The Rise of In-and-Outs:

Declining Labor Force Participation of Prime Age Men

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Abstract

This paper documents that much of the decline in labor force participation of U.S. prime age men comes from "in-and-outs"—who I define as men who temporarily leave the labor force. Individuals moving in and out of the labor force have been an understudied margin of labor supply but account for 20–40% of the decline in participation between 1984 and 2011. In-and-outs are distinct from unemployed individuals, experiencing no loss of future income as a result of their time out of the labor force, and represent a distinct margin of labor supply from long-term labor force dropouts. Examining explanations for the rise of in-and-outs, I find little evidence to suggest that changes in labor demand are responsible.

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1 Introduction

In 1960, more than 97% of American men between the ages of 25 and 54 were either employed or actively looking for work. By 2015, this rate had fallen to 88%, representing nearly 5.5 million fewer prime age workers in the labor force at any point in time. This declining trend has motivated a growing body of work seeking to understand why men are leaving the labor force.[1]

In this paper, I document that participation has changed along an understudied margin of labor supply. I find that "in-and-outs"—men who temporarily leave the labor force—represent a growing fraction of prime age men across multiple data sources and are responsible for 20–40% of the decline in the participation rate between 1984 and 2011. In-and-outs take short, infrequent breaks out of the labor force in between jobs, but they are otherwise continuously attached to the labor force. Leading explanations for the growing share of permanent labor force dropouts, such as disability, do not apply to in-and-outs. Additionally, evidence indicates that the rise of in-and-outs does not result from a decline in labor demand for prime age men. Together, these facts paint a different picture of declining labor supply among prime age men than documented previously.

The rise of in-and-outs is not apparent from measures of the participation rate taken at a single point in time, resulting in prior work overlooking this margin of labor supply. If the participation rate falls by one percentage point, it could have been driven by one percent of men leaving the labor force permanently, or two percent spending half of their time out of the labor force, or twelve percent deciding to take one month of the year to spend out of the labor force. It is important to distinguish between these scenarios because they each may have different implications for inequality, human capital accumulation, and policy responses.

I show that the rise of in-and-outs is a robust phenomenon observed over the last several decades in a number of different longitudinal data sources. In the Survey of Income and Program Participation (SIPP), the share of men who are out of the labor force in any given month rose 5.3 p.p. from 1984 to 2011, with between 1.3 and 2.0 p.p. of this increase coming from nonparticipation spells lasting less than two years. Similar increases in temporary nonparticipation are evident in other longitudinal datasets, including administrative earnings records. Additionally, retrospective data sources inaccurately estimate the number of in-and-outs, as measurement error in retrospective collection is growing over time, possibly due to recall problems or increased rounding by respondents. After returning to the labor force, most in-and-outs are highly attached to the workforce over the subsequent decade.

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[1]Examples include Juhn (1992; 2003), Moffitt (2012), CEA (2016), and Eberstadt (2016).

In-and-outs are different from unemployed individuals in a number of ways. First, in-and-outs are not actively searching for work while out of a job. In-and-outs' consumption dynamics are similar to retirees', and do not experience as large of a decline after a job separation as that of unemployed individuals. Additionally, in-and-outs experience no decline in future income relative to their peers as a result of their time out of the labor force, in contrast to the large long-run costs faced by unemployed individuals.

The rise of in-and-outs appears to be a distinct margin of labor supply from changes in permanent dropouts. The two groups cite different reasons for leaving the labor force, report different qualities of life, and show up in different regions. While some in-and-outs could turn into dropouts, the distinctions between these two groups make it more natural to treat them as separate components of the participation decline, with separate explanations, rather than intertwined aspects of the same phenomenon. Additionally, some of the most common explanations that have been put forward for the growth of permanent dropouts, such as disability insurance or incarceration, cannot explain the rise of in-and-outs.

In-and-outs do not represent men switching between market-sector work and home production. While out of the labor force, in-and-outs replace time spent working with leisure activities, primarily watching television. In-and-outs do not spend much more time on child care, care for adults, educational activities, or job search during these breaks.

Next, I turn to understanding the forces responsible for the rise of in-and-outs more formally. In particular, I differentiate between explanations related to changes in labor demand, reflected in diminished market opportunities, from changes in labor supply, representing lower participation holding market opportunities constant.

I find that changes in men's market opportunities can explain little of the rise of in-and-outs. Since in-and-outs are in the labor force at least some of the time, I can directly measure the market opportunities available to them and examine how they have changed.[2] While factors such as automation and offshoring have reduced market opportunities for some prime age men, average real wages have actually risen slightly since 1977, casting doubt on this explanation. Furthermore, I show that even among groups that have experienced wage declines, such as less-educated men, these declines are not nearly large enough to explain the rise of in-and-outs using conventional labor supply elasticities from the literature. In-and-outs have risen across all industries and occupations, suggesting this phenomenon is not limited to particular types of jobs. Additionally, even though changes in labor demand could directly affect employment in the short run (as is the case if wages are rigid), these effects appear to be temporary and

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[2]This provides a large advantage for studying the growth of in-and-outs as opposed to dropouts, since potential wages are unobserved for the latter group. As such, it is unknown whether dropouts' potential wages have increased or decreased appreciably over the last several decades.

therefore cannot explain the long-term downward trend of participation.

This paper relates to several literatures. First, the pattern of changing participation among prime age men documented in this paper contrasts with several prior examinations of the change in prime age male participation. Juhn (1992; 2003), Juhn et al. (1991; 2002), and Moffitt (2012) conclude that the decline in participation was driven almost entirely by an increase in dropouts, based on evidence from the March CPS, and they attribute this to changing market opportunities. Elsby and Shapiro (2012), Autor, Dorn and Hanson (2013), Autor and Wasserman (2013), and CEA (2016) also point to reduced market opportunities for prime age men explaining some of the decline in participation. The availability of disability insurance has been highlighted by Autor and Duggan (2003), Eberstadt (2016), and Winship (2017) as a potential explanation for the decline. Schmitt and Warner (2011) and Eberstadt (2016) also point to the rising population of men with a criminal record as a factor in lowering the share of men working. Aguiar, Bils, Charles and Hurst (2017) focus on young men and show that improvements in video game technology may account for much of the decline in participation among this group. Krueger (2017) shows that the decline in participation among prime age men may be related to the opioid crisis, as participation has fallen more in areas with higher rates of opioid prescriptions.

Documenting the rise of in-and-outs also provides evidence for a key margin of adjustment for aggregate labor supply. In-and-outs rising in response to a decrease in desired labor supply is a key prediction of the time-averaging aggregation theory of Mulligan (2001) and Ljungqvist and Sargent (2007), who introduce this approach to reconcile large aggregate labor supply elasticities with small micro elasticities. In contrast, prior theories of labor supply aggregation point more towards labor supply adjusting along the dropout margin (Hansen, 1985; Rogerson, 1988). Additionally, the rise of in-and-outs documented in this paper contributes to the discussion of homogeneity versus heterogeneity in participation rates dating back to Heckman and Willis (1977). While Goldin (1989) shows that the rapid growth of female labor supply during the 20th Century reflects heterogeneity in participation rates, the analysis presented in this paper shows that the decline of male labor supply in substantial part reflects homogeneity (i.e. in-and-outs).

The rise of in-and-outs also stands in contrast to a literature on declining dynamism in US labor markets. Previous studies have noted declines in job-to-job flows Fallick and Fleischman (2004), labor market churn (Davis and Haltiwanger, 2014), geographic mobility (Molloy, Smith and Wozniak, 2011), and short-term jobs (Hyatt and Spletzer, 2017), among other measures. However, the evidence in this paper shows that an understudied dimension of fluidity—cycling in and out of the labor force—has been growing over the same time period.

The remainder of the paper proceeds as follows. Section 2 describes how I mea-

sure the rise of in-and-outs. Section 3 compares in-and-outs to several other types of nonemployment—unemployed individuals, permanent dropouts, and workers engaged in home production. In Section 4, I outline a toy model for understanding how labor demand and supply forces affect the in-and-out margin of labor supply. Section 5 examines explanations for the rise of in-and-outs. Section 6 concludes.

2   Measuring the Rise of In-and-Outs

This section documents the rise of in-and-outs across several different data sources. I begin by showing that short spells of nonparticipation lasting less than two years have become more common over the last few decades. The contribution of this rise of in-and-outs to the total increase of nonparticipation is bounded between 20–40% over the 1984–2012 period. The rise of temporary nonparticipation is evident in longitudinal datasets, but not in retrospective data sources. The latter appear to be suffering from increasing bias over time, resulting in these divergent measures. Lastly, I show that in-and-outs are highly attached to the labor force after returning to work following a nonparticipation spell.

2.1   Growth of Temporary Nonparticipation

I define in-and-outs as individuals who are short-term or temporary nonparticipants. This definition involves two components.

First, the individual must be out of the labor force, meaning neither working nor actively searching for work. Accordingly, in-and-outs are a distinct group from the unemployed, who are actively searching for work, although both groups are jobless. This distinction may seem trivial since neither group is employed, but I show in Section 3.1 that in-and-outs behave differently from the unemployed across a number of dimensions while out of work. In-and-outs are not on paid vacation or time off, as these activities are typically counted as part of employment in household surveys, nor are they on temporary layoff, since this is typically counted as a form of unemployment.

Second, in-and-outs are out of the labor force only temporarily, which I define as less than two years at a time. This definition separates in-and-outs from individuals who are persistently out of the labor force for several years or more, whom I term dropouts. Dropouts have also grown over the last several decades, but appear to be qualitatively distinct from in-and-outs on many dimensions (see Section 3.2 for more). I choose two years out of the labor force as the dividing line between these groups both for ease of measurement, since some datasets I employ are at an annual or biennial frequency.

I start by measuring the rise of in-and-outs using data from the Survey of Income and Program Participation (SIPP). The SIPP records respondents' labor force status at a monthly frequency and follows individuals for several years, even if they change addresses. Using the SIPP panels conducted starting in 1984 through 2008 (excluding the short 1989 panel), I form a sample of civilian men ages 25–54. I define an individual as being in the labor force in a given month if for at least one week out of the month he had a job or business, including if he was absent from work, or if he was actively looking for work or on temporary layoff.

Using the SIPP, I measure the duration of nonparticipation spells among prime age men. Many spells are noncensored, meaning that I observe the individual participating in the labor force for at least one month immediately before the spell of nonparticipation, as well as participating again for at least one month immediately after the spell. The duration of these spells can be directly measured in the data as the number of consecutive months in which the individual reported being out of the labor force. However, other spells are censored, meaning that the individual was out of the labor force during either the first or the last month of the panel, and accordingly their spell of nonparticipation may have started or ended at a different time than observed in the data.[3] For these spells of nonparticipation, the duration as measured in the SIPP is only a lower bound as the true duration could have been longer. To minimize the extent of these censored spells, I drop observations within one year of the beginning or end of the SIPP panel after computing the duration of spells.[4]
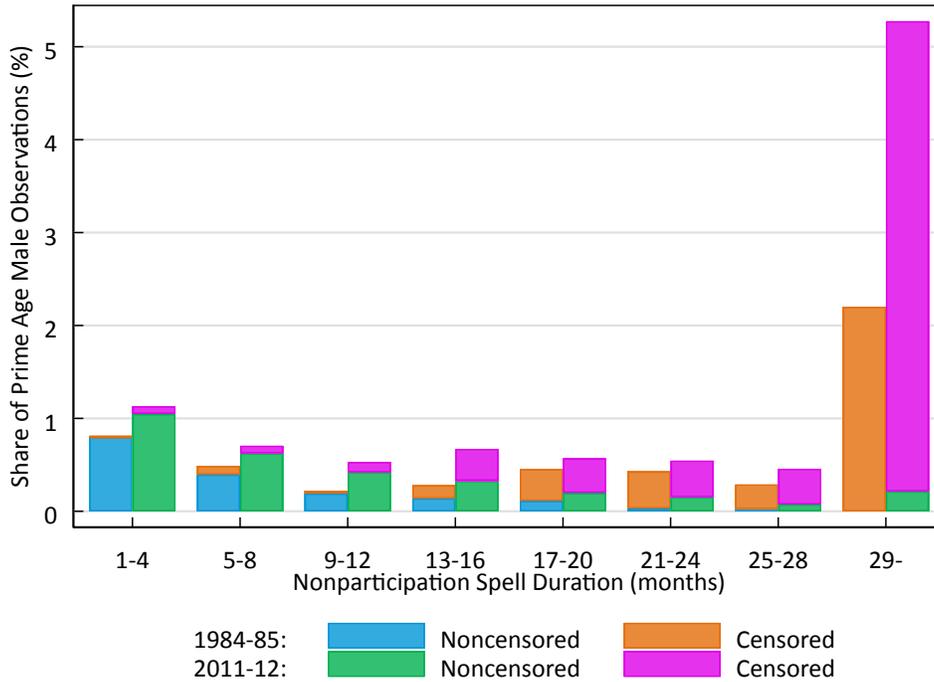
Nonparticipation spells of all durations grew between 1984–85 and 2011–2012, as shown in Figure 1. Each bar of Figure 1 shows the percentage of prime age male observations in the SIPP during the specified years that are nonparticipation of the indicated duration, broken into four month ranges, separating noncensored and censored spells. Nonparticipation as part of noncensored spells lasting one to four months grew from 0.8% in the earlier period to 1.0% in the later period, while censored spells of the same duration grew from 0.0% to 0.1%. Total nonparticipation among noncensored spells of 24 months or less in sample grew from 1.7% to 2.8%, while total censored nonparticipation of the same measured duration grew from 1.0% to 1.4%. Temporary nonparticipation has grown most among shorter durations of nonparticipation, particularly spells lasting less than 16 months, with relatively less growth among spells lasting 1.5–2 years.[5]

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[3]Additionally, some individuals either join the sample after the start of the panel, leave before the end of the panel, or are missing for some subset of the panel, resulting in censored spells of nonparticipation.

[4]Excluding these observations would be problematic if observations are systematically more or less likely to be part of in-and-out spells at the very beginning or end of a SIPP panel. I assume that the timing of the SIPP panel is exogenous to individual's labor supply decisions, which means that the durations are missing at random and these observations can be safely dropped without biasing estimates of the duration distribution (Rubin, 1976).

[5]An implication of this fact is that the choice of two years as the threshold for separating in-and-outs from long-term dropouts is not likely to affect the results substantially. Any threshold between 17 and 28

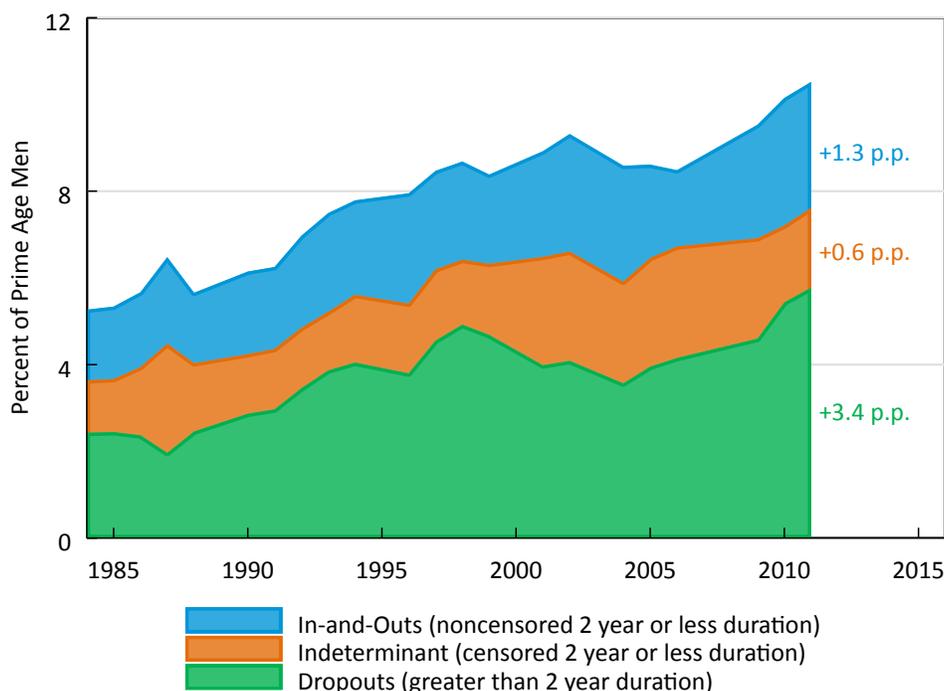Figure 1: Distribution of Nonparticipation Spell Duration

Notes: Sample consists of men ages 25–54 in the 1984–2008 SIPP Panels (excluding 1989). Observations within one year of the beginning or end of each SIPP panel are excluded. Each bar shows the fraction of prime age men in the average month of the specified time period who were out of the labor force as part of a nonparticipation spell of the specified type (non/censored) lasting within the specified duration range. The sum of all bars within each time period is equal to the nonparticipation rate.

Measuring the total rise of in-and-outs requires taking a stance on the contribution of censored spells. Although these nonparticipation spells were only observed for less than two years, they could have in fact lasted substantially longer. If all censored observations were in fact part of in-and-out spells, then in-and-outs would have increased from 2.7% to 4.2% over this time period, accounting for about one third of the total increase in nonparticipation. If instead none of the censored observations were part of in-and-out spells, then in-and-outs would have still grown from 1.7% to 2.8%, accounting for about one quarter of the total increase. These two extremes bound the contribution of in-and-outs to the decline in participation at between 1.1 and 1.5 p.p. between these two time periods.[6]

months would produce a similar rise of in-and-outs. I use two years for consistency across datasets, since some are monthly (e.g. SIPP, CPS) and some are annual (e.g. PSID, SSA).

[6]Without making additional parametric restrictions, it is not possible to substantially narrow these bounds or obtain a point estimate. Nonparametric and semiparametric methods have been developed to account for right-censoring, including the estimators of Kaplan and Meier (1958) and Cox (1972), but these methods do not work with data that is also left-censored. More restrictive parametric assumptions about the hazard rates into and out of nonparticipation are required, which are outside of the scope of

Figure 2: Growth of Temporary Nonparticipation

Notes: Sample consists of men ages 25–54 in the 1984–2008 SIPP Panels (excluding 1989). Observations within one year of the beginning or end of each SIPP panel are excluded. Graph shows the share of individual-month observations in which the respondent was not participating in the labor force, broken down by the length of the nonparticipation spell. Indeterminate spells refer to spells less than two years long in sample, but for which the true duration is unobserved, typically because they begin or end in the same month that the sample begins or ends.

Figure 1 also shows that nonparticipation by long-term dropouts, consisting of spells lasting in excess of two years, more than doubled from 2.5% to 5.7%. These longer spells account for a disproportionate share of the growth of nonparticipation observations, about two-thirds of the total growth of nonparticipation between these time periods, due to the considerable length of these spells. These spells last about ten to fifteen times longer than the average spell lasting between one and four months, yet they only account for about two to five times as many observations, implying that the number of individual spells is about *three to five times smaller* among these long spells than among the very shortest spells. This emphasizes that long-term nonparticipation is heavily concentrated among a smaller number of individuals, while the contribution of in-and-outs comes from many different spells.

The rise of in-and-outs has occurred steadily over time. Figure 2 shows the growth of nonparticipation year by year, collapsing the measures of duration shown in Figure 1 into three categories: in-and-outs, which here are noncensored spells of two years or

this paper.

less; indeterminate spells, which are censored spells of two years or less; and long-term dropouts, consisting of all spells lasting more than two years. While in-and-outs only comprised 1.5% of the prime age male population in any given month in 1984, this share had risen to 2.9% by 2010. Given that there were nearly 62 million prime age men in the US in 2010, the increase in this share represents about 1 million additional men out of work at any point in time due to this margin alone. Depending on the share of the indeterminate spells which were actually in-and-out spells, in-and-outs are responsible for 20-40% of the rise of nonparticipation over this time period.

2.2   Robustness

This section repeats the exercise above with three additional panel datasets: the Current Population Survey (CPS), the Panel Study of Income Dynamics (PSID), and the Social Security Administration (SSA) Earnings Public-Use File. Each of these datasets uses a slightly different measurement frequency and panel length, meaning that it is not straightforward to compare the magnitudes of temporary nonparticipation across datasets. However, it is possible to compare whether temporary nonparticipation is increasing or decreasing across datasets. The details of data construction for each of these datasets are described below, with additional detail provided in Appendix B.1.

Current Population Survey (CPS)   The CPS is a large, nationally-representative, longitudinal household survey which interviews individuals for up to eight months over a sixteen month period (four initial interviews, followed by eight months out of sample, followed by four more interviews). To capture in-and-outs, I measure the fraction of observations coming from nonparticipation spells which both begin and end during the sixteen month interview period. This includes spells which begin or end during the middle eight month out of sample period, as long as those spells end or began (respectively) during the in sample months.

Panel Study of Income Dynamics (PSID)   The PSID is a longitudinal survey of families that began in 1968 conducted annually through 1997 and biennially afterwards. For observations before 1997, I measure in-and-outs as the fraction of individuals who are currently out of the labor force as part of a spell of nonparticipation lasting no more than two consecutive interviews. For observations after 1997, I label an individual as an in-and-out if he responded as being out of the labor force currently but in the labor force for both the preceding and succeeding interviews.

Table 1: Temporary Nonparticipation Across Datasets

Year	(1) SIPP	(2) CPS	(3) PSID	(4) SSA	(5) March CPS
1965				1.7	3.7
1970			0.8	1.8	3.4
1975			0.9	2.4	3.3
1980		1.0	1.1	2.5	3.3
1985	1.7	1.2	1.5	2.9	2.9
1990	1.9	1.1	1.6	2.6	3.2
1995	2.3	1.3	1.6	2.4	3.3
2000	2.3	1.4	*2.0**	2.2	2.8
2005	2.2	1.4	*1.8**		2.7
2010	2.8	1.8	*1.7**		2.6
2015		1.8			2.6

Notes: Levels of temporary nonparticipation are not directly comparable across datasets due to differences in frequency and duration of labor force status measurement. Details of each dataset's construction are reported in Appendix B.1. Data sources in columns 1-4 are all longitudinal, column 5 uses retrospective data from the March CPS. Each series is smoothed using an Epanichnikov kernel with bandwidth equal to 1, similar to a three year moving average, to reduce the influence of year-to-year noise.
* The observations for 2000–2010 in the PSID come from biennial data, unlike prior year PSID observations which use annual data.

Social Security Administration (SSA) Earnings Public-Use File The SSA Earnings Public-Use File contains annual earnings records for a 1% sample of all individuals issued Social Security numbers prior to 2007. I create measures of annual participation from SSA records of men ages 25–54 covering the 1960–2006 period.[7] I classify an individual as being in the labor force in a given year if his annual earnings exceed half the minimum wage times 40 hours per week times 13 weeks per year. I label an individual as an in-and-out if he is nonemployed as part of a spell lasting no more than two consecutive years.

The growth of temporary nonparticipation is a robust phenomenon evident across all of these datasets. Table 1 shows the fractions of the prime age male population that were out of the labor force temporarily for each of the four longitudinal datasets I consider in columns 1-4. All of these datasets show an increase in temporary nonparticipation, although the magnitudes are not directly comparable since they measure labor force status at different frequencies and for different lengths of time. Similar to the increase in the SIPP, temporary nonparticipation nearly doubled in the CPS from 1.0% in 1980 to 1.8% in 2015. The PSID experienced an increase from 0.8% in 1970 to 1.6% in 1995, and subsequent measurements using biennial data indicate even higher

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[7]While the dataset contains earnings records starting in 1951, these records are unusually volatile in the mid-1950s and produce a sharp break in the share of in-and-outs between 1958 and 1959, possibly due to changes in measurement. To avoid this break affecting the estimated growth of in-and-outs, I drop records from before 1960.

levels.

In the SSA dataset, temporary nonemployment rose from 1.7% in 1960 to 2.2% in 2000. Since this dataset is constructed from earnings records alone, there is no distinction between unemployment and nonparticipation, complicating comparisons over time. As documented by Hall (1970b), Juhn et al. (1991), and Shimer (1999), the unemployment rate rose from the 1960s to the 1980s, before falling afterwards. Accordingly, temporary nonemployment rose dramatically through the 1980s and fell slightly afterwards, but ended up more than 0.5 p.p. higher by the late 1990s than the mid-1960s, despite similar unemployment rates during those two time periods. This indicates a secular trend upward in temporary nonemployment not accounted for by unemployment, which provides evidence of in-and-outs rising. Since the SSA dataset is constructed from administrative sources, this indicates that the rise of in-and-outs is not an artifact of measurement error problems affecting household surveys.
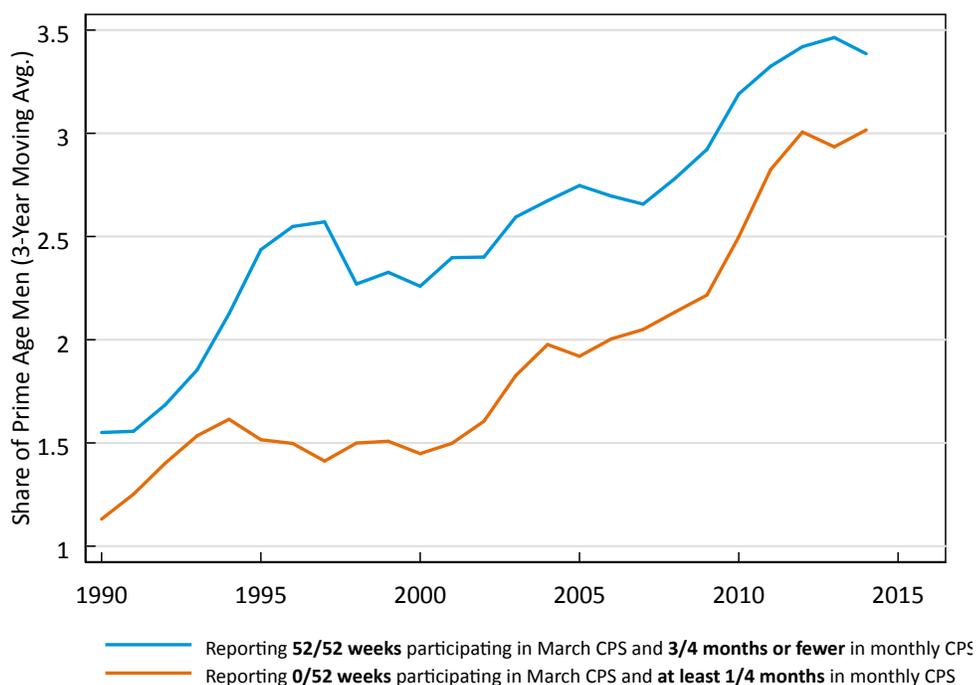
Throughout much of the rest of the paper, I use a simple approximate measure of the extent of in-and-outs using the CPS. I label an individual an in-and-out in the CPS if he is out of the labor force for between one and seven out of the eight total months in sample. This has the advantage of being tractable and simple to compute, but could potentially miscategorize nonparticipation spells that are actually longer than two years as in-and-out spells. Appendix B.3 reconstructs this measure using observations in the 2008 SIPP panel in which durations of less than two years are guaranteed to be observed and shows that this CPS approximation almost entirely captures temporary nonparticipation, addressing this concern.

2.3 Bias of Retrospective Sources

All of the datasets examined previously are panels that measure labor force status more or less contemporaneously, but some other data sources rely on retrospective collection of this information. In particular, the March CPS Supplement has been used previously to measure temporary nonparticipation by looking at the number of weeks an individual reported being in the labor force over the previous calendar year (see Juhn et al. 1991, 2002; Moffitt 2012). However, retrospective collection of labor force status may introduce some bias due to imperfect recall or rounding of recalled spell duration (Akerlof and Yellen, 1985).

Looking at the March CPS, one would conclude that temporary nonparticipation has decreased over the last several decades. Table 1 shows that only 2.5% of prime age men reported participating in the labor force between one and fifty-one weeks in 2015, down from 3.6% in 1965. This trend was noted by Juhn et al. (1991) and Juhn et al. (2002), who concluded that permanent nonparticipation was responsible for the entire

Figure 3: Bias in the March CPS

Notes: IPUMS March CPS matched to longitudinal monthly IPUMS CPS, 1990–2014. Individuals who participate in the March CPS during months 5-8 of their CPS rotation are matched to their responses during months 1–4, which all took place during the prior year. March CPS observations are matched to monthly CPS using the method of Flood and Pacas (2016). Both series are computed using survey weights.

increase of nonparticipation. The trend in the March CPS stands in contrast to the other datasets, though, which suggests that either it is biased or all of the other datasets are biased.

I directly test for the presence of bias in the March CPS trend by examining the accuracy of its respondents' answers. Since the March CPS sample is a follow-on survey from the monthly CPS, I can examine whether respondents' retrospective reports match their contemporaneous reports during the previous year. Specifically, I match respondents to the March CPS who are in their second rotation in the monthly CPS to their four monthly responses in their first rotation, which fall in the previous year.

Two types of misreporting can be unambiguously measured in the data: a) respondents who reported being in the labor force for all fifty-two weeks of the prior year in the March CPS, but in the monthly CPS reported participating only three out of four months or fewer, and b) respondents who reported being out of the labor force for fifty-two weeks in the March CPS, but in the monthly CPS reported participating at least one month out of four. Figure 3 displays the prevalence of these two types of errors from 1989-2015, showing that both types of errors have become more common. The increases

in these unambiguous errors are large enough to explain most of the divergence between the March CPS and other datasets.
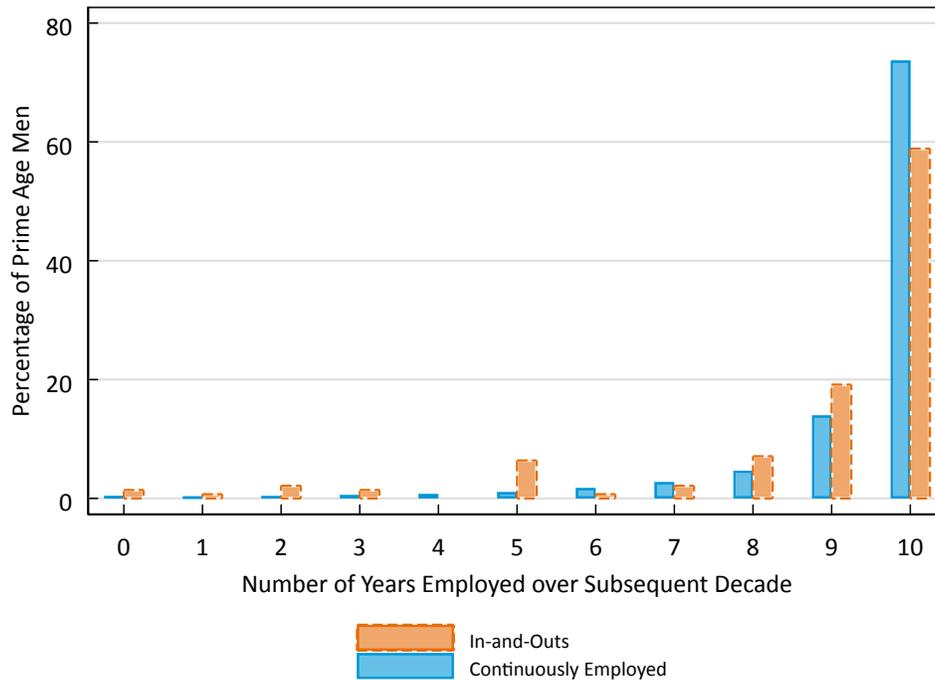
2.4 Persistence of In-and-Outs

In addition to the rise of temporary nonparticipation, it is important to consider the persistence of in-and-outs. One possibility is that the in-and-outs measured above consist of a small minority of individuals taking repeated breaks out of the labor force year after year. On the other end of the spectrum is the possibility that the measures above omit many individuals who have taken a temporary spell of nonparticipation at some point in their career, but happened not to do so during the period in which they were interviewed. As a result, the total number of individuals who are ever an in-and-out could be quite a bit larger than computed above. Distinguishing between these extremes requires knowing the labor supply of in-and-outs following their breaks—do they take more subsequent breaks or do they work continuously?

To examine in-and-outs' long-term labor supply, I use a sample of prime age men from the PSID, which allows me to examine labor force participation over many years for each individual.[8] I narrow this sample to individuals with a temporary nonparticipation spell lasting two years or less between ages 25 and 54 and compute the total years of employment for each individual over the ten years following their return to the labor force. I repeat this procedure for individuals who were continuously employed to get a benchmark to compare to, allowing me to measure how persistent in-and-outs are. If in-and-outs are very persistent, then they should exhibit substantially lower employment rates than the benchmark over the decade following their break, while if they are not persistent at all then their employment should be close to the benchmark.

In fact, in-and-outs appear to be not very persistent at all as they are highly attached to employment after their break, as shown in Figure 4. Nearly 60% of in-and-outs work continuously for every year of the subsequent decade after their break, and an additional 30% or so work either eight or nine years out of ten. These employment rates are similar to those of workers who were continuously employed in the pre-period. In-and-outs are more likely to work for only five years or less following their break compared to the continuously employed benchmark, but these differences are small.

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[8]In the CPS I am limited to observing individuals' labor force participation only over a one-and-a-half year period and in the SIPP I can observe labor force participation for up to five years. In contrast, the PSID measures labor force participation over multiple decades for many respondents.

Figure 4: Distribution of Employment over 10 Years Following In-and-Out Spells

Source: PSID, men ages 25-54 with at least 12 consecutive years in sample. In-and-out spells are defined as an employment separation followed by a period of non-participation of two years or less. In-and-outs and continuously employed are determined based on observations in periods $t-3$ through t, then total years of employment over $t+1$ to $t+10$ is computed for each of these individuals. Individuals who are not either an in-and-out or continuously employed in $t-3$ to t are excluded.

3   Comparison to Other Forms of Nonemployment

This section examines how in-and-outs compare to other types of nonemployed workers. Although in-and-outs have been relatively understudied, other forms of nonemployment have been more extensively studied in the literature. I start by showing that in-and-outs appear to be different from unemployed workers, experiencing different dynamics of consumption and income. Additionally, in-and-outs have little in common with permanent labor force dropouts, suggesting that these are distinct margins of labor supply. Lastly, I show that in-and-outs are not switching between formal work and home production, and instead are substituting between labor and leisure.

3.1   Unemployment

This section examines whether the in-and-out phenomenon is simply a new form of unemployment. Although in-and-outs are not actively engaged in job search, they may

be waiting for a job offer to arrive and thus are in similar economic circumstances as those who are actively searching. However, the consumption and income dynamics of in-and-outs and unemployed individuals show very different patterns. While consumption of unemployed individuals falls substantially after a job separation, in-and-outs' consumption dynamics are more similar to that of retirees. Additionally, in-and-outs do not appear to suffer permanently lower income as a result of their time out of the labor force. Taken together, these suggest that in-and-outs are not simply unemployed individuals with a different name.

3.1.1 Consumption Dynamics

In-and-outs may also differ from the unemployed in terms of their consumption behavior. Household expenditures of individuals who become unemployed typically fall upon separation (Browning and Crossley, 2001; Chetty and Szeidl, 2007; Ganong and Noel, 2015; Gruber, 1997). This evidence is consistent with unemployment being a unanticipated or uninsured negative shock to permanent income for these individuals.
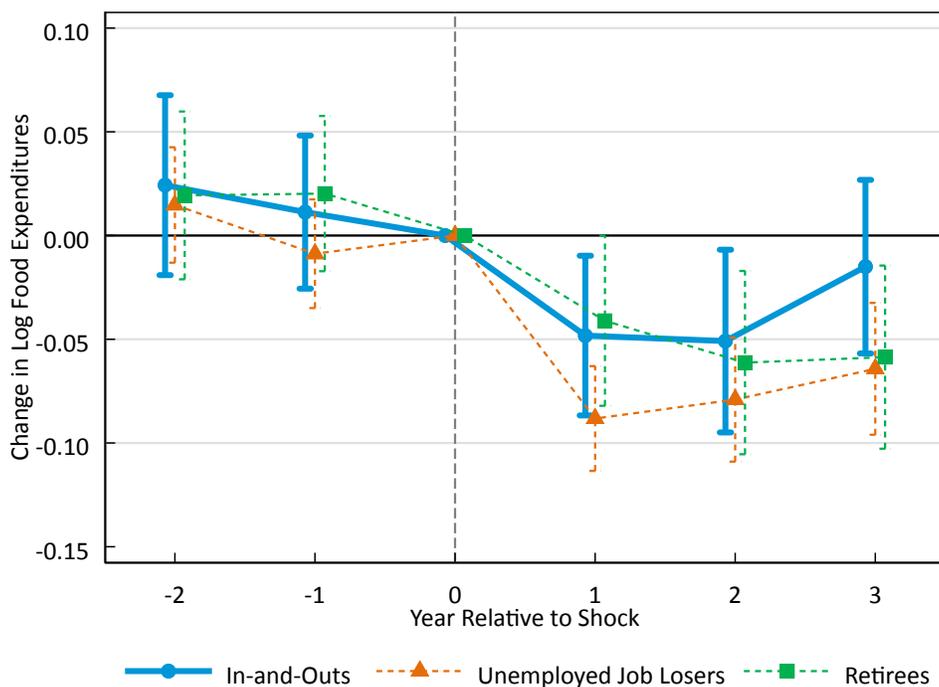
To compare the evolution of consumption for in-and-outs and the unemployed, I use longitudinal data from the PSID. I proxy for consumption with total household food expenditures (including both food at home and food away from home). The evolution of expenditures for in-and-outs and the unemployed are captured by regressing the k-period change in log household food expenditures on an indicator for each type of separation s, repeating this over different horizons k:

$$\Delta y_{i,t,t+k} = \beta_s^{(k)} \delta_s + \alpha X_{i,t} + \Delta \epsilon_{i,t,t+k} \tag{1}$$

where δ_s is an indicator for separations of type s and $X_{i,t}$ is a vector of individual controls containing a cubic in age as well as time period fixed effects. I first conduct these regressions with $s =$ "In-and-Out" and exclude all other types of separations from the sample, such that $\beta_{\text{In-and-Out}}^{(k)}$ measures the evolution of in-and-outs' expenditures relative to continuously employed individuals, and then repeat this procedure replacing in-and-outs with unemployed individuals.

In contrast to the unemployed, in-and-outs' expenditures fall only slightly when leaving the labor force and rebound within two years of the separation. Figure 5 shows that in-and-outs' expenditures are flat before separation, decrease by 4.8% after separating, before recovering two years later to end up only 1.5% below the pre-separation baseline. In contrast, unemployed individuals' expenditures drop by 8.8% in the year of job loss and remain more than 6% below the baseline for at least three years following the separation. The differences in the evolution of expenditures between these two groups suggest that in-and-outs may not experience shocks to permanent income when

Figure 5: Consumption of In-and-outs

Sample: Men in the PSID from 1968–1997. In-and-outs are prime age men employed in year 0, nonpartici-
pating in year 1, and participating again by at least year 2 or 3. Unemployed are prime age men employed
in year 0 and unemployed job losers in year 1. Retirees are men ages 62-68 employed in year 0 and non-
participants after. For each group, I plot the coefficients from estimating equation 1 over $k = -2, \ldots, 3$.
Since I control for year fixed effects and a cubic in age, the change in log food expenditures is relative
to continuously employed individuals of the same age in the same year. Standard errors are clustered at
the individual level. Food expenditure includes food purchased for consumption at home as well as food
away from home. I exclude observations with an annual change in log food consumption in excess of 3 to
avoid problematic measurement error.

separating from a job, as unemployed individuals do, or alternatively may be insured
from the effects of such shocks.

The evolution of in-and-outs' expenditures more closely resembles that of retirees.
Figure 5 also plots the evolution of food expenditures for retirees as a comparison rep-
resenting a voluntary separation from employment. Retirees cut food expenditures by
4.1% in the first year of retirement, only slightly less than the change for in-and-outs.
Even though retirement is voluntary, expenditures may decline if they partially reflect
work-related expenses. Aguiar and Hurst (2005) show that retirees decrease spending on
food away from home, but compensate by spending more time cooking, and as a result
total consumption is unchanged. In-and-outs may be decreasing work-related expenses
as well when leaving a job, which would imply that their consumption is the same while
in and out of the labor force.
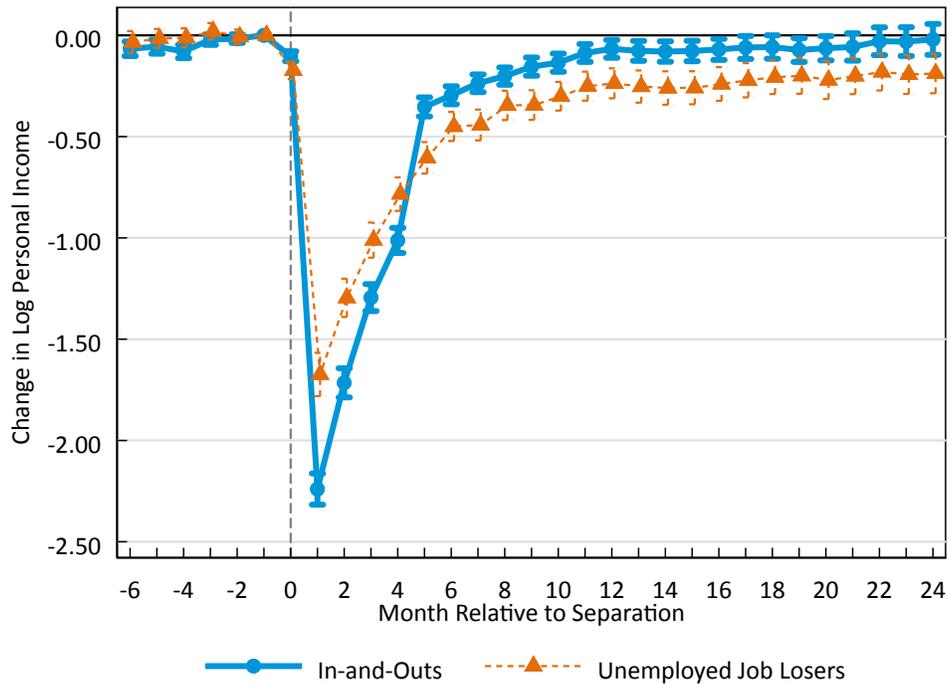
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3.1.2 Income Dynamics

A common consequence of becoming unemployed is a persistent decline in earnings, continuing even after reemployment (Davis, Von Wachter et al., 2011; Jacobson, LaLonde and Sullivan, 1993). However, it is not clear that in-and-outs necessarily suffer the same consequences from losing a job. If in-and-outs have job opportunities available, but choose to delay these opportunities while taking a break in between jobs, they may not experience any wage cut.

To determine whether in-and-outs experience similar consequences from joblessness as the unemployed, I examine how in-and-outs' income evolves before and after they leave the labor force. I use the same set of regressions as in equation 1 above to measure the evolution of personal income for in-and-outs and the unemployed at a monthly frequency in the SIPP. I vary the horizon k from -6 to 24 in order to cover a two-and-a-half-year window around job separation for both groups. As with consumption, I control for a cubic in age as well as time-period fixed effects to estimate the evolution of income for each group relative to their continuously employed peers.

In-and-outs do not appear to suffer the same loss of earnings ability as the unemployed, as shown in Figure 6. In fact, not only are in-and-outs' earnings two years after separation above unemployed workers' earnings, they actually catch back up to the earnings of their continuously employed peers. Nearly all of this recovery happens within the first 10 months after job separation, which is when the large majority of in-and-outs have returned to the labor force. In comparison, the earnings of individuals who become unemployed fail to fully recover even two years later and end up about 20% lower relative to their continuously employed peers.

This event study shows that in-and-outs do not face large costs of nonemployment on average, but it may not mean that nonparticipation more broadly has no long-term costs. In-and-outs by definition have returned to the labor force within two years of a separation, which introduces the potential for selection to explain why in-and-outs experience don't experience the same costs as the unemployed. For instance, individuals might experience earnings shocks while out of the labor force, and only the ones with positive shocks return to employment. A necessary condition for selection of this kind to be explaining the result is that reemployment should be unpredictable before the initial job separation, since it will depend on the shocks received while out of the labor force. To test this condition, I use a machine learning algorithm to examine the extent to which reemployment is predictable based only on pre-separation characteristics. I find that reemployment is largely predictable, indicating that selection explains little of the above results. Full details of this analysis and the results are contained in Appendix D.

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Figure 6: Personal Income of In-and-outs around Labor Force Transitions

Source: SIPP 1984–2008, men ages 25–54. In-and-outs are employed in month 0, non-participants in month 1, and are employed again by at least month 12. Unemployed job losers are employed in month 0 and fired or laid off but looking for work in month 1 and re-employed by at least month 12. For each group, I plot the coefficients from estimating equation 1 over $k = -6, \ldots, 24$, where k refers to a monthly frequency. Since I control for year fixed effects and a cubic in age, the change in log personal income is relative to continuously employed individuals of the same age in the same year. Standard errors are clustered at the individual level. Personal income includes labor income, business income, transfers, and other income attributed to the respondent, but not income of other family members.

3.2 Dropouts

This section compares in-and-outs and dropouts across a range of different characteristics. The two groups report different reasons for leaving the labor force, show large disparities in terms of health outcomes, and appear in different regions of the country. Taken together, this suggests that these two groups are distinct and represent separate margins of labor supply.

Reasons for Non-Participation In-and-outs and dropouts report being out of the labor force for very different reasons. In the CPS, non-participants are asked about their main activity and their reasons for non-participation. I combine these into six mutually exclusive categories and compute the shares of in-and-outs and dropouts who cite each reason, as shown in Table 2. Relatively few in-and-outs report being retired, disabled, or

Table 2: Reasons for Non-Participation

Self-Reported Reason	Dropouts	In-and-Outs
Disability	74.6	24.3
Sickness	0.6	3.3
Retired	10.4	5.6
Taking Care of House/Family	6.6	21.8
In School	4.9	13.9
Other	2.9	30.9

Source: IPUMS CPS matched longitudinally, 1993–2015. For both dropouts and in-and-outs, I compute the share of individuals within that category who report each reason for non-participation (i.e. shares add to 100% for both dropouts and in-and-outs). Shares are pooled over the whole time period. Non-participating individuals are first asked if they are disabled, retired, or other, and, if the latter category, they are asked what their main activity during the reference week was. The reason for non-participation is only available for in-and-outs during months in which they are out of the labor force, overweighting in-and-outs that are out more often, so I reweight these observations to count all in-and-outs equally. All statistics are computed using survey weights.

ill, and these shares have not changed much in the last few decades. Instead, the rise of in-and-outs has all come from non-participants who say they are either in school, taking care of their house or family, or out of the labor force for some other reason.[9] In contrast, the majority of dropouts report that they are disabled and this category accounts for most of the growth of dropouts over the last few decades.

Quality of Life   In-and-outs report having a higher quality of life than dropouts. Appendix Table A.1 shows several measures of quality of life from the American Time Use Survey (ATUS), which has been matched to the monthly CPS to separate in-and-outs from other groups. In-and-outs report a higher level of life satisfaction on a 10-point scale compared to dropouts, averaging 6.3/10 and 5.9/10 respectively.[10] Dropouts also appear to have higher levels of pain and disabilities. A majority of dropouts (61%) report taking some form of pain medication yesterday, compared to 29% for in-and-outs and only 19% for always participators. Dropouts are also much more likely than in-and-outs or always participators to report experiencing physical or cognitive difficulties.

Geographic Distribution   In-and-outs and dropouts are regionally distinct. Appendix Figure A.1 shows the change in participation along each of these margins for all 50 states and DC over the period 1980-2013. The rise of in-and-outs has not correlated with growth of dropouts across states. Dropouts have grown most in states like Kentucky

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[9]Despite the growth of in-and-outs citing school as the reason for non-participation, the share of in-and-outs who are actively attending school is very small and has not risen substantially. I measure attendance in any type of schooling from the CPS October Education Supplement.

[10]The 10-point Cantril ladder measure used by the ATUS is described in more detail by Krueger (2017).

Table 3: Time Use of In-and-Outs While In and Out of the Labor Force

Activity	Hours per Weekday		Activity	Hours per Weekday	
	In LF	Out of LF		In LF	Out of LF
Child Care	0.3	0.5	Leisure	4.1	7.2
Care for Adults	0.1	0.1	*Watching TV*	*2.7*	*4.5*
Education	0.3	0.5	*Computer Use*	*0.2*	*0.4*
Household Activities	1.1	2.1	*Video Games*	*0.1*	*0.2*
Personal Care	8.7	10.0	*Socializing*	*0.5*	*0.7*
Health-related care	*0.0*	*0.3*	Job Search	0.1	0.1
Sleeping	*8.0*	*9.3*	Working	6.6	0.1

Source: IPUMS American Time Use Survey, 2003–2015, matched to basic monthly IPUMS CPS.
Note: Subcategories listed in grey italics. Categories are not exhaustive, so time use may not add to 24 hours. Unemployed in-and-outs have been excluded for comparability. Unemployed in-and-outs have time use similar to men out of the labor force. Each category includes travel time associated with that activity. All statistics are computed using survey weights.

and West Virginia as well as many states in the Rust Belt. Meanwhile, in-and-outs have grown across many different regions of the US, with the largest increases of in-and-outs coming in New Mexico, Alabama, Delaware, and New York. Dropouts appear to be rising most in states that have seen declining opportunities relative to other states over this time period, but no such clear pattern emerges for in-and-outs.

3.3   Home Production

When individuals leave formal employment, one possibility is that they substitute into home production. If in-and-outs are switching between formal work and home production, they may be expending a similar amount of effort when in and out of the labor force.

I construct measures of time spent on different activities from the American Time Use Survey (ATUS) through IPUMS (Hofferth, Flood and Sobek, 2017). Since the ATUS is a follow-up survey from the CPS, I can match ATUS responses to individuals' labor force participation during their 8 months in the CPS. This allows me to examine the time use of in-and-outs who are subsequently in the labor force versus out of the labor force at the time of the ATUS interview.

In-and-outs replace time spent on work mostly with additional leisure activities. When working, in-and-outs work an average of 6.6 hours per weekday. Upon leaving the labor force, this time is mainly split between leisure activities (increase of 3.1 hours), sleeping (1.3 hours), and household activities (1.0 hour). In-and-outs do not substantially increase their time spent on child care, care for adults, education, or health-related care. Out of the three-hour increase in leisure, more than two thirds is spent watching TV,

bringing total TV watching up to nearly 5 hours per day on average. In-and-outs only slightly increase their time spent on video games when leaving the labor force.[11]

4   Determinants of In-and-Outs

This section presents a framework describing how different forces affect labor supply along the in-and-out margin. The rise of in-and-outs represents a different type of change in labor supply than in classical labor supply models, which focus on the choice of hours per week at the margin. In constrast, in-and-outs appear to adjust lifetime labor supply at the margin through taking short breaks out of the labor force for several months at a time. However, this margin responds to changes in wages and unearned income just as the hours margin does in a classical labor supply model.

Consider an individual choosing whether to work or not at every point in time over some period. The individual also chooses instantaneous consumption subject to an intertemporal budget constraint equating total consumption with total income. For the moment, I assume that the individual does not discount the future and that the individual can save or borrow across periods with no interest. A utility maximizing agent faces the problem:

$$\max_{c(t),e(t)} \int v_t(c(t),e(t))dt \quad s.t. \int c(t)dt = \int we(t)dt + Y$$

where $v_t(c(t),e(t))$ is the utility function over consumption and labor supply respectively, w is the wage the individual faces, and Y is the total amount of unearned income. The labor supply choice at each point in time is whether to work or not, i.e. $e(t) \in \{0,1\}$.

For the moment, I additionally make the assumption that utility is additively separable between consumption and labor supply. This implies that the utility function can be written as:

$$v_t(c(t),e(t)) = u_t(c(t)) - \gamma_t e(t)$$

where γ_t is the time-varying disutility of labor supply. For simplicity, I assume that the utility of consumption is constant over time, i.e. $u_t(\cdot) = u(\cdot)$, which results in a constant consumption path $c(t) = c$ for the usual reasons.

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[11]This finding is in contrast to recent results by Aguiar et al. (2017), which suggest that declining participation can accompany increasing time spent playing video games. In Appendix C, I decompose the contributions of different restrictions to the divergence between these results, finding that the main reasons for the difference in results are that I focus on in-and-outs as opposed to all non-employed individuals and that I examine a sample of men ages 25–54 instead of men ages 21–30.

It is convenient to recast the problem in terms of the individual choosing the fraction of the period to work in, which I denote by $n \in [0,1]$. In-and-outs will have n close to, but strictly less than, 1 since they are in the labor force for most periods but have at least one short break out of the labor force. For a given value of n, optimizing individuals will choose to work in the fraction n of the time period with the lowest disutility of labor γ_t. With this framing, the problem above becomes:

$$\max_{c,n} u(c) - v(n) \quad s.t. c = wn + Y$$

where $v(n) = \int_0^n \gamma dF(\gamma)$ is the cumulative disutility of labor over the points in time in which the individual works (with $F(\gamma)$ as the cumulative distribution of γ_t ordered from smallest to largest).

The first order condition of this model returns a standard result from classical models of labor supply, where individuals equate the marginal rate of substitution with the marginal rate of transformation:

$$-\frac{v'(n^*)}{u'(c^*)} = w$$

This condition can be log-linearized around the optimum to examine how changes in wages and consumption affect labor supply n:

$$\tilde{n} = \theta \left[\tilde{w} - \phi \tilde{c} \right]$$

where $\tilde{x}$ is the percentage deviation of x from its steady-state value. The coefficient θ represents the Frisch, or consumption-constant, elasticity of labor supply and the coefficient ϕ is the individual's relative risk aversion.

Changes in labor supply may be driven by changes in the returns to work, although this may be attenuated by corresponding changes in consumption. If wages increase holding consumption constant, then labor supply should increase by $\theta \tilde{w}$; however, consumption may increase as well in response to the wage change. As an extreme example, in a case with balanced-growth preferences ($\phi = 1$) and no unearned income ($Y = 0$), consumption will increase in perfect proportion with wages (i.e. $\tilde{c} = \tilde{w}$) resulting in no net effect on labor supply. This is the well-known case where income and substitution effects cancel.

Changes in unearned income may also affect labor supply, but only through effects on consumption. In response to an increase in Y, consumption rises $\tilde{c}$ and labor supply falls by $\theta \phi \tilde{c}$.

In examining the explanations for the rise of in-and-outs, it is important to distinguish between these two channels. The first channel involves changes in the available wage that stem from changes in labor demand. The second channel, rising unearned

income, affects labor supply through altering the marginal rate of substitution.

This framework omits several key factors that may affect real world labor supply. The return to work in reality is affected both by the pre-tax wage as well as the marginal rate of income tax. Additionally, search frictions may further attenuate the returns to work if individuals anticipate that some fraction of their work effort will go to job search instead of formal employment. Individuals may also choose the amount of hours to work at each point in time in addition to the choice of whether to work. I abstract from these elements to focus on the two explanations highlighted above, since none of these factors appear to have a first-order effect.

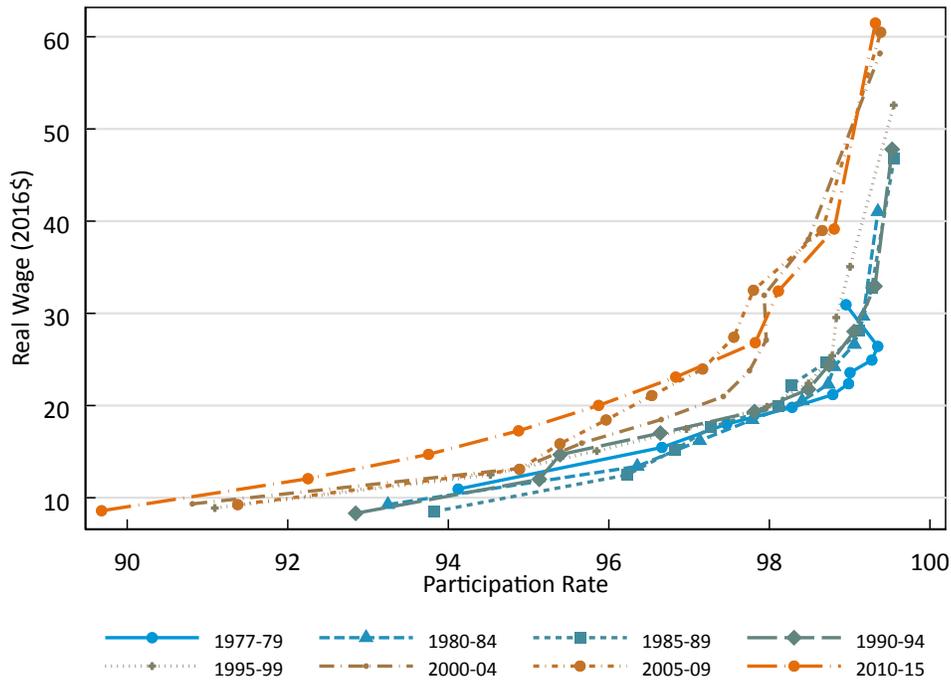# 5   The Role of Labor Demand

The decline of prime age male labor force participation is commonly attributed to diminished labor demand or lower work incentives from taxes and transfers, but this section shows that neither of these forces can explain the rise of in-and-outs. I start by examining the wages available to in-and-outs, since lower wages could induce men to work less, but the rise of in-and-outs appears to have occurred at constant wages. Based on conventional estimates of labor supply elasticities, these changes in wages cannot explain a decrease in participation of the magnitude observed. The rise of in-and-outs has occurred across all industries and occupations, suggesting that this phenomenon is not related to particular types of jobs. Additionally, while wage rigidities can lead labor demand shocks to result in a temporary rise of in-and-outs, these effects disappear in the long-run. Lastly, I show that rising tax rates leading to diminished earnings cannot explain the rise of in-and-outs, neither the explicit income tax rates in-and-outs face nor the implicit tax rates created by receipt of means-tested transfers.

5.1   Wages

Declining wages could be an important driver of diminished participation among men. Over the last few decades, several forces have emerged that could reduce the available wages for men, including skill-biased technological change, declining manufacturing, and decreased union coverage. Falling wages could induce men to spend less time working and take more time out of the labor force. Additionally, if wages fall to just above mens' reservation wage, small temporary shocks to productivity could lead men to leave the labor force for a short time before returning to work.

Fortunately, I can directly observe the wages of in-and-outs and examine how they have changed over time. I compute real hourly wages from the CPS Outgoing Rotation

Figure 7: Wages and Participation Across Skill Levels

Source: CPS men ages 25–54 excluding dropouts, 1977–2015. Individuals are assigned to a wage decile based on the annual wage distribution in their year. For each five-year period, the average participation rate and average real wage are computed for each decile and plotted, pooling individuals across years within the five-year period. Nominal hourly wages are deflated by PCE price index. All statistics are computed using survey weights.

Groups for all prime age men, adjusting for top coding.[12] Wages for some in-and-outs are missing if they happened to be out of the labor force during the month of the ORG interview, but since CPS cohorts are randomly selected, this meets the missing-at-random criterion so dropping these observations will not confound the estimates (Rubin, 1976).[13] The full details describing how I construct wage data are contained in Appendix B.

Across the skill distribution, participation has fallen holding market opportunities constant. In Figure 7, I divide men into wage deciles based on their rank in the annual wage distribution and plot average participation (excluding dropouts) against average wages within each decile, repeating this separately for several eras. In-and-outs have become more common at every wage level, resulting in this curve shifting to the left over time. This shift is more pronounced at the bottom of the skill distribution, where real

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[12]Nominal wages are deflated by the PCE price index. I impute top-coded wages with the average above the top-code using a log-normal approximation following the method of Schmitt (2003).

[13]Alternatively, these missing wages can be imputed from the wages of other in-and-outs with similar labor force attachment, but the results are nearly identical under several different imputation strategies.

wages have slightly declined, but higher skill levels have seen rising in-and-outs as well, even as wages have increased. Although there are some groups that have experienced declining wages, the leftward shift of this curve at every wage level makes it unlikely that changing wages are the main factor responsible for the rise of in-and-outs.

It is worth asking how much of the rise of in-and-outs can be attributed to the observed changes in wages of prime age men. The response of labor supply to changes in wages over the long-run is summarized by the uncompensated, or Marshallian, labor supply elasticity. Given the observed change in wages, the portion of the decline in participation attributable to labor demand can be expressed as

$$\Delta \log \widehat{\text{LFPR}} = \underbrace{\varepsilon_{l,w}}_{\substack{\text{Uncompensated} \\ \text{Labor Supply Elasticity}}} \cdot \underbrace{\Delta \log \frac{w}{p}}_{\substack{\text{Change in} \\ \text{Real Wages}}}$$

To measure the uncompensated elasticity, I average estimates of this elasticity from a long literature on male labor supply.[14] The average of these estimates is 0.04, although the estimates range from a minimum of -0.02 to 0.14 at maximum.[15] The elasticities used here measure the response of total labor supply to wages, including both in-and-outs and dropouts. Therefore, these can be thought of as an upper bound for the relevant labor supply elasticity, which would measure the response along the in-and-out margin alone.

Changes in wages explain very little of the rise of in-and-outs. Table 4a shows the predicted change in participation implied by the total change in wages and several possible values of the uncompensated labor supply elasticity. Given the 16.6% increase in real wages between 1977 and 2015, the central elasticity estimate from the literature of 0.04 predicts that changes in wages alone would lead to a 0.7% increase in labor supply, or a 0.6 p.p. increase in the participation rate.[16] For higher values of the uncompensated

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[14]Specifically, I take the elasticity estimates from Hall (1970a); Hausman (1981); Pencavel (1986); MaCurdy, Green and Paarsch (1990); Triest (1990); Juhn et al. (1991); Ziliak and Kniesner (1999); Juhn et al. (2002); Pencavel (2002); Eissa and Hoynes (2004); and Moffitt (2012).

[15]This range is lower on average than the range of labor supply elasticities highlighted in the meta-analyses of Chetty, Guren, Manoli and Weber (2013) and Chetty (2012), primarily due to the fact that I am focusing on prime age men in the United States, which excludes some of the higher elasticity estimates included in those meta-analyses.

[16]The average wage for employed prime age men rose 16.6% between 1977 and 2015, but this may overstate the rise in potential wages if lower wage individuals are increasingly not employed. When wages of the non-employed are imputed using the procedures outlined in Juhn (1992) and Blau and Kahn (2007), the increase in overall average real wages falls to 10.6% and 8.7% respectively, suggesting that some selection is occurring. However, when imputing wages of the non-employed using the selection correction of Heckman (1979), the increase in average real wages is 39.5% instead. Regardless, under all of these approaches male labor supply would be predicted to grow between 1977 and 2015 using the central elasticity estimate from the literature. More details on the imputation procedures can be found in Appendix B.

Table 4: Contributions of Changing Wages to Participation Decline, 1977–2015

(a) Constant Elasticity			(b) Heterogeneous Elasticities	
Elasticity Value	ΔLFP		Elasticities Source	ΔLFP
0.04	0.63		Juhn, Murphy, Topel (1991)	1.06
-0.05	-0.78		Pencavel (2002)	-3.05
0.0	0.00			
0.1	1.56			
0.2	3.13			

Source: CPS men ages 25–54, 1977–2015. Predicted percent change in LFP is computed by multiplying the observed change in average wages by the given elasticity, which is then converted into the predicted percentage point change in LFP, which is reported above. For the heterogeneous elasticity calculations, this procedure is conducted separately for each decile of the wage distribution and the resulting predictions are aggregated to form an estimate of the overall predicted change. Wage changes are computed using survey weights.

elasticity an even larger increase in participation would be predicted. Only under a negative elasticity, indicating that income effects are substantially larger than substitution effects, would the observed changes in wages predict a decline in labor supply.

Table 4b relaxes the assumption of an identical labor supply elasticity for every individual, allowing elasticities to vary across the skill distribution. I take estimates of the elasticities at different skill levels from Juhn et al. (1991) and Pencavel (2002). I assign individuals to skill deciles based on their rank in the annual wage distribution and compute the change in average wages within each skill decile. Multiplying this change in wages by the elasticity for the decile and aggregating yields an estimate of the overall predicted change in participation. Using the elasticity estimates of Juhn et al. (1991), I estimate that the participation rate would have risen by 1.06 p.p. between 1977 and 2015, due to a small decline in participation for the lower half of the skill distribution being more than offset by an increase in participation among the top half.[17] In contrast, the elasticities estimated by Pencavel (2002) imply a net reduction in participation of 3.05 p.p. over this time period, mainly driven by large income effects among the top two deciles. Neither of these approaches matches the observed pattern of rising in-and-outs across deciles, with in-and-outs rising among every wage decile and larger increases at the bottom end of the distribution.

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[17]This calculation uses average wages among employed prime age men without imputing wages to the non-employed. If wages are imputed using the methods of Juhn (1992) and Blau and Kahn (2007), the predicted changes are reduced to 0.45 p.p. and -0.45 p.p. respectively as both of these methods estimate larger declines in wages among the bottom half of the skill distribution relative to the no-imputation baseline. If wages are imputed with the selection correction of Heckman (1979), the predicted change rises to 4.7 p.p. instead as wages are estimated to have risen among the bottom half of the distribution. More details on the imputation procedures can be found in Appendix B.

Table 5: Rise of In-and-Outs Across Occupations

Occupation Group	ΔIn-and-Outs, 1980–2015 (p.p.)
High Abstract Tasks	2.2
High Routine Tasks	3.7
High Manual Tasks	3.7

Source: IPUMS CPS, 1980–2015. In-and-outs are defined as men ages 25–54 with between 1 and 7 months in the labor force out of 8 total. Individuals are categorized to occupations based on the occupation of their job when they are employed. Individuals who are not employed in any of their 8 CPS responses are excluded. For task content groups, I take occupations in the highest third of task content for each task type, where task content is measured as in Autor, Levy, & Murnane (2003). For each occupational category, I report the change in the share of individuals within that category who are in-and-outs between 1980 and 2015. All statistics are computed using survey weights.

5.2 Industries and Occupations

The increase of men cycling in and out of the labor force has happened in every industry, despite large differences in how industries have evolved over this time period. I take in-and-outs in the CPS and categorize them based on the industry (or industries) they work in while they are employed. Appendix Table A.2 shows the change in the share of employment made up by in-and-outs within each industry from 1980 to 2015. All industries have seen at least some increase in the share of in-and-outs and across most industries the shares of in-and-outs have risen between 3 and 7 p.p. over this time period. Industries with very different types of jobs have nonetheless seen similar increases in in-and-outs, as well as industries on different trajectories. The common growth of in-and-outs across a wide array of industries with different work patterns and different prospects for the future suggest that the rise of in-and-outs may not be strongly related to characteristics of jobs.

In-and-outs have grown as a share of many different types of occupations. Table 5 shows the change in the in-and-out share of employment among occupations involving different types of tasks. Among occupations with high abstract task content, the in-and-out share has risen by 2.2 p.p., only slightly less than the 3.7 p.p. seen in high routine and manual task occupations. Appendix Table A.3 further shows that in-and-outs have risen across six major groups of occupations, providing more evidence against the notion that the rise of in-and-outs is related to particular types of jobs. Since the rise of in-and-outs has occurred similarly across many different types of jobs, this suggests that changes in labor demand are unlikely to explain most of the rise of in-and-outs.

5.3 Shocks to Employment Opportunities

Changing labor demand could alternatively result in lower opportunities for employment without changing wages. For example, if wages are rigid, a fall in productivity may induce employers to ration jobs, which would result in fewer men being employed without a drop in wages. Blanchard and Katz (1992) provide evidence that regional labor demand shocks produce responses in employment and wages consistent with this pattern, although changes in participation in response to these shocks are found to be largely temporary.

I test the contribution of this force using regional shocks to labor demand. Shocks may have long-term effects on participation, which are captured by using an event study design to examine responses to shocks over a long horizon. I regress the change in the in-and-out share over different horizons on shocks to employment and controls:

$$\Delta\text{In-and-Outs}_{s,t,t-k} = \beta^{(k)}\Delta E_{s,t,t-1} + X_{s,t} + \epsilon_{s,t} \tag{2}$$

I repeat this regression for values of k between -4 and 5 to examine the response of in-and-outs to employment shocks in the five years before and after the shock. State-level in-and-out shares are computed from the CPS, and state-level employment growth is taken from the Quarterly Census of Employment and Wages (QCEW).[18] In the baseline, I control for time fixed effects alone, but since I conduct the regression in differences, this implicitly controls for state fixed effects as well. Standard errors are clustered at the state level.
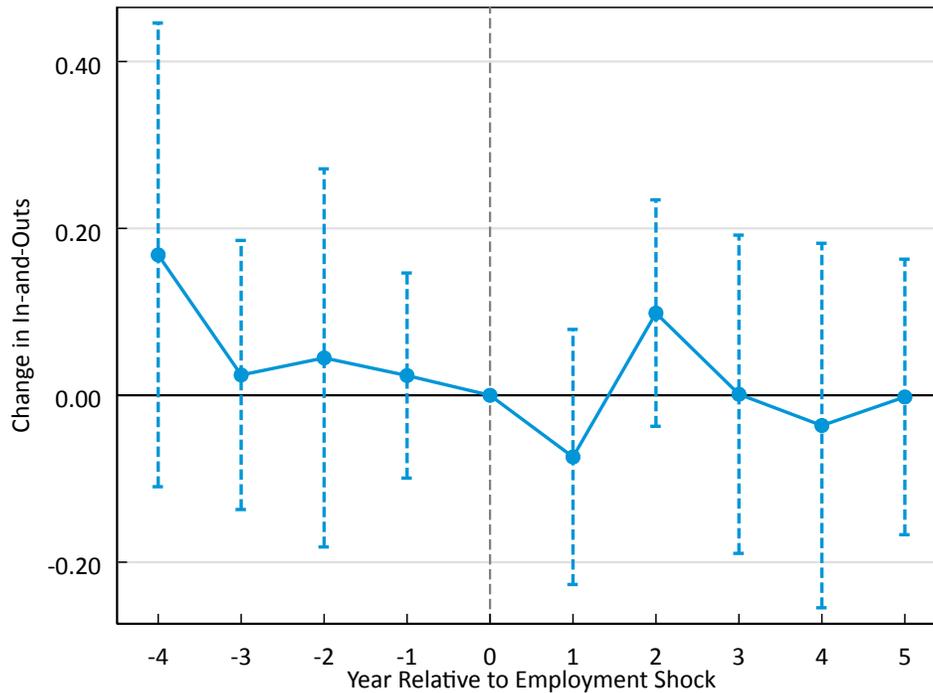
To avoid potential endogeneity of employment changes, I instrument for the actual employment growth with predicted employment growth based on industry composition.[19] I construct the predicted change in state s and year t by combining national growth rates of industries i with lagged local industry shares:

$$\Delta\hat{E}_{s,t,t-1} = \sum_{i}(\log E_{-s,i,t} - \log E_{-s,i,t-1}) \cdot \frac{E_{s,i,t-3}}{E_{s,t-3}} \tag{3}$$

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[18]The QCEW employment count includes jobs worked by non-prime-age-men. One concern could be that prime age men are not affected by general shocks to labor demand, making this a poor measure of labor demand for prime age men. However, employment of prime age men as measured by the CPS responds one-for-one to shocks to QCEW employment, allaying this concern. Another data source, the Quarterly Workforce Indicators (QWI), allows one to break out prime age male employment by state and industry separately, but unfortunately many of these data points are censored for confidentiality purposes and so this data source produces very noisy estimates. For this reason, I present estimates based on the QCEW data series.

[19]I use the approach of Bartik (1991) and Blanchard and Katz (1992) to compute predicted employment growth, but this is similar to using local industry shares directly as instruments (Goldsmith-Pinkham, Sorkin and Swift, 2017).

Figure 8: Response of In-and-Out Share to Labor Demand Shock

Source: State-level in-and-out share computed from IPUMS CPS using survey weights. Employment and Bartik instrument computed from QCEW. Using equation 2, the change in the state-level in-and-out share over a horizon k is regressed on the growth rate of employment instrumented with a Bartik measure of predicted employment growth. By plotting the coefficients $\beta^{(k)}$, this traces out the impact of an exogenous 1% increase in state-level employment on the in-and-out share. The Bartik measure is computed as described in equation 3 using a leave-one-out procedure. The first stage F statistic is above 10 for every horizon.

By using national growth rates excluding state s to predict the change in employment in state s, this avoids mechanical correlation between predicted and actual employment growth. I take data on employment by state and industry from the QCEW.

Employment shocks appear to have little effect on temporary non-participation in the form of in-and-outs. Figure 8 plots the $\beta^{(k)}$ coefficients from the regression above to show the dynamic response of in-and-outs around a positive 1% shock to employment growth. Immediately after the shock, the in-and-out share appears to drops slightly by 0.08 p.p., although a response of zero cannot be ruled out. The immediate response does not seem to be very persistent, though, as the in-and-out share appears unchanged five years after the shock. The confidence intervals rule out an increase or decrease of more than 0.2 p.p. in the five years after a 1% employment shock. This indicates that shocks to labor demand holding wages constant explain little to none of the rise of in-and-outs.

5.4 Taxes & Transfer Programs

Changes in taxes and transfer programs can have significant effects on labor force participation. Increases in marginal tax rates reduce the returns to work and could result in men taking more time out of the labor force. This applies both to explicit marginal tax rates from income taxes as well as the implicit marginal tax rates from means-tested transfers phasing out. Some programs, such as Social Security Disability Insurance (SSDI), phase out completely when a recipient rejoins the labor force. Prior work has documented increases in the tax rates faced by US households, which could result in lower labor force participation (Mulligan, 2002).
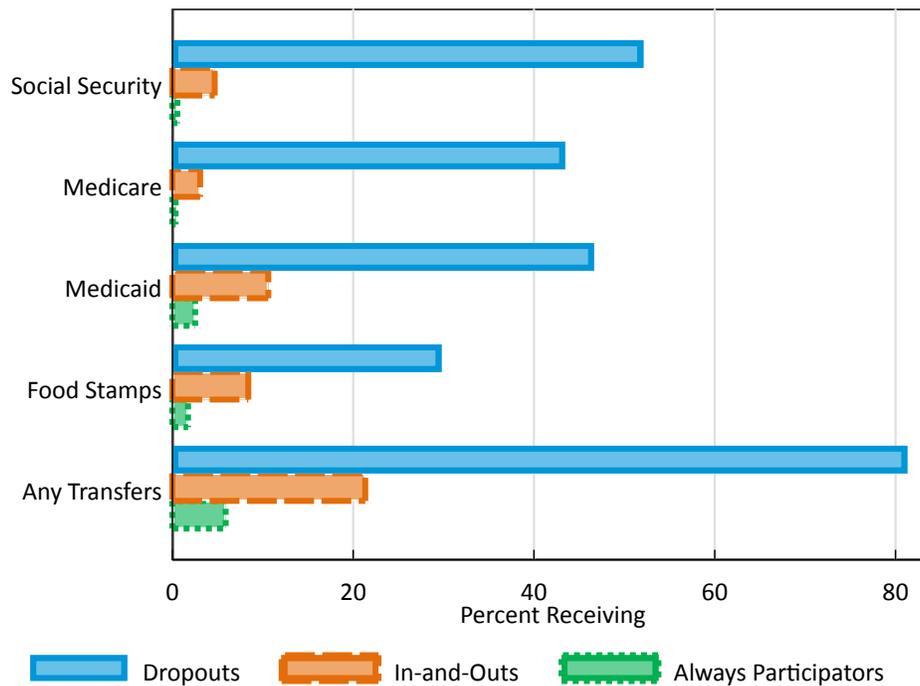
Between the late 1980s and 2015, income tax rates have actually declined somewhat for prime age men. Using a sample from the Basic CPS matched to income information from the March CPS Supplement and taxes computed from NBER's TAXSIM calculator, I estimate the distribution of income tax rates faced by prime age men, including federal, state, and payroll taxes.[20] Appendix Figure A.2 shows that average tax rates for in-and-outs have fallen by nearly half over this period, from slightly more than 15% in the late 1980s to around 10% in 2015, while marginal tax rates are roughly constant at around 25% or perhaps slightly declining. Tax rates are countercyclical due to a progressive tax code; as incomes fall during recessions, tax rates fall accordingly. Beyond the cyclical variation, both average and marginal tax rates exhibit steady downward trends. On the whole, income tax rates for in-and-outs fell substantially over this time period, implying that the rise of in-and-outs cannot be attributed to rising income tax rates.

In-and-outs have been largely unaffected by changes to Social Security Disability Insurance (SSDI) program, one of the largest cash-based transfer programs. Partially due to changes in SSDI eligibility policies, the number of SSDI beneficiaries has risen dramatically in the last several decades, nearly tripling between 1980 and 2015. This program imposes very large implicit marginal tax rates for recipients, since eligibility for the program expires when a worker becomes re-employed, causing some to attribute declining prime age male labor force participation to changes in this program (Autor and Duggan, 2003). While this may have contributed to the increase of dropouts, it cannot explain the rise of in-and-outs. Fewer than 7% of in-and-outs live in a household receiving any SSDI benefits in the March CPS. Additionally, most in-and-outs are not out of the labor force long enough to apply for benefits, have their case examined, and start receiving benefits before rejoining the labor force.

Furthermore, most in-and-outs receive no cash-based transfers of any kind. Using data from the Survey of Income and Program Participation (SIPP), I investigate the share of prime age men living in families that receive any means-tested cash transfers, including General Assistance, Supplemental Security Income, Temporary Assistance for

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[20]More details on the construction of these tax rates are available in Appendix B.

Figure 9: Transfer Receipt by Labor Force Participation Category

Source: SIPP men ages 25-54. Transfer receipt is computed on a monthly basis. Individuals are denoted as receiving a particular form of transfers in a month if anyone in their family reports receiving this form of transfers. The category of "Any Transfers" includes in-kind transfers and means-tested cash-based transfers. All statistics are computed using survey weights.

Needy Families, and other programs. Figure 9 shows that less than 10% of in-and-outs' families received any income from means-tested cash transfers, compared to nearly 40% for dropouts. Prior work has pointed out that the SIPP may suffer from underreporting of participation in some of these programs (Meyer, Mok and Sullivan, 2015), but even if the true rate were double the measured rate, more than 80% of all in-and-outs would be receiving no transfer income.

In-and-outs are also unlikely to be receiving in-kind transfers, such as food stamps or Medicaid. While nearly half of dropouts receive Medicaid benefits, as shown in Figure 9, only about 10% of in-and-outs receive these benefits and even fewer in-and-outs receive food stamps or Medicare benefits. Of those receiving some form of in-kind transfers, many in-and-outs receive more than one form of in-kind transfers, such that only about 17% of in-and-outs receive any form of in-kind transfers. Combining this with cash transfers as mentioned above shows that only about 20% of in-and-outs receive any form of transfers. With such a low rate of transfer receipt, it is unlikely that the implicit taxes created by transfer programs can explain much of the rise of in-and-outs.

6 Conclusion

Many different margins can contribute to a decline in labor supply. This paper has identified an understudied margin responsible for 20–40% of the participation decline among prime age men since the mid-1970s. The rise of in-and-outs forms a different picture of declining labor supply than the common view of men permanently withdrawn from the labor force. In-and-outs are highly attached to the labor force, work typical jobs, and are only notable in that they take brief breaks out of the labor force. I have presented evidence that the increasing prevalence of these breaks does not reflect a change in labor demand. Instead, the rise of in-and-outs may be due to changes in the desired amount of labor supply among prime age men in the US.

Since in-and-outs' breaks are typically short and infrequent, as well as incurring no permanent costs, the rise of in-and-outs likely has had a minimal effect on the inequality of lifetime incomes among men. In contrast, the growth of permanent dropouts over the last several decades, responsible for the other two-thirds of the decline in participation since 1977, likely raised lifetime income inequality substantially. Dropouts not only forgo years of income while out of the labor force but may also experience lower wages if they return to the labor force, compounding the increase in inequality. The differences in consequences between changes along these two margins illustrates the importance of separating in-and-outs from dropouts when studying changes in labor supply.

To the extent that the rise of in-and-outs over the last several decades continues through the next several decades, this phenomenon could have important consequences for many aspects of the economy. For example, reduced labor force growth can slow the overall rate of economic growth, as occurred over the decade following the Great Recession (Fernald, Hall, Stock and Watson, 2017). Additionally, declining labor force participation may make jobless recoveries more common, as employment takes longer to reach its previous peak after a recession. The rise of in-and-outs may have social consequences too, particularly for families, as men more frequently take short breaks out of the labor force. This phenomenon merits continued study to understand the full consequences of rising in-and-outs.

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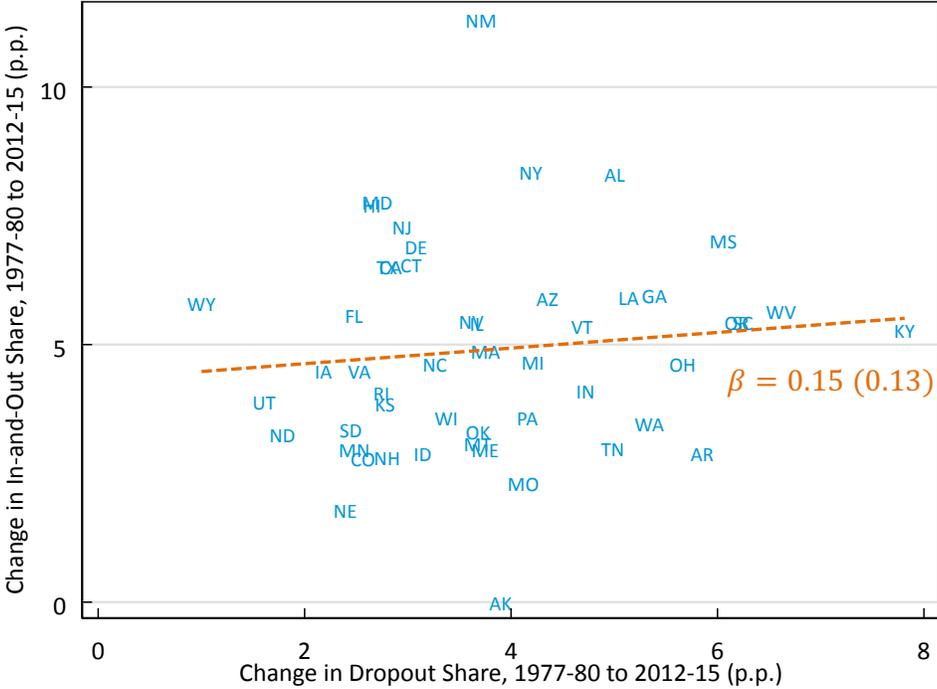
A   Additional Results

Quality of Life

Table A.1: Differences in Quality of Life

	Dropouts	In-and-outs	Always Participators
Life Satisfaction (1-10)	5.9	6.3	7.1
% Took Pain Medication Yesterday	61	29	19
% With Any Physical or Cognitive Difficulty	58	24	8
% With Physical Difficulty	*40*	*8*	*1*
% With Mobility Difficulty	*26*	*4*	*0*
% With Difficulty Remembering	*21*	*5*	*0*
% Very Well Rested	27	42	38

Source: IPUMS CPS matched longitudinally, 2010–2013. IPUMS American Time Use Survey, 2010–2013. All statistics are computed using survey weights.

Geographic Distribution

Figure A.1: Changes in Participation Across States

Source: IPUMS CPS matched longitudinally, 1977–2015. Slope is reported with heteroskedasticity-robust standard error in parentheses. All statistics are computed using survey weights.

Industries and Occupations

Table A.2: Rise of In-and-Outs Across Industries

Industry	ΔIn-and-Outs, 1977–2015 (p.p.)	Industry	ΔIn-and-Outs, 1977–2015 (p.p.)
Agriculture	6.5	Real Estate	0.2
Mining	1.6	Professional Services	3.6
Utilities	7.1	Administrative Services	0.3
Construction	3.0	Education	8.0
Manufacturing	3.6	Health	2.8
Wholesale Trade	3.3	Entertainment	1.1
Retail Trade	6.3	Food and Hospitality	1.0
Transportation	4.9	Other Services	4.5
Information	7.0	Public Administration	1.2
Finance and Insurance	1.6	Multiple or Unknown	4.5

Source: IPUMS CPS, 1977–2015. In-and-outs are defined as men ages 25–54 with between 1 and 7 months in the labor force out of 8 total. Individuals are categorized to industries based on the industry (or industries) they work in when employed. Individuals who are not employed in any of their 8 CPS responses are excluded. For each industry, I report the increase in the share of individuals within that industry who are in-and-outs between 1977 and 2015. All statistics are computed using survey weights.
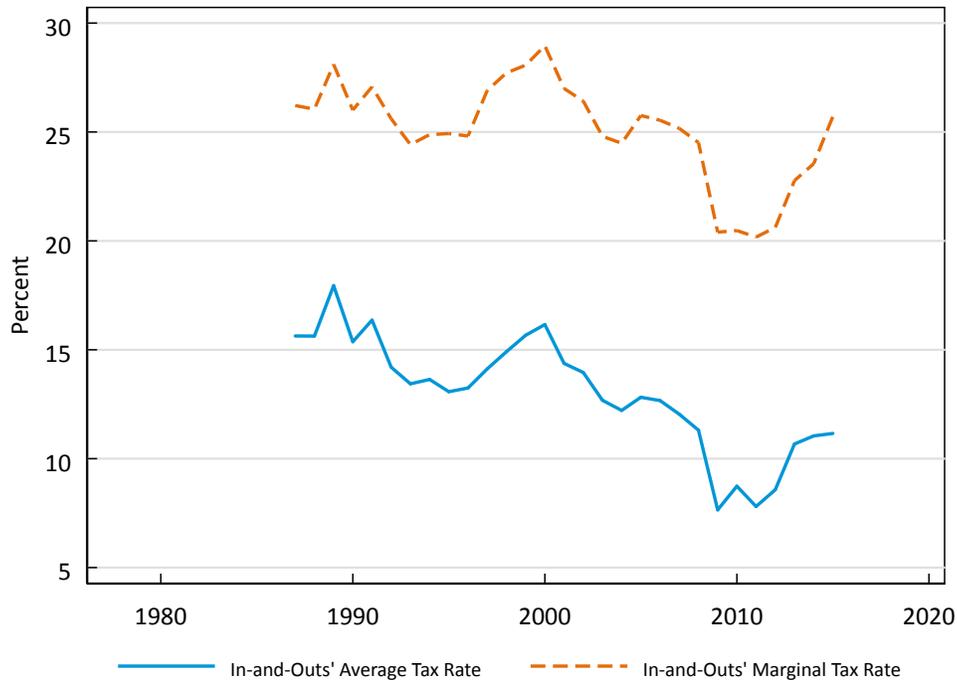
Table A.3: Rise of In-and-Outs Across Occupations

Occupation Group	ΔIn-and-Outs, 1980–2015 (p.p.)	Occupation Group	ΔIn-and-Outs, 1980–2015 (p.p.)
Management, Professional, Technical	2.3	Production and Crafts	4.8
Admin. Support & Retail Sales	3.5	Machine Operators	3.7
Low-Skill Services	3.6	Transportation, Construction, Mining, Agriculture	3.7

Source: IPUMS CPS, 1980–2015. In-and-outs are defined as men ages 25–54 with between 1 and 7 months in the labor force out of 8 total. Individuals are categorized to occupations based on the occupation of their job when they are employed. Individuals who are not employed in any of their 8 CPS responses are excluded. For each occupational category, I report the increase in the share of individuals within that category who are in-and-outs between 1980 and 2015. All statistics are computed using survey weights.

Tax Rates

Figure A.2: Income Tax Rates of In-and-Outs

Source: IPUMS monthly CPS matched to IPUMS March CPS, 1989–2015. Tax rates are computed for all individuals in the sample using NBER's TAXSIM calculator (details in Appendix B). These individual-level tax rates are then averaged across all in-and-outs. All statistics are computed using survey weights.

B   Datasets

This section describes several aspects of the datasets I construct for this analysis. First, I describe how I construct each of the samples I use to measure the growth of temporary nonparticipation. Then, I discuss the methods used to link CPS responses both longitudinally over time as well as between the monthly CPS and March CPS supplement. Next, I describe how I construct wage series along with several alternative imputation procedures. Finally, I outline how I estimate tax rates for individuals.

B.1   Construction

Survey of Income and Program Participation (SIPP)   The SIPP is a nationwide longitudinal survey of individuals, organized into panels lasting typically two to five years. I use monthly interviews from each panel of the SIPP conducted between 1984

and 2008, excluding the short 1989 panel. Monthly labor force participation is defined analogously to the CPS definition.[21] I label an individual as being temporarily out of the labor force for all nonparticipation spells lasting less than twenty four consecutive months.

Current Population Survey (CPS)   Using the method developed by Drew, Flood and Warren (2014) implemented in IPUMS CPS (Flood, King, Ruggles and Warren, 2017), I match individuals' responses across interviews to construct a panel dataset. I restrict the sample to men ages 25–54 who can be matched successfully across all eight interviews, which is about 60% of all prime age men in the sample. These individuals are slightly more attached to the labor force on average compared to all prime age men, but they have experienced nearly the same decline in participation as the overall population of prime age men. To capture temporary nonparticipation spells of less than twenty four months, I report the share of individuals who are currently out of the labor force, but previously and subsequently are in the labor force for at least one month in the CPS. Since the CPS interviews cover a sixteen-month span, this is a conservative measure of the total amount of temporary nonparticipation.

Panel Study of Income Dynamics (PSID)   The PSID is a longitudinal survey of families that began in 1968 and has continued to interview the same families, as well as their descendants and new family members, over several decades. I use all responses to the PSID through 2013, which includes annual responses from 1968–1997 and biennial responses afterwards. The sample includes all men ages 25–54 in the original sample as well as those who join original PSID families for the years in which they are interviewed. Labor force participation is measured at the time of the interview and is defined analogously to the CPS definition.[22] For observations before 1997, I label an individual as an in-and-out if he responded as being in the labor force for one or two of the last three years. For observations after 1997, I label an individual as an in-and-out if he responded as being in the labor force for exactly one of the last two interviews (which cover a three year period). In computing the growth of in-and-outs, I compute growth separately before and after 1997 to allow for a structural break when this definition changes.

Social Security Administration (SSA) Earnings Public-Use File   The SSA Earnings Public-Use File contains annual earnings records for a 1% sample of all individuals

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[21]I denote an individual as employed in a week if he had a job or business, including if he was absent from work. I denote an individual as being unemployed if he is actively looking for work or on temporary layoff in a week. Individuals are counted as being in the labor force in a month if they are employed or unemployed for at least one week out of the month.

[22]Individuals are counted as being in the labor force if they are either employed or unemployed at the time of the interview. Unemployed individuals include those on temporary layoff.

issued Social Security numbers prior to 2007. I create measures of annual participation from SSA records of men ages 25–54 covering the 1960–2006 period.[23] I classify an individual as being in the labor force in a given year if his annual earnings exceed half the minimum wage times 40 hours per week times 13 weeks per year. I label an individual as an in-and-out if he participated for one or two of the last three years. I use observations from the first two years and last two years of the sample to calculate the duration of spells, but exclude these years from the time series to minimize the amount of censoring.

March CPS Supplement Starting in 1976, the March CPS asked respondents to report the number of weeks (out of 52) that an individual was employed or looking for work in the prior calendar year. I label an individual as an being temporarily out of the labor force if that individual reports being in the labor force for between one and fifty-one weeks during the prior calendar year. I also use a more restricted sample limited to individuals whose March CPS responses can be matched to eight basic monthly CPS responses, which is limited to responses from 1989–2015 (matching details are reported in the next section).
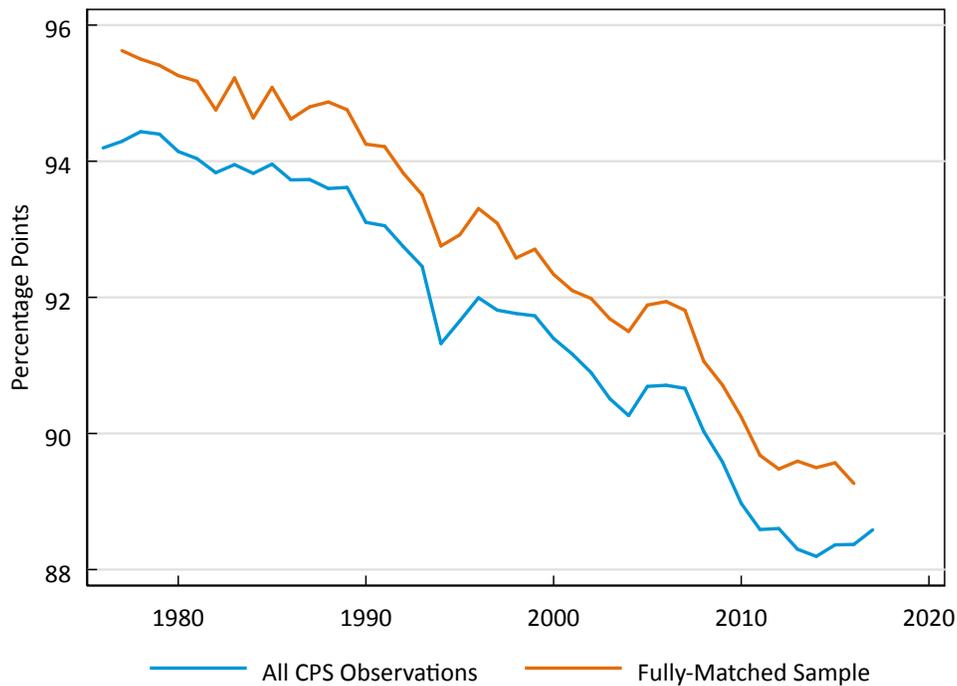
B.2   Linking Responses

I link CPS data in two ways. First, I link responses to the monthly CPS longitudinally over time. Second, I link responses from the monthly CPS in March to the March CPS supplement.

Longitudinal Linking The CPS has a 4-8-4 rotation group structure whereby individuals are interviewed for 4 consecutive months, rotate out for 8 months, and then are interviewed for another 4 months. As a result, individuals' responses can be matched to form a panel of 8 months covering a 16 month period. However, not all individuals can be successfully matched, since respondents are not followed if they move addresses or stop responding to the survey.

I use the method of Drew et al. (2014) to match individuals' responses across CPS interviews, as implemented in the IPUMS CPS Flood et al. (2017). This approach relies on mechanical matches between interviews based on longitudinal links provided in the CPS, as opposed to matching based on characteristics. In most years, about 60% of prime

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[23]While the dataset contains earnings records starting in 1951, these records are unusually volatile in the mid-1950s and produce a sharp break in the share of in-and-outs between 1958 and 1959, possibly due to changes in measurement. To avoid this break affecting the estimated growth of in-and-outs, I drop records from before 1960.

Figure A.3: Comparing Declining Participation Across Samples

Source: IPUMS CPS 1976–2016, men ages 25–54. Fully-matched sample includes only individuals who can be matched across all eight responses. All statistics are computed using survey weights.

age men can be matched for all 8 responses, similar to the rates reported for the overall population by Drew et al. (2014).

Appendix Figure A.3 shows the evolution of the participation rate for all respondents as well as for those who can be matched to all 8 months. The fully-matched group is clearly a selected sample, as their participation rate is consistently higher than the average. However, the decline in participation is nearly identical for the two groups, so that although the fully-matched sample is selected, the degree of this selection has not changed over time.

Linking Monthly CPS to March CPS All respondents to the March monthly CPS are also administered a supplemental survey. However, since the data files for this supplement are released separately the responses must be matched to the monthly CPS to compare responses. Additionally, in some years the March CPS files are released with a different set of identifiers than the monthly CPS, making it impossible to match these responses.

To match responses between the two surveys, I utilize the method of Flood and Pacas (2016). This method focuses on mechanical matches using the identifiers released

in the two surveys. I match responses during the 1989-2015 period, in which all monthly CPS responses can be matched to the corresponding March CPS response. However, not every March CPS response can be matched to a monthly CPS response, since the March CPS includes some individuals who do not appear in the monthly CPS.

B.3 CPS In-and-Out Approximate Measure

One potential concern is that some of the men categorized as in-and-outs in the CPS are actually long-term non-participants, who happened to be interviewed right around the time of leaving the labor force. For example, if individuals retire in the middle of their CPS interview period they will be counted as an in-and-out since they are in the labor force for some of their CPS responses, even if they are subsequently permanent dropouts. Additionally, some of those categorized as dropouts in the CPS may be only temporarily out of the labor force, and should have been counted as in-and-outs. The true contribution of temporary non-participation can be written as

$$\Delta \text{LFPR}^{\text{Temporary}} = \alpha \cdot \Delta \text{LFPR}^{\text{CPS In-and-Outs}} + \beta \cdot \Delta \text{LFPR}^{\text{CPS Dropouts}} \tag{4}$$

where α is the share of non-participation by CPS in-and-outs that is actually temporary and β is the analogous share for CPS dropouts.

Table A.4: CPS In-and-Outs by True Non-participation Duration

	CPS In-and-Outs	CPS Dropouts
% Short-term (< 24 months)	81	6
% Long-term (< 24 months)	15	94
% Left-censored	4	0
% Right-censored	0	0

Source: SIPP 2008 panel. Individuals are classified as in-and-outs or dropouts based on the CPS window. Sample is limited to observations with at least 24 months padding on either side of the window. Table shows the share of non-participation among those classified as in-and-outs or dropouts that is part of non-participation spells less than 24 months in length, greater than 24 months in length, or unknown due to left- or right-censoring. All statistics are computed using survey weights.

I measure α and β by recreating the CPS interview structure in the SIPP where I can observe the duration of non-participation spells. Different iterations of the SIPP have tracked individuals for varying lengths of time, with most panels typically lasting between two and five years. I define temporary non-participation as a spell lasting less than 24 months, which requires me to use data tracking individuals for 64 consecutive months.[24] Only the 2008 panel of the SIPP meets this requirement, so I can only estimate

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[24]I recreate the CPS definition of in-and-outs, which aggregates participation status over a sixteen-

α and β for a single point in time.[25] Of those categorized as in-and-outs by the CPS definition, 81% of their non-participation is temporary as measured by the SIPP, as shown in Appendix Table A.4. At the same time, only 6% of non-participation by CPS dropouts is temporary. This indicates that the CPS approximation is a reasonably accurate measure of the true amount of in-and-outs.

B.4   Wages

I use several measures of wages in this analysis. In this section, I start by outlining the baseline measure of wages, which does not include those who report missing wages. Then I turn to different imputation procedures to estimate the wages available to those reporting missing wages.

Baseline Wage Measure   To measure the wages of employed men, I use information from the CPS Outgoing Rotation Group (ORG) interviews. The ORG interviews take place for all individuals in their 4th and 8th month in the CPS sample and consistent of several questions about work, including nominal wages and hours worked.

From the ORG interviews, I construct a measure of real hourly wages. I start by dropping all observations with missing wages. Many individuals report wages at a weekly frequency instead of hourly. These weekly earnings are subject to a topcode for privacy reasons. I replace topcoded observations with the mean of weekly earnings above the topcode, assuming that weekly earnings follow a lognormal distribution (this method is outlined in Schmitt (2003)). After this adjustment, I convert weekly wages into hourly wages by dividing by hours worked per week. I convert nominal hourly wages to real wages using the PCE price index. Finally, I drop outlier observations, defined as hourly wages below $1/hour or above $300/hour in 2016$.

Imputations   I use three different imputation procedures to estimate the wages available to those with missing wage information.

First, wages can be imputed non-parametrically using the method of Juhn (1992). In this approach, I estimate the distribution of wages within each year, specifically the

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month period (ignoring the middle eight months). To be able to determine whether non-participation is temporary, labor force status must be observable for two years before and after the CPS definition. The combination of these requirements necessitates a 64-month long panel.

[25]When I drop the requirement of a two year window on each side of the sixteen-month CPS period, I can use previous SIPP panels as well. Examining previous SIPP panels provides suggestive evidence that α and β have not changed substantially over time. However, without the window on each side of the CPS period, a substantial share of CPS in-and-outs' and dropouts' non-participation is censored at a duration of less than two years, meaning I cannot rule out substantial changes in α or β over this time period.

average wage within each decile of the wage distribution. Each individual with missing wages is assigned probabilities of appearing in each decile based on the observed distribution of individuals with the same level of labor force attachment, where attachment is measured by the number of months in the labor force out of 8 in the CPS. In this way, each individual with missing wages is imputed the full distribution of wages based on similarly attached individuals.

I also use the regression imputation method of Blau and Kahn (2007). For each year, I regressed wages on a quadratic in age, 4 education dummies (less than high school, high school graduate, some college, and college graduate), 4 racial group dummies (white non-Hispanic, black, non-black Hispanic, and other), 3 marital status dummies (married, widowed/divorced, and never married), 9 census division dummies, a dummy for living in an urban area, and the total number of months the individual spent unemployed in the CPS (out of 8). I take the predicted values from this regression and use them as imputed wages for those with missing wage information.

Lastly, I impute wages using the predicted values from a regression with a selection correction as in Heckman (1979). I use the same covariates as in the regression imputation above, and use weekly spousal wages as the excluded variable to identify the selection equation. For any observation with missing wage information, I impute wages with the predicted value from the selection-corrected regression.

B.5 Tax Rates

I use the NBER TAXSIM program to estimate state and federal taxes for the sample of households I can match from the basic monthly CPS to the March supplement. To calculate taxes, I make the following assumptions: 1) I code all married couples as joint tax filing units and all other individuals as single filers; 2) I ignore mortgage interest, rent paid, child care expenses, and short-term capital gains (unavailable in March CPS).

I compute the marginal tax rate for an individual as the sum of the marginal federal income tax rate, the marginal state income tax rate, and the marginal payroll tax rate (including both employee and employer payroll taxes). The average tax rate is computed by taking total tax payments and dividing by total taxable income for each tax unit. To avoid problems with outliers, I winsorize both marginal and average tax rates at the 1% and 99% levels.

Table A.5: Video Game Time Crosswalk

	2004–07	2012–15
Sample as in Table 3	1.6	
Breaking Out 2004–07 and 2012–15	1.7	1.0
Including All Matched Non-Participants	2.9	1.4
Including All Non-Participants	3.2	2.1
Including All Non-Employed	2.7	2.5
Using Whole Week Time Use	2.4	2.6
Changing to Men Ages 21–30	3.2	6.5
Excluding Full-Time Students	3.5	6.5
Reported by Aguiar et al. (2017)	3.4	5.9

Notes: Top row is estimated as in Table 3. Each subsequent row is one step on the crosswalk to the Aguiar et al. (2017) estimate, which is reported in the last row. First, the pooled average is broken out into the 2004–07 and 2012–15 averages. Then non-in-and-out non-participants who can be matched to the monthly CPS are added, followed by all non-matched non-participants and then all non-employed. Next, I include time use on weekend days, as opposed to weekdays only. After this, I change the age restriction from 25–54 to 21–30. Finally, I drop full-time students ages 24 and under. This second-to-last line is the same concept as Aguiar et al. (2017), but may not be identical if there are differences in weighting. All statistics are computed using survey weights.

C Time Use on Video Games

This section reconciles the results on time use presented in Table 3 with previous results from the literature. Aguiar et al. (2017) point out that non-employed young men spend a growing fraction of their time playing video games. They interpret this fact through a model of time use as implying that the quality of video games has improved, which they then show can account for some of the decline in labor supply among this population since 2000. However, I find that in-and-outs spend relatively little time on video games and experience little increase in time spent on video games when leaving the labor force.

There are many differences between these two analyses that could account for the apparent discrepancy. While I focus on in-and-outs, Aguiar et al. (2017) look at non-employment overall. Additionally, they focus on young men between the ages of 21 and 30, while I examine men between the ages of 25 and 54. There are also some differences in time period and sample restrictions. To examine the influence of these differences, I recompute the time spent on video games, changing one aspect at a time to fully crosswalk the two sets of estimates.

Appendix Table A.5 shows how the estimated hours per week spent on video games changes with each adjustment. The 0.2 hours per day reported in Table 3 is equivalent to 1.6 hours per week. Breaking out separate time periods, as is done by Aguiar et al. (2017), doesn't substantially alter the result. However, including dropouts and other

non-employed individuals raises the average time spent on video games substantially, approximately double the average of just in-and-outs within each time period. This implies that these other groups spend significantly more time on video games than in-and-outs do. Expanding time use to include weekend days makes little difference. Changing the sample to look at 21-30 year olds increases the estimated time spent on video games in both time periods, but especially in 2012-2015. Dropping full-time students has little effect. The second-to-last row gives estimates using the same concept as Aguiar et al. (2017), but although the results are close they are not identical for unknown reasons.

The two deviations between the analyses that make the most difference are: 1) the choice of in-and-outs versus all non-employed, and 2) the focus on 25–54 year olds instead of 21–30 year olds. Both of these choices appear to contribute about equally to the difference in estimates.
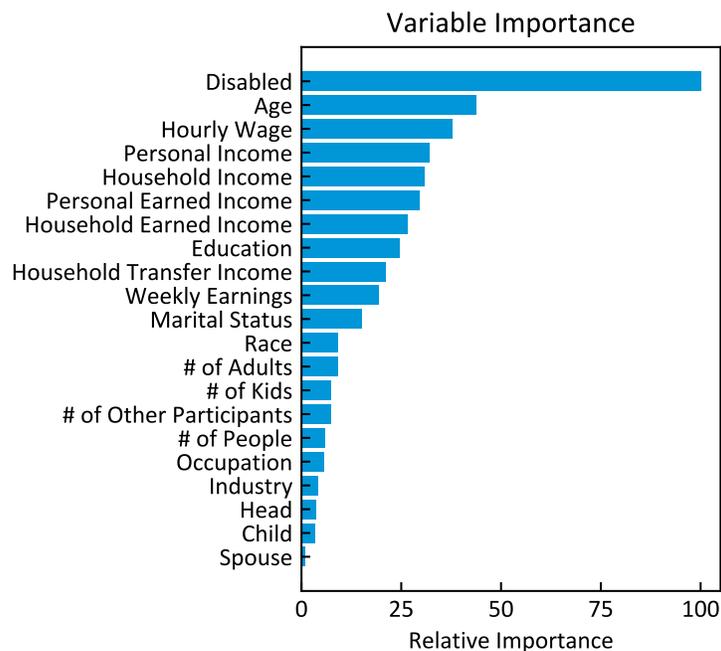
D   Evolution of In-and-Outs' Income

One potential problem with the event study analysis of section 3.1.2 is that the sample of in-and-outs is defined using ex-post information, specifically whether individuals returned to the labor force after a short period of time. In this way, the analysis may exclude individuals who anticipated taking a short break out of the labor force, but ended up experiencing large declines in available wages and remained out of the labor force. This would suggest that while in-and-outs do not suffer permanent income loss, this is merely because they were lucky rather than because a short break out of the labor force cannot incur a permanent cost.

The extent of this problem can be gauged by using a sample selected based on ex-ante characteristics only, since this avoids using ex-post information. Using the SIPP sample, I examine all employment to non-participation separations and use pre-separation characteristics to predict the duration of the non-participation spell. This relies on the notion that individuals with similar characteristics are likely to spend similar amounts of time out of the labor force, or put another way that in-and-outs can be separated from dropouts by only examining their pre-separation characteristics. This is an empirically testable statement. I use all individuals who transition from $E \rightarrow N$ at least two years before the end of the sample and use as covariates their demographic, household, job, and income characteristics from 4 months before the separation.[26]

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[26]The restriction that the transition must occur at least two years before the end of the sample avoids including transitions where the non-participation spell duration is right-censored under two years. It is unclear whether these excluded observations are in-and-outs or dropouts due to this censoring. I use covariates from four months before the separation so that all characteristics are measured in a previous SIPP wave, since characteristics may be mechanically correlated within a SIPP wave.

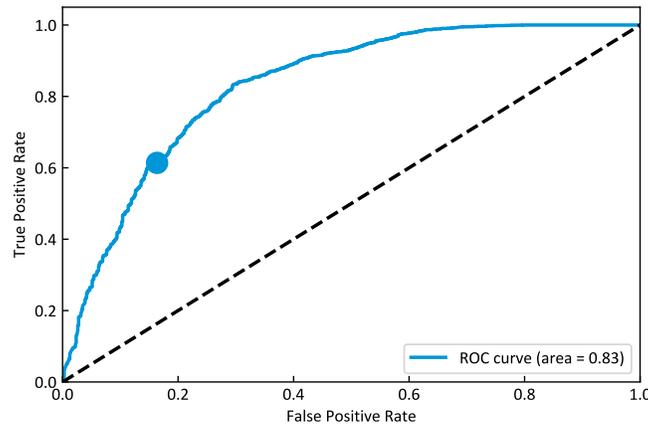Figure A.4: Importance of SIPP Characteristics in Predicting Non-Participation Duration

To predict the duration of non-participation based on pre-separation characteristics, I use a machine learning algorithm known as Gradient Boosted Trees (GBT).[27] GBT fits the outcome by iteratively applying a series of small decision trees. The first tree is fit to the raw data, splitting branches of the tree to maximize the share of variation explained by the tree. The next tree is fit to the residuals from the first tree and the process repeats, with each tree in the series fitting the residuals of the previous one. However, each tree is weighted according to the marginal improvement in fit, resulting in later trees receiving less weight as the algorithm reaches a point of diminishing returns in improving the fit of the model. Each tree is constrained to be very shallow. By repeatedly applying shallow trees to the residuals of past iterations, this method can approximate very flexible functional forms, with later trees correcting for misspecifications introduced by earlier trees. I use a total of 50 trees with a learning rate of 0.05, as selected by cross-validation.

Each characteristic's contribution to the prediction can be quantified. I compute the total "gain" provided by a variable by summing up the reduction in the sum of squared residuals from every time that variable is used to split a branch across all of the 50 trees. Appendix Figure A.4 shows this measure for each variable, expressed as a share of the highest gain. Disability is the most important characteristic for separating in-and-outs from dropouts, accounting for more than double the importance of any other variable.

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[27]GBT is described in detail in Hastie, Tibshirani and Friedman (2009). I use the LightGBM package to implement this algorithm.

Figure A.5: ROC Curve for Predicted In-and-Outs

Age, income, and education are also judged to be important predictors of time spent out of the labor force.
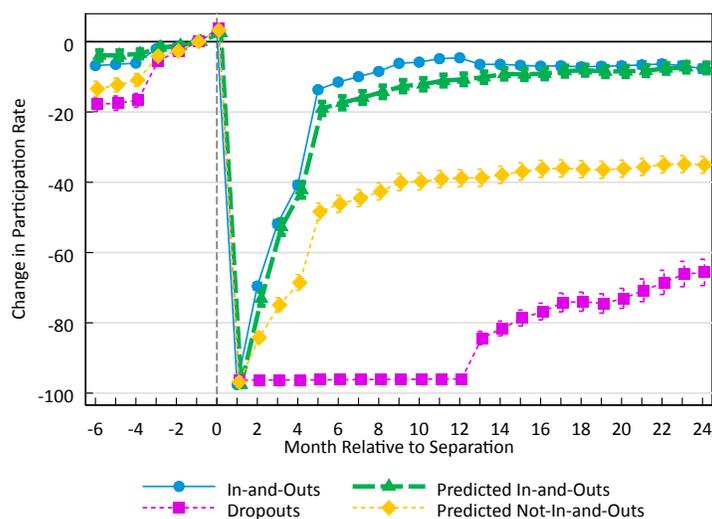
Next, I examine whether this algorithm is able to adequately separate in-and-outs from dropouts. I order individuals by their predicted duration and categorize all individuals with predicted duration below some threshold to be predicted in-and-outs. For a given threshold, this results in some true positive rate, i.e. the share of actual in-and-outs who are categorized as such, and a false positive rate, i.e. the share of dropouts who are incorrectly categorized as in-and-outs. I vary this threshold to trace out a curve trading off these two different rates, known in the machine learning literature as a Receiver-Operating Characteristic (ROC) curve, which is plotted in Appendix Figure A.5. The ROC curve can be compared to the 45° degree line to measure the predictability of in-and-outs. If in-and-outs are completely random, the ROC curve will coincide with the 45° line, while if in-and-outs are perfectly predictable, the ROC curve will be equal to 1 everywhere. In this case, the ROC curve is quite a bit above the 45° line, indicating that in-and-outs can be fairly easily separated from dropouts. The area under the ROC curve measures the deviation from randomness and in this case it is equal to 0.83, indicating a strong degree of prediction, although not quite complete prediction.

Using these predictions, I construct a sample of predicted in-and-outs and repeat the event study from above. I select a sample of predicted in-and-outs that captures about 60% of actual in-and-outs while including less than 20% of actual dropouts (marked with a dot in Appendix Figure A.5). As above, I estimate the following equation for an outcome Y,

$$\Delta Y_{i,t,t+k} = \beta^{(k)} \mathbf{1} \left(\text{In-and-Out}_{i,t} \right) + \delta X_{i,t} + \Delta \epsilon_{i,t,t+k} \tag{5}$$

varying k between -6 and 24 to cover a two-and-a-half year window, controlling for a cubic in age as well as time fixed effects.

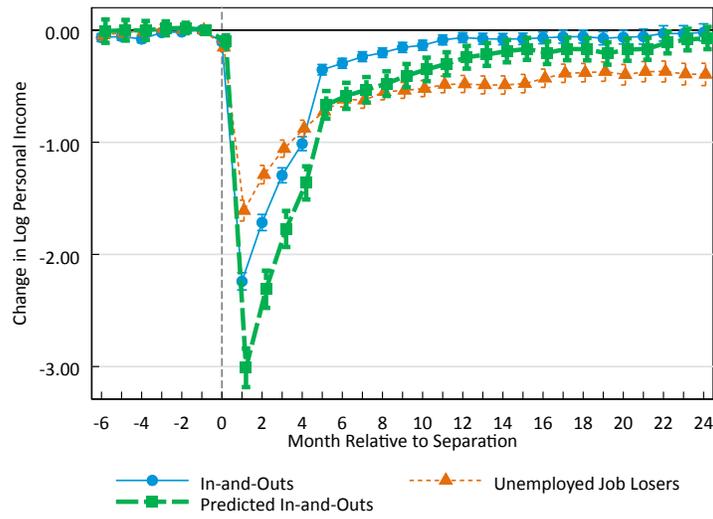Figure A.6: Evolution of Predicted In-and-Outs' Participation

Sample: 25–54 year old men in the SIPP. In-and-Outs are employed in month 0, nonparticipants in month 1, and are employed again by at least month 12. Dropouts are employed in month 0 and nonparticipants in months 1-12. For predicted in-and-outs and dropouts, re-employment time is predicted from covariates four months before the separation using gradient boosted trees and individuals are categorized based on whether the predicted time is less than a threshold delivering a false positive rate below 20%.

First, I show that the predicted in-and-outs behave like actual in-and-outs using this event study. I estimate equation 5 using labor force participation as the outcome and plot the resulting coefficients in Appendix Figure A.6. Predicted in-and-outs return to the labor force quite quickly, with the majority returning within the first six months. By twelve months after the separation, predicted in-and-outs have similar participation rates as actual in-and-outs. Predicted dropouts, on the other hand, remain disconnected from the labor force even after two years, as do actual dropouts. The event study shows how the choice of trading off true positive rates and false positive rates affects the groups, as I have chosen a sample of predicted in-and-outs that contain very few actual dropouts, but exclude some actual in-and-outs, resulting in a gap between predicted dropouts and actual dropouts. However, I examine the evolution of income for the predicted in-and-outs only and not for predicted dropouts, so this tradeoff is sensible.

Next, I turn to the evolution of income for the group of predicted dropouts. Appendix Figure A.7 shows the estimated evolution of income for predicted in-and-outs, actual in-and-outs, and unemployed job losers, where all three sets of estimates are computed using equation 5. While predicted in-and-outs experience an even larger decline in personal income than actual in-and-outs at the time of separation, this gap narrows as both groups return to the labor force and the income of the two groups is statistically indistinguishable by one year after the separation. Both groups experience no significant change in income between the month before the separation and two years after the

Figure A.7: Evolution of Predicted In-and-Outs' Income

Sample: 25–54 year old men in the SIPP. In-and-Outs are employed in month 0, nonparticipants in month 1, and are employed again by at least month 12. Unemployed job losers are employed in month 0 and fired or laid off but looking for work in month 1. Re-employment time is predicted from covariates four months before the separation using gradient boosted trees and individuals are categorized based on whether the predicted time is less than a threshold delivering a false positive rate below 20%.

separation, while unemployed job losers experience significantly lower income.