Some Evidence on the Importance of Sticky Wages
Online Appendix

Alessandro Barattieri[*] Susanto Basu[†] Peter Gottschalk[‡]

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This appendix serves multiple purposes: i) It contains a brief discussion of the issue of attrition in our data. ii) It gives some more details about the practical implementation of the statistical procedure explained in section 3 of Barattieri, Basu and Gottschalk (2012), iii) it discusses the relation between change in wages and change in hours in SIPP and iv) it reports the distribution of the adjusted wage spells length.

A Attrition

Figure 1 reports the distribution of the number of interviews for each person. About 30% of the people register the full set of interviews (12). While there is substantial attrition in the SIPP this dos not necessarily lead to attrition bias. As discussed in Fitzgerald, Gottschalk and Moffitt (1998) attrition leads to bias estimates only if the attrition is correlated with the outcome of interest. In our case attrition would lead to bias estimates of the probability of a wage change only if the conditional probability of a wage change was systematically higher or lower for those who attrite. While it is possible that decreased probability of wage changes leads to higher attrition rates we know of no such evidence. Fitzgerald Gottshalk

[*]ESG-UQAM, *e-mail* barattieri.alessandro@uqam.ca
[†]Boston College and NBER, *e-mail*: susanto.basu@bc.edu
[‡]Boston College and IZA, *e-mail*: peter.gottschalk@bc.edu

and Moffitt (1998) find that while the PSID has high levels of attrition, this attrition is largely random and hence has little impact on point estimates, though the reduced sample sizes do increase standard errors.

B Implementation of the Statistical Procedure to Adjust for Measurement Error

The implementation of the statistical procedure described in Barattieri, Basu and Gottschalk (2012) can be disaggregated into four interrelated steps that are applied to within job wage changes then to between job wage changes.

1. the first step is to obtain the critical values for the F statistic used to test for wage changes when the measurement error is not classical and the F statistic is the maximum value across all possible points where a wage change could have occurred within a job. We use Monte-Carlo simulation to obtain the critical values for our test statistic. We generate 10,000 constant wage series of length l. We add measurement error from an error process consistent with that found in the replication study of Gottschalk and Myingh (2010). For each of the l sub-periods, we compute an F-statistic : $F = \frac{rss-uss}{\frac{uss}{l-2}}$, where rss is the sum of squared residuals around a constant mean across all l periods (the restricted model), and uss is the sum of squared residuals around a series with constant wages equal to the average wage before and after the tested break. We take the maximum F statistic across the l possible break points and rank these 10,000 maximum F statistics to find the (1-α)th percentile of the distribution (where α is the significance level of the test). This corresponds to the critical value where we falsely reject a null of no wage change. We repeat our simulations for $l = 3, 4, ..12$. We thus have critical values that differ for different number of observations over which we run our tests on the SIPP data.

2. The second step is to use these non-classical F critical values to test for structural breaks at each point in each individual's SIPP wage history. We start by taking each

individual's full wage history to find the maximum F over all possible dates. We use the critical values described above to test whether the break in wages at the maximum F is statistically significant. If it is not then no break is detected. Since the test is based on the maximum F we also know that tests at any other point would also fail to reject. If the F is statistically significant then the algorithm assigns a break to that point and continues by repeating the process for the sub-periods before and after the significant break. The algorithm repeats the procedure, which goes on until no significant break is detected. Once all the significant breaks are detected, the algorithm compute an "adjusted" wage series, where the wages are equal to the average reported wages between breaks. Our estimate of the probability of a change in wages is based on the proportion of changes that are statistically significant.

3. The third step consist in obtaining the power of the test, for which we again use Monte-Carlo simulations. But in this case we simulate data with structural breaks to determine the proportion of time we falsely reject that there was a wage change. Since the power of the test depends on the size of the break as well as the length of the wage series, we simulate for different size breaks, based on the distribution of observed wage changes tested in step 2. From the distribution of the size of the wage changes that we were testing in step 2, we take the median values of the 5 quintiles of the distribution. So we have 10 possible lengths l of our break test and five representative break sizes (Δ for which we simulate the power of our tests based on non-classical measurement error.

4. The fourth step is to correct our estimates for Type I and Type II error. Type I error is set by the significance level of the test while Type II is determined by the power of the test (from step 3). We can then correct the proportion of significant within job wage changes for type I and II errors as described in the text.

Once we obtain this information about the within-job wage changes, we apply a similar procedure to between-jobs wage change. The key difference is that we know when the job change occurred so we know the point where we need to test for a between job wage change. This implies that we repeat step 2 using the F statistic when a job change occurred rather than the maximum F statistic. We run our test at each job change. The relevant period considered goes from the last significant within-job wage change that the person experienced in the previous job, to the first within job wage change that the person experience in the following job. The size of the wage change tested is the difference between the two adjusted wage series obtained from the step 2 above. We then calculate the power of these between job wage changes in the same way we calculate the power of within job wage changes. This allows us to correct between job wage changes for type I and II errors.

Finally, we obtain standard errors by bootstrapping. This requires that we repeat steps 1 to 4 using a different seed for the random generating process of the measurement error for each replication. This generates different critical values, which in turn translates into different adjusted and corrected probability estimates. Thus we obtain the variability needed to attach a standard error to our point estimates. Naturally, bootstrapping is a bit more computationally demanding so our bootstrapped standard errors are based on 100 replications.

Although seemingly computationally intensive, our procedure requires between 15 and 20 minutes of computing time on an average speed machine. All the replication do-files are available on-line with some further practical explanations.

C Wage dynamics and Hours dynamics

Our dataset contains also information about the average hours worked. While a serious analysis of the allocative nature of nominal wages certainly goes beyond the scope of this paper, a natural question is whether we do observe hours worked to react to change in wages. We present in table 1 some evidence coming from the inner 98-percentile of the distribution of percent changes in hours worked [1] and relate them to the percentage changes in our adjusted wages series (we only consider changes that happens on the same job). Conditional

[1] to avoid including too many outliers.

on no wage change, the average change in hours is close to zero. Interestingly, the larger the wage change, the more the changes in hours become significant. The mean changes in hours tend to be positive following a wage increase and negative following a wage decrease. As a consequence (last column), the relation between change in hours and change in wages seems to be a positive one, and it is highly statistically significant when the change in wages are in the fourth and fifth percentile of the distribution of observed changes in adjusted wages. We stress that we are not dealing with possible issues of measurement error in hours. However, we present prima-facie evidence of an intuitive hypothesis, namely that change in wages might in fact matter for behavior in terms of hours worked, and the more so the more important is the size of the change in wage considered.

D Distribution of the Adjusted Wages Spells Length

Figure 2 report the distribution of the within-job wage spells length. Unsurprisingly, given the results obtained from the hazard analysis, the distribution of the wage spell lengths has a peak at 12 months (3 observation in our dataset). However, as the graph shows, there is also a significant amount of short spells (4 or 8 months, corresponding to one or two observations in our dataset).

References

[1] Barattieri, A., S. Basu and P. Gottschalk (2012) "Some evidence on the Importance of Sticky Wages"

[2] John Fitzgerald, P. Gottschalk and R. Moffitt, 1998. "An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics," Journal of Human Resources, University of Wisconsin Press, vol. 33(2), pages 251-299.

Table 1: **Correlation Between Percentage Changes in Wages and Percentage Changes in Hours**

	Average Δh			
Size of Δw	$\Delta w > 0$	$\Delta w = 0$	$\Delta w < 0$	Corr(Δw, Δh)
0		-0.004		
≈ 0.023	0.003		0.000	0.022
≈ 0.058	0.005		-0.005	0.029
≈ 0.095	0.011**		-0.001	0.018
≈ 0.155	0.006		-0.035**	0.102***
≈ 0.322	0.022***		-0.027***	0.122***

Figure 1: **Number of interview, per individual**

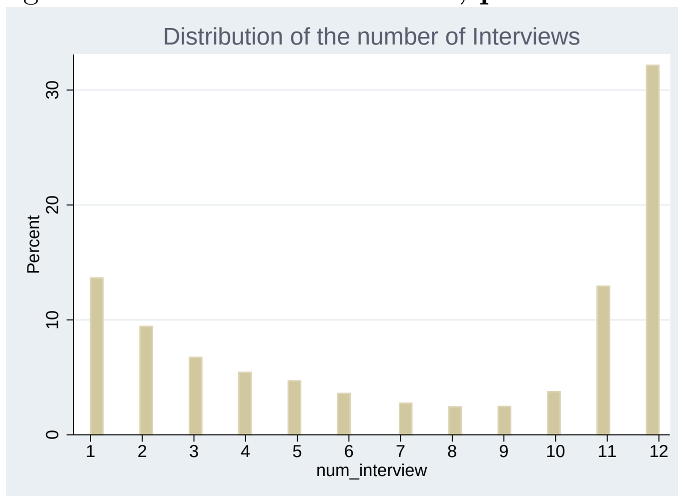

Figure 2: **Distribution of Wage Spells Length**