Econometrica Supplementary Material

SUPPLEMENT TO "SEARCHING FOR JOB SECURITY AND THE CONSEQUENCES OF JOB LOSS"

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APPENDIX A: PROOFS

A.1. *Proof of Proposition 1*

THE FIRST PART OF THIS PROOF ESTABLISHES THAT the surplus function is strictly increasing in productivity and job security. It follows that workers move towards more productive and secure jobs along the job ladder. The second part then establishes that it follows that the expected probability of job loss is a strictly decreasing function of the time since the last unemployment spell (employment tenure).

Part 1: Slope of the Surplus Function

We want to prove that $S(\theta, s)$ is strictly increasing in productivity θ_y when $S(\theta, s)$ is strictly positive. To that end, whenever $S(\theta, s)$ is strictly positive, $S(\theta, s) = \hat{S}(\theta, s)$, where

$$\begin{aligned}\hat{S}(\theta, s) = {} & p(\theta_y, s) - z \\ & + \beta(1-\theta_\delta)\int_{\mathcal{S}}\Big(\max\{0, \hat{S}(\theta, s')\} \\ & + \int_{\hat{M}_{1(\theta,s')}} \lambda_1\alpha\big(\hat{S}(\theta, s') - \max\{0, \hat{S}(\theta, s')\}\big)\Big)\, dF(x)\, dG_e(s'|s) \\ & - \Big(\int_{\mathcal{S}}\int_{\hat{M}_{1(u,s')}} \lambda_0\alpha\hat{S}(x, s')\, dF(x)\, dG_u(s'|s)\Big) \\ & + \int_{\mathcal{S}} U(s')\, dG_e(s'|s) - \int_{\mathcal{S}} U(s')\, dG_u(s'|s)\big).\end{aligned}$$

This auxiliary function is identical to the surplus function when strictly positive but does not restrict it to be non-negative. The set $\hat{M}_1(\theta, s)$ here collects all jobs x such that $\hat{S}(x, s) > \hat{S}(\theta, s)$ and $\hat{S}(x, s) > 0$ and is hence identical to $M_1(\theta, s)$.

To show that the surplus is strictly increasing in θ_y, it then suffices to show that

$$\begin{aligned}\mathcal{T}\hat{S}(\theta, s) = {} & p(\theta_y, z) \\ & + \beta(1-\theta_\delta)\int_{\mathcal{S}}\Big(\max\{\hat{S}(\theta, s'), 0\} \\ & + \lambda_1\alpha\int_{M_1(\theta,s')}\big(\hat{S}(x, s') - \max\{0, \hat{S}(\theta, s')\}\big)\, dF(x)\Big)\, dG_e(s'|s) \qquad (1)\end{aligned}$$

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is a contraction and that it maps weakly increasing into strictly increasing functions. Note that I have omitted the constants that are independent of θ which is without loss. The operator is a contraction because it satisfies Blackwell's sufficient conditions.

Next, denote the integrand in (1) by $\tilde{S}(\theta,s) \equiv \max\{\hat{S}(\theta,s),0\} + \lambda_1\alpha\int_{M_1(\theta,s)}(\hat{S}(x,s) - \max\{0,\hat{S}(\theta,s)\})\,dF(x)$. We will show that when $\hat{S}(\theta,s)$ is non-decreasing in θ_y, then $\tilde{S}(\theta,s)$ is non-decreasing in θ_y. To do so, take two jobs θ_1, θ_2 with $\theta_{1,2} < \theta_{y,2}$ and $\theta_{\delta,1} = \theta_{\delta,2} = \theta_\delta$. Assuming $\hat{S}(\theta,s)$ is non-decreasing in θ_y, we have that

$$\begin{aligned}
&\tilde{S}(\theta_2,s) - \tilde{S}(\theta_1,s) \\
&\quad = \big(\max\{S(\theta_2,s),0\} - \max\{S(\theta_1,s),0\}\big)\left(1 - \lambda_1\alpha\int_{M_1(\theta_2,s)} dF(x)\right) \\
&\qquad - \lambda_1\alpha\left(\int_{M(\theta_1,s)\setminus M(\theta_2,s)} S(x,s)\,dF(x) - S(\theta_1,s)\int_{M(\theta_1,s)\setminus M(\theta_2,s)} dF(x)\right) \\
&\quad \geq \big(\max\{S(\theta_2,s),0\} - \max\{S(\theta_1,s),0\}\big) \\
&\qquad \times \left(1 - \lambda_1\alpha\left(\int_{M(\theta_2,s)} dF(x) + \int_{M(\theta_1,s)\setminus M(\theta_2,s)} dF(x)\right)\right) \\
&\quad = \big(\max\{S(\theta_2,s),0\} - \max\{S(\theta_1,s),0\}\big)\left(1 - \lambda_1\alpha\int_{M(\theta_1,s)} dF(x)\right) \\
&\quad \geq 0.
\end{aligned} \tag{2}$$

Next, we show that if $\hat{S}(\theta,s)$ is weakly increasing in θ_y, then $\mathcal{T}\hat{S}(\theta,s)$ is strictly increasing in θ_y. Again consider θ_1, θ_2 with $\theta_{1,2} < \theta_{y,2}$ and $\theta_{\delta,1} = \theta_{\delta,2} = \theta_\delta$. We have that

$$\begin{aligned}
\mathcal{T}\hat{S}(\theta_1,s) &= p(\theta_{y,1},z) + \beta(1-\theta_\delta)\int_{\mathcal{S}} \tilde{S}(\theta_1,s')\,dG_e(s'|s) \\
&\leq p(\theta_{y,1},z) + \beta(1-\theta_\delta)\int_{\mathcal{S}} \tilde{S}(\theta_2,s')\,dG_e(s'|s) \\
&< p(\theta_{y,2},z) + \beta(1-\theta_\delta)\int_{\mathcal{S}} \tilde{S}(\theta_2,s')\,dG_e(s'|s) \\
&= \mathcal{T}\hat{S}(\theta_2,s),
\end{aligned}$$

which implies the result. The weak inequality follows from (2). The strict inequality follows from the assumptions on the production function. The proof for $1-\theta_\delta$ is almost analogous and therefore omitted. It follows that $\hat{S}(\theta,s)$ and hence $S(\theta,s)$ is strictly increasing in θ_y and strictly decreasing in θ_δ whenever $S(\theta,s) > 0$.

Part 2: Declining Rate of Job Loss

Consider newly employed workers with employment tenure $\tau = 1$ which just exited unemployment. Expected job security $1 - \mathbf{E}[\theta_\delta|\tau = 1]$ depends on the expected θ_δ in the offer distribution conditional on $S(\theta) > 0$. We show that $\mathbf{E}[\theta_\delta|\tau = 2] < \mathbf{E}[\theta_\delta|\tau = 1]$. Consider the workers who move from θ to $\hat{\theta}$ after the first period. If $\hat{\theta}_y < \theta_y$, it must be that $\hat{\theta}_\delta < \theta_\delta$ for $S(\hat{\theta}) > S(\theta)$. If $\hat{\theta}_y > \theta_y$, we have that $\mathbf{E}[\hat{\theta}_\delta|\hat{\theta}_y] < \theta_\delta$ by Assumption 1. Thus, conditional on a job-to-job transition, $\mathbf{E}[\theta_\delta|\tau = 2] < \mathbf{E}[\theta_\delta|\tau = 1]$. Because of search frictions, the share of workers transitioning to a new job $\hat{\theta}$ is strictly positive for all τ. Since non-movers have unaltered θ, we have that $\mathbf{E}[\theta_\delta|\tau = 2] < \mathbf{E}[\theta_\delta|\tau = 1]$ unconditionally.[1] For $\tau > 2$, proceed by induction.

A.2. *Wages*

The moment the wage gets set, the current skill and (new) benchmark skill are identical and the firm receives an expected value $J(\theta, \hat{\theta}, s, s)$ that is given directly from the bargaining rules. Thus, the wage can be obtained from equation (6), evaluated at $\hat{s} = s$:

$$\begin{aligned} &J(\theta, \hat{\theta}, s, s) \\ &\quad = p(\theta_y, s) - w(\theta, \hat{\theta}, s) + \beta \int_S (1 - \theta_\delta)\bigg(\lambda_1 \int_{M_2} J\big(\theta, x, s', s'\big)\, dF(x) \\ &\qquad + \bigg(1 - \lambda_1 \int_{M_3} dF(x)\bigg)\big(\mathbb{I}_1 J\big(\theta, \hat{\theta}, s', s\big) + \mathbb{I}_2 J\big(\theta, u, s', s'\big)\big)\bigg)\, dG_e\big(s'|s\big). \end{aligned} \tag{3}$$

The left-hand side is known and $J(\theta, x, s', s')$ is known for all s' for the same reason. The set M_1 is known and contains all jobs with joint higher surplus. The indicators are likewise straightforward to construct. However, the values $J(\theta, x, s', s)$ for $s' \neq s$ are not generally known and neither are the renegotiation sets M_2 since these depend on the wage. These objects must hence be solved for jointly with wages.

A.3. *Planning Problem*

Because of the partial equilibrium nature of the model, the utilitarian planner's problem is simple. The planner decides which jobs are acceptable for the unemployed and which jobs are preferable for the employed. Her objective is to maximize the expected present value of flow output (which includes z when unemployed) produced by a worker.

Denote by $Y^P(\theta, s)$ the expected present value of output produced by a type s worker currently matched with firm θ. The worker moves to another job θ' only if it falls into the set $M_1^P(\theta, s)$ chosen by the planner. Denote by $U^P(\theta, s)$ the expected present value of output produced by an unemployed worker who accepts a job offer θ' only if it falls into the set $M_1^P(u, s)$ chosen by the planner. As in the equilibrium cases, I will suppress the dependence of these sets on employment status and skill. Define $S^P(\theta, s) \equiv \max\{0, Y^P(\theta, s) - U^P(s)\}$, the social net value of an employed worker and her job. Pro-

[1]This argument contrasts $\mathbf{E}[\theta_\delta|\tau = 2]$ with $\mathbf{E}[\theta_\delta|\tau = 1]$ conditional on not losing a job at the end of the period. The unconditional comparison includes an additional composition effect. Workers with high θ_δ are more likely to lose their job. That is, the distribution of θ_δ among job losers first-order stochastically dominates the one among stayers. This effect just reinforces the argument, which is why the proof is restricted to job-stayers.

ceeding like in the decentralized case gives

$$Y^P(\theta, s) = p(\theta_y, s) + \beta \int_S \bigg[(1-\theta_\delta)\bigg(\lambda_1 \int_{M_1^P} Y^P(x, s')\, dF(x) + \bigg(1 - \lambda_1 \int_{M_1^P} dF(x)\bigg) \max\{Y^P(\theta, s'), U^P(s')\}\bigg) + \theta_\delta U^P(s')\bigg] dG_e(s'|s),$$

$$U^P(s) = z + \beta \int_S \bigg(\lambda_0 \int_{M_1^P} (Y^P(x, s') - U^P(s'))\, dF(x) + U^P(s')\bigg) dG_u(s'|s), \tag{4}$$

$$\begin{aligned} S^P(\theta, s) = \max\bigg\{0,\ & p(\theta_y, s) - z + \beta \bigg(\int_S (1-\theta_\delta)\bigg(S^P(\theta, s') \\ & + \lambda_1 \int_{M_1^P} (S^P(x, s') - S^P(\theta, s'))\, dF(x)\, dG_e(s'|s)\bigg) \\ & - \lambda_0 \int_S \int_{M_1^P} S^P(x, s')\, dF(x)\, dG_u(s'|s) \\ & + \int_S U^P(s')\, dG_e(s'|s) - \int_S U^P(s')\, dG_u(s'|s)\bigg)\bigg\}. \end{aligned} \tag{5}$$

The solution to $S^P(\theta, s)$ implies the sets M_1^P for all firms θ and u, that is, it implies the solution to the planner problem. Therefore, comparing equations (5) and (4) with the expressions for bilateral surplus in (7) and the value of unemployment in (4), we have that

$$S^P(\theta, s) = S(\theta, s) \quad \text{if } \alpha = 1. \tag{6}$$

It follows immediately that the socially efficient ranking of jobs and reservation strategies can be derived from solving the equilibrium value functions under $\alpha = 1$. I notice that these expressions can also be derived from a constrained maximization problem where the planner maximizes aggregate output subject to frictions.

APPENDIX B: DATA AND ESTIMATION

The SIAB comes in spell format. I convert the main data set into a monthly panel which I use to compute the moments used in the estimation. Section B.1 describes the construction of the main monthly panel data set and how I construct the moments that are used in the estimation. I collapse the monthly panel into an annual panel which is used in the regressions in Section D.1.

B.1. *Monthly Panel and Construction of Variables and Moments*

I use the publicly available code by Eberle, Schmucker, and Seth (2013) to convert the spells into monthly cross-sections which we then merge into a monthly panel covering 1993–2010.[2] This assigns the spell information pertaining to a particular reference date

[2] I also use this code to assign a main employer. Download link accessed under http://doku.iab.de/fdz/reporte/2013/MR_04-13_EN.pdf.

during a month as the monthly observation. I record a worker as employed for a given month if the worker is full-time employed subject to Social Security (at the reference date) and otherwise as non-employed.[3]

During non-employment, I assign a value of 0 for earnings. During employment, I assign the average daily wage during the spell as reported by the employer as the wage observation. To deflate, I use the OECD's CPI for Germany.[4] During months of employment, I assign the average daily wage as the average daily earnings. This is consistent with restricting employment to full-time employment. I note that the data are censored at the Social Security contribution ceiling which I do not make any adjustments for. Finally, I censor the bottom percent and top per-mille of all wage observations in any given year.

I restrict the sample to workers of age 18–65. I next describe how I construct the empirical moments discussed in Section 3.3. For transitions into unemployment, I compute the rate at which currently employed workers exit employment. Specifically, I record an EU transition whenever a worker is full-time employed subject to Social Security in one month but not in the month thereafter and, in addition, shows up as receiving unemployment insurance (UI) the month thereafter (or is still non-employed in the month 2 or 3 after separation and then starts receiving UI).[5]

For transitions into employment, I compute the rate at which currently non-employed workers who are receiving UI transition into employment. In order to compute the rate of EE transitions, I compute the rate at which currently employed workers are employed at another establishment the following month.

The set of controls in regression (8) are listed in Figure 2. In regressions (9) and (10), I restrict to unemployment spells up to 2 years and job spells up to 8 years. In order to compute the ratio of the wages of the newly employed to the wages of the average worker, I project wages on fixed effects for age, gender, education, and calendar year and residualize. I then take the ratio of average residualized wages of those with 25 months of employment tenure and the average of all residualized wages. To construct the 50–10 and 90–50 wage ratios, I project log wages on an individual fixed effect and year fixed effects. I residualize and take the difference. Finally, to compute average wage growth, I compute individual 12 month ahead wage growth and normalize by the aggregate wage growth (in the same calendar year) to normalize for aggregate growth which the model does not have. I eliminate the top and bottom percentile of wage growth observations and take the pooled mean. For remaining details, see the main text.

B.2. *Annual Panel for Section 4*

I construct annual earnings in year y as the mean earnings across all months within the year. I construct annual wages as mean wages during months of employment. When

[3]The main reason for only including full-time employment is that the data do not contain detailed information on hours but rather just a part-time indicator. Thus, constructing wages, which are key for the estimation, is problematic for part-time workers. I thus follow Card, Heining, and Kline (2013) in restricting attention to the full-time employed. However, in Appendix C, I check whether the displacement regressions are sensitive to the classification of part-time workers.

[4]https://data.oecd.org/price/inflation-cpi.htm, downloaded on 9/11/2018.

[5]Thus, some very brief (within-month) E-U-E transitions go undetected. Germany has two different tiers of unemployment insurance. I lump both unemployment benefits (ALG) and unemployment assistance (ALHI) as UI. In contrast to the United States, the German social code classifies someone as unemployed only if they register as unemployed with the employment agency. As such, it is natural to condition on being registered in either of the two UI tiers when detecting an unemployment spell.

collapsing the monthly panel into the annual panel, I record job loss in year y if I record at least one job loss in the monthly panel during that year. Further, I merge information on the number of full-time employees at an establishment to register a mass layoff as described in the robustness Section 4.1.3. I record as employer the establishment the worker works at in January.

B.3. *Details of the Estimation*

I estimate the parameter vector ϕ via Simulated Method of Moments,

$$\hat{\phi} = \arg\min_{\phi} \mathcal{L}(\phi) \equiv g(\phi)' W g(\phi),$$

where W is a weighting matrix and $g(\phi)$ is a $K \times 1$ vector of differences between several statistics in the data and their model counterparts in simulated data. K is the number of targets, 14 in total, listed in Section 3.3 and Table 2. I target the log difference between all the moments listed in these sections.

W is a diagonal matrix. Because λ_0 exactly equals the job-finding-rate, I fix it at that value and set its weight to zero. The rest of W is an identity matrix, except I triple the weight on three targets: the rate of job loss, the job-to-job rate, and the ratio of the wage of newly hired workers to the average wage.

To find $\hat{\phi}$, I proceed as follows. Starting from a set of externally calibrated parameters, I follow Lise (2013) and Lise, Meghir, and Robin (2016) in using a Metropolis–Hastings algorithm to further reduce $\mathcal{L}(\phi)$: I create chains $(\phi^0, \dots, \phi^N)$ starting at ϕ^0. To update the parameter vector from ϕ^j to ϕ^{j+1}, I draw a new vector of parameters $\phi^{j'}$ from $\mathcal{N}(\phi^j, \Xi)$, where the diagonal matrix Ξ is scaled proportionally to ϕ^0. I then compute $\mathcal{L}(\phi^{j'}) - \mathcal{L}(\phi^j)$. If positive, $\phi^{j+1} = \phi^{j'}$. If negative, $\phi^{j+1} = \phi^{j'}$ with probability $\exp(\mathcal{A}(\mathcal{L}(\phi^j) - \mathcal{L}(\phi^{j'})))$, where $\mathcal{A}$ is a tuning parameter that is chosen—jointly with the scaling factor of Ξ—so as to obtain an average rejection rate of 0.77, as suggested by Gelman, Carlin, Stern, and Rubin (2003), over the first 10 iterations. I choose the length of the chains N to be 350 and simulate 4000 chains. I pick the global minimum from all 1.4 million model simulations as $\hat{\phi}$.

To construct standard errors for these parameter estimates, we can cast this indirect inference approach in terms of GMM under standard regularity conditions (see, for instance, Honore, Jorgensen, and de Paula (2020)). Then we have that

$$\hat{\phi} \xrightarrow{d} N(\phi, \Sigma),$$

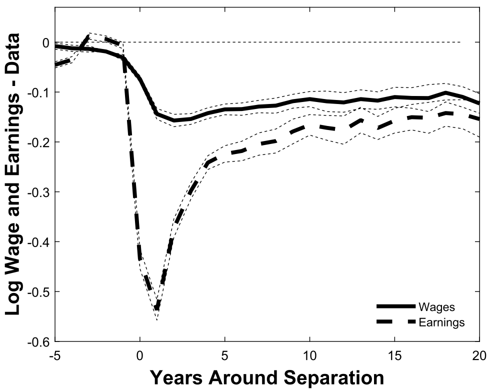
where

$$\Sigma = \left(G'WG\right)^{-1} G'WSWG\left(G'WG\right)^{-1}.$$

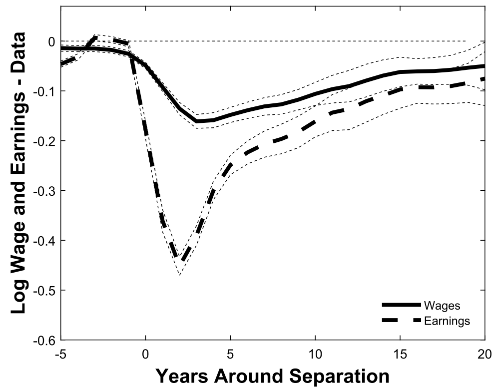
S contains the standard errors of the empirically measured moments. As is common practice, I set the off-diagonal elements of S to zero (Altonji and Segal (1996)). G is a $M \times K$ matrix that contains the gradient of each model-generated statistic with respect to the model parameters evaluated at $\hat{\phi}$ which I compute based on numerical simulations.

APPENDIX C: ADDITIONAL ROBUSTNESS FOR REDUCED-FORM RESULTS

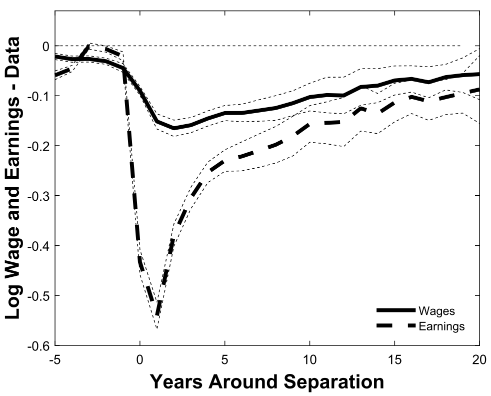
This subsection computes the empirical wage and earnings response to displacement as measured by specification (15) in a few additional ways. I contrast the results with the baseline specification in Figure C.1.



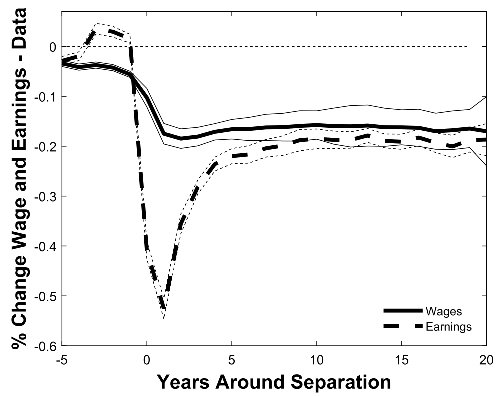
(a) Baseline



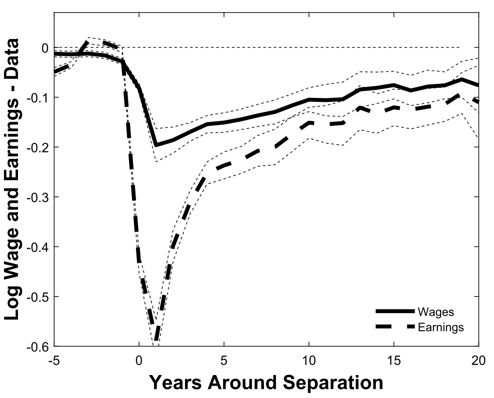
(b) Expanded Treatment Group



(c) Men Only



(d) Worker Fixed Effects



(e) Different Treatment of Part-Time Earnings

FIGURE C.1.—Earnings and wage response—additional robustness. *Notes:* (a) baseline, (b) the treatment group in year y includes all separators in years y, $y+1$, $y+2$, (c) only men in the sample, (d) and (e) see description in text. Two-way clustered standard errors used to construct 95% confidence intervals.

First, a common practice is to define the treatment group somewhat differently. For instance, Davis and von Wachter (2011) included in the treatment group in year y all separators in years y, $y+1$, $y+2$. This mechanically smooths earnings and wages losses around the layoff year as can be seen in Figure C.1(b).

Second, I restrict the sample to men only. Earnings and wages recover more strongly over time compared with the baseline. Third, I include results for log earnings and log wages where, instead of including the average pre-separation earnings/wage decile, I include a worker fixed effect. The results are similar but there is even less recovery in wages and earnings in the long run.

Finally, I treat part-time wages and earnings differently. Recall that I do not observe hours, so for the main analysis I treat workers as employed only when full-time employed. That is, whenever a worker is not full-time employed, I assign earnings of zero and a missing wage. Here, I also treat workers that are part-time employed ("geringfuegig beschaeftigt") as employed and assign their daily wage as the relevant value for both wages and earnings (I merely see that status but still no hours). I report the corresponding results in Figure C.1(e). The long-run recovery in earnings and wages is more pronounced but the overall picture remains the same.

APPENDIX D: ADDITIONAL MATERIAL

D.1. *Derivation of Surplus*

The exposition used that the joint surplus does not depend on the internal division of rents, something we have yet to show. Therefore, write the joint surplus in general form, $S(\theta, \hat{\theta}, s, \hat{s}) \equiv \max\{W(\theta, \hat{\theta}, s, \hat{s}) - U(s) + J(\theta, \hat{\theta}, s, \hat{s}), 0\}$ and plug in equations (5) and (6). This gives

$$
\begin{aligned}
S(\theta, \hat{\theta}, s, \hat{s}) = \max\Bigg\{0,\ & p(\theta_y, s) \\
& + \beta \int_S \Bigg[(1-\theta_\delta)\Bigg(\lambda_1\Bigg(\int_{M_1} W(x, \theta, s', s')\, dF(x) \\
& + \int_{M_2} \big(W(\theta, x, s', s') + J(\theta, x, s', s')\big)\, dF(x)\Bigg) \\
& + \Bigg(1 - \lambda_1 \int_{M_3} dF(x)\Bigg)\big(\mathbb{I}_1\big(W(\theta, \hat{\theta}, s', \hat{s}) + J(\theta, \hat{\theta}, s', \hat{s})\big) \\
& + \mathbb{I}_2\big(W(\theta, u, s', s') + J(\theta, u, s', s')\big) \\
& \times \mathbb{I}_3 U(s')\big)\Bigg) + \theta_\delta U(s')\Bigg]\, dG_e(s'|s) - U(s)\Bigg\}.
\end{aligned}
$$

Plug in (4) for $U(s)$, add and subtract $\beta \int_S U(s')\, dG_e(s'|s)$ to get

$$
\begin{aligned}
S(\theta, \hat{\theta}, s, \hat{s}) = \max\Bigg\{0,\ & p(\theta_y, s) - z + \beta\Bigg(\int_S (1-\theta_\delta) \\
& \times \Bigg(\lambda_1\Bigg(\int_{M_1} \big(W(x, \theta, s', s') - U(s')\big)\, dF(x)
\end{aligned}
$$

$$
\begin{aligned}
&+ \int_{M_2} \big(W\big(\theta, x, s', s'\big) + J\big(\theta, x, s', s'\big) - U\big(s'\big)\big)\, dF(x)\Big) \\
&+ \Big(1 - \lambda_1 \int_{M_3} dF(x)\Big) \\
&\times \big(\mathbb{I}_1\big(W\big(\theta, \hat{\theta}, s', \hat{s}\big) + J\big(\theta, \hat{\theta}, s', \hat{s}\big) - U\big(s'\big)\big) \\
&+ \mathbb{I}_2\big(W\big(\theta, u, s', s'\big) + J\big(\theta, u, s', s'\big) - U\big(s'\big)\big)\big)\big)\, dG_e\big(s'|s\big) \\
&- \int_{\mathcal{S}} \int_{M_1} \lambda_0\big(W\big(x, u, s', s'\big) - U\big(s'\big)\big)\, dF(x)\, dG_u\big(s'|s\big) \\
&+ \int_{\mathcal{S}} U\big(s'\big)\, dG_e\big(s'|s\big) - \int_{\mathcal{S}} U\big(s'\big)\, dG_u\big(s'|s\big)\big)\Big\}.
\end{aligned}
$$

Using the bargaining rules and the definition of surplus:

$$
\begin{aligned}
S(\theta, \hat{\theta}, s, \hat{s}) = \max\Big\{&0, p(\theta_y, s) - z + \beta\Big(\int_{\mathcal{S}} (1 - \theta_\delta) \\
&\times \Big(\lambda_1\Big(\int_{M_1} S\big(\theta, \hat{\theta}, s', \hat{s}\big) + \alpha\big(S\big(x, \theta, s', s'\big) - S\big(\theta, \hat{\theta}, s', s'\big)\big)\, dF(x) \\
&+ \int_{M_2} S\big(\theta, x, s', s'\big)\, dF(x)\Big) \\
&+ \Big(1 - \lambda_1 \int_{M_3} dF(x)\Big)\big(\mathbb{I}_1 S\big(\theta, \hat{\theta}, s', \hat{s}\big) + \mathbb{I}_2 S\big(\theta, u, s', s'\big)\big)\Big)\, dG_e\big(s'|s\big) \\
&- \int_{\mathcal{S}} \int_{M_1} \lambda_0 \alpha S\big(x, u, s', s'\big)\, dF(x)\, dG_u\big(s'|s\big) \\
&+ \int_{\mathcal{S}} U\big(s'\big)\, dG_e\big(s'|s\big) - \int_{\mathcal{S}} U\big(s'\big)\, dG_u\big(s'|s\big)\Big)\Big\}.
\end{aligned}
$$

Conjecture that the surplus function does not depend on the negotiation benchmark $S(\theta, \hat{\theta}, s, \hat{s}) = S(\theta, s)$. Hence,

$$
\begin{aligned}
S(\hat{\theta}, s) = \max\Big\{&0, p(\theta_y, s) - z \\
&+ \beta\Big(\int_{\mathcal{S}} (1 - \theta_\delta)\Big(\lambda_1\Big(\int_{M_1} S\big(\theta, s'\big) + \alpha\big(S\big(x, s'\big) - S\big(\theta, s'\big)\big)\, dF(x)\Big) \\
&+ \Big(1 - \lambda_1 \int_{M_1} dF(x)\Big)(\mathbb{I}_1 + \mathbb{I}_2 + \mathbb{I}_3) S\big(\theta, s'\big)\Big)\, dG_e\big(s'|s\big) \\
&- \int_{\mathcal{S}} \int_{M_1} \lambda_0 \alpha S\big(x, s'\big)\, dF(x)\, dG_u\big(s'|s\big) + \int_{\mathcal{S}} U\big(s'\big)\, dG_e\big(s'|s\big) \\
&- \int_{\mathcal{S}} U\big(s'\big)\, dG_u\big(s'|s\big)\Big)\Big\},
\end{aligned}
$$

where I use that $\mathbb{I}_1 + \mathbb{I}_2 + \mathbb{I}_3 = 1$ and $S(\theta, s') = 0$ if $\mathbb{I}_3 = 1$. Canceling terms, we arrive at

$$\begin{aligned} S(\hat{\theta}, s) = \max\Bigg\{0,\ & p(\theta_y, s) - z \\ & + \beta\bigg(\int_{\mathcal{S}} (1-\theta_\delta)\bigg(S(\theta,' s) + \int_{M_1} \lambda_1 \alpha\big(S(x, s') - S(\theta, s')\big)\, dF(x)\bigg)\, dG_e(s'|s) \\ & - \int_{\mathcal{S}} \int_{M_1} \lambda_0 \alpha S(x, s')\, dF(x)\, dG_u(s'|s) + \int_{\mathcal{S}} U(s')\, dG_e(s'|s) \\ & - \int_{\mathcal{S}} U(s')\, dG_u(s'|s)\bigg)\Bigg\}. \end{aligned}$$

This is the expression offered in the main text which also verifies that the joint surplus does not depend on the negotiation benchmark.

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