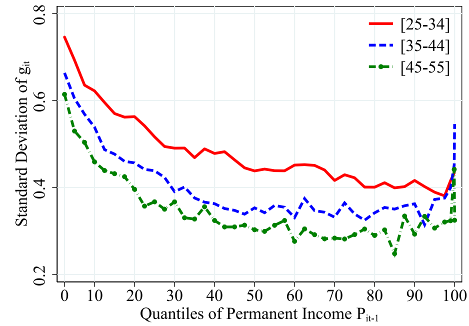


(a) Men (b) Women

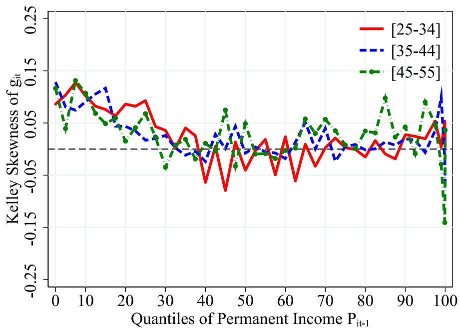
FIGURE A.17. Evolution of 5-year mobility over time. *Notes*: Figure A.17 plots average rank-rank mobility over a 5-year period by showing average rank of permanent income in $t+5$ as a function of the permanent income rank in t. Results are reported for $t = 2000$ and $t = 2005$. *Source*: Authors' calculations based on the RELS, 1996–2015.



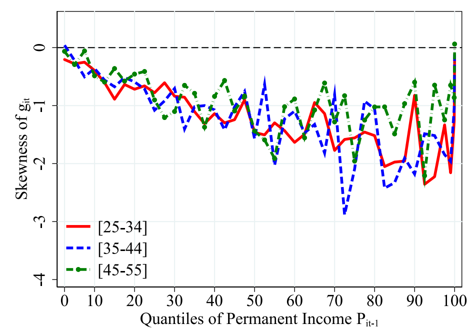
(a) P90-P10



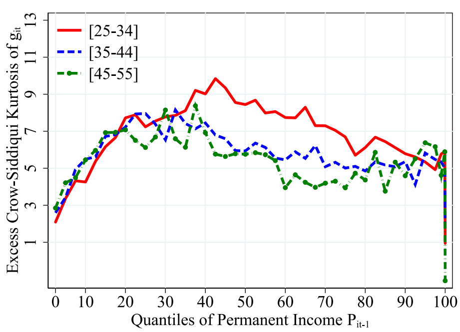
(b) Standard deviation



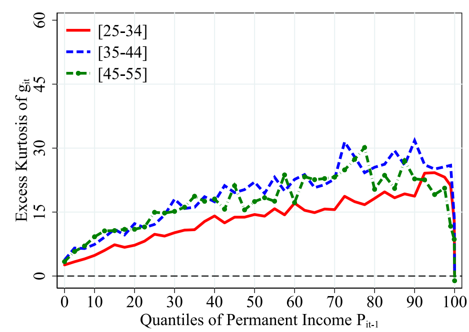
(c) Kelley skewness



(d) Skewness



(e) Excess Crow–Siddiqui kurtosis



(f) Excess kurtosis

FIGURE A.18. Dispersion, Kelley skewness and excess Crow–Siddiqui kurtosis of 1-year log earnings changes, pooled men and women. *Notes*: Using residual 1-year earnings changes and the LS^+ sample, Figure A.18 plots the following variables against permanent earnings quantile groups for the three age groups: (a) Pooled men and women: P90-10, (b) Pooled men and women: Standard deviation, (c) Pooled men and women: Kelley skewness, (d) Pooled men and women: Skewness (e) Pooled men and women: Excess Crow–Siddiqui kurtosis, (f) Pooled men and women: Excess kurtosis. Excess Crow–Siddiqui kurtosis is calculated as $\frac{P97.5-P2.5}{P75-P25} - 2.91$, where the first term is the Crow–Siddiqui measure of kurtosis and 2.91 corresponds to the value of this measure for the Normal distribution. Excess kurtosis is the standardized fourth moment minus 3.0, which evaluates identically to zero for the Normal distribution. *Source*: Authors' calculations based on the RELS, 1996–2015.

Appendix B: Model appendix

B.1 *Description of statistical model for total and regular wages*

The statistical model for total wages is defined at the job-spell level. Total wages are the sum of two components, a transitory wage w_t^T and a regular wage w_t^R, so that $w_t = w_t^T + w_t^R$. The transitory component captures small deviations or significant but short-lived deviations around a regular wage. The evolution of the regular wage follows a model that combines elements of a fixed cost model (Barro (1972)) and a Taylor model (Taylor (1980)) with unit root shocks to the optimal static wage. We now describe the mathematical formulation for an individual worker.[3]

Time is discrete and denoted by t. We normalized time so that the second month of a job spell corresponds to $t = 0$. Let w_t^* be a worker's target nominal wage that follows a discrete-time random walk with drift,

$$w_t^* = w_{t-1}^* + \pi_t - \sigma_\epsilon \eta_t, \tag{S3}$$

where $\eta_t \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\eta)$ with its initial value normalized to zero, that is, $w_0^* = 0$. Here, π_t captures the monthly wage inflation rate, which we construct in two steps. First, we extract monthly seasonality from observed wage-inflation series using a linear regression with calendar-month dummies. Second, we regress these seasonally adjusted changes in wages on a set of age, sector, and gender dummies in addition to time fixed effects. We then recover π_t as the predicted time fixed effects from this specification.

With the target wage in hand, we construct the wage gap as $\tilde{w}_t^R = w_t^R - w_t^*$. We assume that the regular wage is changed whenever the wage gap hits an upper or lower trigger or if the last regular-wage adjustment occurred more than T periods before. Under these assumptions, the joint stochastic process of the wage gap and the time elapsed since the last adjustment of the regular wage, denoted by a, follows:

$$z_t \equiv \tilde{w}_{t-1}^R - \pi_t + \sigma_\epsilon \eta_t, \tag{S4}$$

$$\left(\tilde{w}_t^R, a_t\right) = \begin{cases} (0, 0) & \text{if } a_{t-1} + 1 \geq T \text{ or } z_t \notin \left[\tilde{w}^-, \tilde{w}^+\right], \\ (z_t, a_{t-1} + 1) & \text{otherwise.} \end{cases} \tag{S5}$$

Here, z_t is an auxiliary variable, and $\tilde{w}^-$ and $\tilde{w}^+$ denote the lower and upper bounds of the wage gap that trigger an adjustment of the regular wage, respectively. We assume that the initial regular wage is equal to the target nominal wage; thus, $(\tilde{w}_0^R, a_0) = (0, 0)$.

Fluctuations in the wage gap come from variations in the nominal target or wage shocks η_t. During periods of adjustment in the regular wage, $\tilde{w}_t^R - z_t$ captures the regular-wage change. Thus,

$$w_t^R = \begin{cases} w_{t-1}^R + \tilde{w}_t^R - z_t & \text{if } a_{t-1} + 1 \geq T \text{ or } z_t \notin \left[\tilde{w}^-, \tilde{w}^+\right], \\ w_{t-1}^R & \text{otherwise.} \end{cases} \tag{S6}$$

[3] See Caballero and Engel (1993) for the original formulation of defining the probability of adjustment using an optimal static target and its application to producer-level employment. See Alvarez, Lippi, and Paciello (2011) for a microfoundation in a price-setting context and Baley and Blanco (2021) for capital producer-level investment.

The transitory component of total wages is modeled as the sum of random transitory deviations across months, denoted by γ_t, and another random deviation that captures the payment of the 13th salary, denoted by ϕ_t. Formally, $w_t^T = \gamma_t + \phi_t$, with

$$\gamma_t \sim \begin{cases} \mathcal{N}(0, \sigma_\gamma) & \text{with probability } \beta, \\ 0 & \text{with probability } 1-\beta, \end{cases} \tag{S7}$$

and ϕ_t is drawn from a Normal distribution with mean m_ϕ and variance σ_ϕ in June and December and is zero otherwise.

B.2 *Details of model estimation*

We use the simulated method of moments (SMM) to estimate the parameters of the stochastic process of (w_t^R, w_t^T). We match moments of the wage-change distribution at the two-digits sectoral level to account for the pervasive heterogeneity in wage behavior across sectors. Table B.1 reports the estimation results (from rows 1 to 14) for the manufacturing and trade sectors and the average across sectors weighted by sectoral

TABLE B.1. Estimated threshold values and break test evaluation.

	Manufacturing	Retail	Sector Average
Moments (data,model):			
Mean of 1-yr Δw	(0.20, 0.20)	(0.22, 0.23)	(0.21, 0.21)
Std. of 1-yr Δw	(0.23, 0.24)	(0.20, 0.21)	(0.22, 0.22)
CV(3) of 1-yr Δw	(4.06, 4.14)	(2.38, 2.41)	(3.46, 3.37)
Std. of 1-mo Δw	(0.19, 0.19)	(0.14, 0.13)	(0.17, 0.17)
Mean of 1-mo Δw in Jun/Dec	(0.35, 0.35)	(0.30, 0.30)	(0.30, 0.30)
Std. of 1-mo Δw in Jun/Dec	(0.21, 0.21)	(0.20, 0.20)	(0.21, 0.21)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.03, 0.03)	(0.03, 0.03)
Share of 1-mo $\Delta w = 0$	(0.15, 0.15)	(0.24, 0.24)	(0.23, 0.22)
Share of 1-mo $\Delta w > 0$	(0.47, 0.45)	(0.44, 0.41)	(0.43, 0.42)
Parameters:			
$(T, \tilde{w}^-, \tilde{w}^+)$	(26, −0.20, 1.5)	(30, −0.22, 1.5)	(29, −0.20, 1.5)
σ_η	0.06	0.06	0.06
(m_ϕ, σ_ϕ)	(0.38, 0.03)	(0.36, 0.04)	(0.35, 0.06)
(σ_γ, β)	(0.15, 0.58)	(0.11, 0.46)	(0.14, 0.49)
Threshold and break test evaluation:			
Threshold value $\mathcal{K}$	0.47	0.49	0.47
$\Pr(w_t^R \neq w_{t-1}^R)$ (model,break test)	(0.12, 0.12)	(0.11, 0.11)	(0.13, 0.13)
Pr(no break in t|no break t)	0.91	0.93	0.91
Pr(break between $t-2, t+2$ |break t)	0.76	0.85	0.81

Note: The table presents moments used in and parameter estimates from the SMM estimation. Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the threshold value $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third-order generalized coefficient of variation, that is, $\text{CV}(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector. *Source*: Authors' calculations based on the RELS, 1996–2015, and simulations.

employment. Tables B.2 to B.5 in the Appendix B.6 report the same statistics for all the sectors in the economy.

The set of targeted moments includes the monthly and annual frequencies of wage changes and moments of the distributions of 1-month and 1-year wage changes. Intuitively, moments of the 1-month wage change distribution discipline the dispersion and frequency of transitory changes of total wages, while moments about the distribution of 1-year wage changes inform parameters affecting the regular wage. We select the 1-year moments suggested by the theory in Baley and Blanco (2021) as sufficient statistics for aggregate wage flexibility (see Corollary 3). More specifically, we choose moments reflecting the size (i.e., frequency, mean, and standard deviation of 1-year wage changes) and dispersion (i.e., the third-order coefficient of variation) of wage changes. Intuitively, the size of wage changes identifies the variance of permanent worker-level shocks and the total wage change frequency due to Taylor or fixed cost adjustments. The dispersion of wage changes identifies the composition of the wage change frequency due to wages hitting the adjustment trigger or reaching the maximal date before adjustment.

The statistical model is able to generate the wage setting patterns observed in the data within sectors. The outcome of the estimation reveals a highly asymmetric adjustment policy toward wage increases for the regular wage. Finally, note that despite the fact that the frequency of total wage changes is 80% in the data (see the row labeled "Share zero 1-month Δw"), the frequency of regular-wage changes is around 10% in the model.

B.3 *Details of regular-wage construction*

In the last step of the measurement exercise, we apply the Break Test to simulated data from the estimated model to compute the model-implied frequency of regular-wage changes. We relegate a formal description of the Break Test algorithm to Appendix B.5 and present the main intuition here. The method follows an iterative approach. First, it starts by assuming that there is no break in the wage series within a job spell. Under this assumption, it computes the maximum distance across two subseries defined by all possible breaks (i.e., by all the dates in the series). If that maximum distance is larger than the threshold $\mathcal{K}$, then the method adds a new break at the date in which the distance is maximized. The method continues these iterations within each resulting subseries until the maximum distance across all breaks is less than $\mathcal{K}$. Once all the breaks have been identified, we construct the regular wage as the median wage in between breaks and the frequency of regular-wage changes as the fraction of regular wages that changed between $t-1$ and t. Finally, we calibrate $\mathcal{K}$ to match the (known) monthly frequency of wage changes in the model.

Table B.1 reports the calibrated values for $\mathcal{K}$. The estimated $\mathcal{K}$ ranges from 0.38 to 0.51 across sectors, with a mean of 0.47 across sectors. For comparison, Stevens (2020) recovers $\mathcal{K} = 0.61$ from weekly data on grocery store prices. By construction, the Break Test generates the same model-implied frequency as regular-wage changes. The last two rows evaluate the accuracy of the Break Test. If in the model there is no break in period t, the test correctly identifies no change in regular wages with a probability of at least

0.9. As we show below, most wage changes are concentrated in June and December, 2 months with particularly large transitory shocks due to the payment of the 13th salary. For this reason, the method cannot always accurately identify the exact date of the break. Intuitively, there is no useful information for the test if a break occurs during months of large transitory shocks. Therefore, the last row of Table B.1 reports the probability of correctly identifying changes in regular wages in a 2-month window around an actual change, which is equal to 0.81 across sectors.

Panels (a) and (b) of Figure 14 show the log regular wages (blue triangles) for Diana and Mario. Inspection of the figures, together with the results of the structural model, suggests that while the break test is not perfect, it captures well the theoretical notion of a regular wage in the data and in the simulated data.

B.4 *Comparison with alternative filtering methods*

In the paper, we provide a set of facts that rely on the Break Test for the construction of regular wages. Here, we highlight the advantages of this test over three other methods commonly used in the literature (see Stevens (2020), for a similar discussion using price data). In particular, we construct series of regular wages following three alternative filtering methods proposed by Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), and Blanco (2021). Based on model simulation and inspection of the raw data, we find that the Break Test performs better in constructing series of regular wages—Figure B.1 in Appendix B.6 shows two examples of the Break Test algorithm successfully recovering true regular wages in simulated data. The main intuition why this is the case is that the Break Test does not change the regular wage after small deviations around a stable value; see Figures B.2 and B.3 in Appendix B.6, which reproduce Figure 14 of the main text (Blanco, Diaz de Astarloa, Drenik, Moser, and Trupkin (2022)) under all four methods.

In addition, we have further analyzed the robustness of our results by computing different critical $\mathcal{K}$ values for periods of high and low average inflation. More specifically, we split job spells according to their start date into two subsamples: jobs that started before January 2002 and those that started after. Those samples correspond to periods of low and high inflation, respectively. Then we repeated the same steps described above to each of the two samples. While there are considerable differences in the estimated moments and parameters across periods, we do not find a significant difference in the calibrated critical $\mathcal{K}$ values across samples and regular-wage statistics analyzed below.[4] The reason for this result is that there is no significant change in the stochastic process for *transitory* shocks across periods.

B.5 *Algorithms to construct regular wages*

This section describes the algorithms to construct regular wages, including the Break Test algorithm. We focus on the methods proposed by Nakamura and Steinsson (2008),

[4] Table B.6 in Appendix B.6 shows the threshold values for the entire sample and the two subsamples. Figures B.9 and B.10 reproduce Figures 16 and 19 of the main text, respectively.

Kehoe and Midrigan (2015), Stevens (2020), and Blanco (2021). Let $\{w_{jt}\}_{t=0}^{T_j}$ be the monthly wage in job spell j with a duration given by T_j. For simplicity, from now on, we suppress the job-spell identifier.

B.5.1 *Stevens (2020) method* The method constructs an increasing sequence of breaks $\{\tau_s\}_{s=0}^{m}$, with $\tau_0 = 0$ and $\tau_m = T$. It depends on two parameters: $\mathcal{L}$ and $\mathcal{K}$. The minimum T to apply the method to construct the regular wage within a job spell is described by $\mathcal{L}$, and $\mathcal{K}$ describes the minimum of the maximum distances to add new breaks.

The method works as follows:

1. Drop all spells with $T \leq \mathcal{L}$.
2. Set $m = 1$.
3. For each $\{\{w_t\}_{t=\tau_i}^{\tau_{i+1}}\}_{i=0}^{m}$, compute the following statistics:

$$S_i = \sqrt{\tau_{i+1} - \tau_i + 1} \max_{\tau_i \leq t \leq \tau_{i+1}} \left[\frac{t - \tau_i}{\tau_{i+1} - \tau_i + 1} \frac{\tau_{i+1} + 1 - t}{\tau_{i+1} - \tau_i + 1} D_t \right], \tag{S8}$$

$$D(t) = \sup_w \left| F_{\tau_i, t}(w) - F_{t+1, \tau_{i+1}}(w) \right|. \tag{S9}$$

Here, $F_{j,h+1}(w)$ is the empirical cumulative distribution functions of the sample $\{w_t\}_{t=j}^{h+1}$; that is, $F_{j,h+1}(w) = \frac{1}{h-j} \sum_{t=j}^{h+1} \mathbb{I}(w_t \leq w)$, where $\mathbb{I}(\cdot)$ denotes the indicator function.

4. If $S_i \leq \mathcal{K}$ for all i, stop and compute the regular wage as

$$w_t^r = \text{median}\{w_t : \tau_i \leq t \leq \tau_{i+1} \text{ for some } i + 1\}. \tag{S10}$$

5. For every i such that $S_i \leq \mathcal{K}$, add a new break at

$$\arg \max_{\tau_i \leq t \leq t_{i+1}} \sqrt{\frac{t - \tau_i}{\tau_{i+1} - \tau_i + 1} \frac{\tau_{i+1} + 1 - t}{\tau_{i+1} - \tau_i + 1} D_t}. \tag{S11}$$

Increase m by the new number of new breaks and go to step 3.

B.5.2 *Nakamura and Steinsson (2008) method* The method removes inverse-V-shaped wage changes. Since the method was originally designed for V-shaped wage changes, we modify it to detect the inverse pattern. This method depends on three parameters: $\mathcal{J}_{\text{NS}}$, $\mathcal{L}_{\text{NS}}$, and $\mathcal{K}_{\text{NS}}$. The number of periods for the wage to return to the regular wage is described by $\mathcal{J}_{\text{NS}}$, and $\mathcal{L}_{\text{NS}}$ and $\mathcal{K}_{\text{NS}}$ describe the prevalence of the regular wages.

The method is summarized as follows:

1. If $w_{t-1}^r = w_t$, then $w_t^r = w_t$.
2. If $w_t < w_{t-1}^r$, then $w_t^r = w_t$.
3. If $w_{t-1}^r \in \{w_{t+1}, \dots, w_{t+J}\}$ and $w_{t+j} \geq w_{t-1}^r \; \forall j \leq \mathcal{J}_{\text{NS}}$, then $w_t^r = w_{t-1}^r$.
4. If $\{w_t, \dots, w_{t+L}\}$ has $\mathcal{K}_{\text{NS}}$ or more elements, $w_t^r = w_t$.

5. Set $w_t^{\min} = \min\{w_t, \ldots, w_{it+L}\}$, $k_t^{\min} = \text{first-time-min}\{w_t, \ldots, w_{t+L}\}$,

$$\text{If } w_t^{\min} = \min\{w_{k_t^{\min}}, \ldots, w_{k_t^{\min}+L}\}, \quad \text{then } w_t^r = w_t^{\min}$$

6. Set $w_t^r = w_t$.

In the first time period, the method begins at step 4.

B.5.3 *Kehoe and Midrigan (2015) method* The method constructs the regular wage as the running mode of the original series. This method depends on three parameters: $\mathcal{L}_{\text{KM}}$, $\mathcal{C}_{\text{KM}}$, and $\mathcal{A}_{\text{KM}}$. The length of rolling window periods to construct the mode is described by $\mathcal{L}_{\text{KM}}$, $\mathcal{C}_{\text{KM}}$ describes the number of periods to use the running modes, and $\mathcal{A}_{\text{KM}}$ describes the number of non-missing wages to compute the mode.

The method works as follows:

1. Construct $h_t = \sum_{j=-\mathcal{L}_{\text{KM}}}^{\mathcal{L}_{\text{KM}}} \mathbb{I}(w_{t+j} \text{ nonmissing})/(2\mathcal{L}_{\text{KM}})$ for all $t \in [1 + \mathcal{L}_{\text{KM}}, T - \mathcal{L}_{\text{KM}}]$.

2. Set $f_t = \sum_{j=-\mathcal{L}_{\text{KM}}}^{\mathcal{L}_{\text{KM}}} \mathbb{I}(w_{t+j} \text{ nonmissing}, w_{t+j} = w_t^m)/(2\mathcal{L}_{\text{KM}})$, where

$$w_t^m = \begin{cases} \text{mode}\{w_{t-\mathcal{L}_{\text{KM}}}, \ldots, w_{t+\mathcal{L}_{\text{KM}}}\} & \text{If } h_t \geq \mathcal{A}_{\text{KM}}, \\ . & \text{Otherwise.} \end{cases} \tag{S12}$$

3. Define w_t^r with the recursive algorithm

   (a) Set $w_{\mathcal{L}_{\text{KM}}+1}^r = w_{\mathcal{L}_{\text{KM}}+1}^m$ if $w_{\mathcal{L}_{\text{KM}}+1}^m$ is not missing or set $w_{\mathcal{L}_{\text{KM}}+1}^r = w_{\mathcal{L}_{\text{KM}}+1}$ otherwise.

   (b) For $t \in [\mathcal{L}_{\text{KM}} + 2, T - \mathcal{L}_{\text{KM}}]$

$$w_t^r = \begin{cases} w_t^m & \text{if } w_t^m \neq . \text{ and } f_t > \mathcal{C}_{\text{KM}} \text{ and } w_t = w_t^m, \\ w_{t-1}^r & w_t^m = . \text{ or } f_t \leq \mathcal{C}_{\text{KM}} \text{ or } w_t \neq w_t^m. \end{cases} \tag{S13}$$

4. Repeat the following algorithm five times:

$$w_{\{\mathcal{R}\cap\mathcal{C}\}-1}^r = w_{\{\mathcal{R}\cap\mathcal{C}\}} \quad \text{and} \quad w_{\{\mathcal{R}\cap\mathcal{P}\}}^r = w_{\{\mathcal{R}\cap\mathcal{P}\}-1}. \tag{S14}$$

   Here, $\mathcal{R}$ denotes periods of changes in regular wage:

$$\mathcal{R} = \{t : w_{it}^r \neq w_{it-1}^r \ \wedge \ w_{it-1}^r \neq . \ \wedge \ w_{it}^r \neq .\}; \tag{S15}$$

   $\mathcal{C}$ denotes periods with regular wages:

$$\mathcal{C} = \{t : w_{it}^r = w_{it} \ \wedge \ w_{it}^r \neq . \ \wedge \ w_{it} \neq .\}; \tag{S16}$$

   and $\mathcal{P}$ denotes periods where the last wage was regular:

$$\mathcal{P}_1 = \{t : w_{t-1}^r = w_{t-1} \ \wedge \ w_{t-1}^r \neq 0 \ \wedge \ w_{t-1} \neq 0\}, \tag{S17}$$

$$\mathcal{P} = \mathcal{P}_1/(\mathcal{P}_1 \cap \mathcal{R} \cap \mathcal{C}). \tag{S18}$$

B.5.4 *Blanco (2021) method* The method drops wage changes with two properties: (i) a new wage that is preceded and followed by the same wage and (ii) inverse-V-shaped wage changes for which the rise and fall are asymmetric, as long as their magnitude falls above a threshold value. This method depends on three parameters: $\mathcal{K}_B$, $\mathcal{P}_B$, and $\mathcal{E}_B$. Here, $\mathcal{K}_B$ describes the number of periods to drop wages changes for wages when they are preceded and followed by the same wage, $\mathcal{P}_B$ denotes ignored small wage changes, and $\mathcal{E}_B$ denotes the threshold for dropping an inverse-V-shaped wage change.

The method works as follows:

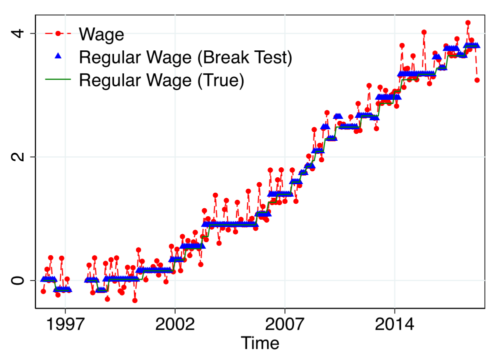
1. Set $K = 1$.
2. Construct $\mathcal{F}$ and $\mathcal{Z}$

$$\mathcal{F}_K = \left\{ t : \left| \sum_{j=0}^{K} \Delta w_{t+j} \right| < \mathcal{P}_B \right\}, \qquad \mathcal{Z}_K = \left\{ t : \left| \sum_{j=0}^{K} \Delta w_{t-j} \right| < \mathcal{P}_B \right\}. \tag{S19}$$

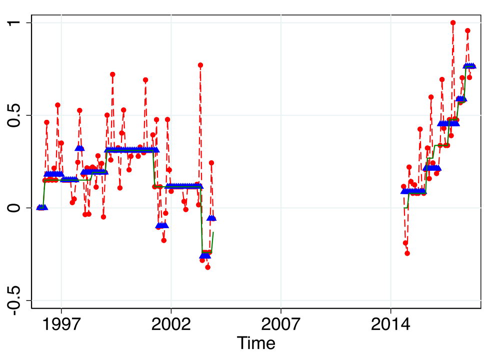
   Observe that $t^* \in \mathcal{F}_K \iff t^* + K \in \mathcal{F}_K$.

3. Replace $\Delta w_t = 0$ for all dates between t^* and $t^* + K$, where $t^* \in \mathcal{F}_K$. If $K < \mathcal{K}_B$, go to step 1 and set $K = K + 1$. If $K = \mathcal{K}_B$, go to step 3.
4. Replace Δw_t if $\Delta w_t > \mathcal{E}_B$ and $\Delta w_{i,t+1} < -\mathcal{E}_B$.

B.6 *Additional model results*



(a) Sample path 1



(b) Sample path 2

FIGURE B.1. Two sample paths of wages and regular wages. *Notes*: Panels (a) and (b) plot the evolution of the (log) wage (red line with dots), the simulated (log) regular wage (green dashed line), and the regular wage (blue triangle) recovered with the Break Test for two workers in our sample. *Source*: Authors' calculations based on the RELS, 1996–2015, and simulations.

Table B.2. Estimated threshold values and break test evaluation, sectors 1–4.

	Sectors			
	1	2	3	4
Moments (data,model):				
Mean of 1-yr Δw	(0.19, 0.18)	(0.17, 0.14)	(0.24, 0.27)	(0.20, 0.20)
Std. of 1-yr Δw	(0.20, 0.20)	(0.67, 0.42)	(0.26, 0.29)	(0.23, 0.24)
CV(3) of 1-yr Δw	(3.78, 3.39)	(39.73, 25.66)	(3.59, 3.43)	(4.06, 4.14)
Std. of 1-mo Δw	(0.17, 0.18)	(0.69, 0.35)	(0.24, 0.23)	(0.19, 0.19)
Mean of 1-mo Δw in Jun/Dec	(0.21, 0.21)	(0.34, 0.32)	(0.31, 0.31)	(0.35, 0.35)
Std. of 1-mo Δw in Jun/Dec	(0.21, 0.24)	(0.62, 0.54)	(0.24, 0.23)	(0.21, 0.21)
Share of 1-yr $\Delta w = 0$	(0.04, 0.04)	(0.02, 0.00)	(0.02, 0.00)	(0.02, 0.02)
Share of 1-mo $\Delta w = 0$	(0.43, 0.39)	(0.12, 0.12)	(0.14, 0.14)	(0.15, 0.15)
Share of 1-mo $\Delta w > 0$	(0.32, 0.34)	(0.46, 0.46)	(0.46, 0.47)	(0.47, 0.45)
Parameters:				
$(T, \tilde{w}^-, \tilde{w}^+)$	(36, −0.11, 1.5)	(31, −0.12, 1.1)	(3, −0.83, 1.5)	(26, −0.20, 1.5)
σ_η	0.02	0.09	0.07	0.06
(m_ϕ, σ_ϕ)	(0.30, 0.17)	(0.34, 0.45)	(0.32, 0.08)	(0.38, 0.03)
(σ_γ, β)	(0.18, 0.28)	(0.30, 0.58)	(0.20, 0.51)	(0.15, 0.58)
Threshold and break test evaluation:				
Threshold value $\mathcal{K}$	0.42	0.39	0.38	0.47
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.17, 0.17)	(0.21, 0.23)	(0.34, 0.33)	(0.12, 0.12)
Pr(no break in t|no break t)	0.90	0.82	0.72	0.91
Pr(break between $t \pm 2$ |break t)	0.89	0.78	0.85	0.76

Note: The table presents selected moments of the wage data in the SMM estimation for sectors 1 (i.e., agriculture), 2 (i.e., fishing), 3 (i.e., mining), and 4 (i.e., manufacturing). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third-order generalized coefficient of variation, that is, $\text{CV}(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector. *Source*: Authors' calculations based on the RELS, 1996–2015, and simulations.

Table B.3. Estimated threshold values and break test evaluation, 5–8.

	Sectors			
	5	6	7	8
Moments (data,model):				
Mean of 1-yr Δw	(0.20, 0.20)	(0.22, 0.22)	(0.22, 0.23)	(0.22, 0.22)
Std. of 1-yr Δw	(0.24, 0.26)	(0.26, 0.24)	(0.20, 0.21)	(0.20, 0.20)
CV(3) of 1-yr Δw	(4.65, 4.93)	(4.14, 3.68)	(2.38, 2.41)	(2.62, 2.55)
Std. of 1-mo Δw	(0.27, 0.24)	(0.19, 0.20)	(0.14, 0.13)	(0.13, 0.13)
Mean of 1-mo Δw in Jun/Dec	(0.34, 0.33)	(0.31, 0.31)	(0.30, 0.30)	(0.30, 0.30)
Std. of 1-mo Δw in Jun/Dec	(0.26, 0.25)	(0.21, 0.23)	(0.20, 0.20)	(0.19, 0.19)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.02, 0.01)	(0.03, 0.03)	(0.03, 0.03)
Share of 1-mo $\Delta w = 0$	(0.14, 0.14)	(0.14, 0.16)	(0.24, 0.24)	(0.24, 0.23)
Share of 1-mo $\Delta w > 0$	(0.46, 0.45)	(0.47, 0.45)	(0.44, 0.41)	(0.44, 0.42)
Parameters:				
$(T, \tilde{w}^-, \tilde{w}^+)$	(25, −0.20, 1.5)	(36, −0.18, 1.5)	(30, −0.22, 1.5)	(29, −0.21, 1.5)
σ_η	0.03	0.09	0.06	0.06
(m_ϕ, σ_ϕ)	(0.36, 0.05)	(0.33, 0.09)	(0.36, 0.04)	(0.35, 0.06)
(σ_γ, β)	(0.19, 0.60)	(0.17, 0.54)	(0.11, 0.46)	(0.10, 0.47)
Threshold and break test evaluation:				
Threshold value $\mathcal{K}$	0.50	0.41	0.49	0.49
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.10, 0.10)	(0.17, 0.17)	(0.11, 0.11)	(0.11, 0.12)
Pr(no break in t|no break t)	0.92	0.87	0.93	0.93
Pr(break between $t \pm 2$ |break t)	0.70	0.79	0.85	0.83

Note: The table presents selected moments of the wage data in the SMM estimation for sectors 5 (i.e., construction), 6 (i.e., retail), 7 (i.e., hotel and restaurant), and 8 (i.e., transport). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third-order generalized coefficient of variation, that is, $\text{CV}(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector. *Source*: Authors' calculations based on the RELS, 1996–2015, and simulations.

Table B.4. Estimated threshold values and break test evaluation, 9–12.

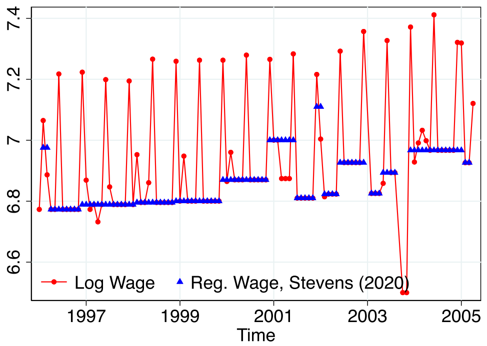
	Sectors			
	9	10	11	12
Moments (data,model):				
Mean of 1-yr Δw	(0.20, 0.20)	(0.21, 0.21)	(0.21, 0.21)	(0.22, 0.09)
Std. of 1-yr Δw	(0.22, 0.22)	(0.23, 0.26)	(0.21, 0.21)	(0.23, 0.23)
CV(3) of 1-yr Δw	(3.53, 3.54)	(3.82, 4.11)	(2.88, 2.86)	(3.12, 3.23)
Std. of 1-mo Δw	(0.17, 0.17)	(0.24, 0.20)	(0.15, 0.15)	(0.15, 0.14)
Mean of 1-mo Δw in Jun/Dec	(0.32, 0.31)	(0.32, 0.31)	(0.29, 0.28)	(0.17, 0.18)
Std. of 1-mo Δw in Jun/Dec	(0.19, 0.20)	(0.23, 0.23)	(0.20, 0.20)	(0.20, 0.17)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.05, 0.05)	(0.04, 0.04)	(0.08, 0.10)
Share of 1-mo $\Delta w = 0$	(0.16, 0.16)	(0.21, 0.23)	(0.25, 0.25)	(0.52, 0.35)
Share of 1-mo $\Delta w > 0$	(0.46, 0.45)	(0.43, 0.41)	(0.42, 0.41)	(0.29, 0.35)
Parameters:				
$(T, \tilde{w}^-, \tilde{w}^+)$	(20, −0.21, 1.5)	(36, −0.26, 1.5)	(30, −0.21, 1.5)	(32, −0.19, 1.4)
σ_η	0.05	0.06	0.06	0.08
(m_ϕ, σ_ϕ)	(0.34, 0.05)	(0.37, 0.04)	(0.35, 0.04)	(0.25, 0.06)
(σ_γ, β)	(0.13, 0.57)	(0.16, 0.49)	(0.12, 0.45)	(0.12, 0.36)
Threshold and break test evaluation:				
Threshold value $\mathcal{K}$	0.49	0.52	0.47	0.48
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.11, 0.12)	(0.09, 0.09)	(0.11, 0.12)	(0.09, 0.09)
Pr(no break in t|no break t)	0.92	0.95	0.93	0.95
Pr(break between $t \pm 2$ |break t)	0.77	0.79	0.82	0.84

Note: The table presents selected moments of the wage data in the SMM estimation for sectors 9 (i.e., financial activities), 10 (i.e., real estate activities), 11 (i.e., education), and 12 (i.e., social services). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third-order generalized coefficient of variation, that is, $\mathrm{CV}(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector. *Source*: Authors' calculations based on the RELS, 1996–2015, and simulations.

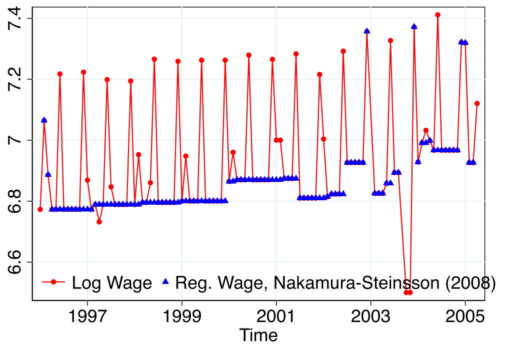
TABLE B.5. Estimated threshold values and break test evaluation, sectors 13–14.

	Sectors	
	13	14
Moments (data,model):		
Mean of 1-yr Δw	(0.20, 0.19)	(0.21, 0.21)
Std. of 1-yr Δw	(0.20, 0.19)	(0.21, 0.21)
CV(3) of 1-yr Δw	(2.99, 2.82)	(3.05, 2.95)
Std. of 1-mo Δw	(0.15, 0.15)	(0.15, 0.16)
Mean of 1-mo Δw in Jun/Dec	(0.31, 0.30)	(0.28, 0.28)
Std. of 1-mo Δw in Jun/Dec	(0.20, 0.22)	(0.21, 0.21)
Share of 1-yr $\Delta w = 0$	(0.02, 0.02)	(0.04, 0.04)
Share of 1-mo $\Delta w = 0$	(0.27, 0.26)	(0.29, 0.28)
Share of 1-mo $\Delta w > 0$	(0.41, 0.41)	(0.40, 0.39)
Parameters:		
$(T, \tilde{w}^-, \tilde{w}^+)$	(28, −0.14, 1.5)	(31, −0.20, 1.5)
σ_η	0	0
(m_ϕ, σ_ϕ)	(0.37, 0.09)	(0.36, 0.06)
(σ_γ, β)	(0.13, 0.42)	(0.13, 0.42)
Threshold and break test evaluation:		
Threshold value $\mathcal{K}$	0.43	0.50
$\Pr(w_t^R \neq w_{t-1}^R)$	(0.17, 0.16)	(0.10, 0.11)
Pr(no break in t|no break t)	0.89	0.94
Pr(break between $t \pm 2$ |break t)	0.87	0.83

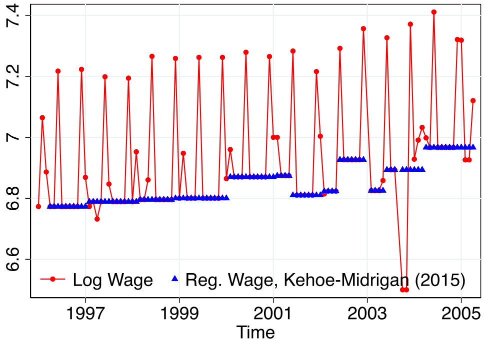
Note: The table presents selected moments of the wage data in the SMM estimation for sectors 13 (i.e., health) and 14 (i.e., personal and community services). Δw denotes wage changes. The first block of rows (i.e., rows 1 to 9) describes the wage change moments in the data and in the model. The second block of rows (i.e., rows 10 to 13) describes the estimated parameters. The last block of rows (i.e., rows 14 to 17) describes the value of $\mathcal{K}$ across sectors and some statistics to evaluate the validity of the methodology. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. CV(3) denotes the third-order generalized coefficient of variation, that is, $\mathrm{CV}(3) = E[\Delta w^3]/E[\Delta w]^3$. The last column shows the average results across sectors weighted by the number of workers in each sector. *Source*: Authors' calculations based on the RELS, 1996–2015, and simulations.



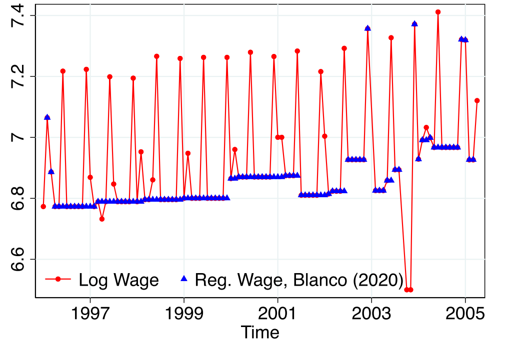
(a) Stevens (2020) method



(b) Nakamura and Steinsson (2008) method

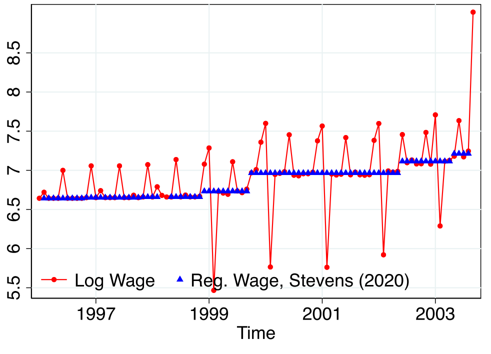


(c) Kehoe and Midrigan (2015) method

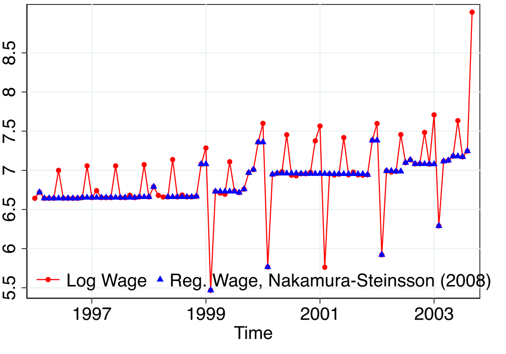


(d) Blanco (2021) method

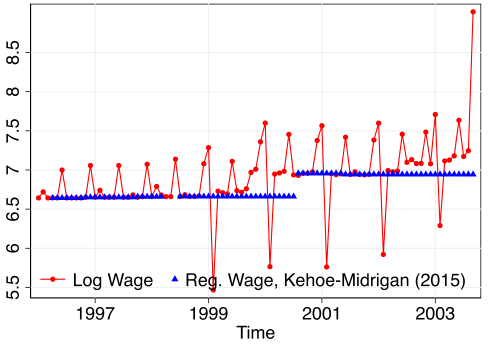
FIGURE B.2. Wages and regular wages under different filtering methods. *Notes*: Panels (a) to (d) of Figure B.2 show the (log) wage (red line with dots) and the regular wage (blue triangle) for a worker in our sample constructed with four methods by Stevens (2020), Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), and Blanco (2021), respectively. *Source*: Authors' calculations based on the RELS, 1996–2015.



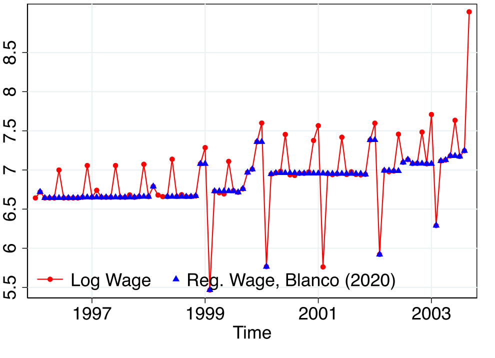
(a) Stevens (2020) method



(b) Nakamura and Steinsson (2008) method

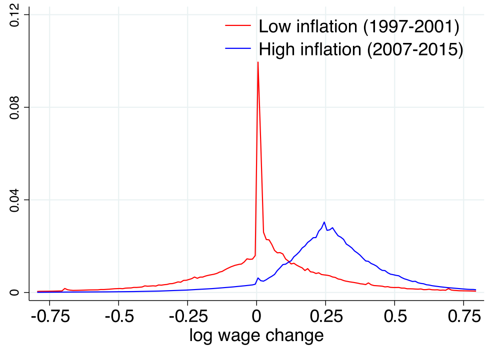


(c) Kehoe and Midrigan (2015) method

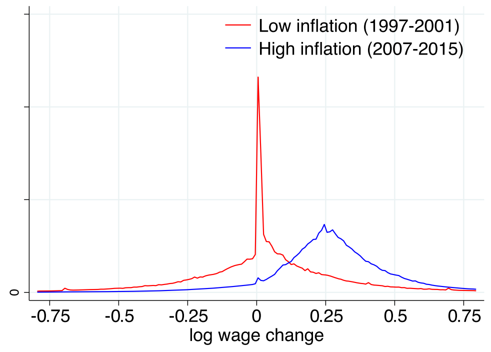


(d) Blanco (2021) method

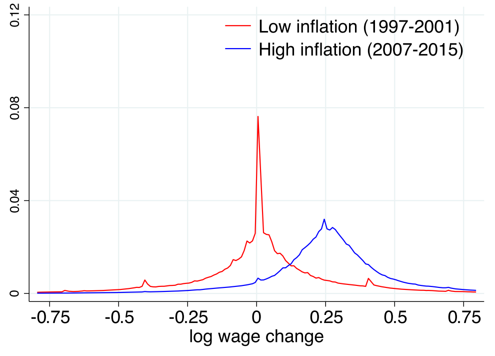
FIGURE B.3. Wages and regular wages under different filtering methods. *Notes*: Panels (a) to (d) of Figure B.3 show the (log) wage (red line with dots) and the regular wage (blue triangle) for a worker in our sample constructed with four methods by Stevens (2020), Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), and Blanco (2021), respectively. *Source*: Authors' calculations based on the RELS, 1996–2015.



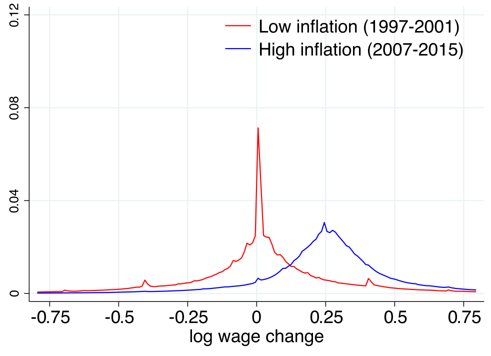
(a) Regular-wage changes within jobs



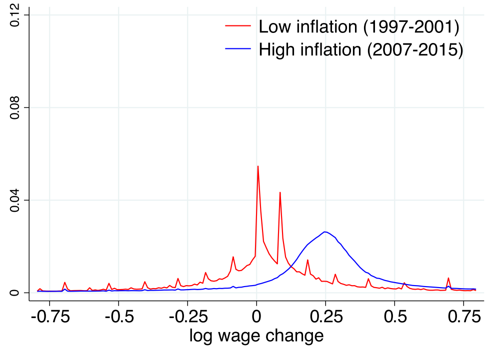
(b) Regular-wage changes



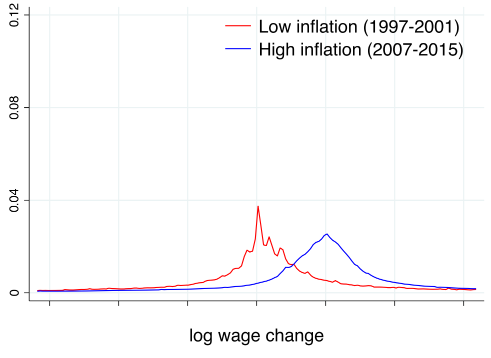
(c) Wage changes within jobs



(d) Wage changes



(e) Annual regular-wage growth



(f) Annual wage growth

FIGURE B.4. Distribution of 12-month regular-wage changes across inflation regimes. *Notes*: Panel (a) of Figure B.4 plots the distribution of 12-month regular-wage changes within jobs in the low- and high-inflation regimes (i.e., 1997–2001 and 2007–2015, respectively). Panel (b) plots the distribution of 12-month regular-wage changes within and across jobs in both regimes. Panels (c) and (d) repeat panels (a) and (b) for total wages. Panels (e) and (f) plot the growth rate of the sum of regular wages and total wages across workers within a year. *Source*: Authors' calculations based on the RELS, 1997–2015.

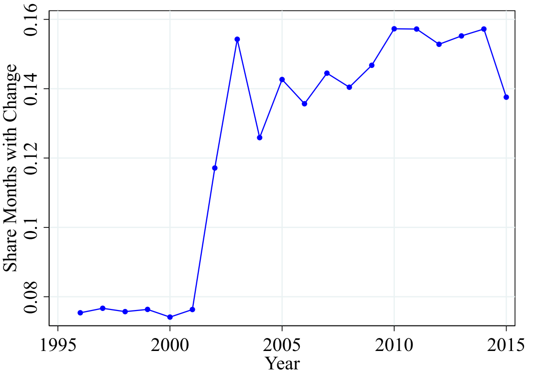
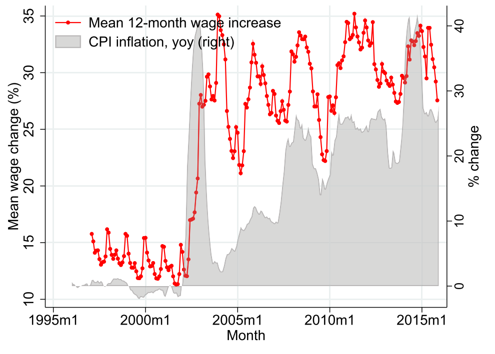
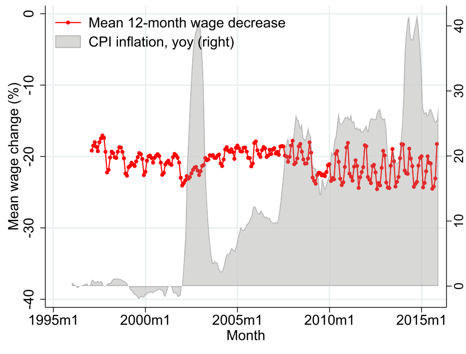


FIGURE B.5. Wage adjustment within job spells. *Notes*: Figure B.5 plots the time series of the average across job spells of the share of months with regular-wage changes within the year. *Source*: Authors' calculations based on the RELS, 1996–2015.

FIGURE B.6. Seasonal patterns of wage changes.*Notes*: Figure B.6 plots the average frequency of regular-wage changes by calendar month. The left panel shows the results for the subperiod of low inflation (i.e., between 1997 and 2001), and the right panel shows the results for the subperiod of high inflation (i.e., between 2007 and 2015). *Source*: Authors' calculations based on the RELS, 1997–2015.



(a) Increase



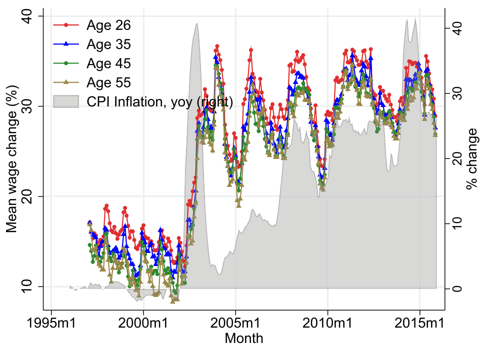
(b) Decrease

FIGURE B.7. Average 12-month regular-wage change. *Notes*: Panels (a) and (b) of Figure B.7 plot the 12-month average change in regular wages conditional on positive and negative changes, respectively. *Source*: Authors' calculations based on the RELS, 1997–2015.

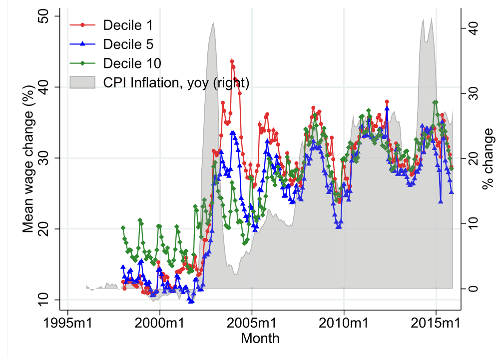
TABLE B.6. Estimated threshold values and break test evaluation under high and low inflation. Regimes.

Sector	Threshold value, all sample	Threshold value, low inflation	Threshold value, high inflation
1	0.42	0.46	0.40
2	0.39	0.39	0.39
3	0.38	0.38	0.38
4	0.47	0.46	0.46
5	0.50	0.50	0.50
6	0.41	0.41	0.41
7	0.49	0.45	0.49
8	0.49	0.42	0.47
9	0.49	0.42	0.47
10	0.52	0.47	0.47
11	0.47	0.45	0.48
12	0.48	0.37	0.39
13	0.43	0.43	0.45
14	0.50	0.46	0.50

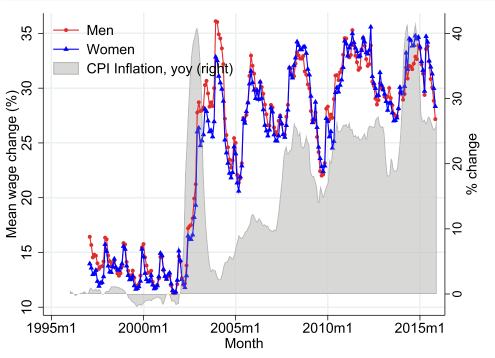
Note: The table presents the value of $\mathcal{K}$ across sectors in the entire sample (second column) and for the low- (third column) and high- (fourth column) inflation periods. For each job spell, we divide the starting date of that job before 2003 and after 2003. If the staring date is before 2003 (resp., after 2003), then we include that job spell in the SMM routine for the low- (resp., high-) inflation period. We truncate the wage change distribution at the 2nd and 98th percentiles in the data and in the model. *Source*: Authors' calculations based on the RELS, 1997–2015, and simulations.



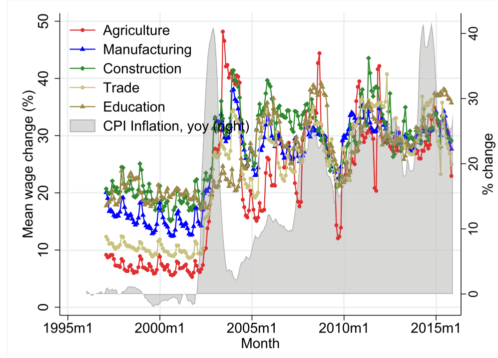
(a) Age



(b) Earnings

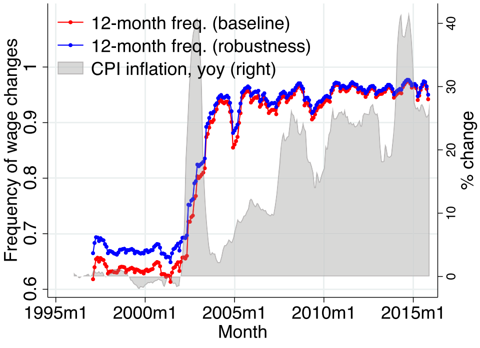


(c) Gender

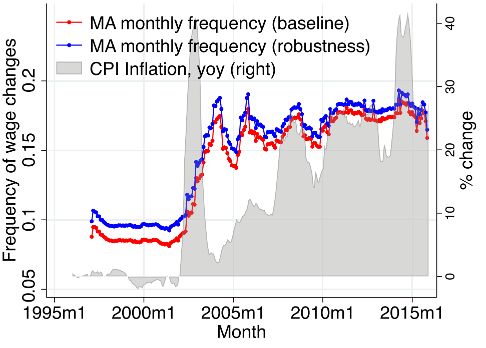


(d) Sectors

FIGURE B.8. Average of 12-month regular-wage increases by groups of workers. *Notes*: Figure B.8 plots the average size of annual wage increases for the following groups of workers: (a) Ages 26, 35, 45, and 55; (b) Income deciles: 1, 5, and 10; (c) Women and Men; (d) Sectors: Agriculture, Manufacturing, Construction, Trade, and Education. The shaded area shows the annual percentage change in the consumer price index. *Source*: Authors' calculations based on the RELS, 1997–2015.



(a) 12-month changes



(b) Monthly changes

FIGURE B.9. Frequency of 12-month regular-wage changes: Robustness with different construction of regular wages. *Notes*: Panels (a) and (b) of Figure B.9 show the annual frequency of regular-wage changes and the 12-month moving average of the monthly frequency of regular-wage changes. The shaded area shows the annual percentage change in the consumer price index. The red lines plot the yearly or monthly frequency of wage change in the main text—where the regular wage is constructed with only one $\mathcal{K}$ across high- and low-inflation periods. The blue lines plot the yearly and monthly frequency of wage change when the regular wage is constructed with two $\mathcal{K}$ for high- and low-inflation periods. *Source*: Authors' calculations based on the RELS, 1997–2015.

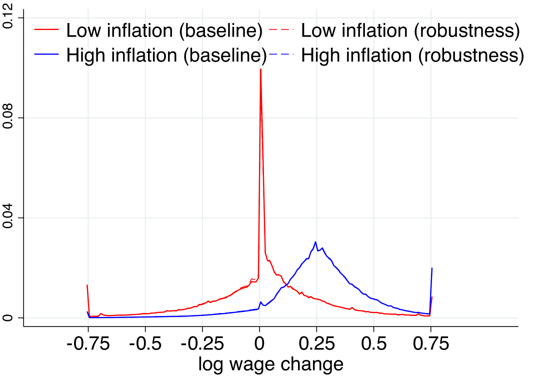
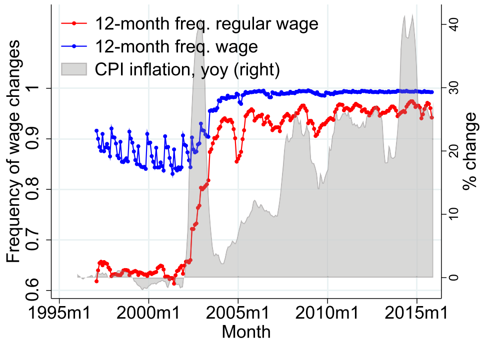
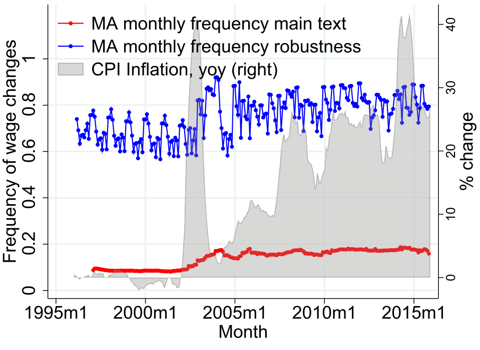


FIGURE B.10. Distribution of 12-month regular-wage changes across inflation regimes. *Notes*: Figure B.10 plots the distribution of 12-month regular-wage changes under low- and high-inflation regimes (1997–2001 and 2007–2015, respectively). The solid lines plot the distribution of regular-wage changes using only one $\mathcal{K}$ and the dashed lines plot the distribution of regular-wage changes with a $\mathcal{K}$ with high and low inflation. *Source*: Authors' calculations based on the RELS, 1997–2015.



(a) 12-month changes



(b) Monthly changes

FIGURE B.11. Frequency of 12-month wage changes and regular-wage changes. *Notes*: Panels (a) and (b) of Figure B.11 show the annual frequency of wage and regular-wage changes and the 12-month moving average of the monthly frequency of regular-wage changes. The shaded area shows the annual percentage change in the consumer price index. The red lines plot the yearly or monthly frequency of wage changes as in the main text. The blue lines plot the yearly wage change and the monthly wage change. *Source*: Authors' calculations based on the RELS, 1997–2015.

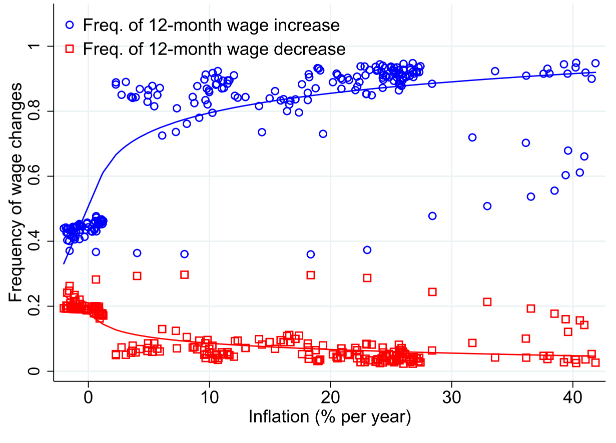
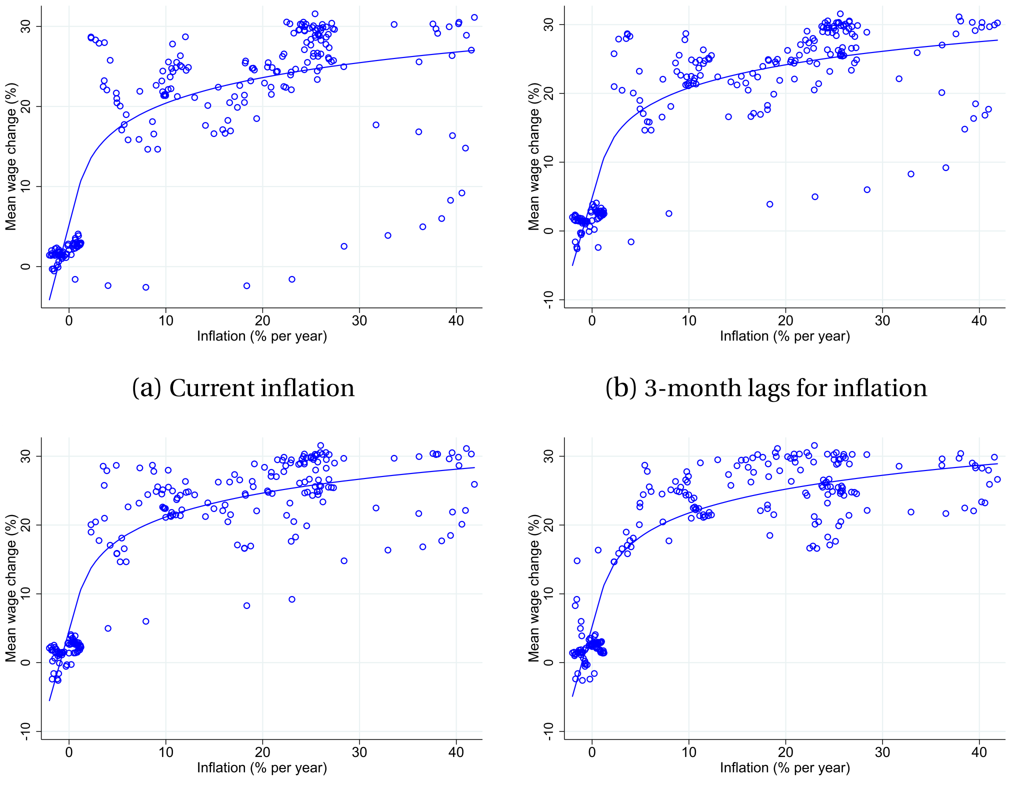


FIGURE B.12. Inflation and frequency of 12-month upward and downward regular-wage changes. *Notes*: Figure B.12 plots the frequency of 12-month upward and downward regular-wage changes against the annual percentage change in the consumer price index. The blue circles show the frequency of upward changes, while the red squares represent the frequency of downward adjustments. Blue and red lines show least-squares, fitted values for each frequency against $\log(\pi_t)$, for $\pi_t > 1$, and against $(\pi_t - 1)$, for $\pi_t \leq 1$. π_t is the annual percentage change in the consumer price index. *Source*: Authors' calculations based on the RELS, Central Bank of Argentina, and INDEC, 1997–2015.



(a) Current inflation

(b) 3-month lags for inflation

(c) 6-month lags for inflation

(d) 12-month lags for inflation

FIGURE B.13. Inflation and average 12-month regular-wage changes. *Notes*: Figure B.13 plots the average magnitude of 12-month regular wage adjustments against the annual percentage change in the consumer price index. Panel (a) shows the contemporaneous relationship between regular-wage inflation and price inflation. Panels (b) to (d) plot regular-wage inflation against lags of 3, 6, and 12 months for price inflation. Lines are least-squares, fitted values for the magnitude of 12-month regular wage adjustments against $\log(\pi_{t-j})$, for $\pi_{t-j} > 1$, and against $(\pi_{t-j} - 1)$, for $\pi_{t-j} \leq 1$. π_{t-j} is the annual percentage change in the consumer price index at month $t - j$, for $j = 0, 3, 6$, and 12. *Source*: Authors' calculations based on the RELS, Central Bank of Argentina, and INDEC, 1997–2015.

TABLE B.7. Frequency and size of 12-month wage changes and correlation with inflation.

Group	Average frequency				Average size (percent)				Correlation with inflation		
	Change		Cond. prob. of increase		Increase		Decrease		Frequency of wage change		
	Low Inflation	High Inflation	Low Inflation	High Inflation	Low Inflation	High Inflation	Low Inflation	High Inflation	All sample (1997–2015)	Low Inflation	High Inflation
All workers	0.64	0.95	0.69	0.95	13.4	30.2	20.2	21.4	0.67	0.16	0.66
By age:											
226	0.65	0.95	0.72	0.95	15.6	31.9	20.6	21.3	0.66	−0.14	0.60
35	0.63	0.95	0.69	0.95	14.0	30.2	20.4	22.2	0.67	0.29	0.64
45	0.63	0.95	0.67	0.95	12.5	29.4	20.4	20.5	0.68	0.12	0.66
55	0.59	0.94	0.69	0.95	11.7	29.0	21.0	20.3	0.68	−0.37	0.60
By income decile:											
Decile 1	0.64	0.96	0.73	0.94	12.9	31.4	21.9	19.8	0.58	0.29	0.42
Decile 2	0.69	0.96	0.75	0.93	9.5	30.9	22.0	23.4	0.61	−0.61	0.57
Decile 3	0.64	0.96	0.78	0.94	7.5	29.5	19.7	22.7	0.60	−0.56	0.50
Decile 4	0.65	0.97	0.73	0.96	9.8	28.9	18.7	21.3	0.61	−0.71	0.44
Decile 5	0.65	0.97	0.67	0.96	12.3	29.0	19.2	19.5	0.65	−0.53	0.64
Decile 6	0.65	0.96	0.65	0.96	13.6	29.3	20.0	19.3	0.66	−0.48	0.67
Decile 7	0.63	0.95	0.63	0.95	15.0	29.6	19.9	19.9	0.65	−0.09	0.67
Decile 8	0.61	0.94	0.61	0.95	15.6	29.8	20.1	19.8	0.65	0.08	0.63
Decile 9	0.60	0.93	0.62	0.94	16.6	29.9	21.3	20.1	0.68	0.40	0.66
Decile 10	0.58	0.92	0.67	0.93	17.1	31.3	21.6	23.5	0.72	0.80	0.69
By gender:											
Women	0.64	0.96	0.74	0.95	13.1	30.3	20.6	24.3	0.68	−0.12	0.64
Men	0.64	0.95	0.67	0.94	13.6	30.1	20.1	20.1	0.66	0.53	0.67
By sector:											
Agriculture	0.82	0.97	0.79	0.93	7.1	28.6	19.3	18.5	0.64	0.14	0.42
Manufacturing	0.60	0.93	0.62	0.94	15.4	30.0	21.3	19.6	0.70	−0.71	0.52
Construction	0.72	0.96	0.58	0.89	19.6	31.1	21.6	20.0	0.66	0.14	0.35
Trade	0.59	0.96	0.75	0.96	10.2	30.1	19.2	22.9	0.67	−0.02	0.60
Education	0.64	0.98	0.74	0.94	19.9	30.9	24.9	25.9	0.55	0.48	0.51

Note: This table reports, for both the low- and high-inflation periods (1997–2001 and 2007–2015, respectively) and the aggregate and different groups of workers (i) the average frequency of 12-month regular-wage changes, (ii) the conditional probability of an increase, that is, the share of changes that are increases calculated as freq. of increase / (freq. of increase + freq. of decrease), (iii) the average size of annual regular wage increases and decreases (in absolute terms), and (iii) the correlation of the annual frequency of regular-wage changes with annual inflation. *Source*: Authors' calculations based on the RELS, Central Bank of Argentina, and INDEC, 1997–2015.

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