



First Quarter 2018

Volume 103, Number 1

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Has the Anchoring of Inflation Expectations Changed in the United States during the Past Decade?

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# FEDERAL RESERVE BANK OF KANSAS CITY ECONOMIC REVIEW

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# Why Are Prime-Age Men Vanishing from the Labor Force? By Didem Tüzemen

The labor force participation rate for prime-age men (age 25 to 54) has declined dramatically in the United States since the 1960s, but the decline accelerated more recently. In 1996, 4.6 million prime-age men did not participate in the labor force. By 2016, this number had risen to 7.1 million. Better understanding these men and the personal situations preventing them from working may be crucial in evaluating whether they are likely to return to the labor force.

Didem Tüzemen documents changes in the nonparticipation rates of prime-age men with different demographic characteristics as well as changes in their personal situations during nonparticipation. She finds nonparticipation rates increased most among younger men and men with only a high school degree, some college, or an associate's degree. In addition, she finds that job polarization has been a key contributor to the rise in nonparticipation. Overall, her results suggest prime-age men are unlikely to return to the labor force if current conditions hold.

# Has the Anchoring of Inflation Expectations Changed in the United States during the Past Decade? By Taeyoung Doh and Amy Oksol

The financial crisis and Great Recession led to dramatic shifts in U.S. monetary policy over the past decade, with potential implications for inflation expectations. Prior to the crisis, inflation expectations were wellanchored. But during the crisis and recovery, the Federal Reserve turned to new policies such as large-scale asset purchases (LSAPs). In addition, the Federal Open Market Committee adopted a formal inflation target in 2012, with the stated goal of keeping longer-term inflation expectations stable. Did inflation expectations remain anchored during this period of unconventional policy?

Taeyoung Doh and Amy Oksol use three metrics of inflation expectations to assess whether inflation expectations became unanchored after the financial crisis. They find that the degree of anchoring deteriorated somewhat in late 2010, but returned to its pre-crisis level more recently. They also find that shifts in the three metrics coincide with consecutive rounds of LSAPs and the adoption of a formal inflation target. Overall, their results suggest the Federal Reserve's actions helped anchor inflation expectations after the crisis.

# Structural and Cyclical Trends in the Supplemental Nutrition Assistance Program By Kelly D. Edmiston

Participation in the Supplemental Nutrition Assistance Program (SNAP) has increased sharply over the past 20 years. Average monthly participation grew from 17.3 million people in 2001 to a peak of 47.6 million people in 2013. Although participation declined somewhat as the economy recovered from the Great Recession, SNAP participation remains well above its pre-recession level.

Kelly D. Edmiston investigates the forces driving long-term patterns in SNAP participation as well as its cyclical variation. He finds that three structural factors—legislative and programmatic changes, poverty, and a rising share of the working population not in the labor force—have made the largest contributions to SNAP participation over time. His results suggest growth in SNAP participation is unlikely to unwind in the near future.

# Why Are Prime-Age Men Vanishing from the Labor Force?

#### By Didem Tüzemen

he labor force participation rate for prime-age men (age 25 to 54) in the United States has declined dramatically since the 1960s, but the decline has accelerated more recently. From 1996 to 2016, the share of prime-age men either working or actively looking for work decreased from 91.8 percent to 88.6 percent. In 1996, 4.6 million prime-age men did not participate in the labor force. By 2016, this number had risen to 7.1 million.

Prime-age men are at their most productive in terms of working years, and a decline in their participation has important implications for the future of the labor market and economic growth. But this decline is unlikely to be uniform across prime-age men of different ages, education levels, and skill levels. Profiling these men in greater detail may be important to better understand the demographic factors driving nonparticipation as well as the personal situations preventing nonparticipants from working or actively searching for work.

In this article, I examine two decades of data from the Current Population Survey (CPS) to document changes in the nonparticipation rates among prime-age men with different demographic characteristics as well as changes in their personal situations during nonparticipation. I find that from 1996 to 2016, the nonparticipation rate increased most

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for men with only a high school degree, some college, or an associate's degree and for men on the younger end of the prime-age range (age 25–34). During this period, the most common personal situation reported among nonparticipating prime-age men was disability or illness, while the least common personal situation was retirement.

In addition, I argue that "job polarization," a phenomenon that describes declining demand for middle-skill workers in response to advancements in technology and globalization, has been a key contributor to the increase in nonparticipation among prime-age men. I show that if job polarization had not changed the composition of jobs in the labor market in the past two decades, 1.9 million more men would likely be employed in 2016, representing a 3.6 percent increase in overall employment of prime-age men. However, the effects of job polarization are unlikely to unwind any time soon—survey evidence suggests nonparticipating prime-age men are unlikely to return to the labor force if current conditions hold.

Section I documents changes in the nonparticipation rates for different education and age groups of prime-age men from 1996 to 2016. Section II reviews recent explanations for the increase in nonparticipation among prime-age men and shows job polarization has contributed to the decline. Section III examines the likelihood that nonparticipants will return to the labor force.

# I. Changes in Nonparticipation among Prime-Age Men in the Past Two Decades

Labor force nonparticipation has increased for the population as a whole over the last two decades. During the Great Recession, this overall increase accelerated, primarily due to large-scale layoffs (Aaronson and others 2014; Erceg and Levin 2014; Hotchkiss and Rios-Avila 2013; and Van Zandweghe 2012). But the increase in nonparticipation was especially stark for prime-age men. Chart 1 shows that the nonparticipation rate for prime-age men increased from 8.2 percent to 11.4 percent over the past two decades.

To understand the forces behind this stark increase in nonparticipation, I first examine the characteristics of nonparticipating prime-age men using micro-level data from the CPS, also known as the household survey. The CPS is the primary source of labor force statistics and



## *Chart 1* Nonparticipation Rate of Prime-Age Men

Notes: Gray bars denote National Bureau of Economic Research (NBER)-defined recessions at a monthly frequency. Nonparticipation rates correspond to monthly observations averaged for each year. Sources: CPS, NBER, and author's calculations.

demographic data for the U.S. population. The U.S. Census Bureau collects survey data for the Bureau of Labor Statistics at a monthly frequency from approximately 60,000 households.<sup>1</sup> For the purposes of this article, I restrict the data sample to men age 25–54 and base the analysis on annualized data from 1996 to 2016.<sup>2</sup> I then examine changes in nonparticipation by educational attainment, age, and the interaction between them as well as by prime-age men's personal situations.

#### Changes in nonparticipation rates by educational attainment

A change in the educational composition of the workforce could lead to a change in the labor force nonparticipation rate. Workers with lower educational attainment, for example, historically have higher nonparticipation rates than their more-educated counterparts. To facilitate comparison, I group workers by education level into one of four groups: those with less than a high school degree, those with only a high school degree, those with some college or an associate's degree, and those with a bachelor's degree or higher. Chart 2 shows that while the nonparticipation rates rose for all education groups over the past

#### Chart 2



### Nonparticipation Rates of Prime-Age Men by Education Group

two decades, the largest increase was for those in the middle-education groups, who had only a high school degree, some college, or an associate's degree. More specifically, the nonparticipation rate for prime-age men with only a high-school degree rose from 8.8 percent in 1996 to 14.9 percent in 2016 (a 70.3 percent increase), while the nonparticipation rate for prime-age men with some college or an associate's degree rose from 6.8 percent in 1996 to 11.0 percent in 2016 (a 61.7 percent increase). The nonparticipation rate for prime-age men in the highest education group, who had a bachelor's degree or higher, increased more modestly, from 4.1 percent in 1996 to 6.0 percent in 2016 (a 45.9 percent increase). Similarly, the nonparticipation rate for those in the lowest education group, who had less than a high school degree, rose only slightly, from 18.3 percent in 1996 to 20.3 percent in 2016 (only a 10.6 percent increase).

These changes in nonparticipation rates have shifted the educational composition of nonparticipating prime-age men toward the middleeducation groups. Chart 3 shows how the educational composition of all prime-age men has changed over the past 20 years, while Chart 4 narrows this focus to show how the educational composition of nonparticipating prime-age men has evolved. Among nonparticipating

Notes: Gray bars denote NBER-defined recessions at a monthly frequency. Nonparticipation rates correspond to monthly observations averaged for each year. Sources: CPS, NBER, and author's calculations.



# *Chart 3* Composition of Prime-Age Men by Education Group

Note: Monthly data are averaged for each yes Sources: CPS and author's calculations.

## *Chart 4* Composition of Nonparticipating Prime-Age Men by Education Group



Note: Monthly data are averaged for each year. Sources: CPS and author's calculations.

prime-age men, the shares in the lowest and highest education groups those with less than a high school degree or a bachelor's degree or higher, respectively—have moved in the same directions as the overall shares among prime-age men from 1996 to 2016. But for men in the middleeducation groups, this pattern reversed. The share of all prime-age men with only a high school degree decreased from 32.6 percent to 29.5 percent over the last two decades, but the share of *nonparticipating* men with only a high school degree actually increased from 34.9 percent to 38.6 percent. Similarly, while the share of all prime-age men with some college or an associate's degree decreased by less than a percentage point over the past two decades, the share of *nonparticipating* men with some college or an associate's degree increased from 21.8 percent to 24.6 percent.

### Changes in nonparticipation rates by age

As with education, a change in the age composition of the labor force could influence nonparticipation. I divide prime-age men into three age groups: those age 25–34, those age 35–44, and those age 45–54. Chart 5 shows the nonparticipation rates for all three groups over the past two decades. Although the nonparticipation rates for all three groups increased over time, younger prime-age men saw the largest increase. From 1996 to 2016, the nonparticipation rate for younger prime-age men surged from 6.7 percent to 11.3 percent, a 67.0 percent increase. Over the same period, the nonparticipation rate for men in the 35–44 age group rose from 7.6 to 9.5 percent (a 25.1 percent increase), while the nonparticipation rate for men in the 45–54 group rose from 10.8 to 13.4 percent (a 24.4 percent increase).

As the nonparticipation rate for prime-age men in the 25–34 age group increased, so did their share of all prime-age nonparticipants. Chart 6 shows that among nonparticipants, each age group had nearly equal shares in 1996, with men in the 25–34 age group having a slightly smaller share at 28.8 percent. By 2016, however, the share of nonparticipating men age 25–34 increased to 34.4 percent, the largest increase of all three age groups. The share of nonparticipating men age 45–54 also increased over this period, from 36.6 percent to 39.4 percent. In contrast, the share of nonparticipants age 35–44 declined by 8.5 percentage points, from 34.7 percent to 26.2 percent.

# Chart 5

Chart 6



# Nonparticipation Rates of Prime-Age Men by Age Group

Notes: Gray bars denote NBER-defined recessions at a monthly frequency. Nonparticipation rates correspond to monthly observations averaged for each year. Sources: CPS, NBER, and author's calculations.



# Composition of Nonparticipating Prime-Age Men by Age Group

Note: Monthly data are averaged for each year. Sources: CPS and author's calculations.

### Changes in nonparticipation rates by the interaction between age and education

To get a more complete picture of how the composition of primeage workers has changed over time, I next examine the breakdown across both age and educational attainment. Within every age group, nonparticipation rates increased most for those in the middle education groups. Although nonparticipation rates increased for men age 25–34 in all education groups from 1996 to 2016, the largest increases were for those with a high-school degree (6.4 to 14 percent) and some college or an associate's degree (5.7 to 11.1 percent), as shown in Table 1. Nonparticipation rates for men age 35–44 increased most for those with a high-school degree (8.3 to 13.4 percent) and a bachelor's degree or higher (3.0 to 4.3 percent). Interestingly, the nonparticipation rate for men 35–44 with less than a high school degree fell slightly, from 18 percent to 17.4 percent. Among men in the 45–54 age group, the highest increase in the nonparticipation rate was for those with some college or an associate's degree (8.9 to 13 percent).

Overall, prime-age men in the age 45–54 group and prime-age men with less than a high school degree had the highest nonparticipation rates throughout the analysis period. However, younger prime-age men and those in the middle-education groups—specifically, those who had only a high school degree, some college, or an associate's degree—experienced the largest *increases* in their nonparticipation rates over the past two decades.

## Changes in the self-reported "situations" of nonparticipants

Although the nonparticipation rates for prime-age men in different age and education categories have changed over the past 20 years, the reasons for these changes are not obvious. One way to identify these reasons is to look at CPS respondents' answers to a question about their personal situations. Each month, the CPS asks respondents about their labor force status (employed, unemployed, or not in the labor force). Those who report their status as "not in the labor force" also respond to another question, which asks, "what best describes your situation at this time? For example, are you disabled, ill, in school, taking care of house or family, in retirement, or something else?" Based on the responses to these questions, I group nonparticipating prime-age men into one of five

Age group	Nonparticipation rates				
	Less than high school (percent)	High school degree (percent)	Some college or associate's degree (percent)	Bachelor's degree or higher (percent)	Total (percent)
1996					
Age 25–34	13.6	6.4	5.7	4.8	6.7
Age 35–44	18.0	8.3	6.3	3.0	7.6
Age 45–54	25.0	13.0	8.9	4.7	10.8
Total	18.3	8.8	6.8	4.1	—
2016					
Age 25–34	17.1	14.0	11.1	7.4	11.3
Age 35–44	17.4	13.4	8.7	4.3	9.5
Age 45–54	25.9	17.2	13.0	6.2	13.4
Total	20.3	14.9	11.0	6.0	_
Difference					
Age 25–34	25.8	118.9	96.6	55.2	67.0
Age 35–44	-3.8	61.4	37.8	42.4	25.1
Age 45–54	3.4	32.7	44.8	32.9	24.4
Total	10.6	70.3	61.7	45.9	—

# Nonparticipation Rates of Prime-Age Men by Education and Age Group

Table 1

Note: Monthly data are averaged for each year.

Sources: CPS and author's calculations.

categories: retired, disabled or ill, in school, taking care of family, and other reasons.

Throughout the sample period, the most common situation nonparticipants reported was having a disability or illness, while the least common situation was retirement. In 1996, 56.0 percent of nonparticipating prime-age men reported they were disabled or ill, while only 7.2 percent said they were retired (Table 2). At the same time, 10.3 percent reported being in school, 10.8 percent reported taking care of family, and 15.7 percent reported other reasons for nonparticipation. By 2016, the share of nonparticipating men who reported they were disabled or ill declined to 48.3 percent, while the share who were retired rose to 10.0 percent. The share who reported being in school rose to 13.8 percent, the share taking care of family rose to 14.6 percent, and the share reporting other situations declined to 13.2 percent.

	Years	Disabled or ill (percent)	Family care (percent)	In school (percent)	Retired (percent)	Other (percent)
All nonparticipating prime-age men	1996	56.0	10.8	10.3	7.2	15.7
	2016	48.3	14.6	13.8	10.0	13.2
Education groups	1996					
	LHS	70.6	10.2	2.0	3.7	13.5
	HS	62.3	11.4	3.1	7.3	15.9
	SC	47.0	10.4	19.0	8.4	15.2
	BA+	24.5	11.1	31.2	12.6	20.6
	2016					
	LHS	63.9	12.0	6.3	5.5	12.3
	HS	58.2	16.0	4.9	8.3	12.6
	SC	41.2	13.5	22.0	11.4	11.8
	BA+	20.2	16.0	29.7	16.5	17.6
Age groups	1996					
	25-34	38.7	12.7	24.1	1.4	23.1
	35–44	61.2	14.0	7.0	2.1	15.7
	45-54	64.7	6.3	2.4	16.6	9.9
	2016					
	25-34	32.9	14.8	29.5	5.0	17.8
	35-44	49.9	19.6	8.6	8.4	13.5
	45-54	60.6	11.2	3.6	15.4	9.1

# Table 2Situations Reported among Nonparticipating Prime-Age Men

Notes: LHS denotes less than a high school degree, HS denotes high school degree, SC denotes some college or an associate's degree, and BA+ denotes bachelor's degree or higher. Monthly data are averaged for each year. Sources: CPS and author's calculations.

I observe similar patterns for prime-age men across education and age groups. From 1996 to 2016, the shares of prime-age men in all age and education groups reporting disability as their situation declined slightly. In contrast, the shares reporting retirement, being in school, and taking care of family increased slightly. A natural question is whether the increased share of nonparticipating prime-age men in school could explain the especially dramatic hike in the nonparticipation rate for younger prime-age men. However, schooling does not appear to be the main driver of nonparticipation. Based on the self-reported responses, only one-third of the increase in the number of nonparticipating younger prime-age men was related to being in school. Similar to the other age groups, the majority (one-third) of younger prime-age men reported disability as their reason for nonparticipation in 2016.

While self-reported responses offer some insight into the reasons for nonparticipation, the limited survey options may mask other, potentially more important reasons behind the increase in nonparticipation. For example, some individuals may have left the labor force because they were unable to find jobs suitable for their skills. Others may have recovered from disability or illness but become dependent on pain medication, rendering them unable to work. In such cases, self-reported responses about the "situation" of nonparticipants would not fully capture the reasons they left the labor force. To account for these alternatives, I review some recent explanations from researchers for the rise in nonparticipation among prime-age men.

# II. Possible Explanations for the Increase in Nonparticipation among Prime-Age Men

Changes in both labor supply and labor demand could have contributed to the increase in prime-age men's nonparticipation. For example, prime-age men may have chosen to leave the labor force because they have easier access to alternative income sources—such as a working spouse or public assistance programs—compared with two decades ago. However, prime-age men may also have been forced out of the labor force as jobs suitable for their skills vanished.

## Changes in labor supply: alternative income sources and pain

One explanation for the decline in labor force participation among prime-age men could be a change in labor supply—that is, prime-age men may be choosing not to work. A rise in alternative income sources, such as a working spouse or access to public assistance programs such as Social Security Disability Insurance (SSDI), Temporary Assistance for Needy Families (TANF), or the Supplemental Nutrition Assistance Program (SNAP) might explain this choice.

However, none of these alternative income sources seems sufficient to have shifted the labor supply. In fact, survey evidence shows that the share of nonparticipating prime-age men who are married has declined over the past two decades. In 2016, almost half of nonparticipating prime-age men reported they had never been married (author's calculations). Moreover, nearly 36 percent of nonparticipating prime-age men lived in poverty in 2014 (Council of Economic Advisers 2016). Almost half of all households with a male prime-age nonparticipant were in the bottom quintile of income (Hamilton Project 2017). All in all, evidence does not support the claim that alternative income through a working spouse encouraged men to choose to leave the labor force.

Likewise, increased reliance on public assistance does not seem to be a credible explanation for the increase in nonparticipation among prime-age men. While the share of prime-age men receiving SSDI increased from 1 percent to 3 percent from 1967 to 2014, the labor force participation rate among prime-age men declined by 7.5 percentage points over the same period (Council of Economic Advisers 2016). Analysis by the Council of Economic Advisers (CEA) suggests that an increasing share of SSDI recipients can explain at most 0.5 percentage point of the decline in the participation rate of prime-age men over this period. Additionally, according to the CEA, other government programs, such as TANF and SNAP, have become increasingly hard to access. Therefore, reductions in labor supply due to alternative income sources seem to explain relatively little of the increase in nonparticipation among prime-age men.

A more recent explanation for rising nonparticipation is that daily pain and dependence on pain medication have become barriers to regular employment for many prime-age men who are out of the labor force. Krueger (2016) argues that nearly half of nonparticipating primeage men are taking pain medication on a daily basis, nearly two-thirds of whom are using prescribed pain medication.

While this evidence is compelling, it is hard to identify the direction of this relationship—that is, it is hard to know whether these men left the labor force because of a disability that required pain medication or whether they became dependent on pain medication because they were forced out of the labor force for other reasons. Some anecdotal evidence suggests individuals are likely to claim disability when they are unable to find new jobs after losing their jobs, perhaps because a local mill shuts down or a factory closes.<sup>3</sup>

Moreover, if a reduced labor supply has been the key driver of the increase in nonparticipation, the wages of workers with only a high

#### Chart 7





Notes: Gray bars denote NBER-defined recessions at a monthly frequency. All other data are annual. Sources: CPS (Bureau of Labor Statistics) and author's calculations.

school degree—the group of workers who experienced the largest increase in their nonparticipation rate—might be expected to increase relative to those with a bachelor's degree or higher. However, Chart 7 shows that the ratio of the median weekly earnings of workers with a high school degree to the median weekly earnings of workers with a bachelor's degree or higher has actually declined. As such, reduced labor demand has likely played a more important role in the increase in labor force nonparticipation among prime-age men.

#### Changes in labor demand: job polarization

Labor demand and the skill composition of jobs have changed dramatically over the past 40 years in response to advancements in technology and globalization. The employment share of middle-skill jobs has declined significantly, while the employment shares of low- and highskill jobs have rapidly increased. This aggregate shift in employment away from middle-skill jobs and toward low- and high-skill jobs is called "job polarization" (Goos and Manning 2007; Autor and others 2006; Autor 2010; Acemoglu and Autor 2011; and Tüzemen and Willis 2013).

Technological advancements help explain why the share of workers employed in middle-skill jobs has fallen so sharply. Middle-skill jobs are considered "routine" occupations, as workers typically perform tasks that are procedural and rule-based. The tasks performed in many of these jobs have become automated by computers and machines.

Tasks performed in high- and low-skill jobs, however, are more difficult to automate, making them "non-routine" jobs. Workers in lowskill jobs typically have lower educational attainment and work in jobs that are physically demanding. Many of these jobs are service oriented, such as food preparation, cleaning, and security and protective services. In contrast, workers in high-skill jobs are typically highly educated and perform tasks requiring analytical ability, problem solving, and creativity. Many of these jobs are managerial, professional, and technical in nature in fields such as engineering, finance, management, and medicine.

International trade and weakening unions have also contributed to the decline in middle-skill jobs. Many jobs in this category, particularly those in manufacturing, have been offshored to countries where workers can perform similar tasks for lower wages (Goos and others 2011; Oldenski 2012). In addition, some firms have contracted out portions of their businesses to workers in foreign countries through outsourcing.

Overall, job polarization has led to a large increase in the demand for highly educated workers and a decline in demand for less-educated workers, many of whom were employed in middle-skill jobs. Chart 8 shows how the shares of jobs in each skill category changed over the past 20 years. In 1996, 53.9 percent of all jobs were middle-skill jobs, and low- and high-skill jobs accounted for 14.4 percent and 31.7 percent of total jobs, respectively. By 2016, however, only 43.2 percent of jobs were middle-skill jobs, and low- and high-skill jobs accounted for 18.2 percent and 38.6 percent of all jobs, respectively.<sup>4</sup>

The decline in middle-skill jobs disproportionately affected primeage men. Table 3 shows that 57.8 percent of all employed, prime-age men worked in middle-skill jobs in 1996. These jobs were largely routine occupations in sales, office and administrative services, production, construction, installation, maintenance, and transportation—most of which employed disproportionately more men than women. By 2016, the share of employed men in middle-skill occupations had declined by 8.5 percentage points. The largest employment losses for prime-age men were in production occupations, reflecting the decline in manufacturing employment. Employment of prime-age men shifted almost



*Chart 8* Employment Shares by Skill Level

Notes: Data are restricted to workers age 16 to 64 who are not self-employed or working without pay and are not employed in military or agricultural occupations or mining or agricultural industries. Monthly data are averaged for each year. Sources: CPS and author's calculations.

	Share of men within occupation			Employment shares of men		
Occupations	1996 (percent)	2016 (percent)	Change (percentage point)	1996 (percent)	2016 (percent)	Change (percentage point)
High-skill						
Management, business, and financial	51.8	51.9	0.2	14.7	16.5	1.8
Professional and related	44.2	41.3	-2.9	17.8	20.5	2.7
Middle-skill						
Sales and related	51.4	52.2	0.8	10.0	9.0	-1.0
Office and administra- tive support	20.6	27.8	7.2	6.4	6.4	0.0
Construction, extraction, installation, maintenance, repair, and production	79.1	86.6	7.5	33.7	24.4	-9.3
Transportation and material moving	89.8	82.4	-7.4	7.7	9.5	1.8
Low-skill						
Service	41.7	44.3	2.6	9.7	13.7	4.0

## *Table 3* Employment Shares of Prime-Age Men by Occupation

Notes: Data are restricted to working prime-age men who are not self-employed or working without pay and are not employed in military or agricultural occupations or mining or agricultural industries. Monthly data are averaged for each year.

Sources: CPS and author's calculations.

equally toward high- and low-skill jobs. The share of employed primeage men in managerial and professional occupations, which are classified as high-skill jobs, rose by 4.5 percentage points. At the same time, the share of employed prime-age men in low-skill service jobs rose by 4.0 percentage points.

Prime-age men with a high school degree or less have been especially vulnerable to job polarization. Table 4 shows the shares of primeage men with different levels of educational attainment employed in each occupation type. In 1996, 78.4 percent of workers with a high school degree and 80.0 percent of workers with less than a high school degree were employed in middle-skill jobs. By 2016, these employment shares had declined to 71.0 percent and 72.0 percent, respectively. Employment gains for both groups were primarily in low-skill jobs, likely because workers in these groups lacked the education or training to find employment in high-skill jobs. Workers with some college degree

Level of educational attainment	Occupation type	1996 (percent)	2016 (percent)	Change (percentage point)
Less than high school	Low-skill	16.2	24.1	7.9
	Middle-skill	80.0	72.0	-8.0
	High-skill	3.8	3.9	0.1
High school degree	Low-skill	11.2	17.8	6.6
	Middle-skill	78.4	71.0	-7.4
	High-skill	10.4	11.2	0.8
Some college or associate's degree	Low-skill	11.6	16.7	5.1
	Middle-skill	60.5	57.6	-2.9
	High-skill	27.9	25.7	-2.2
Bachelor's degree or higher	Low-skill	4.1	6.3	2.2
	Middle-skill	25.0	22.6	-2.4
	High-skill	70.9	71.1	0.2

# Table 4Employment Shares of Prime-Age Men by Education Group

Notes: Employment shares are computed separately for each respective level of educational attainment. Data are restricted to working prime-age men who are not self-employed or working without pay and are not employed in military or agricultural occupations or mining or agricultural industries. Monthly data are averaged for each year. Sources: CPS and author's calculations.

or an associate's degree fared similarly: the share of these workers in both middle- and high-skill jobs declined from 1996 to 2016, while the share in low-skill jobs increased. Prime-age men with a bachelor's degree or higher were less affected. In 1996, 29.1 percent of these workers were in low- and middle-skill occupations. By 2016, the share in middle-skill jobs had declined by 2.4 percentage points, accompanied by almost an equal increase in the share in low-skill jobs.

As the demand for workers in middle-skill jobs declined, some displaced middle-skill workers were able to transition to high-skill jobs, while other workers moved to low-skill service sector jobs. However, most of the displaced middle-skill workers permanently dropped out of the labor force (Cortes and others 2014). Thus, job polarization likely contributed to the increase in nonparticipation among prime-age men, especially among those without a bachelor's degree.

## The effect of job polarization on the increase in nonparticipation

How much of the increase in nonparticipation among prime-age men from 1996 to 2016 can job polarization explain? To answer this question, I run a simple counterfactual exercise that considers how employment of prime-age men would have changed if job polarization had not affected the composition of jobs in the labor market over the past two decades.

Employment in low-, middle-, and high-skill jobs varies greatly across education groups. However, if the composition of jobs and demand for skills in the labor market had not changed from 1996 to 2016, the share of prime-age men in each age-education group who were employed in each skill category would have remained the same. In other words, the employment-to-population ratios for men in each age-education group would be unchanged across low-, middle-, and high-skill employment. In that case, any change in the total employment of prime-age men from 1996 to 2016 would result only from the changes in the number of prime-age men in each age-education group.

To calculate the counterfactual employment level in 2016, I hold each age-education group's employment-to-population ratios in low-, middle-, and high-skill jobs at their 1996 levels. I then multiply these ratios by the population of each age-education group in 2016.

My calculation shows that if the skill composition of jobs had not changed, 1.9 million more prime-age men would have been employed in 2016 (54.4 million versus the actual level of 52.5 million). The actual number of nonparticipating prime-age men rose from 4.6 million in 1996 to 7.1 million in 2016, a 2.5 million increase. My simple counterfactual exercise suggests that if job polarization had not changed the demand for skills in the labor market, almost 80 percent of these 2.5 million nonparticipants could be employed in 2016.

Other studies provide further support for the relationship between job polarization and nonparticipation. For example, Aaronson and others (2014) find that the participation rates among less-educated individuals (those without a bachelor's degree) fell more in states with greater declines in middle-skill employment. Moreover, the authors find that participation rates among less-educated individuals were more responsive to job polarization compared with the participation rates among adults with higher educational attainment. More recently, Foote and Ryan (2015) use both an individual-level model of unemployment transitions and a more theoretically grounded empirical model based on demographic groups to show that the increase in nonparticipation among prime-age men was a quantitatively important response to job polarization. The authors interpret this empirical relationship between job polarization and nonparticipation as pointing to a lack of employment alternatives for a large share of middle-skill workers and thus a lower probability of these workers willingly leaving their jobs in recessions to search for alternative employment.

Together, my simple counterfactual exercise and research by other economists provide evidence that a change in labor demand—specifically, the decline in the employment share of middle-skill jobs—helps explain a significant part of the recent increase in labor force nonparticipation among prime-age men.

# III. Are Nonparticipants Likely to Return to the Labor Market?

If the increase in nonparticipation among prime-age men is the result of a long-term change in labor demand, how likely are these men to return to the labor market? To answer this question, I analyze prime-age men's flows into and out of the labor force in 1996 and 2016. I then document changes in the profile of nonparticipating prime-age men who report that they want a job.

The structure of the CPS makes it possible to follow individuals over two consecutive months and observe flows between employment, unemployment, and nonparticipation. Panels A and B of Table 5 categorize these flows based on whether participants are flowing into or out of nonparticipation from one month to the next.

In 1996, most nonparticipating prime-age men—82.9 percent were also nonparticipants in the previous month. Only 10.2 percent of nonparticipants were employed in the previous month, while only 6.9 percent were unemployed in the previous month. The shares were similar for those flowing out of nonparticipation: 8.9 percent of nonparticipating prime-age men became employed in the subsequent month, and only 6.2 percent became unemployed.

In 2016, the flows between employment and nonparticipation remained largely unchanged, while the flows between unemployment

Table 5			
Flows into a	nd out of Nonpa	rticipation for	Prime-Age Men

	I I I						
Year	From employment (percent)	From unemployment (percent)	From nonparticipation (percent)				
1996	10.2	6.9	82.9				
2016	10.3	5.9	83.8				

#### Panel A: Flows into Nonparticipation

#### Panel B: Flows out of Nonparticipation

Year	To employment (percent)	To unemployment (percent)	To nonparticipation (percent)
1996	8.9	6.2	84.9
2016	9.0	5.0	86.0

Note: Monthly data are averaged for each year. Sources: CPS and author's calculations.

and nonparticipation declined. The share of nonparticipating primeage men who were also nonparticipants in the previous month rose to 83.8 percent in 2016.

Although the flows at the start and end of the sample period may look similar, they have not been constant over time. During the Great Recession, nonparticipation among prime-age men increased rapidly due to large-scale layoffs. The economic downturn resulted in many temporary dropouts from the labor market. In the aftermath of the recession, some of these individuals re-entered the labor force: Chart 9 shows that the share of nonparticipants remaining out of the labor force from one month to the next declined rapidly from 2008 to 2009. However, this share started rising again in mid-2010 and reached an average of 83.8 percent (higher than its pre-recession rate) in 2016. Thus, recent flows data do not suggest nonparticipating prime-age men are likely to return to the labor force.

Another way to assess whether nonparticipating prime-age men are likely to return to the labor force is by examining whether they want a job. The CPS asks respondents who are "not in the labor force" whether they want a job. Chart 10 shows that the share of prime-age men who want a job has fluctuated over the past 20 years. In 1996, around 17.9 percent of nonparticipating prime-age men reported they wanted a job. This share declined to 13.9 percent by 1999 but increased again during the Great Recession. Since 2011, the share of nonparticipating primeage men who want a job has steadily declined, reaching 14.8 percent in



# *Chart 9* Probability of Remaining a Nonparticipant for Prime-Age Men

Notes: Gray bars denote NBER-defined recessions. Chart shows 12-month moving average. Sources: CPS, NBER, and author's calculations.

# *Chart 10* Share of Nonparticipating Prime-Age Men Who Want a Job



Notes: Gray bars denote NBER-defined recessions at a monthly frequency. Shares correspond to monthly observations averaged for each year. Sources: CPS, NBER, and author's calculations.

		Nonparticipating prime-age men who want a job			
Group	Characteristic	1996 (percent)	2016 (percent)	Difference (percentage point)	
Education groups	Less than high school	24.6	16.2	-8.4	
	High school degree	35.8	38.2	2.4	
	Some college or associate's degree	23.8	25.7	1.9	
	Bachelor's degree or higher	15.8	19.8	4.0	
Age groups	Age 25–34	40.6	44.3	3.7	
	Age 35–44	36.5	27.7	-8.8	
	Age 45–54	22.9	28.0	5.1	
Note: Monthly data are overaged for each year					

## *Table 6* Characteristics of Prime-Age Men Who Want a Job

Note: Monthly data are averaged for each year

Sources: CPS and author's calculations.

2016. This low share suggests nonparticipants are not likely to return to the labor force soon, possibly due to a lack of available jobs suitable for their skills.

Changes over time in the education and age composition of those who want a job support this interpretation. In 1996, over 60 percent of nonparticipating prime-age men who wanted a job had at most a high school degree—24.6 percent had less than a high school degree, while 35.8 percent had completed high school (Table 6). In 2016, however, the share of those with less than a high school degree who wanted a job fell to 16.2 percent. For all other education groups, the shares of nonparticipating prime-age men who wanted a job increased from 1996 to 2016. This compositional change is not surprising given that the job opportunities for individuals with lower educational attainment declined as a result of job polarization. As Table 4 showed, prime-age men with less than a high school degree saw the largest decline of any education group in their share of middle-skill jobs. Consistent with this explanation, the largest increase in the share of prime-age nonparticipants who wanted a job was among those with a bachelor's degree or higher-the education group least affected by the decline in middle-skill jobs.

The age composition of men who wanted a job shifted toward the younger and older edges of the prime-age range. From 1996 to 2016,

the share of nonparticipants who wanted a job in the 35–44 age group declined by 8.8 percentage points. In contrast, the shares in the 25–34 and 45–54 age groups increased by 3.7 and 5.1 percentage points, respectively. The change in the age composition of those who want a job largely reflects the change in the age group composition of prime-age male nonparticipants.

### **IV.** Conclusion

Over the past two decades, the nonparticipation rate among primeage men rose from 8.2 percent to 11.4 percent. This article shows that the nonparticipation rate increased the most for men in the 25–34 age group and for men with a high school degree, some college, or an associate's degree. In 1996, the most common situation prime-age men reported during their nonparticipation was a disability or illness, while the least common situation was retirement. While the share of primeage men reporting a disability or illness as their situation during nonparticipation declined by 2016, this share still accounted for nearly half of all nonparticipating prime-age men. This result is in line with Krueger's (2016) finding, as many of these men with a disability or illness are likely suffering from daily pain and using prescription painkillers.

I argue that a decline in the demand for middle-skill workers accounts for most of the decline in participation among prime-age men. In addition, I find that the decline in participation is unlikely to reverse if current conditions hold. In 2016, the share of nonparticipating prime-age men who stayed out of the labor force in the subsequent month was 83.8 percent. Moreover, less than 15 percent of nonparticipating prime-age men reported that they wanted a job. Together, this evidence suggests nonparticipating prime-age men are less likely to return to the labor force at the moment.

The stark increase in prime-age men's nonparticipation may be the result of a vicious cycle. Skills demanded in the labor market are rapidly changing, and automation has rendered the skills of many less-educated workers obsolete. This lack of job opportunities, in turn, may lead to depression and illness among displaced workers, and these health conditions may become further barriers to their employment. Ending this vicious cycle—and avoiding further increases in the nonparticipation rate among prime-age men—may require equipping workers with the new skills employers are demanding in the face of rapid technological advancements.

## Endnotes

<sup>1</sup>The survey has a response rate ranging from 91 to 93 percent, one of the highest response rates among government surveys.

<sup>2</sup>To construct annual series, I average monthly observations for each year.

<sup>3</sup>In 2013, such a story was featured in "Unfit for Work," an episode of the National Public Radio (NPR) podcast *Planet Money*.

<sup>4</sup>In calculating these skill shares, I restrict the data to workers who are not self-employed and not employed in military or agricultural occupations.

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# Has the Anchoring of Inflation Expectations Changed in the United States during the Past Decade?

### By Taeyoung Doh and Amy Oksol

onetary policy has changed dramatically in the United States over the past decade, with potential implications for investors' inflation expectations. During the financial crisis and Great Recession of 2007–09, the Federal Reserve's conventional policy tool, the nominal short-term interest rate, was constrained by its effective lower bound. At the time, monetary policy makers were concerned the U.S. economy might slip into a deflationary trap similar to Japan's during the period of 1999–2003. As a result, the Fed responded aggressively to stabilize the economy through multiple rounds of large-scale asset purchases (LSAPs) and forward guidance on the future interest rate. In addition, the Federal Open Market Committee (FOMC) adopted a formal inflation target at its meeting in January 2012, emphasizing that "communicating this inflation goal clearly to the public helps keep longer-term inflation expectations firmly anchored."

Well-anchored inflation expectations are a key measure of successful monetary policy, because in the long run, inflation is mainly determined by monetary policy. Inflation expectations drifting away from the central bank's implicit or explicit inflation targets can generate highly inflationary or disinflationary episodes. For example, businesses expecting a higher inflation rate may increase current prices to offset

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high future costs of production. Similarly, consumers expecting prices to fall may delay their spending, reinforcing disinflationary pressures with the resulting lack of demand.

Prior to the financial crisis, researchers found that the level and volatility of inflation expectations decreased dramatically from 1981:Q3 to 2008:Q2, suggesting investors' inflation expectations were well anchored (Clark and Davig 2011). But did their expectations remain anchored after the crisis, during a period of unconventional monetary policy?

We use a model consistent with previous research to examine whether inflation expectations became unanchored after the crisis. Our analysis of three metrics of inflation expectations—their level, volatility, and persistence—suggests that the degree of anchoring deteriorated somewhat in late 2010, coinciding with the start of the second round of LSAPs, but has improved since then. Other rounds of LSAPs and the adoption of a formal inflation target are associated with better anchoring of inflation expectations to varying degrees. Finally, we find inflation expectations have remained well anchored more recently (2017:Q3), returning to their pre-crisis behavior.

Section I defines the level, volatility, and persistence metrics as well as the data used to construct inflation expectations. Section II discusses the channels through which monetary policy can affect inflation expectations. Section III introduces a model for inflation expectations and analyzes how the Federal Reserve's monetary policy actions affected the anchoring of inflation expectations over the past decade.

## I. Measuring the Degree of Anchoring in Inflation Expectations

To evaluate the degree to which inflation expectations have been anchored over time, we first examine the level, volatility, and persistence that summarize their long-run predictive distribution.<sup>1</sup> These metrics allow us to quantify the degree to which inflation expectations are anchored. If the level of inflation expectations gets closer to the central bank's longer-run objective, for example, then inflation expectations are better anchored. If the volatility of inflation expectations declines, then inflation expectations are also better anchored. Finally, if unanticipated shocks to inflation expectations have less persistent effects over the long run, then inflation expectations are better anchored. All three metrics are consistent with the FOMC's interpretation of price stability in terms of "preventing persistent deviations of inflation from its longer-run objective."

Both financial market data and survey forecasts can be used to measure inflation expectations. One widely used, market-based measure of inflation expectations is the "breakeven inflation rate," calculated as the difference between yields on nominal U.S. Treasury bonds and Treasury Inflation-Protected Securities (TIPS) of the same maturity. The breakeven inflation rate reveals the additional compensation that bond market investors demand for putting money in nominal bonds whose value will decline in real terms with inflation. As the risk of higher future inflation increases, investors will demand more compensation, thereby driving down the prices of nominal bonds and driving up their yields relative to TIPS. Therefore, a higher breakeven rate suggests investors perceive a higher risk of future inflation. The advantage of using financial market data is that they provide high-frequency information about inflation expectations and are available at more horizons than survey data. However, they can also be contaminated by market-related factors other than inflation expectations, such as trading liquidity.

One alternative is to use direct observations of investors' inflation expectations from survey data. Since survey participants provide their actual inflation expectations, the data are not contaminated by other factors.<sup>2</sup> Additionally, inflation forecasts using survey data tend to generate more accurate out-of-sample forecasts than those using actual inflation data or financial market data (Ang, Bekaert, and Wei 2007; Faust and Wright 2013; Mertens 2016). However, available forecast horizons in survey data are limited compared with market-based measures.

Aruoba (2016) overcomes this shortcoming by fitting an inflation expectations curve, which plots the average inflation expected between today and any point three to 120 months in the future, with survey data from three different sources: the Survey of Professional Forecasters (SPF), Blue Chip Economic Indicators (BCEI), and Blue Chip Financial Forecasts (BCFF).<sup>3</sup> Table 1 summarizes the forecast horizons and frequency of collection and publication for all three surveys. One complication in combining data from these surveys is that the frequencies and forecast horizons differ significantly. To account for these differences, Aruoba (2016) starts out by assuming that the spot inflation expectations for a particular horizon (h), which represent the expected

Source	Frequency of publication	Frequency of forecasts	Horizons
Survey of Professional Forecasters	Quarterly	Quarterly, annual	-1 quarter to +4 quarters; current year to +2 years; average over +5 yrs, average over +10 years
Blue Chip Economic Indicators	Monthly	Quarterly, annual*	From current quarter** to +7 quarters; +5 years following next year, 5 year forward
Blue Chip Financial Forecasts	Monthly	Annual***	+5 years following next year, 5 year forward

## *Table 1* Survey Data Sources Used in the Inflation Expectations Curve

\* Annual forecasts only available in March and October issues

\*\* May also include previous quarter if currently in first month of a quarter

\*\*\* Annual forecast only available in June and December issues

Source: Aruoba (2016).

inflation averaged between the current period, (t), and a specific future period, (t+h), are spanned by three latent variables that vary at the monthly frequency.<sup>4</sup> In the fitted curve, any point in the spot inflation expectations curve is a function of the three latent variables. We estimate parameters and latent variables by matching the curve-implied forecasts of inflation with the observed median survey forecasts for consumer price index (CPI) inflation.<sup>5</sup>

Once we obtain the spot inflation expectations curve from Aruoba (2016), we can compute inflation expectations at any horizon, analogous to the five-year, five-year forward breakeven inflation measure. Since the spot inflation expectations curve spans multiple horizons, from three to 120 months, it can provide one-month-forward inflation expectations at any horizon from three to 119 months. For example, the value of the forward inflation expectations for the 12-month horizon at time *t* represents the expected inflation between t+12 and t+13. Chart 1 illustrates the spot inflation expectations curve and the corresponding one-month-forward inflation expectations curve as of October 2017. Each point on the spot inflation expectations curve shows the expected inflation between the current month and some point in the future-for example, the spot curve suggests that expected inflation would average a little over 2.1 percent between today and 60 months from now. The corresponding one-month-forward inflation expectations curve shows what expected inflation would be one-month ahead of that future point-for example, the expected inflation between month 60 and



## Chart 1 Inflation Expectations at Multiple Horizons

Notes: Each point on the spot inflation expectations curve shows what the expected inflation would be between the current month and the future month given by the horizon at the point. The corresponding one-month-forward inflation expectations curve shows what the one-month-ahead expected inflation would be from the horizon at the point. Sources: Federal Reserve Bank of Philadelphia and authors' calculations.

month 61. The flattening of the forward inflation expectations curve after 36 months suggests that inflation expectations beyond that horizon would converge to the long-run level in three years.

## II. Using Monetary Policy to Anchor Inflation Expectations

Changes in monetary policy can directly or indirectly affect all three metrics of anchored inflation expectations—level, volatility, and persistence. For instance, a central bank can directly affect the level of inflation expectations by announcing an explicit target rate for inflation. This action can, in turn, indirectly reduce the volatility of inflation expectations by reducing uncertainty about the central bank's intent. In addition, both the volatility and persistence of inflation expectations may decline if the central bank adjusts the nominal interest rate more aggressively to stabilize inflation around its target. If investors anticipate the central bank will respond aggressively to inflationary shocks, they may assume the effects of these shocks will dissipate sooner and set prices accordingly. As a result, actual inflation and inflation expectations will be less responsive to exogenous shocks (Davig and Doh 2014). Furthermore, the central bank can boost aggregate
demand and thereby push up inflation expectations by easing financial market conditions. Through these channels, monetary policy can affect both near-term and long-term inflation expectations.

Although monetary policy makers are mostly concerned about movements in long-term inflation expectations, they must also monitor fluctuations in near-term inflation expectations, which may spill over into long-term inflation expectations in the future.<sup>6</sup> Chart 2 plots two measures of inflation expectations—the two-year and 10-year inflation rates—along with the actual inflation rate from January 1998 to October 2017. Although two-year inflation expectations moved together with the actual inflation rate, 10-year inflation expectations remained relatively stable. Nonetheless, if movements in two-year inflation expectations spilled over into 10-year inflation expectations over time, the distribution of 10-year inflation expectations might shift.

Japan's experience in the 1990s provides a cautionary tale regarding this risk. While long-term (five-to-10 year) inflation expectations were quite stable in Japan during the late 1990s, near-term (one-year) inflation expectations often deviated quite noticeably on the downside. Actual inflation became negative from 1999 to 2003, tracking the plunge in short-run inflation expectations (Fuhrer 2017). Long-term inflation expectations eventually dropped below 1 percent in the early 2000s, concurrent with this prolonged period of deflation.<sup>7</sup> Japan's experience suggests substantial changes in near-term inflation expectations should be watched carefully, as they could augur similar changes in long-term inflation expectations.

Changes in monetary policy actions and inflation expectations in the United States over the past decade highlight how a concern for drifting inflation expectations shaped monetary policy. During the financial crisis of 2008, policymakers were concerned about the possibility of deflation and stagnation and took aggressive steps to avoid it. Table 2 summarizes the timing and purpose of the Fed's policy responses during this period, including multiple rounds of LSAPs intended to facilitate economic recovery by easing financial market conditions. Each of these unprecedented, aggressive policy responses had the potential to better anchor inflation expectations at the FOMC's implicit (before January 2012) or explicit (after January 2012) long-run target. In each statement that announced LSAPs, the FOMC acknowledged the risk that

# *Chart 2* Inflation Expectations and Actual Inflation



Note: Data are quarterly, constructed by taking three-month averages. Sources: Federal Reserve Bank of Philadelphia and U.S. Bureau of Labor Statistics (Haver Analytics).

# *Table 2* Timing of LSAPs and the Adoption of a Formal Inflation Target

Event	Date	Policy action announced
LSAP 1	March 2009	Fed purchases up to \$1.75 trillion in total assets, intended to "facilitate the extension of credit to households and small businesses."
LSAP 2	Nov. 2010	Fed purchases \$600 billion of longer-term Treasury securities to promote a stronger recovery and stable inflation.
Inflation target	Jan. 2012	FOMC adopts a 2 percent inflation target to keep inflation expectations "firmly anchored" and to uphold the Fed's statutory mandate.
LSAP 3	Sept. 2012	Fed increases holdings of long-term securities by \$85 billion per month to "increase policy accommodation."

Source: Board of Governors of the Federal Reserve System.

inflation might run below a rate consistent with stable prices. For instance, in the March 18, 2009 statement announcing the first round of LSAPs, the FOMC mentioned that it saw "some risk that inflation could persist for a time below rates that best foster economic growth and price stability in the longer term." The FOMC raised a similar concern in the statement announcing the second round of LSAPs, stating that "measures of underlying inflation have trended lower in recent quarters" (2010b). And the FOMC also mentioned a subdued outlook for inflation in the statement following the September 13, 2012 meeting that announced the third round of LSAPs: specifically, the Committee anticipated that "inflation over the medium term likely would run at or below its 2 percent objective."

However, the projected effect of LSAPs on inflation expectations was not without controversy. Although most FOMC participants saw the second round of LSAPs as helpful for lifting inflation expectations, some participants, such as then-Governor Kevin Warsh, expressed concern that the second round would increase the risk of future inflation and distortions in currency and capital markets without much effect on economic growth (FOMC 2010a).

In addition to multiple rounds of LSAPs, the adoption of a formal inflation target in January 2012 might also have affected the anchoring of inflation expectations. Although the FOMC announced the adoption of a formal inflation target in a consensus statement, academic researchers and policymakers had previously debated its merits. Some researchers argued that it would lower long-run inflation and provide more room for countercyclical stabilization policy by reducing concerns about the Federal Reserve's ability to achieve stable prices (Goodfriend 2005). But some policymakers resisted the idea of a formal inflation target, arguing that adopting a target would constrain policy flexibility in future contingencies with little additional benefit, given that long-run inflation expectations had been as stable in the United States as in other inflation-targeting countries, such as Sweden, since 1990 (Kohn 2005).

The Great Recession of 2007–09 enhanced the case for adopting a formal inflation target. Policymakers at that time wanted to make sure the Federal Reserve's credibility in achieving price stability had not eroded in a way that would hamper aggressive policy responses to stabilize the economy. As then-Chair Ben Bernanke noted during a press conference on January 25, 2012, the FOMC adopted a formal inflation target of 2 percent, measured by the price index for personal consumption expenditures (PCE), to "foster price stability" and "enhance the FOMC's ability to promote maximum employment in the face of significant economic disturbances." According to this view, LSAPs and the adoption of a formal inflation target were complementary measures to achieve the same goal of well-anchored inflation expectations.

To evaluate whether LSAPs and the adoption of the inflation target were indeed associated with well-anchored inflation expectations, we track the time variation in the degree of anchoring around these major monetary policy events in the subsequent analysis.

# III. Analyzing the Effect of Monetary Policy on Anchoring Inflation Expectations: Evidence from Survey Data

To quantitatively measure how well inflation expectations are anchored, we incorporate survey data information into an empirical macroeconomic forecasting model and use this model to predict future values of inflation expectations. While the model's predictions may differ from the current level of inflation expectations, the predicted future value of inflation expectations is still a relevant measure for monetary policy, as it may help a central bank take preemptive actions to reduce the risk of unanchored inflation expectations.

Anchored inflation expectations require inflation expectations to be stable not only at the current level but also in future projections. Therefore, we look at changes in the probability distribution of future projected values of inflation expectations to observe possible shifts in the degree of anchoring of inflation expectations. In general, characterizing changes in the distribution over time is a very challenging, complex task. However, the three metrics of anchored inflation expectations discussed in the previous section provide an effective way to summarize changes in the long-run predictive distribution. By associating the timing of shifts in these metrics with the timing of major changes in monetary policy—such as LSAPs and the adoption of a formal inflation target—we can examine whether policy changes helped long-term inflation expectations become better anchored.

We use two measures of inflation expectations in our estimated forecasting model to examine possible spillovers from changes in near-term inflation expectations to long-term expectations. We choose the 10-year and two-year inflation expectations from the spot inflation expectations curve in Aruoba (2016) as proxies for long-term inflation expectations and near-term inflation expectations, respectively. We choose 10-year expectations because 10 years is the longest horizon for which we can obtain survey data on inflation forecasts; we choose twoyear expectations because monetary policy typically affects inflation with a one-year lag (Svensson 1996). Our estimated forecasting model links future values of 10-year inflation expectations to the current and past values of two-year inflation expectations. Whether the two measures move together has implications for the degree of anchoring. If the current and past values of two-year inflation expectations influence 10-year inflation expectations, the persistence metrics for both horizons are likely to move together, because forecastable variations in two-year inflation expectations would show up as forecastable variations in 10year inflation expectations, too. In this way, increased persistence in two-year inflation expectations-an increased probability of inflation deviating from its long-run average level-would likely lead 10-year inflation expectations to become unanchored. However, if two-year inflation expectations do not influence 10-year inflation expectations, the two persistence metrics should move independently.

### A multivariate forecasting model of inflation and inflation expectations

We consider a vector autoregression model (VAR) of five macroeconomic variables to estimate the three metrics of anchored inflation expectations. Following Clark and Davig (2011), we use monthly observations for headline CPI inflation ( $\pi_t$ ) and the Chicago Fed National Activity Index (CFNAI, denoted  $a_t$ ) as well as the short-term interest rate ( $r_t$ ) and two-year ( $\pi_{t,2yr}^e$ ) and 10-year ( $\pi_{t,10yr}^e$ ) inflation expectations. To measure the stance of monetary policy when the federal funds rate was constrained at its effective lower bound, we use the estimated shadow rate in Doh and Choi (2016). This measure backs out the short-term interest rate implied by government and private borrowing conditions, including long-term rates, and is not constrained by the effective lower bound on the short-term interest rate.<sup>8</sup> Thus, the shadow rate can capture the additional monetary stimulus the Federal Reserve provided by influencing long-term interest rates through LSAPs and forward guidance on the future path of the short-term interest rate. When the short-term interest rate is not constrained by the effective lower bound, the shadow rate is highly correlated with the federal funds rate itself, making it a useful metric to capture the monetary policy stance both on and off the effective lower bound. In the VAR, we order inflation expectations before inflation, real activity, and the shadow rate.<sup>9</sup> The variables are summarized in the vector y:

$$\boldsymbol{y}_t = \left[ \boldsymbol{\pi}_{t,10\,yr,}^e \boldsymbol{\pi}_{t,2yr}^e, \boldsymbol{\pi}_t, \boldsymbol{a}_t, \boldsymbol{r}_t \right].$$

We transform monthly variables into quarterly variables by taking three-month average values of inflation and the activity index. Since our inflation expectations data are only available starting in January 1998, our sample period is 1998:Q1 to 2017:Q3. We estimate VAR(1) to obtain the three metrics of anchored inflation expectations.<sup>10</sup> The model can be written as:

$$y_{t} = A_{0,t} + A_{1t}y_{t-1} + \Sigma_{t} \in t, Var(\in t)$$

The five VAR residual shocks ( $\epsilon_t$ ) follow a multivariate normal distribution and are serially and cross-sectionally uncorrelated. The VAR coefficients ( $A_{a,t}, A_{1,t}$ ) and covariance matrix ( $\Sigma_t \Sigma_t'$ ) are time varying, because we estimate the VAR(1) for rolling samples of 40 quarters. In this way, we can identify the timing of shifts in the metrics of anchored inflation expectations.

## The anchoring of U.S. inflation expectations during the recent decade

From the estimated VAR model, we can derive a long-run predictive distribution of inflation expectations that provides information on the probabilities of possible future outcomes.<sup>11</sup> As the debates on LSAPs considered the future risk of inflation expectations drifting above the Federal Reserve's long-run objective, we use the long-run predictive distribution to quantify the probability of this risk.

Because the long-run predictive distribution considers the cumulative effects of future shocks, the range of possible outcomes is much wider than in the short-run predictive distribution. For this reason, we look at changes in the long-run predictive distribution of inflation expectations in our analysis. Furthermore, the long-run distribution allows us to see through the temporary effects of unanticipated shocks. Under our assumptions about the distribution of the VAR's residual shocks, the long-run predictive distribution is completely determined by the long-run mean and the long-run variance, which are closely related to the three metrics of anchored inflation expectations.<sup>12</sup>

The level metric can be equated with the long-run mean, while the volatility metric can be equated with the long-run variance. The persistence metric provides information on the factors driving the long-run variance. The long-run variance of inflation expectations may go up either because persistence goes up or because the range of potential shocks widens. In other words, by looking at the long-run variance metric together with the persistence metric, we can identify which factor drives the long-run variance metric. The distinction is relevant for policy, because monetary policy can reduce the long-run volatility of inflation expectations more effectively by influencing the parameters determining persistence than by influencing the volatility of unanticipated shocks, which are more likely to change for reasons other than monetary policy.

To assess whether inflation expectations became less anchored after the financial crisis, we first look at the level metric, defined as the mean of inflation expectations in the long-run predictive distribution. This value represents the central point around which future values of inflation expectations would fluctuate over a long time. A significant shift in the level metric would change the probability of inflation expectations crossing certain thresholds in the future, influencing the calculation of risks in both directions. The rolling-sample estimates of the VAR model provide time-varying estimates of this level metric, which we use to calculate the future risk of inflation expectations becoming unanchored.

Chart 3 shows the evolution of the model-implied, long-run mean values for both two-year and 10-year inflation expectations. The horizontal axis represents the timing of the last observation used in each sample. As the 40-quarter window rolls forward, estimates change due to changes in the rolling sample's first and last observations. For instance, the change in the level metric from the rolling sample ending in 2010:Q4 when the second round of LSAPs was adopted to the rolling sample ending in 2011:Q1 can be attributed to the deletion of the 2001:Q4 observation and the addition of the 2002:Q1 observation—only these two observations differ from the previous rolling sample.

Chart 3



# Long-Run Average and Current Values of Inflation Expectations

Note: "Level" represents the long-run mean from the VAR model, while "spot" describes the current value of the spot inflation expectations.

Sources: Federal Reserve Bank of Philadelphia and authors' calculations.

For this particular change in rolling samples, we find that estimates of the three metrics barely change even if we use an alternative rolling sample that adds the observation for 2011:Q1 but does not drop the initial observation from the previous rolling sample (2000:Q4). For the other rounds of LSAPs and the adoption of a formal inflation target, retaining the initial observation from the previous rolling sample produces changes in the metrics that are qualitatively similar but have some quantitative differences. Hence, we attribute changes in the metrics related to anchoring during these quarters to changes in the ending quarter rather than changes in the beginning quarter of rolling samples.

After the global financial crisis of 2008, the two-year and 10-year measures drifted down by 15 and 30 basis points, respectively, until 2010:Q3. However, both estimates recovered two-thirds of their declines by the start of the second round of LSAPs in 2010:Q4. Afterward, 10-year inflation expectations gradually declined by 10 basis points and stabilized at 2.33 percent as of 2017:Q3, while two-year inflation expectations experienced small ups and downs before stabilizing at 2.15 percent in the same quarter.

Because we derive our inflation expectations from CPI inflation forecasts, the overall level of inflation expectations is higher than the FOMC's 2 percent target, which is based on the PCE inflation rate. Haubrich and Millington (2014) suggest that the CPI inflation rate is about 0.5 percentage point higher than the PCE inflation rate on average. Therefore, the 2.33 percent CPI-based level of 10-year inflation expectations can be translated to 1.83 percent PCE-based inflation, a level close to but lower than the 2 percent target.

The level metric of inflation expectations suggests that the second round of LSAPs coincided with the reversal of a downward trend in inflation expectations. Chart 3 shows that our level metric declined more than the corresponding spot value of inflation expectations around this time, suggesting spot values underestimate the extent to which inflation expectations became unanchored. Interestingly, announcing a formal inflation target barely moved the long-run mean value of 10-year inflation expectations. One explanation for this subdued response is that the announced 2 percent target of PCE inflation was roughly consistent with a CPI inflation rate of about 2.4 percent, which was the long-run mean of 10-year inflation expectations at the time, suggesting that the average level of long-run inflation expectations was already anchored around 2 percent.

The volatility metric of 10-year inflation expectations declined substantially over the past decade, suggesting inflation expectations have become better anchored more recently. To compute this metric, we calculate the model-implied long-run standard deviations of inflation expectations. These statistics likely capture how much the future outcomes of inflation expectations will vary over a long time. Chart 4 shows that the volatilities of inflation expectations jumped in 2009:Q1 and 2010:Q4 (corresponding to the first and second round of LSAPs, respectively) but dropped quickly after. Given the lag in collecting survey responses, however, the effect of LSAPs on the inflation expectations of survey participants is more likely to show up in the following quarters (2009:Q2 and 2011:Q1).<sup>13</sup> Hence, the timing of changes in the volatility metric may be consistent with the interpretation that the start of LSAPs led survey participants to revise their expectations. Overall, the volatility of 10-year inflation expectations declined by 49 percent from the start of the sample ending in 2008:Q1 to the sample ending in 2017:Q3. For comparison, the level metric declined by only 4 percent. The more substantial decline in the volatility metric relative to the level metric implies



# Chart 4 Long-Run Volatility of Inflation Expectations

that the risk of inflation expectations surging or plummeting has been significantly reduced.

By combining the level and volatility metrics, we can calculate the probability of any future outcome for inflation expectations. In this way, we can use the probability of inflation falling below a certain threshold—1 percent for the PCE inflation rate or 1.5 percent for our CPI inflation measure-to measure whether inflation expectations have become unanchored.<sup>14</sup> Chart 5 shows that the probability of inflation falling below the CPI threshold was negligible (below 1 percent) for 10-year inflation expectations throughout the past decade. The probability was similarly negligible for two-year inflation expectations much of the past decade-for the rolling sample ending in 2010:Q4, however, the probability of two-year expectations falling below 1.5 percent spiked to 21 percent before declining again to a negligible level by 2011:Q3. Taken together, however, our estimates of the levels and volatilities in the longrun predictive distribution of inflation expectations suggest that the second round of LSAPs was associated with a large reduction in the risk of inflation expectations falling substantially below the FOMC's target.

Finally, we look at the persistence of inflation expectations as a measure of anchoring. The persistence of a variable in a multivariate



# model is often measured by the variable's model-implied predictability (R<sup>2</sup>), which is the relative magnitude of predictable variation to total variation.<sup>15</sup> If shock volatility is unchanged, a higher predictability means that a temporary shock can trigger persistent deviations of inflation expectations from their long-run means.

Although the level and volatility of inflation expectations at the two different horizons generally co-moved over our sample, the persistence (or predictability) of two-year and 10-year inflation expectations differed significantly. Chart 6 shows the evolution of this metric for both two-year and 10-year inflation expectations. While the predictability of two-year inflation expectations fluctuated closely around the magnitude that prevailed during the pre-crisis sample period, the predictability of 10-year inflation expectations fell dramatically after 2010:Q4, when the second round of LSAPs began. The downward trend continued after the second round of LSAPs ended in June 2011 and after the adoption of a formal inflation target in 2012. This discrepancy in the predictabilities of 10-year and two-year inflation expectations implies that fluctuations in two-year inflation expectations became less important over time in explaining fluctuations in 10-year inflation

Chart 5

Chart 6



# Percentage of Forecastable Variations for Inflation Expectations

Note: "Predictability" represents the percentage of variations in inflation expectations that are forecastable by the VAR model.



expectations—in other words, the spillovers from short-term to long-term inflation expectations diminished.

The timing of the shifts in the persistence of long-term inflation expectations suggests that the announcement of a formal inflation target as well as multiple rounds of LSAPs contributed to better anchored inflation expectations.<sup>16</sup> Overall, the timing of shifts in the three metrics (level, volatility, and persistence) of the anchoring of inflation expectations suggests that the second round of LSAPs was consequential in reversing the downward drift in inflation expectations. Other policy actions, such as the first round of LSAPs and the adoption of a formal inflation target, were also largely consistent with the timing of shifts in the volatility and persistence metrics toward better anchoring. While the realized value of long-term inflation expectations might have changed little during the recent decade, our time-varying estimates show that the model-implied distribution of inflation expectations has changed significantly at certain times. Our analysis is consistent with the view that the Federal Reserve's actions, such as LSAPs and the adoption of a formal inflation target, led to better anchored inflation expectations. Furthermore, we do not find any meaningful evidence that the anchoring of inflation expectations in

2017:Q3, the final quarter for our sample, deteriorated relative to the degree of anchoring in the pre-crisis period.

Our results may seem to conflict with Reis (2016), who finds little change in inflation expectations around the announcement of the second round of LSAPs. Reis's analysis uses an event study methodology and inflation swap market data to back out the distribution of inflation expectations. We attribute the difference in our results mostly to the fact that financial markets already anticipated the second round of LSAPs before the November 3, 2010 announcement. Indeed, breakeven inflation and other market-based inflation measures of inflation expectations jumped after August 27, 2010, when then-Chair Bernanke strongly suggested the possibility of additional asset purchases.<sup>17</sup>

#### **IV.** Conclusion

Inflation expectations have become better anchored in the United States during the past decade. We use three different metrics (level, volatility, and persistence) to quantify the degree of anchoring in inflation expectations and find that the timing of shifts in these metrics is associated with the Federal Reserve's unconventional policy actions. Our findings are consistent with the interpretation that the second round of LSAPs, which the Federal Reserve began in November 2010, was significant in preventing long-term inflation expectations from drifting down. In addition, the timing of shifts in the volatility and persistence metrics of inflation expectations is consistent with the interpretation that other rounds of LSAPs and the adoption of a formal inflation target also helped reduce the volatility and persistence of long-term inflation expectations. In general, our results as of 2017:Q3 suggest that inflation expectations have not become less anchored after the financial crisis and Great Recession when compared with their pre-crisis level. In particular, our results suggest the Federal Reserve's policies during the recent decade may have played a role in keeping them that way.

### Appendix A

#### **Constructing the Inflation Expectations Curve**

The inflation expectations curve describes the expected inflation averaged from the current period until a particular time horizon. If we define  $\pi_t(\tau)$  as the inflation expectations from the end of month *t* to the end of month  $t + \tau$ , Aruoba (2016) fits the following Nelson-Siegel (1987) yield curve for  $\pi_t(\tau)$ :

$$\pi_t(\tau) = L_t - \left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau}\right) S_t + \left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau} - e^{-\lambda \tau}\right) C_t, \quad (A-1)$$

where  $L_t$ ,  $S_t$ ,  $C_t$  are assumed to follow independent autoregressive processes of the third order (AR[3]) and are interpreted as the level, slope, and curvature factor, respectively, given  $\lambda$ .

Aruoba (2016) obtains 59 inflation forecasts,  $x_t$ , by combining quarterly, annual, five-year, and 10-year forecasts from the SPF with quarterly and long-range forecasts from BCEI and BCFI. At each point in time, inflation forecasts in survey data can be well approximated by a linear function of various components in the inflation expectations curve, because we can construct the forward inflation expectations curve from  $t + \tau$  to  $t + \tau + 1$  ( $\pi_{t+\tau \to t+\tau+1}$ ) by  $(t + \tau + 1)\pi_t(t + \tau + 1) - (t + \tau)\pi_t(t + \tau)$ . By using information in the forward inflation expectations curve, we can match any inflation forecast at any horizon included in different surveys.

For instance, BCFFs ask participants for their forecasts for fouryear-ahead "year-over-year" inflation  $(x_t^{4y,1y})$ . Since the assumed time unit in the inflation expectations curve is one month, we can calculate the annual forward inflation at each month  $(\pi_{t+\tau \rightarrow t+\tau+12})$  from the curve by summing monthly forward inflation forecasts during a year. To match the fact that survey data cover "year-over-year" inflation forecasts, Aruoba (2016) takes the average of annual forward inflation expectations during the 12 months four years from the current year. If survey data are obtained at March of any given year, we can construct the following variable from the inflation expectations curve to match the data:

$$x_t^{4y,1y} = \frac{1}{12} \sum_{s=46}^{57} \pi_{t+s\to t+s+12}^{18}.$$
 (A-2)

We can specify similar measurement equations for other survey forecasts, too. For the actual estimation, we add measurement errors that follow mean-zero normal distributions to survey forecasts. The resulting equation is:

$$x_t = Z\alpha_t + \epsilon_t, \ \epsilon_t \sim \mathcal{N}(0, H), \tag{A-3}$$

where  $\alpha_t = [L_t S_t C_t L_{t-1} S_{t-1} C_{t-1} L_{t-2} S_{t-2} C_{t-2}]$  and  $\alpha_t$  evolves according to

$$(\boldsymbol{\alpha}_{t}-\boldsymbol{\mu})=T\left(\boldsymbol{\alpha}_{t-1}-\boldsymbol{\mu}\right)+\boldsymbol{\eta}_{t},\boldsymbol{\eta}_{t}\sim N\left(0,Q\right). \tag{A-4}$$

Since (A-3) and (A-4) represent a linear and Gaussian state-space model, all the model parameters can be estimated by the maximum likelihood method using the Kalman filter. Once we obtain parameter estimates, we can back out the estimate for  $\alpha_t$  and construct the inflation expectations curve at time *t* using that information.

#### Appendix B

#### **Alternative Measures of Long-Term Inflation Expectations**

One potential caveat to our results is that our measure of longterm inflation expectations considers inflation averaged over 10 years, a window sufficiently short for a temporary but moderately persistent shock to influence inflation expectations. In contrast, a forward inflation expectations measure, such as expected inflation eight to 10 years from now, is insulated from a temporary shock, because it is outside a typical business cycle frequency of six to 32 quarters (Burns and Mitchell 1946). To check the robustness of our findings against this alternative measure of long-run inflation expectations, we calculate eight-year, two-year forward inflation ( $\pi^e_{t,8yr2yr}$ ) from the inflation expectations curve in Aruoba (2016). We recompute the three metrics of anchored inflation expectations with eight-year, two-year forward inflation as a proxy for long-term inflation expectations.

As Charts B-1 through B-3 illustrate, the overall pattern of the time variation in the three metrics is largely consistent with our previous analysis. Specifically, the significant shifts in the three metrics toward better-anchored inflation expectations coincide with the second round of LSAPs. The other rounds of LSAPs and the adoption of a formal inflation target are also associated with shifts in the volatility and predictability metrics toward better-anchored inflation expectations. However, one notable difference is the run-up in the predictability metric of the 10-year inflation expectations near the end of the sample period. Still, the degree of predictability remains lower than its value during the precrisis period and does not indicate any material deterioration in the anchoring of inflation expectations.





the eight-year, two-year forward inflation expectations. Sources: Federal Reserve Bank of Philadelphia and authors' calculations.

# *Chart B-2* Long-Run Volatility of Forward Inflation Expectations



Note: "Volatility" represents the long-run standard deviation from the VAR model. Sources: Federal Reserve Bank of Philadelphia and authors' calculations.





Note: "Predictability" represents the percentage of variations in inflation expectations that are forecastable by the VAR model.

Sources: Federal Reserve Bank of Philadelphia and authors' calculations.

#### Endnotes

<sup>1</sup>Kumar and others (2015) define five statistics to measure the degree of anchoring in inflation expectations based on individual responses to a survey: 1) the average expectation of each individual forecaster, 2) the cross-sectional dispersion in individual forecasts, 3) uncertainty in each individual's forecast, 4) the magnitude of forecast revision, and 5) the predictability of long-run expectations using shortrun expectations. Although we do not consider the cross-sectional dispersion of forecasts because we focus on median forecasts, the four other statistics are strongly connected with our level (1), volatility (3), and persistence measures (4, 5).

<sup>2</sup>In fact, Andreasen and Christensen (2017) show that breakeven inflation measures are more correlated with survey-based measures of inflation expectations after adjusting for liquidity-related factors.

<sup>3</sup>Kozicki and Tinsley (2012) and Chernov and Mueller (2012) construct the term structure of inflation expectations using alternative methods. We choose to use Aruoba (2016)'s dataset because Kozicki and Tinsley (2012) rely on only one survey dataset (the Livingston Survey) and while the no-arbitrage term structure model used in Chernov and Mueller (2012) is theoretically appealing, it is not robust to the misspecification of the asset pricing model used in the paper. Aruoba (2016)'s data on inflation expectations are available on the Federal Reserve Bank of Philadelphia's website (https://www.philadelphiafed.org/research-and-data/real-time-center/atsix).

<sup>4</sup>The three variables are called "level," "slope," and "curvature," because empirical proxies for these factors are closely related to the average across different horizons, the difference between the long end of the curve and the short end of the curve, and the change in the slope of the curve, respectively. Further details on the construction of the inflation expectations curve are provided in Appendix A.

<sup>5</sup>Since the inflation expectations curve fits only median forecasts, it ignores the cross-sectional dispersion of inflation forecasts among survey participants, which may reduce the uncertainty surrounding inflation expectations. Williams (2003) attributes most of the cross-sectional dispersion in forecasts to the fact that each participant may use a different model that the available data cannot convincingly reject. Although this model uncertainty may be important, it is beyond the scope of our article.

<sup>6</sup>Policymakers may monitor spillover risk by looking at the evolution of forward inflation expectations above certain horizons instead of long-horizon inflation expectations. Since the forward inflation measure strips away short-term fluctuations, this measure may provide a cleaner proxy for anchored long-term inflation expectations.

<sup>7</sup>While Japan again experienced persistent deflation from 2009 to 2012 after the global financial crisis, long-term inflation expectations remained stable around 1 percent during this period, perhaps reflecting unconventional policies adopted by major central banks around the world. However, the international repercussions of the Federal Reserve's policies are beyond the scope of this article.

<sup>8</sup>The construction of this measure relies on the assumption that the historical relationship between the short-term interest rate and long-term rates that prevailed before the federal funds rate reached its effective lower bound would be maintained once the effective lower bound became a binding constraint.

<sup>9</sup>This ordering follows Clark and Davig (2011), who identify a monetary policy shock from its lagged effect on the real economy and inflation. However, in this article, we do not focus on the identification of a structural shock, and the ordering does not matter much in our discussion of changes in metrics related to well-anchored inflation expectations.

<sup>10</sup>The VAR contains only one lag of the five variables. Longer lags would introduce too many additional parameters, since we use only 40 quarters of data in the rolling-sample estimation. We also estimate a model with two lags and find that the changes in our metrics of anchored expectations are essentially the same.

<sup>11</sup>Whether the linear and Gaussian VAR(1) model can adequately capture the probabilities of tail events is unclear. One way to address this concern is to introduce nonlinearities explicitly using a time-varying parameter VAR(1) model in which VAR coefficients are assumed to follow random walk processes. Our rolling sample estimation approximates a time-varying parameter VAR(1) model in a simple way by allowing changes in the stationary distribution of the model each period. In fact, our volatility estimate of 10-year inflation expectations at the first rolling sample ending in 2008:Q4 is consistent with the volatility estimate of 10-year inflation expectations in Clark and Davig (2011), who estimate a timevarying parameter VAR model.

<sup>12</sup>Technically, any normal distribution is fully characterized by the mean and the variance. In our case, the long-run mean of  $y_t$  is  $(I_5 - A_{1,t})^{-1} A_{0,t}$ , and the long-run variance is  $\sum_{j=0}^{\infty} A_{1,t}^j \sum_t \sum_t A_{1,t}^{j'}$ .

<sup>13</sup>Our interpretation linking the timing of the change in the volatility metric with LSAPs is also consistent with the month-to-month shift in the inflation expectations curve around LSAP events in Aruoba (2016).

<sup>14</sup>The comparable upside risk that inflation expectations would cross 3.5 percent was negligible throughout the past decade for both 10-year and two-year inflation expectations. Therefore, we omit a detailed discussion of the upside risk.

<sup>15</sup>Of course, if inflation expectations were constant without any variation, this metric would not be well defined, because the denominator (total variation) would be zero. However, constant inflation expectations with no future variation would be a very strong assumption. More realistically, we can assume the total predictable variation is zero under well-anchored inflation expectations but with non-zero chances for them to change in the future due to unanticipated shocks. In this case, the predictability is zero, in line with our definition of well-anchored inflation expectations.

<sup>16</sup>Our finding about the timing of the shift in the predictability metric after the adoption of a formal inflation target is consistent with Bundick and Smith (2018), who find that the sensitivity of long-horizon-forward breakeven inflation to surprise news in realized inflation declined after the adoption of a formal inflation target. In both cases, forecastable variations in the long-run inflation expectations declined. Our findings are also robust to the use of long-horizon-forward inflation instead of 10-year inflation expectations, as shown in Appendix B.

<sup>17</sup>This interpretation is consistent with Chart 6 of Reis (2016, p. 447).

<sup>18</sup>This derivation relies on the approximation using continuous compounding and geometric averaging as discussed in the appendix of Aruoba (2016).

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# Structural and Cyclical Trends in the Supplemental Nutrition Assistance Program

## By Kelly D. Edmiston

Program (SNAP), formerly known as the Food Stamp Program, has increased sharply over the past 20 years. Average monthly participation grew from 17.3 million people in 2001 to a peak of 47.6 million people in 2013. Although participation declined somewhat as the economy recovered from the Great Recession—dropping to 41.7 million people in November 2017—this decline failed to offset the program's rapid growth over the past 10 years. SNAP participation remains well above its pre-recession level of 25.9 million people, suggesting longer-term structural forces may be driving its trend.

Understanding the forces driving SNAP participation is important for several reasons. First, SNAP is an important safety net during economic downturns, as it allows unemployed individuals and others with reduced incomes to continue to purchase food. Second, SNAP is also a critical component of the package of public assistance programs available to support low-income individuals and families. Third, because eligibility for SNAP is almost exclusively based on income, SNAP participation is often considered an "automatic stabilizer," rising when economic conditions deteriorate and falling when the economy is growing. But continued high levels of SNAP participation far into the recovery from the

Kelly D. Edmiston is a senior economist at the Federal Reserve Bank of Kansas City. This article is on the bank's website at **www.KansasCityFed.org**  Great Recession suggest its efficacy as an automatic stabilizer may have changed, further motivating an analysis of its underlying forces.

In this article, I investigate the forces driving long-term patterns in SNAP participation as well as its cyclical variation. I find that three structural factors—legislative and programmatic changes, poverty, and a rising share of the working population not in the labor force—have made the largest contributions to SNAP participation. However, I also find that cyclical factors played a relatively large role in driving participation during the Great Recession. Together, the structural and cyclical factors I examine explain over 63 percent of the observed pattern in SNAP participation.

Section I reviews the SNAP program, including factors that determine eligibility and benefit levels, and discusses the rate of growth in the program. Section II discusses multiple factors that determine SNAP participation. Section III analyzes the relative contribution of these factors in a statistical framework.

# I. SNAP Eligibility, Benefits, and Growth

Although SNAP is part of an extensive set of federal food and nutrition programs, it is unique in both size and structure. First, SNAP is the largest nutrition assistance program, exceeding other nutrition programs in both participation and cost. In 2017, a monthly average of 42.1 million people—12.9 percent of the resident population—received SNAP benefits at a cost of \$68 billion.<sup>1</sup> By comparison, the next largest program, the National School Lunch Program, served 30 million students-roughly 44 percent of the school-age population-and cost \$12.2 billion (U.S. Department of Agriculture [USDA] Food and Nutrition Service 2018a, 2018b).<sup>2</sup> Second, eligibility for SNAP is based on income and asset limits, and, unlike most other public assistance programs, has no nonpecuniary requirements, such as the presence of children in the household. Under federal rules, eligibility for SNAP benefits requires households to meet specific criteria, although there are comparatively few of them. Typically, households must fall below certain gross income limits, net income limits, and asset limits (see box).

SNAP benefits are intended to fill the gap between a needs standard and cash resources available to purchase food. Benefits are tied to the USDA's Thrifty Food Plan, which is designed to provide adequate

#### Box

# **SNAP Eligibility**

SNAP eligibility depends on gross income, net incomegross income less certain deductions—and assets. To qualify for SNAP benefits, a household's gross monthly income cannot exceed 130 percent of the poverty guideline, and its net monthly income cannot exceed 100 percent of the poverty guideline, which is determined by family size. As of 2017, a household's gross monthly income cannot exceed \$1,307 for a one-person household and \$2,212 for a three-person household. In addition, a household's net income cannot exceed \$1,005 monthly for an individual and \$1,702 monthly for a three-person household.

In calculating net income, households can deduct 20 percent of earned income, excess shelter costs (amount of rent or payment over half of household income), a standard deduction determined by the size of the household, and several other, specific items such as dependent care and medical care from their gross income. Net income is pre-tax cash income and therefore does not include in-kind assistance such as housing, which could be substantial, or tax credits such as the Earned Income Tax Credit.

In addition to income limitations, households must fall below certain asset thresholds. Generally, households may have only \$2,250 or less in countable resources (\$3,250 if age 60 or older). However, many resources are exempt. Not included in the asset calculation are homes, the resources of those on Supplemental Security Income (SSI), the resources of those who receive Temporary Assistance for Needy Families (TANF), and most retirement and pension plans. In addition, SNAP has a standard auto exemption of \$4,650, but 42 states exempt larger amounts, and 39 of these states exempt the entire value of vehicles. Regardless of the size of the exemption, exempted articles such as vehicles are subject to federal restrictions on how they are used.



# Chart 1 SNAP Participation

nutrition at minimum cost (USDA Center for Nutrition Policy and Promotion 2018). Those with no income receive the maximum benefit. Those with income have their benefits reduced by 30 percent of their net income (as measured for SNAP eligibility). For example, the maximum benefit for a three-person household with no income in 2018 is \$504 per month. If the household were to receive \$1,000 monthly in net income, its SNAP benefit would fall to \$504 - 0.3(\$1,000) = \$204 per month.

SNAP participation was relatively stable until 2001 but has since climbed significantly higher. Chart 1 shows overall participation in SNAP from 1975 to 2017.<sup>3</sup> From 1975 to 2001, SNAP participation increased, on average, by 14,000 per month. But starting in 2001, participation increased by an average rate of 184,000 per month. The rate of increase accelerated during the Great Recession and early recovery.

While most of the increase in SNAP participation can be attributed to increased eligibility, a smaller, but significant amount of the increase can also be attributed to a higher take-up rate—that is, a higher share of eligible individuals and households participating in the program (Ganong and Liebman 2013). The apparent "break" in SNAP participation's long-term pattern in 2001 is due in part to the implementation of policies that eased access to SNAP. Once these policies took effect, the take-up rate increased from about 54 percent of eligible households in 2001 to about 69 percent in 2006 (Eslami, Leftin, and Strayer 2012). Overall, the increase in the take-up rate contributed 15 percentage points to the 46 percent increase in participation over that period, roughly one-third of the total increase. But two-thirds of that increase remains unexplained, potentially driven by both structural and cyclical factors.

## **II.** Factors Affecting SNAP Participation

If SNAP-related legislation, program rules, eligibility, and the distribution of income were fixed—and the economy experienced no cyclical fluctuations—SNAP participation would be expected to follow a consistent long-term trend as some fraction of the population. But of course, all of these factors have changed over time: the distribution of income has changed, SNAP has undergone a series of significant legislative and programmatic changes, and the labor market has experienced structural change—specifically, in labor force participation. Moreover, the economy has expanded and contracted over time, with an especially deep recession in 2007–09. Each of these factors could credibly affect SNAP participation.

The limited prior research on this topic points to several of these factors as explanations for SNAP participation. Ganong and Liebman (2013) use family-level data from the Survey of Income and Program Participation (SIPP) and county-level data to show that local unemployment can explain roughly two-thirds of the increase in SNAP enrollment from 2007 to 2011 (see also Hanson and Oliveira 2012). They find relaxed income and asset thresholds and temporary changes in program rules for childless adults explain another 18 percent (see also Mulligan 2012). In addition, they find welfare reform significantly reduced SNAP take-up rates, while mid-2000s policies designed to ease access to SNAP increased them.

Rutledge and Wu (2014) use administrative data and the SIPP in a study of both SNAP and SSI. The authors argue that the continued expansion of both SNAP and SSI participation following the Great Recession—even as unemployment fell—resulted from a persistent poverty rate and an increased share of the population reporting poor or fair health.

I extend previous research in several ways. First, I examine a much longer time series for SNAP, analyzing the data from July 1974 to

December 2016. Ganong and Liebman (2013), by comparison, evaluate the welfare reform era, the "Bush era" of 2001–07, and the Great Recession era separately. Second, I look at a much wider set of legislative and programmatic changes to SNAP. Third, I treat short-term and long-term unemployment as separate phenomena and consider other structural changes in the labor market as well. To identify the most significant factors affecting SNAP participation, I consider a variety of factors that may affect the long-term trend in SNAP participation or its cyclical variation.

#### Population

One likely reason why SNAP participation has increased over time is that the resident population has increased substantially—by 63 percent since 1969. The raw correlation between population and SNAP participation is 0.82. When adjusted for population, annual growth in SNAP from 1974 to 2016 declines from 3.1 percent to 2.1 percent.

### People in poverty

The income test for qualifying for SNAP benefits is income relative to the poverty threshold. Specifically, households must have gross incomes less than 130 percent of the poverty threshold and net incomes (gross income less a number of deductions) less than 100 percent of the poverty threshold.

The poverty threshold is a needs-based measure derived from the cost of a minimum food diet multiplied by 3. In 2017, the poverty threshold was \$19,749 for a household of three with two related children under 18. The poverty threshold changes over time and moves closely with the Consumer Price Index (CPI), of which food cost is a significant component. Adjusting for changes in the CPI, the poverty threshold has remained around \$19,730 (in 2017 dollars) since 1986, except for a \$20 bump up in 2016.

While the poverty threshold has been relatively stable, rates of poverty change over time. Poverty rates are partly cyclical, but structural factors, including some policies, drive the long-term trend in poverty. What is most important for my analysis is the number of people who are in poverty, which would be expected to be a primary driver of SNAP participation. The number of people in poverty rose sharply during the Great Recession and stayed historically high through 2014, when it



peaked at 46.7 million (Chart 2). Over time, the number of people in poverty has increased at an annual rate of 1.3 percent per year. In 2016, 40.6 million people were in households below the poverty threshold.

## Labor force nonparticipation

Labor force nonparticipation is another important driver of SNAP participation. Excepting transfers, most income earned by households in lower-income quantiles is from labor.<sup>4</sup> Thus, a change in the number of workers in the labor force could lead to a change in SNAP participation. A changing number of workers may be due to structural changes, such as an aging workforce, or cyclical changes, such as a recession that leads to layoffs. To account for structural changes in the labor force, I examine the number of individuals who are considered "not in the labor force" (NILF)—that is, those who are not employed and not currently looking for work.<sup>5</sup>

Accounting for these people is important, as many of them are eligible for SNAP. For example, most retirees who rely on Social Security benefits for all or nearly all of their income would qualify for SNAP on a gross income basis.<sup>6</sup> Others who are NILF have a disability or other situation that prevents them from working. Among adults age 21–64, about 59 percent of those with a disability do not work, compared with 21 percent of those without a disability (U.S. Census

Bureau 2012). Most of those with qualifying disabilities who do not work receive income through the Social Security Disability Insurance or SSI programs—but for some, this income is sufficiently low to also qualify for SNAP benefits. Moreover, SSI is not included in SNAP calculations (Social Security Administration 2017). Finally, some people who are out of the labor force would like a job but are technically unattached to the labor force because they have not looked for work in the past month. Many of those out of work for long periods likely have exhausted financial resources and may qualify for SNAP.

In October 2017, the labor force nonparticipation rate (NILFR) was 37.3 percent, significantly higher than the NILFR of 33.8 percent in 2007, just prior to the Great Recession. The rise in labor force nonparticipation was much faster than its long-term trend would predict, with cyclical factors accounting for 50 percent of the increase (Van Zandweghe 2012).<sup>7</sup> Still, the cyclical component of NILF is usually relatively small in magnitude. As a result, I focus on the structural component of labor force nonparticipation, which is based on its long-term trend as estimated by Van Zandweghe.

#### Legislative and programmatic changes

SNAP has undergone various legislative and programmatic changes since its inception, each of which has the potential to affect participation. Chart 3 shows a detailed outline of legislative and programmatic changes to SNAP from 1974 to 2016. The trend in SNAP participation is consistent with the developments in legislation, rules, and regulations.

At the beginning of the original Food Stamp Program (FSP), participation was modest.<sup>8</sup> In April 1965, approximately half a million people participated. As more states adopted the program, participation gradually expanded. The 1973 Agriculture and Consumer Protection Act required all states to have the FSP in place by 1975. By July 1974, all states had complied—and by October 1974, participation had increased to 15 million.

In 1977, Congress passed the Food Stamp Act of 1977. The most significant aspect of the Food Stamp Act was the elimination of the "purchase requirement" from the FSP, which required recipients to, in some sense, pay for their food stamps. An example from a *New York* 



# *Chart 3* Legislative and Programmatic Changes to SNAP

Notes: [1] Program is nationwide as of July 1974; [2] Purchase requirement eliminated; [3] Hunger Prevention Act of 1988; [4] Mickey Leland Memorial Domestic Hunger Relief Act of 1990; [5] Personal Responsibility and Work Opportunity Reconciliation Act ("welfare reform bill"); [6] 2002 Farm Bill; [7] American Recovery and Reinvestment Act of 2009 (ARRA). Shaded region denotes temporary increase in SNAP benefits from April 2009 to November 2013.

Source: USDA Food and Nutrition Service.

*Times* article at the time considered a family of four earning \$300 per month (Hicks 1977). The family might set aside 30 percent of their income, or \$90, to purchase food. It would give the government \$90 for \$106 in food stamps. Those in favor of eliminating the purchase requirement argued that some recipients might be too poor to pay for food stamps. But others were concerned that without the purchase requirement, the FSP might incur more fraud or that the program would be viewed (rightly or wrongly) as a traditional "welfare" program. The purchase requirement was eliminated effective January 1, 1979, and participation in the FSP increased immediately and significantly.

The next significant piece of legislation that led to increased participation was the Mickey Leland Memorial Domestic Hunger Relief Act of 1990 (the Leland Act). Among the Leland Act's most substantial provisions was an increase in the average SNAP benefit (USDA 1990). In addition, the Leland Act offered additional education and training opportunities and expanded FSP eligibility by adding asset exclusions, such as vehicles, as well as exclusions in the determination of net income. Although the economy entered a recession in 1990 followed by an anemic job recovery, the increase in FSP participation over the period was larger than the economic cycle alone would predict (Wiseman 2002). Unlike most of the previous legislative changes to the FSP, the 1996 Personal Responsibility and Work Opportunity Reconciliation Act (more commonly known as "welfare reform") significantly reduced participation in the program. Among the most substantial provisions the Act introduced was a 36-month time limit for able-bodied adults without dependents and a freeze of the standard deduction (used to determine net income), vehicle limits, and maximum benefit. FSP participation fell from 26.3 million residents in 1995 to 22 million in 1997 to 17.1 million by 2000.

Finally, the American Recovery and Reinvestment Act (ARRA), commonly known as the "stimulus bill," was passed in 2009 in an effort to jump-start the struggling economy during the depths of the Great Recession. ARRA provided for a temporary increase in SNAP benefits from April 2009 until November 2013. The average benefit, adjusted for inflation, increased from \$116.34 per recipient per month in 2008 to \$143.17 in 2009 to \$150.40 in 2010. Inflation-adjusted average benefit fell to \$129.44 in 2013 as the temporary fiscal stimulus was unwound. Average monthly participation also increased from 28.2 million in 2008 to 33.5 million in 2009. By 2013, average monthly participation had reached 47.6 million. Because the ARRA was a temporary, direct response to a recession, I treat it as a cyclical factor in the analysis, separate from the other legislative and programmatic changes, which are structural.

### Unemployment

As SNAP is a social safety net, participation would be expected to rise when unemployment rises. Likewise, SNAP participation would be expected to fall when unemployment declines. For the most part, this is the observed relationship, particularly during recessions—though in general, SNAP participation does not peak until months after the unemployment rate peaks. Chart 4 shows that this lagged relationship holds in expansions as well: although the unemployment rate began to fall in October 2009, SNAP participation did not begin to tick down until October 2012.

One explanation for this lag is that it takes time for unemployed people to exhaust their financial resources, including unemployment compensation and personal savings, before they qualify for or



# *Chart 4* SNAP Participation and the Unemployment Rate

enroll in SNAP. As a result, the long-term component of the unemployment rate may be more closely tied to SNAP participation than the short-term component of the unemployment rate.

The U.S. Bureau of Labor Statistics uses six months as a yardstick for long-term unemployment. I express the long-term component of the unemployment rate as a long-term unemployment rate (that is, the number of people unemployed for more than six months as a share of the total labor force). Similarly, I express the shortterm component as a short-term unemployment rate (the number of people unemployed for six months or less as a share of the total labor force). The headline unemployment rate, known as U3, is the sum of the long-term unemployment rate and the short-term unemployment rate.

Chart 5 shows that while the short-term and long-term unemployment rates move with the business cycle, long-term unemployment typically peaks after short-term unemployment. In addition, during the Great Recession, the long-term unemployment rate increased proportionally more than short-term unemployment rates. Specifically, the long-term unemployment rate tripled, while the short-term unemployment rate did not quite double. After the recession, long-term unemployment continued to expand through 2010



# *Chart 5* Short-Term and Long-Term Unemployment Rates

Notes: The short-term unemployment rate is the share of the labor force that has been unemployed for less than 27 weeks. The long-term unemployment rate is the share of the labor force that has been unemployed for 27 weeks or more. The short-term and long-term unemployment rates sum to the "headline unemployment rate," or U3. Gray bars denote NBER-defined recessions. Sources: U.S. Bureau of Labor Statistics (Haver Analytics), NBER, and author's calculations.

while short-term unemployment declined. Long-term unemployment did not decline appreciably until late 2011. Earlier recessions show similar patterns. In the subsequent analysis, I consider the short-term and long-term unemployment rates separately.<sup>9</sup>

# III. Relative Contribution of Factors to SNAP Participation Rates

To better understand the relative contributions of explanatory factors to the observed pattern in SNAP participation over time, I incorporate the factors from the previous section into a regression framework that relates each of them to SNAP participation. Table 1 provides summary statistics for each of the factors.

The dependent variable in the regression is the percentage change in the number of residents enrolled in SNAP, while the independent variables are the percentage changes in the factors. The regression is estimated in natural logarithms. The difference in logs can be interpreted as the percentage change in a variable over the course of a year.<sup>10</sup>

I use estimates of the structural component of labor force nonparticipation based on research by Van Zandweghe (2012). Because my analysis already accounts for unemployed individuals, I focus on those

Variable	Mean	Standard deviation
SNAP participation (millions)	25.7	9.6
Number in poverty (millions)	35.6	6.2
Labor force nonparticipation: structural component (millions)	34.99	1.59
Short-term unemployment (millions)	6.60	1.04
Long-term unemployment (millions)	1.80	1.43
Leland Act	0.614	0.487
Food Stamp Act of 1977 (purchase requirement eliminated)	0.894	0.308
Welfare reform	0.482	0.500
ARRA	0.108	0.310
Exhibit: unemployment rate (percent)	6.45	1.57

# Table 1

# Summary Statistics for Regression Variables

who are NILF. The structural component of NILF is 1 minus the trend labor force participation rate from Van Zandweghe. The cyclical component, which is typically very small (zero, on average), is not used in the regression.

In addition, I include the legislative and programmatic changes to SNAP as binary variables that take a value of 0 prior to the legislation and a value of 1 after it. The binary ARRA variable takes a value of "1" only from May 2009 to November 2013, when the temporary increase in benefits was in effect.

#### Regression results

Because the model—excepting the legislation factors—was estimated in logs, the coefficients are elasticities, meaning they show the percent change in SNAP participation associated with a one percent change in each factor. Results from the regression show that most of the factors are statistically significant (Table 2).<sup>11</sup>

The coefficient on the number of people in poverty is positive and relatively large in magnitude. The result suggests that a 10 percent increase in the number of people in poverty is associated with 8.8 percent higher SNAP participation. In 2016, 46.2 million people were in poverty, while 44.4 million people participated in SNAP (in March).<sup>12</sup> The results suggest that had 50.8 million people been in poverty (46.2[1.10]), 48.3 million would have participated in SNAP (44.4[1.088]).
# *Table 2* Regression Results

Variable	Parameter estimate (standard error)
Intercept	-2.040** (0.761)
People in poverty	0.877** (0.078)
Labor force nonparticipation: structural component	1.710** (0.328)
Food Stamp Act of 1977 (purchase requirement eliminated)	0.0008 (0.009)
Leland Act	$0.024^{**}$ (0.009)
Welfare reform	-0.039** (0.0008)
ARRA	0.046** (0.009)
Short-term unemployment	-0.041 (0.026)
Long-term unemployment	0.076** (0.010)
Population	-2.004** (0.077)
Adjusted R <sup>2</sup> (transformed regression)	0.637

\*\* Statistically significant at the 99 percent confidence level

\* Statistically significant at the 95 percent confidence level

Note: The dependent variable is the 12-month difference in the natural log of SNAP participation in millions.

The coefficient on labor force nonparticipation suggests that a larger share of the population outside of the labor force is associated with greater participation in SNAP. The estimated coefficient is substantial in magnitude at 1.71, meaning that a 10 percent increase in labor force nonparticipation would be associated with a 17.1 percent higher SNAP participation.

To put this value in perspective, consider that the NILFR was 37.3 percent in November 2017, and the trend NILFR was 37.6 percent. SNAP participation in November 2017, the latest month for which data are available, was 41.7 million. If the NILFR had remained at its prerecession low of 33.6 percent (33.9 percent considering only the structural component), my results suggest the number of SNAP participants would have been much lower at 33.9 million  $\left(41.7\left[1-1.71\left(\frac{0.376}{0.339}-1\right)\right]\right)$ .

The coefficients for legislative changes denote the percentage change in SNAP participation associated with the legislation. The coefficient on the purchase requirement is statistically insignificant. The coefficient for the Leland Act is 0.024, meaning that, on average, the percentage change in SNAP participation was 0.024 percentage point higher after the Leland Act was passed. In other words, the results suggest the Leland Act may account for 1 million of the current 41.7 million SNAP participants. The negative coefficient on the welfare reform act indicates that welfare reform reduced the rate of change in SNAP participation by 0.039 percentage point. This result suggests that without welfare reform, an additional 1.6 million people might be participating in SNAP today. Finally, the parameter estimate for the ARRA is 0.046, meaning that, on average, the percentage change in SNAP participation was 0.046 percentage point higher when the ARRA SNAP provisions were in effect. From May 2009, when the ARRA first came into effect, until May 2010, SNAP participation rose from 33.5 million to 40.4 million, a 20 percent change. The results suggest that had the ARRA not been implemented, the change might have been 16 percent  $\left( \left[ \frac{40.4}{33.5} - 1 \right] - 0.046 = 0.16 \right)$  instead—in other words, the level of SNAP participation in 2010 might have been only 38.9 million.

The regression results confirm that long-term unemployment is associated with SNAP participation, but short-term unemployment is statistically unrelated to SNAP participation. The estimates suggest that a 10 percent increase in the long-term unemployment rate is associated with 0.8 percent higher SNAP participation [10(0.076)]. Given the current SNAP participation level, this percentage change amounts to about 334,000 additional SNAP participants.

Surprisingly, the coefficient on population is negative. Regression models are interpreted as partial effects, so the coefficient on population can be interpreted as the correlation between population and SNAP participation while holding other factors fixed. More specifically, the regression can be interpreted as the correlation between SNAP participation and an increase in the population that is in the labor force, employed, and not in poverty. In theory, the population coefficient might be expected to be zero, or not statistically different from zero. Although the statistically significant negative value has no clear economic interpretation, it likely reflects correlation among variables in the model and the inclusion of variables that are mostly positively associated with SNAP participation.

# Relative contributions

The results from the regression analysis can be used to calculate the relative contributions of each factor to SNAP participation. Chart 6 shows the estimated drivers of the change in SNAP participation from month to month, calculated by multiplying the estimated coefficient on each variable (listed in Table 2) by the annual change in each variable.

As an example, consider the contribution of labor force nonparticipation. Labor force nonparticipation increased by 0.91 percent from December 2015 to December 2016. The estimated coefficient from Table 2 is 1.710. Together, these values suggest labor force nonparticipation contributed 1.56 percent to the change in SNAP participation (1.710[0.0091]=0.0156).

As an additional example, consider growth in the number of people in poverty. The number of people in poverty grew from 43.123 million in December 2015 to 46.247 million in December 2016, a 7.2 percent increase  $\left(\left[\frac{46.247}{43.123}-1\right]=0.072\right)$ . This change was associated with a 6.3 percent change in SNAP participation (0.8767[7.2]), or an additional 2.9 million participants (45.415[0.063]=2.9). Interestingly, total SNAP participation declined from 45.4 million people to 43.2 million people in December 2015–16. The results suggest that had the number of people in poverty *not* increased over this period, SNAP participation might have fallen further to 40.3 million people instead.

Overall, Chart 6 reveals that structural factors explain most of the variation in SNAP participation over time. However, during recessions (highlighted in gray bars) and early recoveries, cyclical factors become significant contributors. The results for the cyclical factors are largely consistent with SNAP's reputation as an automatic stabilizer. Cyclical factors added to SNAP participation during recessions and early in recoveries, but tended to depress SNAP counts later in recoveries. Still, the Great Recession was a notable exception. Unlike in other recessions, cyclical factors contributed to increased SNAP participation years into the recovery from the Great Recession. SNAP participation has only recently begun to drop.



# *Chart 6* Structural and Cyclical Breakdown of SNAP Participation

# **IV.** Conclusion

Participation in SNAP has increased dramatically over time due to numerous factors. I examine multiple structural and cyclical factors to explain why and how they may have affected SNAP participation over time. Results from a regression analysis suggest the number of people in poverty, the number of people out of the labor force, and a variety of legislative and programmatic changes to SNAP are associated with increased participation in SNAP. In contrast, welfare reform in the mid-1990s is associated with reduced participation in SNAP.

A consideration of the factors' relative contributions to SNAP participation shows that the dominant factors explaining SNAP participation over time are largely structural. But cyclical factors were much more prominent during the Great Recession than in other recessions and recoveries.

Overall, the results suggest the growing trend in SNAP participation is unlikely to unwind. Ongoing demographic changes—particularly the aging of baby boomers into retirement—will likely continue, although immigration could mitigate this demographic effect. These demographic changes will affect labor force nonparticipation. Absent a major structural change in the economy or policy initiatives, the number of people in poverty is likely to grow as well. Given demographic changes and the number of people living in poverty, the results in this article suggest that SNAP participation is likely to remain significantly higher than its pre-2001 level in the future.

#### Endnotes

<sup>1</sup>Annual data are for fiscal years unless otherwise noted.

<sup>2</sup>I estimate the school-age population using data from the American Community Survey, U.S. Census Bureau.

<sup>3</sup>While publicly accessible SNAP data begin with January 1969, when states first implemented food stamp programs in earnest, states were not required to have food stamp programs until January 1975. They had all complied by mid-1974.

<sup>4</sup>The labor share of income was 56 percent in 2014 (Armenter 2015). The lowest-income people (bottom income quintile) derive a significant portion of their income from transfers (60.4 percent), but the remainder is largely labor income (38.6 percent) (see Rodriguez and others 2002, especially Table 6). Moderate- and middle-income people (second and third quintiles) derive the bulk of their income from labor (62.4 percent and 77.2 percent, respectively), but receive a significant portion from transfers as well (31.4 percent and 15.3 percent, respectively).

<sup>5</sup>From the mid-1960s until the late 1990s, the NILF rate trended down as baby boomers and women increasingly entered the workforce. The long-term trend leveled off before starting to rise as baby boomers reached retirement and life expectancies increased. Increased life expectancies increase NILF, because participation falls as workers age. In addition, rising school enrollments have increased the labor force nonparticipation rate of younger workers (see also Aaronson and others 2006).

<sup>6</sup>For 22 percent of retirees 65 and older, Social Security benefits account for more than 90 percent of their total income (Joint Economic Committee 2016; Social Security Administration 2016).

<sup>7</sup>Before the 2007 recession, the labor force participation rate (LFPR) was only weakly pro-cyclical compared with its long-term trend (it was modestly higher during booms and modestly lower during recessions). After 2009, the cyclicality strengthened, meaning the LFPR became significantly more sensitive to economic conditions. In recent years, the relationship between cyclical factors and the observed LFPR has weakened, but it has far from disappeared. One factor in the stronger tie between the LFPR and the business cycle is an increase in worker flows from employment to nonparticipation (Van Zandweghe 2012).

<sup>8</sup>Details are available at https://www.fns.usda.gov/snap/short-history-snap. The Food Stamp Program was renamed the Supplemental Nutrition Assistance Program in the 2008 Farm Bill.

<sup>9</sup>The later peak of long-term unemployment compared with short-term unemployment reflects faster transitions out of unemployment for the short-term unemployed relative to the long-term unemployed. Krueger, Cramer, and Cho (2014) find the matching of skills to relevant jobs is weaker for the long-term unemployed than the short-term unemployed. Ghayad (2014) finds that workers who report longer stretches of unemployment are less likely to receive

an interview request, regardless of experience. In addition, long-term unemployment may carry a stigma related to the perception of poor worker quality (Biewen and Steffes 2010; Kroft, Lange, and Notowidigdo 2013).

<sup>10</sup>The percentage change is an approximation of the log difference. Log differences and percentage changes vary little for small changes.

<sup>11</sup>The regression was estimated using generalized least squares (commonly known as GLS). Ordinary least squares (OLS) estimation yielded biased standard errors due to serial correlation. The Durbin-Watson statistic for the OLS estimation was 0.180, indicating significant positive serial correlation.

<sup>12</sup>The annual poverty rate and number in poverty is calculated using data from March of each year.

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First Quarter 2018, Volume 103, Number 1

The *Economic Review* (ISSN0161-2387) is published quarterly by the Federal Reserve Bank of Kansas City, 1 Memorial Drive, Kansas City, Missouri 64198-0001. Subscriptions and additional copies are available without charge. Send requests to the Public Affairs Department, Federal Reserve Bank of Kansas City, 1 Memorial Drive, Kansas City, Missouri 64198-0001. Periodical postage paid at Kansas City, Missouri.

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Federal Reserve Bank of Kansas City 1 Memorial Drive Kansas City, Missouri 64198-0001 First Quarter 2018, Vol. 103, No. 1

