

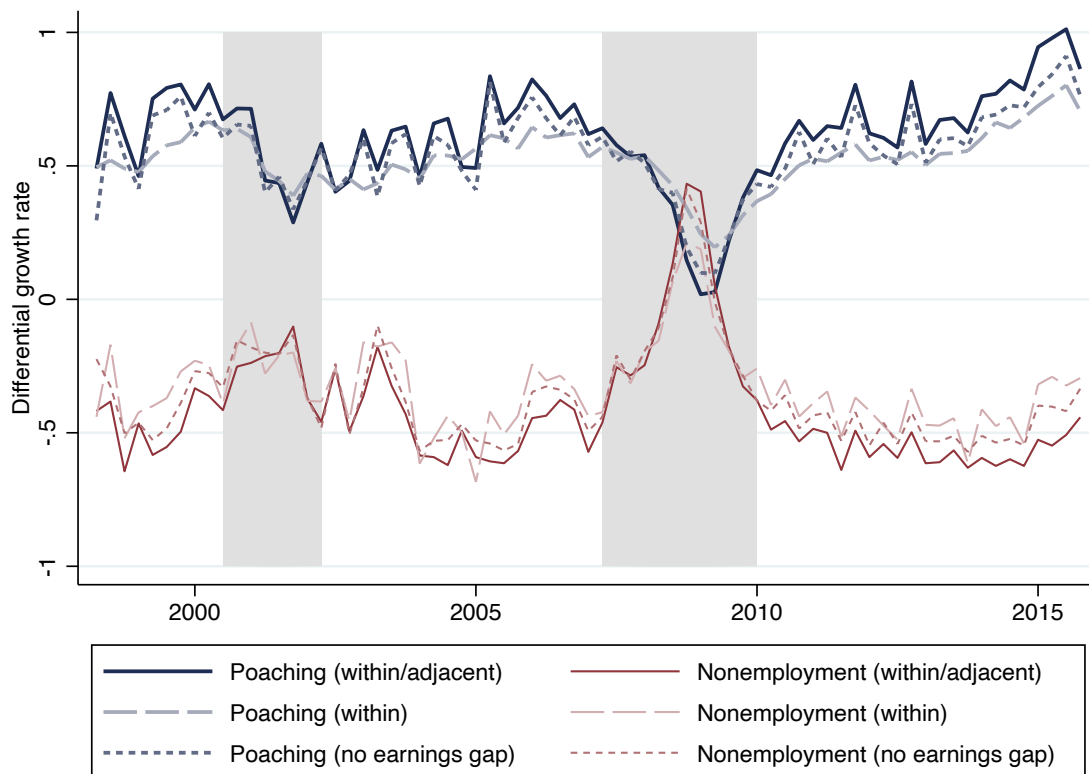
Appendix A Additional Results

Table A.1: Productivity, Employment Growth, and Firm Death

	Employment Growth Rate (1)	Firm Death (2)
Productivity	0.216 (0.00011)	-0.066 (0.00005)
Log of firm size	0.056 (0.00006)	-0.045 (0.00002)

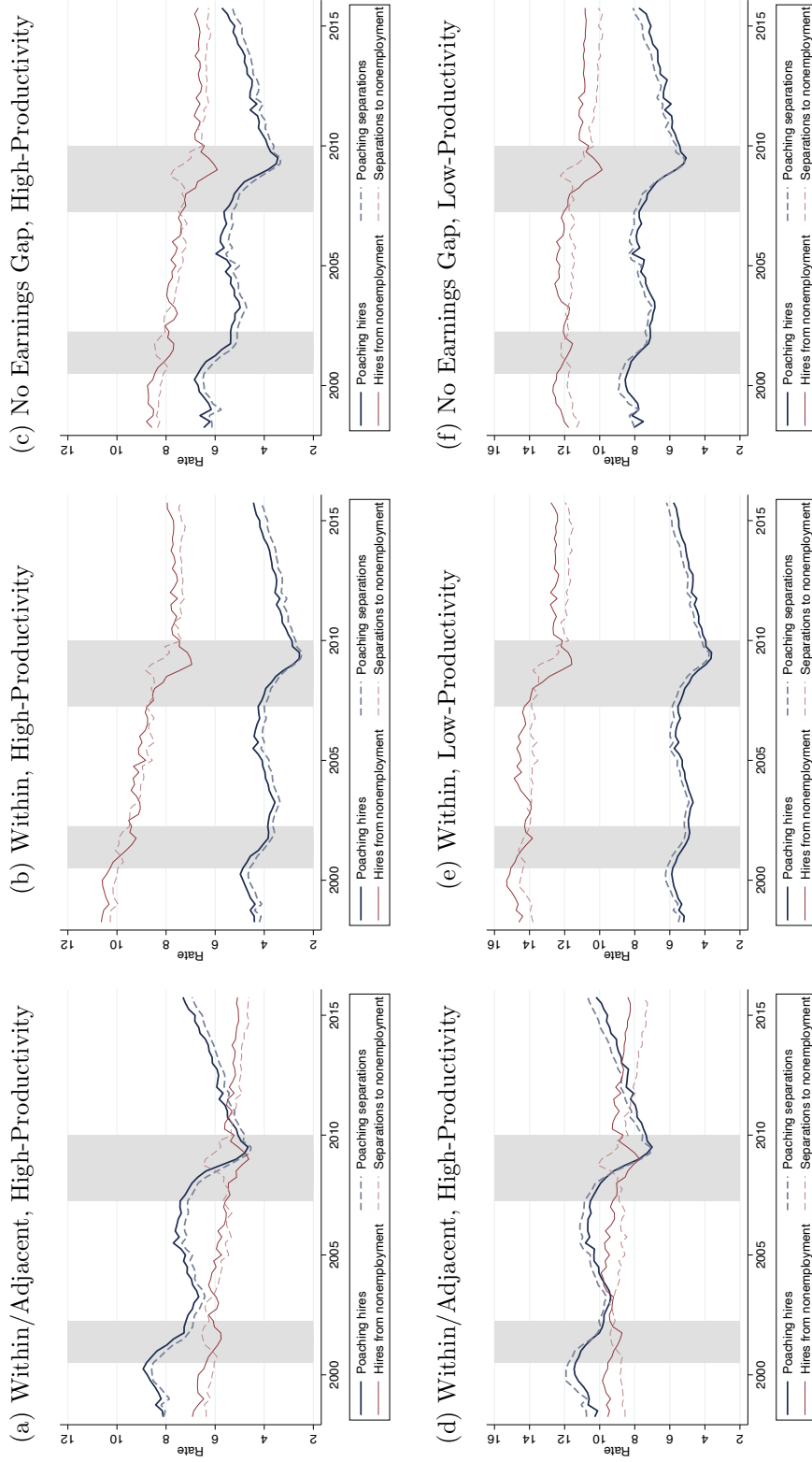
Notes: Each column presents estimates from a separate regression. The dependent variable in column 1 is the employment growth rate between the current and subsequent year and the dependent variable in column 2 is an indicator equal to one if the firm dies in the subsequent year. The independent variables in each regression are the log of firm size and productivity, which is defined as the log revenue per worker deviated from the industry (defined by the 4-digit NAICS code) average. Standard errors are presented in parentheses.

Figure A.1: Differential Flows between High- and Low-Productivity Firms



Notes: Differential growth rates are the difference in quarterly employment growth rates between high-productivity and low-productivity firms. The different series present results in which the job-to-job flows are defined by the within/adjacent, within, and earnings gap measures. Results are presented separately for poaching and nonemployment flows. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

Figure A.2: Gross Worker Flows Based on Alternative Definitions of Job-to-Job Flows



Notes: This figure presents gross worker flows based on three alternative definitions of job-to-job flows: (*within/adjacent*) the new job begins in the same or following quarter as the job separation, (*within*) the new job begins in the same quarter as the job separation and the spell of nonemployment is likely to be short based on the earnings from both employers. High-productivity indicates that the firm is in the top two quintiles of the within-industry productivity distribution. Low-productivity indicates the firm is the bottom three quintiles of the within-industry productivity distribution. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

Table A.2: Robustness to Imputation Methodology

	Preferred Imputation	Random Draw
	(1)	(2)
A. Net Job Flows		
Change in unemployment rate	0.040 (0.015)	0.029 (0.013)
Deviated unemployment rate	-0.023 (0.005)	-0.024 (0.005)
B. Poaching Job Flows		
Change in unemployment rate	-0.052 (0.010)	-0.049 (0.009)
Deviated unemployment rate	-0.024 (0.003)	-0.023 (0.003)
C. Nonemployment Job Flows		
Change in unemployment rate	0.092 (0.009)	0.078 (0.008)
Deviated unemployment rate	0.001 (0.006)	-0.002 (0.005)

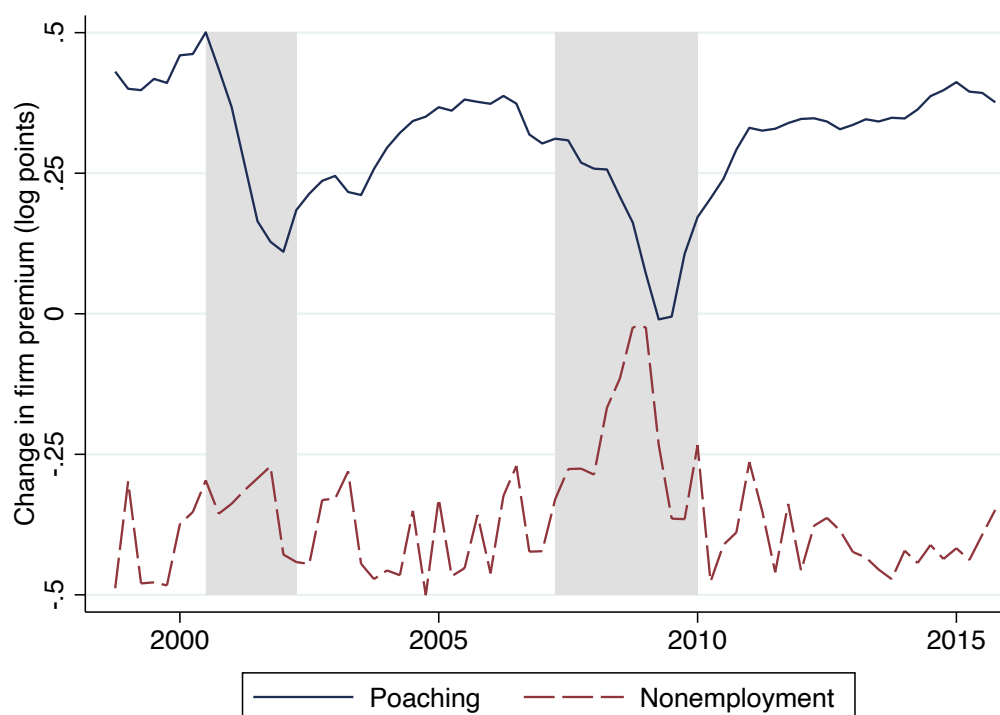
Notes: Each cell presents results from a separate regression estimated on national quarterly data. The dependent variable is the growth in log revenue per worker. Column 1 presents estimates based on the main data build, where missing productivity is imputed using the methodology described in Section 3.2. Column 2 presents estimates based on an alternative data build in which firms with missing productivity are assigned to productivity quintiles based on a random draw from a uniform distribution. The independent variables in each regression include a cyclical indicator as well as a linear time trend and a constant, which are not reported. The cyclical indicators considered include the change in the unemployment rate and the deviations of unemployment from the Hodrick-Prescott trend. Aside from the linear trend, all dependent and independent variables are measured in percentage point units. Standard errors are presented in parentheses.

Table A.3: Productivity Growth Decomposition using Alternative Definitions

	Log Revenue per Worker			
	(1)	(2)	(3)	(4)
A. Net Job Flows				
Change in unemployment rate	0.040 (0.015)	0.006 (0.020)	-0.009 (0.019)	-0.001 (0.019)
Deviated unemployment rate	-0.023 (0.005)	0.008 (0.008)	-0.022 (0.007)	-0.022 (0.007)
B. Poaching Job Flows				
Change in unemployment rate	-0.052 (0.010)	-0.026 (0.006)	-0.052 (0.010)	-0.040 (0.008)
Deviated unemployment rate	-0.024 (0.003)	-0.017 (0.002)	-0.023 (0.004)	-0.020 (0.003)
C. Nonemployment Job Flows				
Change in unemployment rate	0.092 (0.009)	0.033 (0.020)	0.043 (0.013)	0.039 (0.014)
Deviated unemployment rate	0.001 (0.006)	0.025 (0.007)	0.001 (0.005)	-0.002 (0.006)
Variable Definitions				
Job-to-job flow	within/adjacent	within	no earnings gap	within/adjacent
High-productivity	top 2	top 2	top 2	top 3

Notes: Each cell presents results from a separate regression estimated on national quarterly data. The dependent variable is the growth in log revenue per worker. The independent variables in each regression include a cyclical indicator as well as a linear time-trend and a constant, which are not reported. The cyclical indicators considered include the change in the unemployment rate and the deviations of unemployment from the Hodrick-Prescott trend. The last two rows present the definition of job-to-job flows and high-productivity firms. Aside from the linear trend, all dependent and independent variables are measured in percentage point units. Standard errors are presented in parentheses.

Figure A.3: Ranking Firms Across Industries using the AKM Firm Pay Premium



Notes: This figure presents the main decomposition results using the AKM firm pay premium measure of firm performance instead of log revenue per worker. Firms are ranked in the pooled sample across industries instead of within industries. This approach uses the same methodology described in the text but effectively treats all firms as being part of the same industry. Data are seasonally adjusted using X-12. The shaded regions mark quarters in which there was a recession.

Appendix B Assessing Measurement Issues

B.1 Productivity

Intertemporal variation in factor utilization does not appear to meaningfully affect the decomposition results. This is because, to the extent that log revenue per worker is subject to this concern, it affects high- and low-productivity firms to an equal extent. Figure B.1(a) plots, $R_{t-1}^h - R_{t-1}^l$, which is the productivity differential between high- and low-productivity firms. The productivity differential is orders of magnitudes larger than the short-term variation, which may be driven by intertemporal variation in factor utilization. To illustrate that the short-term variation in these differentials does not affect the decomposition exercise, we construct a smoothed series by fitting a linear time trend to the productivity differentials. We then use this smoothed series to implement the productivity growth decomposition. Figure B.1(b) presents the results and shows that the decomposition using the actual and smoothed productivity series yield essentially the same results. To quantify this we regress the component of productivity growth attributable to poaching flows using the observed productivity differentials on the series using the smoothed differentials. The R-squared is 0.99. The analogous R-squared for the nonemployment flows is 0.999.

Variation in factor utilization over the business cycle is a greater issue for our measure of aggregate productivity growth. Fernald (2014) produces a series of growth in business sector TFP that adjusts for factor utilization. Figure B.2(a) presents both the adjusted and unadjusted growth rates from these data. The unadjusted series exhibit a larger decline in TFP during recessions relative to the adjusted series. To get a sense of how sensitive our measure of productivity growth is to changes in factor utilization, we use the difference between the unadjusted and adjusted series from Fernald (2004) to adjust for variation in factor utilization.³⁶ Figure B.2(b) compares the productivity growth attributable to worker reallocation to the adjusted and unadjusted measures of aggregate productivity growth.

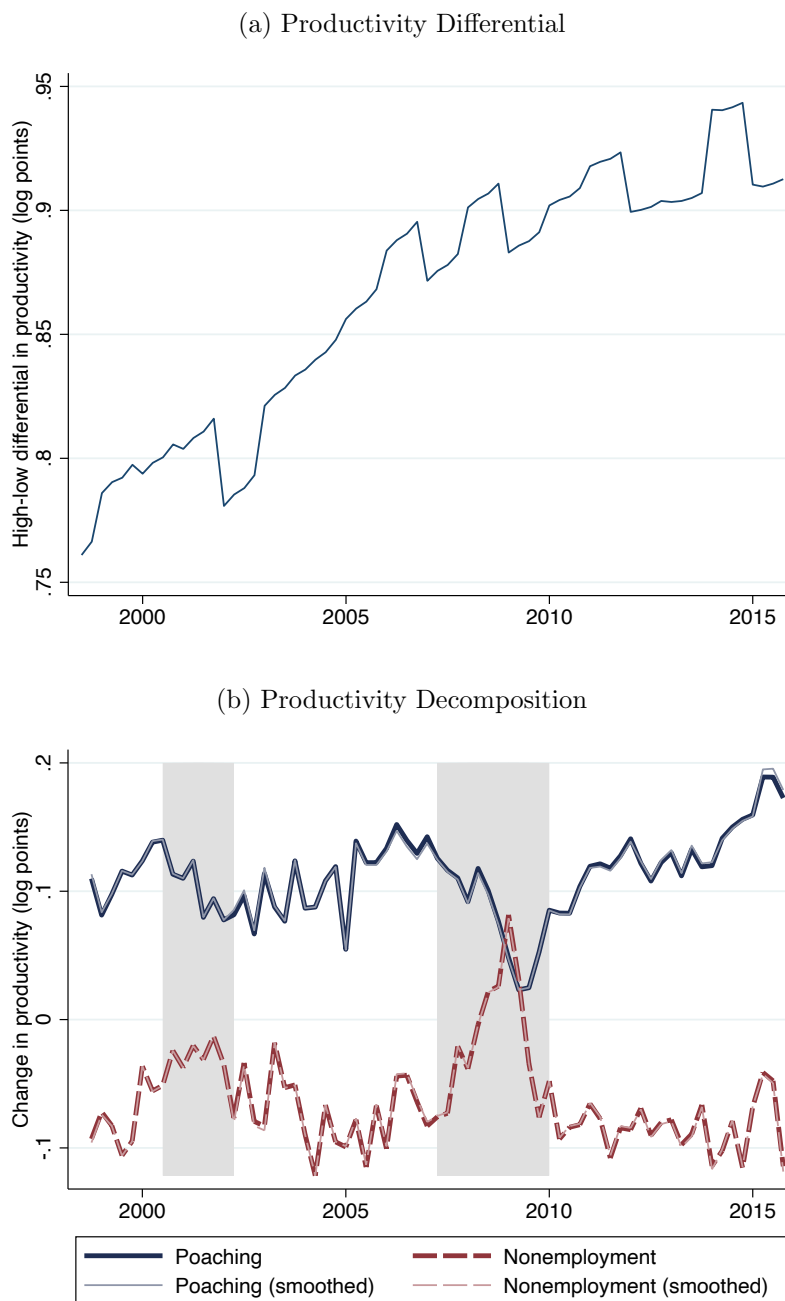
³⁶Specifically, we calculate the difference between the adjusted and unadjusted growth rates in 2001 and 2008. We adjust our growth rate by adding these differences to the growth rates in 2001 and 2008. Because our data also exhibit a large decline in 2009, we also add the 2008 difference from the Fernald (2014) series to the 2009 growth rate.

B.2 Worker Flows

There are two reasons why the equality described in equation 2 does not hold exactly in our data (i.e., why $\Delta\theta_t^h$ does not exactly equal the sum of $\tilde{\lambda}_t^h$ and $\tilde{\delta}_t^h$). First, some workers may move to or from an employer located in a state outside of our 28-state sample. Because we aim to implement an exact decomposition, the counts of hires and separations only include worker flows where both the origin and destination employers are in one of the 28 states in our sample. Second, the administrative code that identifies the employer, the SEIN, can change over time and create a spurious flow of workers between the old and new SEIN. We are able to flag when these changes occur and omit these flows from the poaching and nonemployment flows. However, there is no straightforward way to account for this issue when measuring productivity. Thus, a change in an SEIN could lead to a change in the share of workers at high productivity firms but have no corresponding flow of workers. In unreported results, we directly measure flows of workers in and out of the states in our sample and show that the residual term is primarily attributable to changes in the SEIN over time, not migration in and out of the sample.

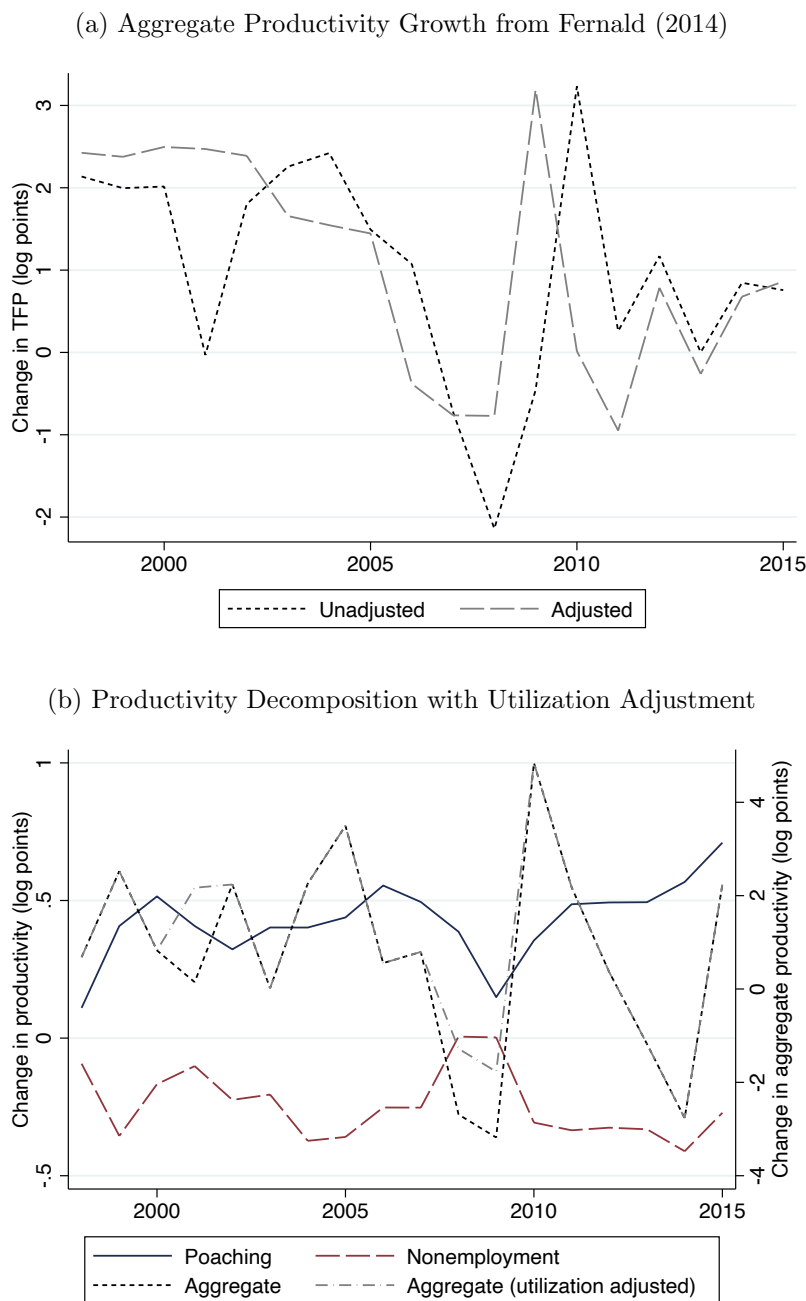
Regardless of the source, these residuals flows are both small in magnitude and do not exhibit a clear pattern across the business cycle. Specifically, the average size of the differential net poaching and nonemployment growth rates are three and five times as large as the differential residual flows, respectively. Figure B.3 in Appendix B presents a version of Figure A.1 that contains the residual flows as well as the poaching and nonemployment flows constructed with and without the restriction that both origin and destination employers are in the 28-state sample. The results indicate that the residual flows do not exhibit any notable cyclicity across the business cycle and the differential net poaching and nonemployment growth rates that exclude workers moving in and out of our 28-state sample are very similar (in levels and movements across time) to the results from Figure A.1. We infer that this residual term is not important for the main results.

Figure B.1: Decomposition and Intertemporal Variation in Factor Utilization



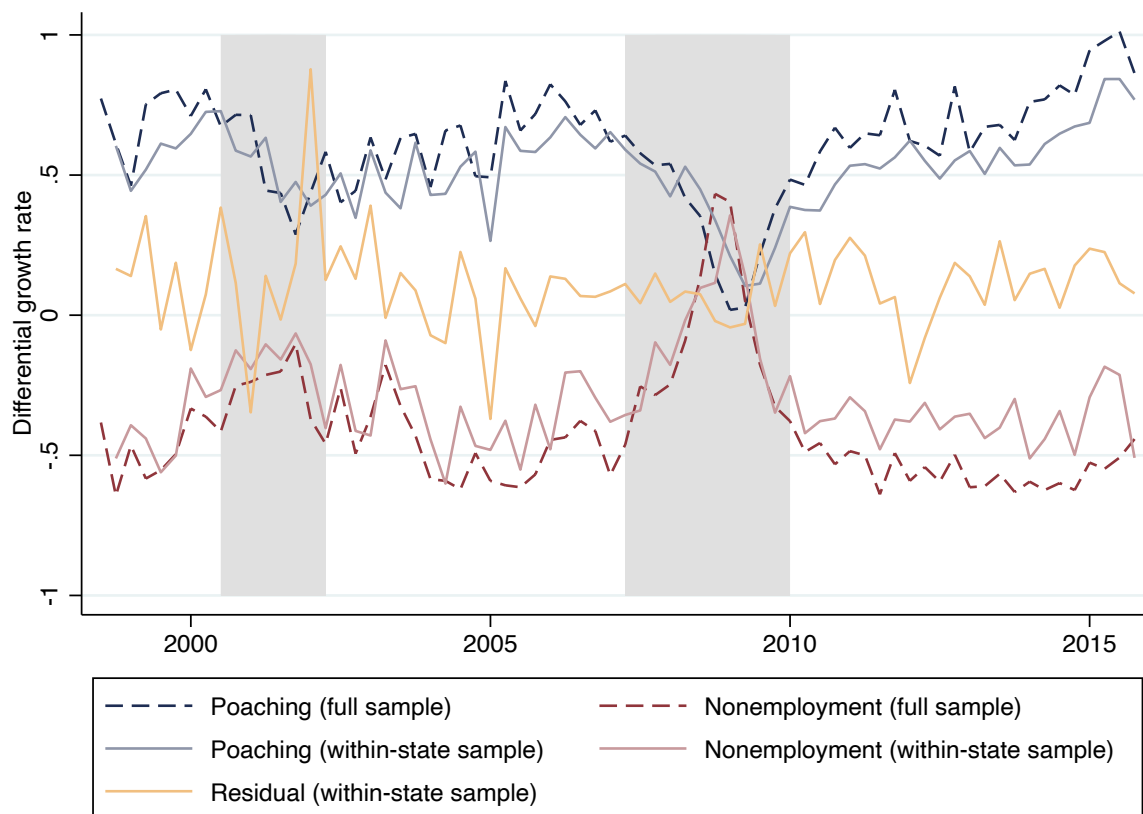
Notes: Panel (a) plots the difference between the average productivity at high- and low-productivity firms. Panel (b) presents the components of productivity growth that attributable to worker reallocation between high- and low-productivity firms through poaching and nonemployment flows. The results in Panel (b) implement the decomposition using both the observed productivity differentials (depicted in Panel (a)) as well as the productivity differentials from a smoothed series generated by fitting the observed productivity differentials with a linear time trend. Data are seasonally adjusted using X-12.

Figure B.2: Aggregate Productivity Growth with Factor Utilization Adjustment



Notes: Panel (a) presents data from Fernald (2014) on the growth in business sector total factor productivity (TFP) as well as a measure that implements an adjustment for variation in factor utilization. Panel (b) presents the annual productivity growth from worker reallocation through poaching and nonemployment flows as well as aggregate productivity growth. In addition, Panel (b) includes a series that adjusts aggregate productivity growth using the difference between the unadjusted and adjusted measures of growth from Fernald (2014).

Figure B.3: Differential Flows between High- and Low-Productivity Firms with Residual



Notes: Differential growth rates are the difference in quarterly employment growth rates between high- and low-productivity firms. Results are presented separately for poaching, nonemployment, and residual flows. The poaching and nonemployment flows depicted by the dashed lines are based on the full sample. The poaching and nonemployment flows depicted by the solid lines are based on a sample that is limited to worker flows in which both the origin and destination employers are in one of the 28 states in our sample. The residual growth rate is the difference between the observed changes in the share of employment at high- and low-productivity firms and what is predicted by the poaching and nonemployment flows. Data are seasonally adjusted using X-12.

Appendix C Decomposition Methodology

Productivity growth for a given industry can be decomposed into two components,

$$\Delta R_t(k) = (R_{t-1}^h(k) - R_{t-1}^l(k))\Delta\theta_t^h(k) + \sum_{i \in \{l, h\}} \theta_t^i(k)\Delta R_t^i(k), \quad (\text{C.1})$$

where the first and second components are productivity growth attributable to worker reallocation between high- and low-productivity firms and productivity growth within the high- and low-productivity firm groups, respectively. Aggregate productivity growth can then be written as the employment weighted average across industries,

$$\sum_k \theta_{t-1}(k)\Delta R_t(k) = \sum_k [\theta_{t-1}(k)(R_{t-1}^h(k) - R_{t-1}^l(k))\Delta\theta_t^h(k)] + \sum_k \left[\theta_{t-1}(k) \sum_{i \in \{l, h\}} \theta_t^i(k)\Delta R_t^i(k) \right]. \quad (\text{C.2})$$

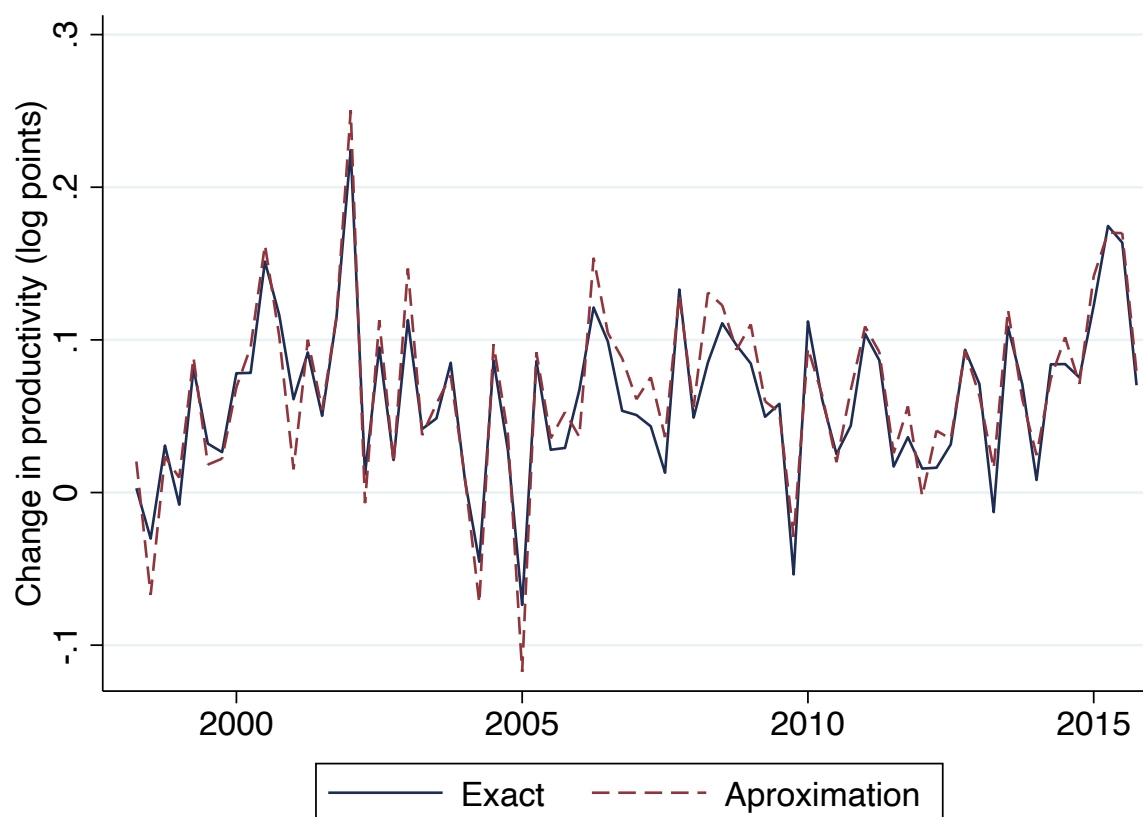
Equation C.2 is an exact decomposition whereas equation 3 is an approximation. The two equations differ only with respect to the first term where,

$$\sum_k [\theta_{t-1}(k)(R_{t-1}^h(k) - R_{t-1}^l(k))\Delta\theta_t^h(k)] \approx (R_{t-1}^h - R_{t-1}^l)\Delta\theta_t^h \quad (\text{C.3})$$

This approximation suggests two ways of quantifying how worker reallocation affects productivity growth. The left-hand-side suggests we could decompose changes in the share of workers at high-productivity firms within each industry, and then aggregate results have. The right-hand-side suggests that we can simply decompose the aggregate share of workers at high-productivity firms. Given that there are 311 distinct 4-digit industry codes, the latter is preferable to the extent that this approximation is accurate.

We directly calculate both sides of equation C.3 show that the approximation is highly accurate. To show that the approximation performs well, we regress the true value, $\sum_k [\theta_{t-1}(k)(R_{t-1}^h(k) - R_{t-1}^l(k))\Delta\theta_t^h(k)]$, on the approximate value, $(R_{t-1}^h - R_{t-1}^l)\Delta\theta_t^h$, which yields a coefficient of 0.85 and an R-squared of 0.91. Figure C.1 plots these two series.

Figure C.1: True Value and Approximation



Notes: The figure presents the exact values of $\sum_k [\theta_{t-1}(k)(R_{t-1}^h(k) - R_{t-1}^l(k))\Delta\theta_t^h(k)]$ and its approximation $(R_{t-1}^h - R_{t-1}^l)\Delta\theta_t^h$.

Appendix D Time Aggregation

This appendix summarizes the time aggregation analysis in HHJM that examined poaching flows by firm wage and firm size. As discussed in HHKM, one limitation of the LEHD data for decomposing net job flows into net poaching and net hiring from non-employment is the exact date of transitions between jobs is not known. Instead, the administrative data permit identifying transitions between jobs that occur within the same quarter as well as transitions that occur in adjacent quarters. In addition, earnings data are available at the individual level for the origin and destination job. This permits constructing measures of job-to-job flows that impose additional restrictions based on the individual-level earnings dynamics around the time of the transition. In particular, using this method, HHKM infer the amount of time a worker might have experienced non-employment during the transition by comparing earnings in the transition quarter to earnings in the surrounding quarters. In what they denote as the no earnings gap approach, HHKM classify a move as job-to-job if earnings losses during the quarter imply at most a transition time of one month with no work, and as a move to/from non-employment if the earnings losses are larger. This measure, on average, categorizes 90% of the within quarter moves as job-to-job and 60% of the adjacent quarter moves. The one month threshold was chosen because it approximately mimics the CPS job-to-job flows that permit up to a month between jobs.

In this appendix, we focus on summarizing the HHJM results for the within/adjacent and no earnings gap approaches for job ladders defined by firm wage and firm size (HHKM also consider the within quarter approach). As HHKM discuss, the within/adjacent quarter approach is the most liberal and likely includes transitions that involve short spells of non-employment. As such, it is the method most vulnerable to time aggregation biases induced by the inclusion of short non-employment spells in job-to-job flows. The no earnings gap approach is more conservative and is less vulnerable to those issues. Note that as discussed further below, the earlier working paper by HHM also considered additional exercises to explore the robustness to time aggregation issues.

HHKM show that (i) the level of overall job-to-job flows rate is (as expected) higher using the within/adjacent compared to the no earnings gap approach; (ii) the two series are highly

correlated (about 0.98); (iii) the no earnings gap approach yields a rate of job-to-job flows that is about the same as implied by the CPS; and (iv) the CPS series is highly correlated with both the within/adjacent and no earnings gap (about 0.95).

It still might be that the within/adjacent approach yields greater differential time aggregation biases that vary across firm types defined by firm size or firm wage. For example, if transitions involving spells of non-employment are more prevalent for inclusion as job-to-job flows with the within/adjacent approach especially for small firms then this would yield a bias. They show that the net differential is slightly negative (about half a percent per quarter) but the mean net differential is essentially the same across the two approaches. So even though there are substantial differences in the level of the gross poaching patterns, the net poaching patterns are very similar across methods. If time aggregation bias was important for accounting for the result that on net small firms are poaching from large firms then we would expect the mean differential to be more negative for the within/adjacent approach. HHKM show that this is not the case.

Turning to firm wage job ladders, HHJM find that both approaches yield a large, positive net poaching differentials indicating that on average each quarter there is a 1.8/1.9 percentage point differential in the net poaching rates between high wage and low wage firms. The magnitudes are very similar again implying that time aggregation or other biases that vary across these methods are not impacting the average pace of differential net poaching flows.

The focus in HHKM is on the cyclicalty of the movements up and down the job ladder. Again, it might be that the time aggregation biases impact the cyclicalty in some differential manner. They find that the cyclicalty is very similar across the methods (see for example their Table 2).

From this evidence alone, HHKM conclude that their results are robust to concerns about time aggregation biases. Further evidence is provided in HHM. They conduct two additional robustness checks. First, they show the patterns discussed above also hold restricting job-to-job flows to within quarter transitions only. Second, they use the methods developed by Mukoyama (2014) approach to continuous time adjustment (which in turn extends the adjustment method of Shimer (2012)) to include job-to-job transitions. The results of this analysis show that the net poaching patterns by firm size are robust to these adjustments.

Overall, HHKM find that there is not much evidence of a firm size ladder and that cyclicalities of the firm size ladder is weak. In contrast, there is strong evidence of a firm wage ladder that is highly procyclical. These findings are robust to alternative measurement approaches that potentially exhibit differential sensitivity to time aggregation issues.