Cyclical and Market Determinants of Involuntary Part-Time Employment

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The fraction of the US workforce identified as involuntary part-time workers rose to new highs during the US Great Recession and came down only slowly in its aftermath. We assess the determinants of involuntary part-time work using an empirical framework that accounts for business cycle effects and persistent structural features of the labor market. We conduct regression analyses using state-level panel data for the years 2003–16. The results indicate that structural factors, notably shifts in the industry composition of employment, have held the incidence of involuntary part-time work slightly more than 1 percentage point above its prerecession level.

I. Introduction

Part-time employment is common in the United States. Since the mid-1990s, on average slightly more than one in six US civilian employees

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worked part-time hours, defined as fewer than 35 hours per week. In their tracking of part-time employment, the US Bureau of Labor Statistics (BLS) distinguishes between individuals who work part time voluntarily ("noneconomic reasons") and those who work part time involuntarily ("economic reasons"). Although the voluntary part-time group is much larger, interest in the involuntary part-time group has increased in recent years as its share of the workforce reached unusually high levels during the Great Recession of 2007–9. Moreover, as the US economy recovered from that recession, the level of involuntary part-time work remained relatively high, raising concerns that it represented labor underutilization beyond that reflected in the unemployment rate (e.g., Yellen 2014; Blanchflower and Levin 2015).

In this paper, we conduct an empirical analysis of the determinants of involuntary part-time work over time, focusing on the business cycle around the US Great Recession—specifically, the period from 2003 through 2016. Existing research on the characteristics and behavior of involuntary part-time workers is relatively limited in quantity and scope. A small literature from the 1990s focused on identifying the behavioral distinction between voluntary and involuntary part-time work and provided information on a limited set of explanatory factors (Tilly 1991; Leppel and Clain 1993; Stratton 1996; Fallick 1999). Several recent studies provided descriptive analyses of patterns in involuntary part-time work around the Great Recession (e.g., Cajner et al. 2014; Canon et al. 2014; Robertson and Terry 2014; Golden 2016). Borowczyk-Martins and Lalé (2016, 2019) used labor market flow data to illustrate the rising importance of transitions between full-time and involuntary part-time jobs in the United States and the United Kingdom.

We expand on existing research by developing a regression-based empirical framework for assessing changes in the incidence of involuntary part-time work. We distinguish between variation associated with the business cycle and variation attributable to more persistent structural features of the labor market, each of which are explicitly measured in our framework. Our approach allows us to move beyond the recent analyses noted above by providing a quantitative decomposition of the contributions of the cyclical and structural factors to changes in the prevalence of involuntary part-time employment over our sample frame.

We rely primarily on state-level panel data for our empirical analyses, supplemented by micro data from the Current Population Survey (CPS). Our state panel regression framework enables us to jointly model and distinguish between cyclical and structural factors, with the latter including demand and supply determinants of involuntary part-time work, in particular

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industry employment shares, labor costs, and population demographics. Direct measurement of the explanatory factors is a key advantage of our regression-based approach. We discuss this further in section III.

To preview the findings, the cyclical and structural factors used in our models can fully account for changes in the incidence of involuntary part-time work since 2006. While the cyclical component fully dissipated between 2010 and 2016, the structural component consistently kept the rate of involuntary part-time work elevated by slightly more than 1 percentage point relative to prerecession levels (measured as a share of total employment). This represents about 1.75 million employed individuals who want full-time work but are stuck in part-time jobs, or 40%–50% more than expected based on the prevalence of such workers prior to the Great Recession.

We proceed as follows. We begin in section II by defining the relevant concepts regarding part-time employment and providing descriptive statistics. The descriptive analysis motivates our conceptual framework discussed in section III, which distinguishes between cyclical and structural determinants of part-time work and discusses the advantages of our regression-based approach. Section IV provides regression results, and section V uses those results to provide a detailed decomposition of the determinants of involuntary part-time employment. We interpret these findings and note implications for future research in section VI.

II. Patterns in Involuntary and Voluntary Part-Time Work (IPT and VPT)

We begin by defining terms and providing descriptive statistics that establish the central facts about involuntary part-time work that we seek to explain, along with related patterns in voluntary part-time work. Similar descriptive analysis has appeared in other existing work.[1] We focus on the specific patterns that motivate our subsequent regression analyses.

Data on part-time work are available from the BLS, based on CPS survey data (the source of official US labor force statistics). Measurement of part-time work in the CPS refers to hours at all jobs, so an individual who works multiple jobs and reaches at least 35 total hours in a week will not be identified as a part-time worker. The survey distinguishes between two broad groups of persons who work part time. The first is those working part time for "noneconomic" reasons, or voluntarily (VPT). These are workers whose part-time status represents a labor supply decision: they prefer a part-time job for personal reasons, such as family obligations, school, or partial retirement. Of the 15%–20% of employed people who work part time, about three-fourths are in this category. The other category is those working part

[1] Golden (2016) provides the most comprehensive descriptive analysis and discussion, with breakdowns of IPT work by industries, occupations, and demographic groups.

time for "economic" reasons, or involuntarily (IPT). This includes workers who report that they would like a full-time job but cannot find one due to constraints arising primarily on the employer or labor demand side of the labor market, such as a cutback in hours at their current job ("slack work") or an inability to find full-time work. The existence of involuntary part-time work indicates that the number of jobs in which only part-time hours are offered exceeds the number of employed individuals who prefer part-time over full-time schedules.

Past research has found the distinction between voluntary and involuntary part-time work to be meaningful, based on the greater tendency for involuntary part-time workers to be working full time in the future than is the case for voluntary part-time workers (Stratton 1996). Our analyses and hence descriptive statistics focus on the IPT group, but given the potential importance of supply considerations for part-time work, we also provide relevant descriptive statistics and supplemental analyses for the VPT group.

Figure 1 illustrates the time-series pattern in IPT, expressed as a share of total civilian employment, and its relationship to the unemployment rate.[2] The figure shows substantial cyclical movements in the IPT series. It typically tracks the unemployment rate entering recessions, suggesting that like the unemployment rate, the IPT rate largely reflects labor underutilization. However, the decline in the IPT rate lagged declines in the unemployment rate during the last two recoveries, especially in the aftermath of the Great Recession.[3]

Table 1 provides additional descriptive statistics that we tabulated from the publicly available CPS micro data, which we also use for regression analyses that supplement our state panel analyses in section IV. The CPS surveys about 60,000 households each month, yielding information on hours worked and related variables for samples of about 650,000–700,000 employed individuals per year, based on our sample restrictions (see the table notes). Our complete analysis period is 2003–16. This period largely covers the business cycle associated with the Great Recession, enabling us to distinguish between purely cyclical versus persistent structural factors that may affect the level of involuntary part-time work. The restriction to 2003-forward eliminates the distorting influence of major changes in industry category definitions applied in 2003.[4]

[2] There is a break in the IPT and VPT series in 1994 due to a change in CPS survey procedures that tightened the IPT criteria and significantly reduced the measured incidence of IPT (Polivka and Miller 1998; Borowczyk-Martins and Lalé 2016).

[3] The BLS distinguishes between two subcomponents of IPT work: slack work, or hours reductions due to weak demand, and inability to find full-time work. Figure A1 (figs. A1–A10 are available online) displays the two subcomponent series.

[4] The redefinitions caused by the switch to the 2000 North American Industry Classification System substantially altered the employment shares for key industries for our analyses, notably retail and personal services.

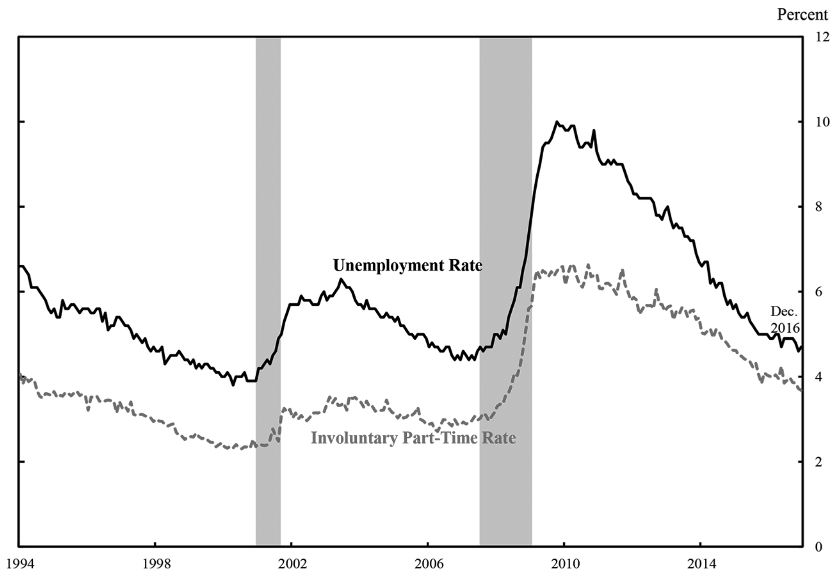

FIG. 1.—Involuntary part-time rate versus unemployment rate, January 1994 to December 2016. Source: US Bureau of Labor Statistics (seasonally adjusted data). Involuntary part-time rate expressed as a share of total civilian employment. Gray areas are recessions. A color version of this figure is available online.

The table provides a breakdown of IPT and VPT rates for three years: 2005, 2010, and 2016. The beginning and end years largely span the sample frame for our subsequent analyses and also represent years with similar aggregate labor market conditions (but a higher IPT rate in the latter year).[5] The middle year, 2010, represents a labor market trough measured on an annual basis, when the unemployment and IPT rates reached cyclical peaks. The tabulations listed in the table refer to the group-specific employment share by part-time status, which can be compared to the "All workers" total in the first row.[6] For reference purposes, the final three columns provide the share of each group in overall employment.

Table 1 shows a relatively consistent pattern over time across the various age/gender and industry groups. IPT work rose substantially between 2005

[5] The US unemployment rate averaged 5.1% in 2005 and 4.9% in 2016, with slightly more rapid payroll employment growth in the earlier year. The IPT rate was 3.1% in 2005 and 3.9% in 2016.

[6] For example, the number in the second row of the first column of the table indicates that 5.8% of employed individuals age 16–24 were involuntary part-time workers in 2005, while the fourth column indicates that 35.3% of that group were voluntary part-time workers in 2005; the remaining 58.9% were employed full time.

Table 1
Part-Time Work by Labor Market Group and Sector (Incidence by Group)

	Involuntary Part-Time Workers[a]			Voluntary Part-Time Workers[a]			Employment Share[b]		
Individual Characteristic	2005 (1)	2010 (2)	2016 (3)	2005 (4)	2010 (5)	2016 (6)	2005 (7)	2010 (8)	2016 (9)
All workers	.032	.066	.041	.143	.136	.142	1.000	1.000	1.000
Demographics (age by gender):									
All 16–24	.058	.117	.075	.353	.357	.367	.143	.125	.127
Men 25–34	.032	.072	.040	.039	.043	.048	.123	.121	.123
Women 25–34	.036	.069	.044	.156	.139	.140	.100	.103	.106
Men 35–54	.023	.053	.029	.025	.025	.029	.251	.240	.225
Women 35–54	.029	.061	.039	.156	.144	.143	.227	.220	.201
All 55–64	.025	.053	.034	.138	.126	.122	.125	.151	.165
All ≥65	.023	.043	.027	.444	.386	.360	.031	.040	.053
Broad industry:									
Mining	.006	.013	.018	.016	.012	.020	.004	.005	.005
Construction	.057	.135	.059	.054	.048	.055	.077	.062	.066
Manufacturing	.017	.035	.017	.035	.036	.039	.121	.107	.107
Wholesale trade	.016	.032	.017	.057	.053	.061	.033	.028	.024
Retail trade	.042	.101	.069	.231	.216	.225	.120	.117	.112
Transportation/communications/utilities	.026	.052	.035	.068	.065	.076	.053	.052	.054
Information	.021	.040	.025	.111	.105	.093	.025	.023	.019
Financial activities	.012	.027	.014	.101	.083	.086	.073	.068	.070
Professional/business services	.039	.067	.038	.125	.109	.106	.099	.108	.119
Leisure and hospitality	.065	.137	.088	.304	.283	.301	.086	.091	.094
Education and health services	.025	.046	.032	.187	.173	.176	.210	.236	.232
Other services[c]	.045	.088	.053	.230	.213	.228	.050	.049	.048
Public administration	.007	.018	.010	.045	.047	.050	.049	.054	.048

NOTE.—Authors' calculations using Current Population Survey micro data (with survey sampling weights). Sample includes nonagricultural wage and salary or self-employed (unincorporated) workers age 16 and over who worked positive hours in the survey week and whose hours data were not allocated.
[a] Numbers in the first six columns represent the share of all employed individuals for the row category who are in the column category of part-time work (by year).
[b] Share of row group in total employment (part time and full time).
[c] Includes repair/maintenance, personal services, and membership organizations.

and 2010 and then fell substantially by 2016 (cols. 1–3). However, for virtually all groups, excepting individuals employed in a small subset of industries, the 2016 levels of IPT work remained well above the 2005 levels. The employment shares in the final two columns show declines over our sample period for some age/gender groups with high rates of part-time work (e.g., age 16–24) and increases for others (e.g., age 65 and over).[7] The VPT

[7] We group men and women together in the youngest and oldest age categories because their rates of IPT work are similar within these age groups and the aggregated categories improve the statistical precision of our subsequent estimates.

rate for individuals age 65 and over is very high compared with other groups, likely reflecting partial retirement in favor of part-time work, but it declined substantially over our sample frame.

Table 1 also shows substantial variation across broad industries in the incidence of part-time work. Both IPT and VPT work are especially high in selected services industries, such as retail, leisure, and hospitality (including restaurants), and "other services" (mostly consisting of personal services, such as barber and beauty shops, dry cleaning, repair services, etc.). By contrast, part-time work of both types tends to be low in manufacturing and related industries, such as wholesale trade and transportation. The employment shares in the final three columns generally show a net shift toward the services industries that rely more heavily on part-time labor. This shift likely put upward pressure on the overall proportion of part-time jobs in the workforce. However, the shift toward industry categories with high incidence of IPT and VPT is not uniform: for example, the employment share of the retail trade sector declined over our sample frame.[8]

Table 1 shows a widespread increase in IPT work within demographic groups and industries, suggesting that shifts in workforce composition do not account for much of the overall increase in IPT work over our sample frame. We confirmed this supposition by accounting for changing composition using a standard reweighting technique (DiNardo, Fortin, and Lemieux 1996; Daly and Valletta 2006). The method and results are described further and displayed in online appendix A (fig. A2). They show that changes in workforce composition explain virtually none of the change over time in the incidence of either type of part-time work.

On balance, the descriptive analyses illustrate an overall shift both within and across workforce groups toward higher incidence of IPT work. In the next section, we discuss the cyclical, demand, and supply factors that likely drive the aggregate movements over time.

III. Understanding Involuntary Part-Time Work: A Conceptual Framework

The empirical patterns illustrated and discussed in the preceding section shed light on the determinants of part-time work. We can usefully divide the determinants into two categories: (i) changes in labor demand occurring

[8] Table A1 (tables A1–A5 are available online) provides additional breakdowns by marital status and gender, educational attainment, race/ethnicity, self-employment (unincorporated) and multiple job holding, and broad occupational groups. Combined, the two tables show that IPT work tends to be especially prevalent among low-skilled and disadvantaged groups, in selected service occupations, and among the self-employed. The potential connection between IPT and self-employment or "gig economy" jobs is explored in the longer working paper version of this article (Valletta, Bengali, and van der List 2018).

at a business cycle frequency and (ii) longer-term changes in workforce structure and conditions, such as industry and demographic composition. We will refer to the first category as "cyclical" factors and the second as "market" or "structural" factors. The key feature of the latter is slow movement over time, reflecting persistent changes in demand and supply conditions rather than variation at a business cycle frequency.

The role of cyclical factors was evident in figure 1, with an especially large increase in IPT work evident during the Great Recession of 2007–9 and its aftermath. Existing literature has identified several reasons for countercyclicality in IPT work, revolving around its role as an adjustment mechanism in response to economic shocks (e.g., Friesen 1997). One compelling reason for this pattern is to minimize current and future turnover costs by relying on hours adjustments for current staff rather than changes in head counts.

Recent papers by Borowczyk-Martins and Lalé (2016, 2019) provide empirical support for this adjustment mechanism. They show that during the US Great Recession the increase in IPT was largely associated with increased direct flows from full-time to part-time employment without a change in employer, consistent with the view that employers used part-time employment to reduce hours worked without incurring turnover costs. As they also note, individuals who prefer to work full time might be more willing to accept part-time work in a downturn, when the value of their outside option declines, thereby reinforcing the employer shift toward part-time labor. Reversal of these factors will tend to cause IPT to decline during economic recoveries. The pronounced countercyclical pattern in the slack-work component of IPT is consistent with this narrative (see online fig. A1).

Such cyclical adjustments in part-time work likely are reinforced by several additional economic and institutional factors. One is frictions in the coordination of work hours that preclude continuous hours adjustment, as reflected in frameworks to model the discrete trade-off between full-time and part-time labor (e.g., Chang et al. 2011). Even during a recovery period, if demand uncertainty is high—as Baker, Bloom, and Davis (2016) suggest was the case—greater reliance on part-time employees may be a cost-effective means for enhancing employment flexibility (Euwals and Hogerbrugge 2006). Reliance on part-time work also may limit the need to pay overtime, since part-time workers are less likely than full-time workers to cross the legally mandated overtime threshold of 40 weekly hours. Part-time work schedules are further reinforced by experience rating in the US unemployment insurance system: by reducing hours rather than laying off workers, firms avoid the additional unemployment insurance taxes that are incurred proportional to their layoff history (Borowczyk-Martins and Lalé 2018).

The second, broader category of IPT determinants encompasses persistent structural factors that tend to evolve independently of the business cycle. These factors include industry structure, labor costs, and workforce demographics, each of which could affect the relative demand and supply for part-time work and consequently the prevalence of IPT.

As established in the preceding section (table 1), VPT and IPT rates vary substantially across industries. One reason for such differences is a "peak-load" pattern in which demand is predictably high at certain times during the day (e.g., a lunch or dinner rush at a restaurant). Relying on part-time workers (e.g., 4–5-hour shifts) is one cost-effective approach to meeting peak-load demands. Such patterns are widespread in retail and in the leisure and hospitality sector. If the employment shares of industries with peak-load dynamics rises, employer demand for part-time labor will rise as well (see Euwals and Hogerbrugge 2006).

Another potential source of changes in demand for part-time labor is labor costs. If the per-hour costs of employees increase, employers may reduce work hours by shifting from full-time to part-time labor and substituting capital for labor.[9] Given that many part-time jobs are low skill and concentrated in the retail and services sectors, the level of the minimum wage may be an important element of labor costs. Employers' cost of employee health benefits is another element of labor costs that may be relevant for the use of part-time labor, particularly given that part-time employees often are excluded from employer health benefit plans (Carrington, McCue, and Pierce 2002).[10]

The impact of employer health benefits on the incidence of IPT work may have been affected in recent years by the 2010 passage of the Affordable Care Act (ACA). The law includes a mandate that employers with at least 50 full-time employees must provide health benefits to employees who work at least 30 hours per week or pay a penalty. This provides a potential incentive for employers to reduce their benefit costs by switching some workers to schedules with fewer than 30 hours per week, in turn raising the incidence of IPT work. The mandate was originally scheduled for implementation in 2014 but was delayed to 2015–16. Employer adjustments to the mandate may have occurred prior to its implementation.

Analysis to date has produced conflicting results about ACA effects on part-time work. Even and Macpherson (2019) and Dillender, Heinrich, and Houseman (2016) find evidence supporting the view that the ACA employer mandate has increased the level of IPT work, whereas Garrett, Kaestner, and Gangopadhyaya (2017), Mathur, Slavova, and Strain (2016),

[9] Part-time wage rates are typically lower than full-time wage rates, which lowers employers' costs of hiring part-time workers. Much of the wage gap appears to be explained by the observable characteristics of part-time vs. full-time workers and jobs, although existing research suggests that a substantial gap remains after accounting for these differences (e.g., Hirsch 2005).

[10] Online app. B includes a discussion of data on health benefit costs and their use in our preliminary analyses.

and Moriya, Selden, and Simon (2016) do not. While a full evaluation of their respective methodologies is beyond the scope of the present work, the findings from the former papers, which report an ACA effect, can be reconciled with our findings regarding industry share contributions to rising IPT work. We provide additional discussion in the conclusion.

On the supply side of the labor market, changing demographics may affect the availability of part-time labor (see the discussion of table 1 in sec. II). Young workers are a key source of VPT, but their share in the workforce and population has been declining. This may cause employers seeking part-time employees to rely more heavily on demographic groups who prefer full-time work, thereby increasing the incidence of IPT. By contrast, workers age 65 and over have a very high incidence of part-time work. Their share of the workforce has been growing, but as shown in the previous section, they have been exhibiting a declining tendency to work part time. The net impact of such demographic changes is ambiguous.

The demand and supply factors that we have identified tend to evolve slowly over time and are likely to vary across different geographic markets. If the demand factors increase aggregate demand for part-time labor while the supply of workers who prefer part-time work is constant or declining, the result is likely to be an increase in the incidence of involuntary part-time work. For example, if relatively rapid employment growth in the leisure and hospitality sector increases overall employer demand for part-time labor in a particular geographic market, an increase in IPT may result unless there is corresponding growth in supply via demographic groups that supply large amounts of part-time labor.

In a frictionless labor market, relative wages should adjust to clear the markets for full-time and part-time labor, eliminating the incidence of IPT. In actual labor markets, however, frictions generate IPT as a persistent or equilibrium phenomenon. In addition to the frictions related to hours coordination noted above, with inelastic labor supply to part-time and full-time work or more general downward wage rigidity, relative wages will adjust slowly to changing market conditions. Moreover, workers choosing between part-time and full-time employment tend to be low skill; hence, the minimum wage may be a binding constraint on the decline in the relative wage paid for full-time work. As such, changes in IPT due to slowly evolving changes in demand and supply conditions are likely to persist.

Assessing the impact of such changes on the incidence of IPT work requires an approach that jointly accounts for the changing demand and supply factors. If they are not jointly included in the analysis, their respective roles may be distorted: for example, in the hypothetical scenario described two paragraphs above, the role of industry shifts may be confounded by offsetting changes in demographic composition of the workforce. We therefore implement a state panel regression framework that jointly accounts for changes in the demand and supply factors described in this section, which are directly measurable in our data. By contrast, composition adjustments applied to micro data, such as that discussed in section II, cannot account for demand and supply interactions across compositional categories. Moreover, such adjustments are valid only under the assumption that the compositional changes do not affect the within-group incidence of involuntary part-time work. That assumption is explicitly violated in our setting: a change in the share of a group with a high incidence of involuntary part-time work is likely to change the incidence for that group and other groups.

Our panel regression framework also readily accommodates direct estimation of the cyclical component to movements in IPT, which is necessary for accurate quantitative assessment of the slowly evolving structural determinants. Aggregate time-series data do not provide the variation necessary for separate estimation of the cyclical and structural components to movements in IPT. In the remainder of the paper, we therefore describe and implement an empirical framework that relies on variation in cyclical conditions and market factors measured over time at the state level.

IV. Regression Analyses Using State Panel Data

The preceding discussion identified cyclical and market factors that are likely to affect the prevalence of IPT work and emphasized that geographic variation may be exploited to assess their impact. Although narrow geographic areas may provide the best market definition to assess the influence of these factors, the required data are most readily available at the state level (51 units, including the District of Columbia). In this section, we describe and implement our state panel data approach. Because cross-state variation in IPT and related variables has not been exploited in other work on part-time employment—other than in very brief and preliminary form in Valletta and van der List (2015)—we start with a descriptive analysis of patterns in these data (sec. IV.A) and then proceed to our regression framework and results (sec. IV.B).

A. Data Description

Our state panel data set consists of annual observations on IPT employment rates and explanatory factors covering the period 2003–16. In addition to unemployment rates and other indicators of business cycle conditions in each state, we incorporate data series that reflect the market factors discussed in section III:[11]

[11] See online app. B for additional details on state data sources and definitions. Our data set and a user guide are also available online.

1. Industry employment shares. We include a complete set of broad industry categories.
2. State labor costs. We use data on the level of real wages (median and other percentiles) and the legislated state minimum wage (measured as a fraction of the state nominal median wage).
3. Population and labor force shares by age group and gender.

To illustrate the strong cyclical component to changes in the IPT rate, figure 2 displays the relationship between state IPT and unemployment rates (expressed as percentages) via a set of scatterplots. The four panels show tabulations for the 3 years displayed earlier in table 1 (2005, 2010, and 2016) and for the full pooled sample. For purposes of direct comparison, the scales are identical across the four panels. The straight line in each panel is the least squares linear fit between the two series, with observations weighted by state employment counts.

For each panel in figure 2, we highlight four specific states: Alabama, California, Hawaii, and Nevada (identified by standard state abbreviations). These were chosen because they illustrate key patterns in the data, not because they fully summarize the relationship between IPT and unemployment across states and over time. That complete relationship is reflected in the fitted lines and will be explored further via the regression analyses in the next section. For readers interested in other states, however, we also provide a version with complete state labeling in online appendix A (fig. A3).[12]

The scatterplots of IPT and unemployment rates in figure 2 are relatively tight in the expansion years of 2005 and 2016 but much wider in 2010, when the labor market reached a trough. Consistent with the countercyclicality at the aggregate level illustrated in figure 1 (sec. II), in all cases the fitted lines show a positive relationship between the unemployment and IPT rates. This relationship is relatively consistent in the cross section: the slope of the fitted line increased somewhat between 2005 and 2010 and then was little changed in 2016.

This cross-state relationship between IPT and unemployment is not precise, however, with substantial deviations from the fitted lines evident. The four highlighted states are informative in this regard. Consistent with its low employment shares for key industries with high rates of part-time work, such as leisure and hospitality, Alabama has a low IPT rate relative to its unemployment rate in all years. The opposite is the case for California, Hawaii, and Nevada. The economies of the latter two states are heavily dependent on travel and tourism, especially Nevada, and hence have much higher shares of leisure and hospitality employment than any other state. Yet Nevada is less of an outlier with regard to high IPT rates than Hawaii. This illustrates the

[12] In online fig. A3, the scales are different across the four panels, enabling visual identification of all state labels.

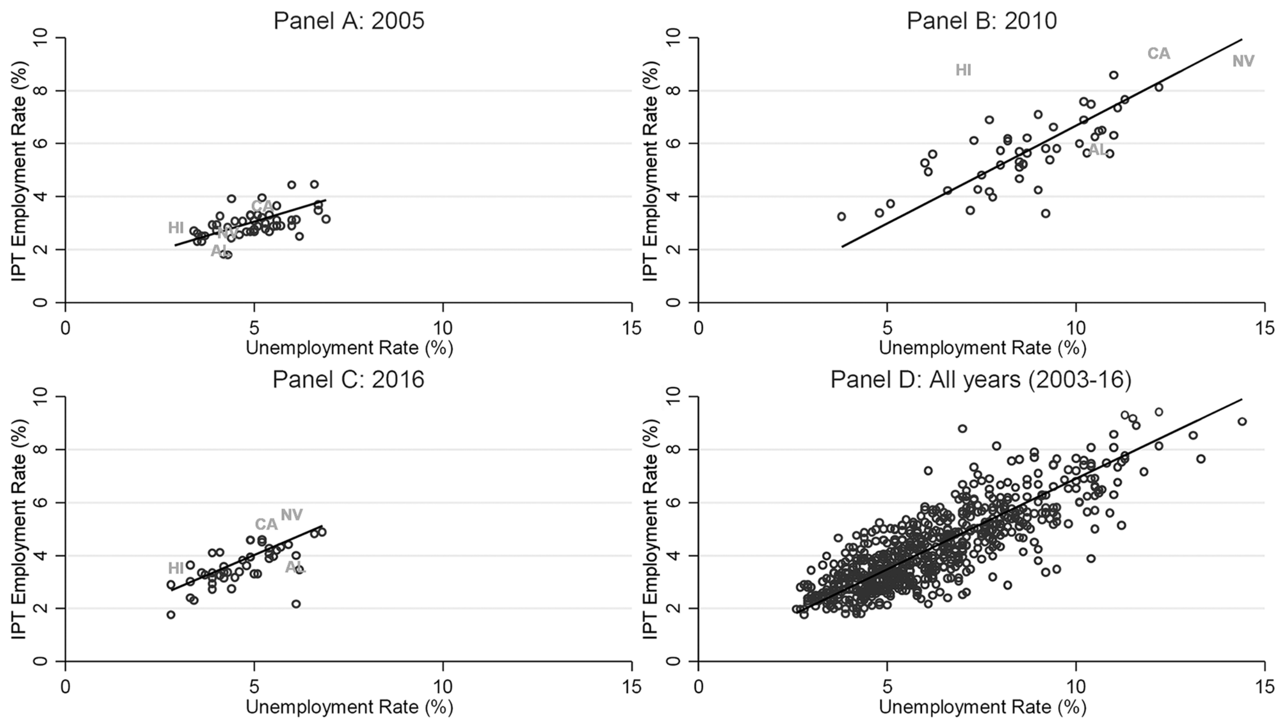

FIG. 2.—Involuntary part-time (IPT) work and unemployment, all states (by period). Source: US Bureau of Labor Statistics and authors' calculations. IPT employment rate measured as a share of civilian employment. Fitted lines weighted by state employment. A color version of this figure is available online.

importance of idiosyncratic state factors, such as Hawaii's long-standing employer health insurance mandate, which has been found to increase part-time employment in that state (Buchmueller, DiNardo, and Valletta 2011).

Given the importance of relatively fixed factors at the state level, our subsequent regression analyses rely on changes within states over time to identify the relationship between IPT and its cyclical and structural determinants. Online figures A4–A10 show the cross-state distribution of the relevant variation over time. Online figures A4 and A5 provide additional scatterplots and time-series plots that illustrate the within-state variation for changes in the IPT and unemployment rates, while online figures A6–A10 provide histograms of the complete distribution of within-state changes for the IPT rate, the unemployment rate, selected industry and population (age/gender) shares, and labor costs (median and minimum wages). Each of these displays shows a relatively wide distribution of within-state changes. This variation underlies the regression specification described in the next subsection.

B. Regression Framework and Results

The descriptive analyses of the state data suggest that cyclical conditions plus other state-specific market factors, both observed and unobserved, will affect changes in IPT work at the state level. Our framework accounts for such observed and unobserved state factors.

We estimate regressions of the following general form using the state panel data:

$$\mathrm{IPT}_{st} = \alpha + f(U_{st})\beta + X_{st}\gamma + \varphi_s + \delta_t + \epsilon_{st}, \tag{1}$$

where s and t index state and time (year). Because the dependent variable, the IPT rate, is measured as a fraction and takes values close to zero but bounded above it, we use the fractional regression methods developed in Papke and Wooldridge (1996, 2008).[13] Observations are weighted by each state's average employment over the sample period, and the standard errors are clustered by state.

The parameters β and γ represent vectors of coefficients to be estimated, to capture the effects of the variable sets $f(U_{st})$ and X_{st} described below. Reported estimates in all cases are average marginal effects reflecting the impact of a unit change in each variable on the fraction of measured IPT in the state, with other explanatory variables held at their mean values. We also report a "within" R^2 statistic that represents the proportion of variation in

[13] The estimator is available via the fracreg procedure starting with Stata ver. 14. We use the logistic functional form. The Papke-Wooldridge estimator relies on quasi-maximum likelihood and hence allows for misspecification in the underlying distribution function. Compared with our reported results, estimation of a conventional linear model for the untransformed fractional outcome variable generates a poor fit, especially for the cyclical component.

the fractional outcome variable occurring within states over time that is explained by the time-varying explanatory variables.[14]

Equation (1) specifies the cyclical component of variation in IPT as a flexible function of the state unemployment rate, $f(U_{st})$. Given the importance of cyclical variation for the overall differences in the IPT rate across states and over time, we explored alternative specifications of the cyclical component, using indicators beyond the unemployment rate (such as the employment-to-population ratio, also used by Bitler and Hoynes [2016]). The alternative results and discussion are provided in online table A2. They show that cyclical variation in the IPT rate is well explained by a quadratic function of the unemployment rate, which we use for all specifications listed in the main tables.

Equation (1) also includes a set of other time-varying state variables (X_{st}) and state fixed effects (φ_s). The variables in X account for persistent structural features of state labor markets that affect the IPT rate, specifically, the industry share, labor cost, and demographic categories discussed in the preceding sections. The state effects account for the influence of unmeasured time-invariant characteristics of state labor markets that may distort the estimated relationship between the IPT rate and the explanatory factors. The possible importance of such factors was suggested by the discussion in the preceding subsection. The state effects are highly statistically significant in all specifications (but not reported in the tables).[15]

In these regressions, the coefficients on the time-varying explanatory variables reflect the effects of changes in the directly measured factors within states over time. The vector of year indicators (δ_t) captures the remaining unexplained variation in IPT over time, attributable to unmeasured cyclical or other determinants. The year effects are a key focus of our analysis below, as we seek to explain them via the identifiable determinants of IPT.

Table 2 presents the main results. The first column focuses on the cyclical component: it reports results for a specification that includes only that component, year effects, and the state fixed effects (which are used in all specifications). The strong cyclical component in the IPT rate is reflected in the large and precisely estimated marginal effect of the unemployment rate, although this is attenuated by the contribution from the quadratic term. For example, calculated at the weighted sample mean unemployment rate of

[14] This is calculated directly from the sums of squares on the fractional outcome variable, following a suggestion in Papke and Wooldridge (1996). We subtract out the variation attributable to the state fixed effects.

[15] The point estimates and measures of statistical precision and fit are very similar when the models are instead estimated using a logistic transformation of the dependent variable and a formal fixed effects estimator. A conventional Hausman test strongly rejects a random effects specification in this alternative framework. We use the Papke-Wooldridge estimator with explicit state effects partly for computational convenience with respect to the calculation of marginal effects.

Table 2
Involuntary Part-Time (IPT) Regression Results, 2003–16

Variable (by Category)	Baseline Specification (Cyclical and Year Effects Only) (1)	Baseline Specification (with State Market Factors)[a] (2)
Cyclical:		
Unemployment rate (fraction)	1.020***	.632***
	(.115)	(.101)
(Unemployment rate squared) × 10	−.338***	−.205***
	(.066)	(.058)
Year (2006 omitted):		
2003	−.002*	.002
	(.001)	(.001)
2004	−.000	.001
	(.001)	(.001)
2005	−.000	.001
	(.001)	(.001)
2007	.002***	.001
	(.001)	(.001)
2008	.007***	.006***
	(.001)	(.001)
2009	.010***	.009***
	(.002)	(.002)
2010	.009***	.007**
	(.002)	(.003)
2011	.010***	.006*
	(.002)	(.003)
2012	.010***	.005
	(.002)	(.003)
2013	.012***	.005
	(.002)	(.004)
2014	.014***	.003
	(.001)	(.004)
2015	.013***	−.001
	(.001)	(.005)
2016	.012***	−.004
	(.001)	(.005)
State market factors (selected):		
Industry shares:[b]		
Construction	. . .	−.276***
		(.053)
Manufacturing	. . .	.029
		(.070)
Wholesale trade	. . .	−.898***
		(.241)
Retail trade	. . .	−.130
		(.131)
Transportation/communications/utilities	. . .	.401**
		(.174)
Information	. . .	−.155
		(.187)

Table 2 (*Continued*)

Variable (by Category)	Baseline Specification (Cyclical and Year Effects Only) (1)	Baseline Specification (with State Market Factors)[a] (2)
Financial activities	. . .	−.054
		(.132)
Professional/business services	. . .	−.096
		(.080)
Leisure and hospitality	. . .	.356***
		(.122)
Education and health services	. . .	.194**
		(.086)
Other services	. . .	.480**
		(.234)
State dummies	Yes	Yes
R^2 (within)	.797	.929
N	714	714

Note.—Dependent variable is IPT as fraction of state civilian employment; average marginal effects reported. Standard errors in parentheses (clustered by state). Mean of state civilian employment used for regression weights.

[a] State market factors included in the model but not listed here are labor costs (median and minimum wage) and population shares (age/gender). See online table A3 for complete results.

[b] Omitted category is government for the industry categories.

* $p < .10$

** $p < .05$.

*** $p < .01$.

6.5%, a 1 percentage point increase in the unemployment rate implies around a 0.6 percentage point increase in the IPT rate.

Despite the large and precisely estimated cyclical component in column 1, the estimated year effects indicate that the IPT rate rose substantially more during the Great Recession and its aftermath than can be explained by changes in state unemployment rates. The reported marginal effects for the year dummies are directly interpreted as percentage point effects on the dependent IPT variable. They indicate a sharp upward drift in the IPT rate during the recession and recovery, peaking at 1.4 percentage points in 2014 and declining to 1.2 percentage points as of 2016. Although the unemployment quadratic explains much of the movement over time in the IPT rate, the year effects are meaningful relative to the typical IPT rate, which averages around 4.5% in our sample. The column 1 results indicate that even well into the economic recovery in 2016, the typical state IPT rate was about 1.2 percentage points above the level expected based on cyclical variation only. The combined cyclical and year effects explain much of the within-state variation in the IPT rate, reflected in a within R^2 value of about 0.8.

Column 2 of table 2 presents the key results from the full specification in equation (1), which includes observable structural characteristics of state labor markets that are likely to affect the relative demand and supply for

IPT employment (X_{st}). Inclusion of the structural factors improves the fit meaningfully. Most importantly, it greatly attenuates the otherwise unexplained increase in state IPT rates over time. The estimated year effects since the Great Recession are much smaller in column 2 than in the baseline cyclical specification from column 1. Meaningful residual cyclical effects remain, as reflected in the statistically significant coefficients on the year dummies in the recession and early recovery period (2008–11). However, the year effects in column 2 decline steadily from about 1 percentage point in 2009, becoming statistically insignificant in 2012 and slightly negative in 2015–16.[16]

The comparison of columns 1 and 2 in table 2 yields our key result: the state structural factors included in column 2 can fully account for the additional amount of IPT work that is not explained by cyclical movements during most of the recovery from the Great Recession. Other than the cyclical component, industry effects are the main time-varying factor that explain changes in the IPT rate over time. Column 2 of table 2 therefore lists the estimated coefficients for the complete set of industry shares. By contrast, the estimated effects for the labor cost and demographic factors are small and statistically insignificant; hence, they are not listed in the table. We provide results for the complete set of explanatory variables in online table A3.[17]

In table 2, column 2, several industry shares have large and statistically precise effects on the IPT rate that are consistent with the earlier tabulations of IPT incidence in table 1. For a few industries with high incidence of IPT and part-time work in general, such as leisure and hospitality and other services, the positive coefficients indicate that increases in their employment shares tend to increase the IPT rate, as expected. The converse is true for the wholesale trade sector, also as expected: it has a low incidence of IPT work, and the negative coefficient indicates that declines in this sector's employment share tend to increase the IPT rate.

It may seem surprising that for retail trade, which like leisure and hospitality also has a high incidence of IPT and part-time work in general, the coefficient on its share is small and statistically insignificant. This likely reflects

[16] Online table A3 explores alternative specifications of the state market (structural) components, including labor force rather than population shares; occupation rather than industry categories, and the two together; and the 25th percentile rather than the median wage. The results from these models do not alter the main conclusions from the baseline model in col. 2 of table 2.

[17] Estimates for the labor cost and demographic factors have the expected signs in several instances. Based on the point estimates, states with a higher median wage tend to have a slightly higher incidence of IPT. States with a higher population share of younger working-age individuals and those age 65 and over tend to have lower IPT rates, consistent with the high incidence of VPT among these groups helping to meet employer needs for part-time labor.

offsetting effects from the pure composition component and the within-industry component: the retail employment share has been declining, likely prompting increased employer reliance on IPT work as a means to reduce work hours in general. Similar considerations likely explain the otherwise counterintuitive coefficients for the construction, transportation/communications/utilities, and education and health services sectors.

We further explored the determinants of part-time work using regressions that rely on the CPS individual micro data described in section II. The specific framework is described in online appendix A, with the results listed in online table A4. They provide a check on the state panel specification and enable stronger tests of the state cyclical and market effects, via the introduction of individual characteristics to explicitly adjust for compositional changes. The micro data also enable comparison of the determinants of IPT and VPT, via a multinomial logit regression framework. The results reinforce the findings based on the state panel data that changes in IPT work over time are fully explained by variation associated with overall labor market slack (state unemployment rates) and structural features of state labor markets.

V. Accounting for IPT: Decomposition of Contributory Factors

The state-panel regression analyses in the preceding section identified cyclical and structural factors that contributed to variation in IPT employment over our sample period of 2003–16. In this section, we examine the quantitative contributions of the modeled factors to the movements in the aggregate IPT rate over time. In particular, we calculate how the average IPT rate varies over time based on variation in the explanatory variables measured at the state level. Our decomposition of the change in the average IPT rate between a base year 0 and year t relies on the following equation:

$$\mathrm{IPT}_t - \mathrm{IPT}_0 = \sum_s [\Pi(\mathrm{T}_{st} - \mathrm{T}_{s0}) \cdot e_s]. \tag{2}$$

In equation (2), T represents the complete set of time-varying explanatory factors from equation (1) (U_{st}, X_{st}, and δ_t), the elements of the vector Π are their corresponding estimated marginal effects from our preferred specification reported in column 2 of table 2, s indexes states, and e_s is a weight equal to each state's share of total US employment averaged over the sample frame. We calculate the contribution of each separate explanatory factor contained in T.[18] Because the regression model for the fractional IPT outcome is nonlinear, the estimated marginal effects do not perfectly predict the change in the IPT, with the size of the discrepancy growing over time relative to the base year. We therefore applied a uniform rescaling to the contributions of each factor to ensure that the components sum to the observed change

[18] As is standard for regression decompositions, we include all estimated effects, even those that are not statistically significant.

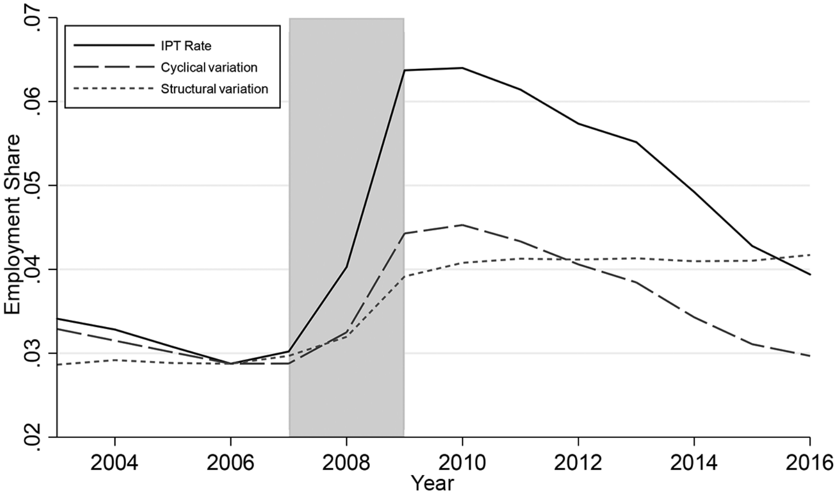

FIG. 3.—Involuntary part-time employment (IPT), 2003–16. Authors' calculations based on decomposition applied to regression results from column 2 of table 2; components measured relative to 2006 (see text for details). Year effects excluded. Series are measured as shares of civilian employment. Gray area denotes recession (approximate). A color version of this figure is available online.

in the actual IPT rate. We use 2006 as our base year; hence, the contributions of all explanatory factors in that year are identically zero.

Figure 3 and table 3 summarize the main results from this analysis. The figure provides a visual display of the cyclical and structural contributions to movements in the IPT rate over time, with the complete set of structural market factors—industry, demographics, and labor costs—combined into a single effect (with year effects excluded).[19] The directly measured cyclical component accounts for much of the increase in the IPT rate during the recession and immediate aftermath period of 2010–11. This component declined along with state unemployment rates, and by 2016 it was down nearly to its prerecession level. By contrast, after rising during the recession, the contribution from the structural factors was largely stable, keeping the aggregate IPT rate elevated by slightly more than a percentage point since 2010.

Table 3 provides the exact numerical listing of the cyclical, structural, and year effects for the period 2006–16. The first column lists the change in the state average IPT rate from 2006 for each subsequent year. The other

[19] We exclude the year effects from the figure because it is unclear whether they reflect unmeasured cyclical or structural factors; hence, the two broad components do not add to the total movement in the IPT series over the sample frame. Table 3 lists the precise quantitative contributions for the components.

Table 3
Decomposition of Involuntary Part-Time Change (2006 Base)

Year	Total Change from 2006 (1)	Cyclical Component (UE) (2)	Industry Composition (3)	Age/Gender Composition (4)	Labor Costs (5)	Year Effects (6)
2007	.001	.000	.001	.000	.000	.001
		(.012)	(.433)	(.178)	(.031)	(.346)
2008	.012	.004	.003	.001	.000	.005
		(.325)	(.218)	(.056)	(.004)	(.397)
2009	.035	.016	.009	.001	.000	.009
		(.444)	(.248)	(.039)	(.010)	(.258)
2010	.035	.017	.011	.001	.000	.007
		(.469)	(.299)	(.034)	(.009)	(.190)
2011	.033	.015	.011	.002	.000	.006
		(.446)	(.325)	(.052)	(.006)	(.171)
2012	.029	.012	.011	.002	.000	.004
		(.414)	(.370)	(.063)	(.001)	(.152)
2013	.026	.010	.011	.002	.000	.004
		(.367)	(.402)	(.074)	(.000)	(.158)
2014	.020	.006	.010	.002	.000	.003
		(.270)	(.501)	(.098)	(−.002)	(.133)
2015	.014	.002	.010	.002	.000	−.001
		(.166)	(.726)	(.138)	(.011)	(−.040)
2016	.011	.001	.011	.002	.000	−.003
		(.087)	(1.010)	(.181)	(.028)	(−.305)

NOTE.—Based on average marginal effects from col. 2 of table 2; fractional contribution to col. 1 total in parentheses. Effects normalized to zero in 2006; years 2003–5 omitted for brevity. See text (sec. V) for description of decomposition methodology. UE = unemployment.

columns show the contributions from the cyclical component, the separate structural components (industry, demographics, and labor costs), and the remaining year effects, with the actual contributions and their share of the total change listed. The key contribution to the total structural effect comes from industry composition; it has stayed stable at about 1.0–1.1 percentage points from 2010 through 2016. Changing demographics made a modest net impact as well, keeping the IPT rate elevated by about 0.2 percentage points over this timeframe. The impact of labor costs is essentially zero, due to the small estimated marginal effects of the wage variables and limited changes in their values over time. As already noted regarding the earlier regression results, the unexplained year effects are largely ignorable after 2013.

These results indicate that persistent changes in industry employment shares at the state level have made important contributions to the elevated level of IPT employment since the Great Recession. Table 4 probes these results further by listing the contributions of key industries to the change in the IPT rate between 2006 and 2016. For readers interested in more details from the decomposition results, online table A5 lists the contributions

Table 4
Decomposition of Involuntary Part-Time Change (2006 Base): Selected Industry Share Effects, 2016 Only

Year	Total Change from 2006 (1)	Construction (2)	Wholesale Trade (3)	Transportation/ Communications/Utilities (4)	Leisure and Hospitality (5)	Education and Health Services (6)	Other Services (7)
2016	.0106	.0023	.0018	.0005	.0031	.0035	−.0001
		(.213)	(.165)	(.050)	(.295)	(.328)	(−.005)

NOTE.—Based on average marginal effects from col. 2 of table 2; fractional contribution to col. 1 total in parentheses. See text (sec. V) for description of decomposition methodology.

from the complete set of explanatory variables for selected years during the recovery (2010, 2013, and 2016).

Table 4 shows that the construction, wholesale, leisure and hospitality, and education and health services sectors each made a substantial contribution to the change in the IPT rate from 2006 to 2016, ranging from about 17% to 33% of the total change. This reflects the combination of their impact on the incidence of IPT work (from the regression models) and their changing shares over the sample frame. As noted regarding the regression results in section IV.B, these results are as expected for the wholesale sector and the leisure and hospitality sector, based on the relative prevalence of IPT work in these sectors and their changing employment shares from table 1. The education and health services sector has low rates of IPT but high rates of VPT in table 1, as well as a rising employment share. It is likely that the expansion of this sector in many states has increased demand for part-time workers and hence overall IPT work.

The results for the construction sector are somewhat anomalous. It tends to have high rates of IPT, so the direct effect of its declining employment share should be to reduce rather than increase IPT. The contribution of the construction sector may reflect the severity of the economic downturn in states most affected by the associated housing bust, with spillover effects to IPT employment in other sectors. Online table A5 shows that its contribution has been diminishing over time. However, this has been matched by rising contributions from other sectors, causing stability in the overall industry share effect.

Overall, the decomposition results show that despite the cyclical recovery from the Great Recession, the IPT rate has remained elevated by a little over a percentage point relative to prerecession levels. The persistent elevation of the IPT rate during the recovery from the Great Recession appears to be primarily attributable to persistent changes in the demand for part-time work hours via changing industry employment patterns.

VI. Discussion and Conclusions

We analyzed the determinants of IPT employment, focusing on its unusually elevated levels as a share of total employment during and after the US Great Recession of 2007–9. Other recent research pointed to elevated levels of IPT during this period but did not reach definitive conclusions about the relative role of cyclical and persistent structural factors (e.g., Cajner et al. 2014; Canon et al. 2014). By contrast, our regression and decomposition methodology enable a quantitative decomposition of contributory factors. Using state panel data for the period 2003–16, we confirmed that the IPT rate depends heavily on cyclical variation in labor market conditions. However, we also identify slower-moving market factors, reflected mainly in industry employment shares, which account for ongoing elevation in the IPT rate despite the cyclical recovery in the labor market. These market or structural factors account for a little over a percentage point of the elevated IPT share of total employment through 2016, with very little change in their overall contribution since the recovery began in 2010. This represents about 1.75 million employed individuals who want full-time work but are stuck in part-time jobs, or about 40%–50% more than expected based on the prevalence of such workers prior to the Great Recession. These results suggest that the incidence of IPT employment is likely to remain elevated in the future as well.

Similar patterns in IPT and part-time work more generally have been observed for other countries. For example, the analysis of Borowczyk-Martins and Lalé (2019) uncovered shared patterns in labor market flows that contributed to recent elevation in IPT work in the United States and the United Kingdom (see also Bell and Blanchflower 2014). The International Monetary Fund recently provided a broad cross-country assessment of trends in IPT work, finding that it remains somewhat elevated in most advanced economies, even those where unemployment has largely returned to prerecession levels (IMF 2017).

The international evidence suggests that our findings regarding elevated IPT work reflect broad labor market developments rather than institutional factors, such as the ACA employer mandate in the United States. As we noted in section III, the direct evidence on the ACA impact currently is mixed. Among papers that report evidence that the ACA mandate increased the incidence of IPT work, the findings are concentrated among workers, occupations, and industries with relatively high IPT prevalence in general, before and after passage of the ACA (Dillender, Heinrich, and Houseman 2016; Even and Macpherson 2019). While we cannot rule out a contribution from the ACA mandate, the empirical findings from these papers likely reflect the broader industry contributions to rising IPT work that we uncover in our regression framework. Also, the structural contribution that we estimate became prominent beginning in 2010, well before employers were likely to start adjusting to the expected implementation of the ACA employer mandate. As such, we interpret the persistent elevation of IPT work as largely reflecting broad structural changes in the US labor market.

An additional structural change that may relate to elevated IPT work is the growth of work hours via the provision of services in the on-demand (or "gig") economy. Poor measurement of such jobs in readily available micro data sources such as the CPS creates challenges for identifying such links (Abraham et al. 2018). However, further investigation using data sources that provide more precise and accurate information on informal gig work may prove to be a fruitful line of research (such as in Bracha and Burke 2017).

Our framework and findings suggest other avenues for future work as well. We focused on recent empirical patterns in involuntary part-time work, discussing a market demand and supply framework in broad conceptual terms to guide our empirical analyses. More formal modeling of the demand and supply sides of the market for part-time work, as well as its general equilibrium properties, could be quite valuable for refining these findings.

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