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# Labor force participation: Is the labor market too hot, too cold, or just right?

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In February 2019, Federal Reserve Chairman Jerome Powell said the U.S. labor market still had slack to pull in more workers. At the time, job growth had been consistently strong for several years, with three-month nonfarm payrolls averaging more than 200,000 jobs for the second consecutive year. Since his statement, the official unemployment rate has reached lows not seen since 1969, and other traditional indicators of labor market slack such as part-time workers and number of discouraged workers have all reached pre-recession lows.[1]

Traditional metrics such as the number of new jobs added and the unemployment rate help us understand whether the labor market is hot or cold. But studying labor force participation—a measure of the supply of labor both utilized (employed) and available for/seeking employment (unemployed)—allows us to understand what drives changes in the unemployment rate and the number of new jobs created each month.

In this note, we deconstruct factors affecting labor force participation to help us understand whether recent changes represent a cyclical reaction to the current state of the economy or, instead, a structural change in factors affecting participation, providing foresight into future participation expectations. Such perspective helps us better interpret headline unemployment figures as well as form expectations for wage and employment growth, all of which are vital to determining whether the labor market is too hot, too cold, or just right.

## How our model estimates labor force participation

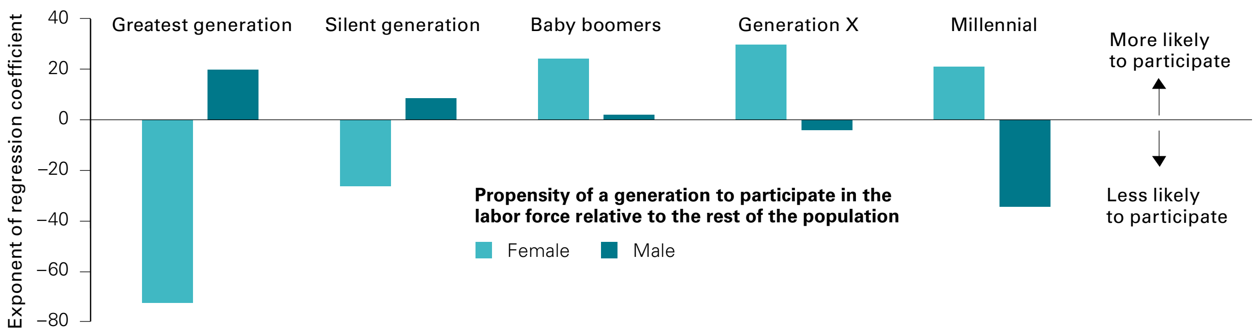
Although previous approaches that use only a country's demographic composition to predict labor force participation rates have yielded fairly accurate results, we believe that a more comprehensive model will provide a deeper understanding of current and future rates. Our model (**Equation 1**) is based on the influence of two factors: changes in the propensity to participate as a person ages, and differences in participation based on the generation a person belongs to (as displayed in **Figure 1**).

Equation 1

$$\log LFPR_{g,t}\ \textit{(Labor force participation rate)} = \log \alpha_g + \frac{1}{n_g} * \textit{Generation indicator (GI)} * \log\beta_{g,t} + e_{g,t}$$

Where:
*$g$ = age cohort, $t$ = time period, $\alpha$ = age effect, $\beta$ = generation effect, $n_g$ = number of ages in age cohort*

Figure 1. Male participation has declined across generations




**Notes:** The estimates represent the generation effect for each gender obtained from the coefficients for generational dummy variables in our model. Each coefficient represents the propensity of one generation to participate in the labor force relative to the total population throughout time (1963–2018). The coefficient represents the exponent of $\beta$.

**Sources:** Vanguard calculations, based on data from the Bureau of Labor Statistics (BLS), the IPUMS Current Population Survey (CPS), and the U.S. Census Bureau's American Community Survey (ACS).

1 Discouraged workers are persons not in the labor force who want to and are available to work but haven't looked for work in the past 12 months.

The age effect ($\alpha$) is a well-understood bell curve of increasing, peak, and decreasing participation as individuals age (Munnell, 2014).[2] The generation effect ($\beta$) captures commonalities between individuals in a generation that influence their participation over the long term (Fallick and Pingle, 2006). We then expand the model to examine how trends in education and family structure influence an individual's decision to participate. (See the Appendix for methodology details.)

## Participation across generations varies by gender

Using traditional definitions of generations, we estimate generational propensities of participation across males and females.[3] We observe that the propensity of men to participate in the labor force has steadily declined across generations, such that had Generation X and millennial males had the same propensity to participate in the labor force as baby boomers, the participation rate would be 2% higher today.

The reverse is observed for female participation before the 2008 global financial crisis. It rapidly increased from the Greatest Generation through Generation X but has since stabilized and even modestly declined for millennials, though not to the same extent as men. The trend in female participation from the Greatest Generation through Generation X accompanied a structural shift in social trends that is unlikely to be replicated (Toossi, 2002); therefore, we would expect changes in both genders' propensity to participate to have limited upside in future generations. This is one reason why expectations for economic growth are lower today than in previous decades.

## Examining the effects of education and family structure

Even after we accounted for age and generation effect, our model left a considerable amount of the trends in labor force participation unexplained. This led us to include socioeconomic variables that are known to influence participation (**Equation 2**). As stated previously, the data show a structural change around 1990 wherein female participation rates started to stabilize after a decades-long expansion. Accordingly, we split our data series into two samples, 1963–1989 and 1990–2018, to analyze how education and other family structure indicators such as average number of children and marriage rate affect participation rates.[4]

**Equation 2**

$$\log LFPR_{g,t} = \log \alpha_g + \lambda_g \log X + \frac{1}{n_g} * \textit{Generation indicator (GI)} * \log \beta_{g,t} + e_{g,t}$$

Where: $X$ = *variables as proxy for socioeconomic indicators*

The impact of these variables has changed substantially over the past 50 years. **Figure 2** shows the elasticity of participation of each factor ($X^{\lambda g}$)—in other words, how sensitive labor force participation is to a 1% change in each variable—across the two data samples. For example, a 1% increase in number of children for women in the 25–34 age cohort would have reduced participation for the whole cohort by 1.18% in the 1963–1989 sample, whereas in the 1990–2018 sample, it would have reduced participation by 0.003%. (See the *Results* section in the Appendix for details.) To put that in perspective, from 1963 to 1989, the average number of children for women in the 25–34 age cohort was 1.3, while between 1990 and 2018 it fell to 0.5. Thus, as the number of children declined, the impact of children on participation decisions declined in tandem for women.

2 Based solely on age, labor force participation will decline as a population's average age increases. However, recent trends and research, including the Vanguard research paper *Megatrends: The Economics of a Graying World* (2019), suggest that participation of those age 55 and older will continue to climb from historical lows as the nature of work evolves and monetary benefits from delaying retirement become more significant.

3 Generations are defined by the Pew Research Center as (years born between): Greatest Generation (1901–1924), Silent Generation (1925–1945), baby boomers (1946–1964), Generation X (1965–1980), millennials (1981–1996), and Generation Z (1997–2012).



4 We eliminate the "number of children" variable for the age 16–19 and 45 and above cohorts because it is not a determining factor of participation.

## Figure 2. Comparing the elasticity of socioeconomic variables

| | Female 1963–1989 | | | | Female 1990–2018 | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Ages 25–34 | 35–44 | 45–54 | 55+ | Ages 25–34 | 35–44 | 45–54 | 55+ |
| Number of children | -1.18 | -0.51 | – | – | 0.00 | -0.28 | – | – |
| Years of education | 0.07 | 0.07 | 0.08 | 0.01 | 0.16 | -0.50 | 1.72 | 3.06 |
| Marriage | 0.68 | -3.54 | -2.91 | -4.65 | -0.12 | 0.13 | 2.07 | 0.05 |

| | Male 1963–1989 | | | | Male 1990–2018 | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Ages 25–34 | 35–44 | 45–54 | 55+ | Ages 25–34 | 35–44 | 45–54 | 55+ |
| Number of children | 0.05 | 0.02 | – | – | -0.05 | -0.28 | – | – |
| Years of education | 0.00 | 0.00 | -0.01 | -0.07 | 0.23 | 0.07 | 0.12 | 0.97 |
| Marriage | 0.04 | 0.14 | 0.02 | -5.35 | 0.12 | 0.39 | 1.00 | -1.65 |

Increases in variables lead to **decreases in participation**

Increases in variables lead to **increases in participation**

**Notes:** Model estimates are over two time periods: 1963–1989 and 1990–2018. The table shows the elasticity of labor force participation for each age-gender cohort against the variables in the first column.

**Sources:** Vanguard calculations, based on data from BLS, IPUMS CPS, and ACS.

Meanwhile, the sensitivity for number of children on male participation has increased. This dichotomy between male and female sensitivity to children is likely a result of social trends surrounding shared parenting duties (Livingston, 2014). Additionally, years of education, which had virtually no effect in the 1963–1989 sample, is a significant positive factor on average in later age cohorts, signifying the increasing importance of education for later-age employability. The effect of marital status on participation has generally lessened across ages and genders but remains low to negative for older workers, possibly as a result of greater wealth accumulation for married couples.

In decomposing the drivers of participation, we calculated how labor force participation today would differ if demographics, generational effects, education, and family structure were fixed at 1990 levels. As **Figure 3** shows, holding all three factors constant at 1990 levels, today's participation rate would be 4.7% higher than current levels.

## Figure 3. An aging population explains a large chunk of labor force participation (LFP) decline

| Factor variable | Units of LFP |
|---|---|
| LFP with all variables and behavior fixed at 1990 levels | 67.7% |
| Current LFP | 63.0 |
| Difference | -4.7 |
| Effect from . . . | |
| aging population | -3.1 |
| change in generational behavior | -2.2 |
| increase in education | 2.3 |
| decrease in marriage rates | -1.6 |
| decrease in number of children | -0.2 |

**Notes:** After obtaining beta estimates from our model, we reverse-calculate the participation rates. To calculate the impact on participation rate of each of the factors (aging population, generation, education, etc.), we hold all other model variables constant at 1990 levels and allow the variable whose effect we wish to capture to fluctuate over time. Thus, we obtain the participation rates that would have prevailed if only one factor had changed, holding all other variables constant.

**Sources:** Vanguard calculations, based on data from BLS, IPUMS CPS, and ACS.

The majority of this decline can be attributed solely to an aging population and lower propensity to participate in each successive generation, as we mentioned earlier. But even as propensity to participate in the labor market has declined across generations, this negative impact is offset by the boost to labor force participation resulting from higher levels of education in the United States, all else equal. **Figure 4** shows how participation would differ under various scenarios, with the gap between the dashed lines representing the impact from generational and behavioral variables.

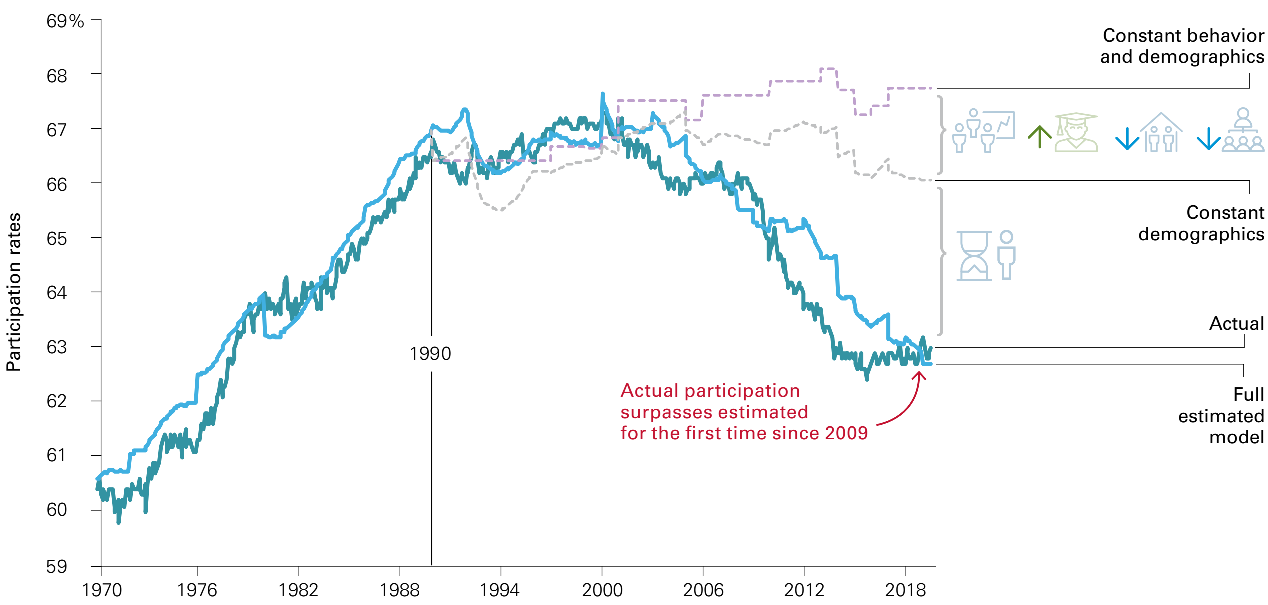
## What does this all mean for the labor market?

Although some economists and market observers still believe that the labor market has room to grow, we see a market with depleted labor slack. Taking into account generational, demographic, and other socioeconomic factors, our model estimates that participation rates today should be a bit below 63%—where they have been hovering for the better part of the last five years. Our model suggests that the labor market started tightening in the latter part of 2018 (Figure 4) when actual participation surpassed our estimates, likely supporting the wage gains we've witnessed since then (see **Figure 5**).

Over a 15-year horizon, our model predicts participation rates that are higher than those estimated by the Congressional Budget Office (CBO), indicating that as future generations continue to gain more education and participate longer in the labor market, participation could persist at a higher level than previously thought (see **Figure 6**). This presents a potential upside to long-term future growth prospects, while tempering the upward pressure on wages. Of course, these estimates are based on generational behavior and socioeconomic conditions to date. As a younger workforce joins the labor market and their behavior changes over time, our estimates will shift in response.

Our analysis of the drivers of participation rates shows that, looking ahead, the prospects for labor supply could be brighter than once thought. And although the pace of job growth is likely to slow through the end of 2019, that doesn't mean the labor market is cooling. In fact, it could mean it is just right.

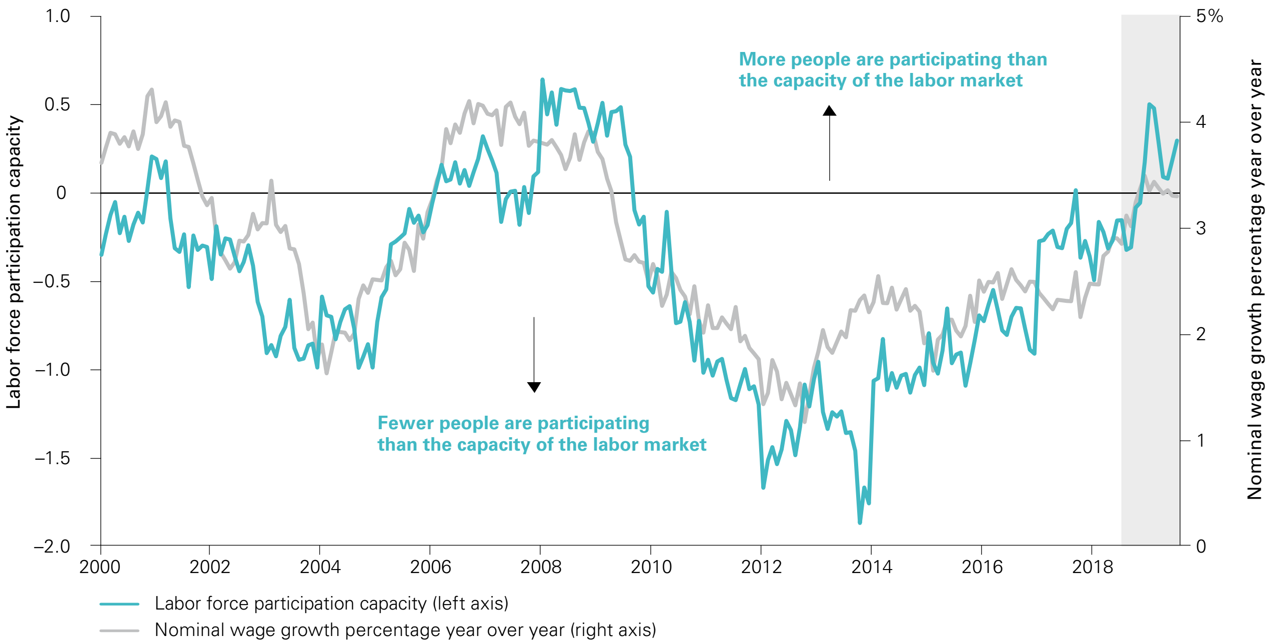
Figure 4. Participation decline: Behavior and demographics combined explain participation trends




**Notes:** After obtaining beta estimates from our model, we reverse-calculate the participation rates. For the "constant behavior and demographics" participation (purple line), we hold constant at 1990 levels the generation effect, other explanatory variables (education, marriage rate, etc.), and population shares of each age-gender bucket. For the "constant demographics" participation (gray line), we hold constant at 1990 levels only the population shares across each age-gender bucket. The full model estimates (light-blue line) allow all variables to vary as time progresses.

**Sources:** Vanguard calculations, based on data from BLS, IPUMS CPS, and ACS.

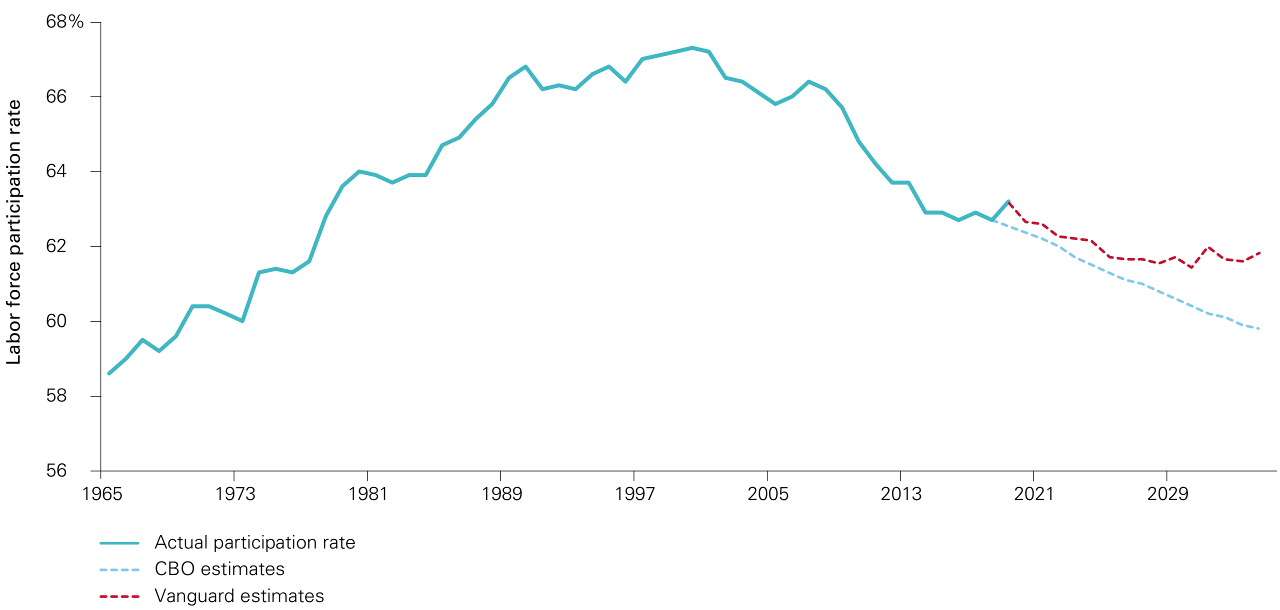
Figure 5. Labor market slack is an important driver of wage growth




**Notes:** The blue line represents the difference between the actual participation rate and the model estimated participation rate. The grey line represents year-over-year wage growth in percentage points.

**Sources:** Vanguard calculations, based on data from our estimated model, Data Buffet, and BLS.

Figure 6. Participation rates could sustain at higher levels




**Notes:** The red line represents the future projection of participation rates obtained from the model estimates. We combine our estimates with BLS future projections of population to calculate the total U.S. participation rate. The dotted blue line represents the CBO's estimate of future participation rates.

**Sources:** Vanguard calculations, based on data from BLS, IPUMS CPS, and ACS.

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## Appendix: Methodology

### *1. Specification*

Our specification borrows from the paper *A Cohort-Based Model of Labor Force Participation* by Fallick and Pingle (2006). Similar to their model, our model assumes that the labor force participation rate (LFPR) of men or women can be specified as:

**Equation A1**

$$\log LFPR_{g,t} = \log \alpha_g + \lambda_g \log X + \tfrac{1}{n_g} * \textit{Generation indicator (GI)} * \log \beta_{g,t} + e_{g,t}$$

Where:
*$g$ = age cohort, $t$ = time period, $\alpha$ = age effect,*
*$\beta$ = generation effect, $n_g$ = number of ages in age cohort,*
*$X$ = variables as proxy for socioeconomic indicators*

The generation indicator separately identifies, via dummy variables, the generation as it passes through each age cohort. We include indicators for six generations in total in our model in the form of dummy variables (see Table 1). There are six age cohorts included in the model for both males and females: 16–19, 20–24, 25–34, 35–44, 45–54, and 55 and above.

Table 1

| Generation name | Years born between |
|---|---|
| Greatest | 1901–1924 |
| Silent | 1925–1945 |
| Boomer | 1946–1964 |
| X | 1965–1980 |
| Millennial | 1981–1996 |
| Z | 1997–2012 |

Because average participation rates for males and females have differed by quite a bit historically, we model their participation rates separately. Thus the model structure (**Equation A2**) is a stacked 12-equation model that is estimated simultaneously to arrive at coefficients.

Equation A2

$$\log LFPR_{16\text{–}19,f,t} = \log \alpha_{16\text{–}19,f} + \lambda_{16\text{–}19,f} \log X + \frac{1}{n_{16\text{–}19,f}} * GI * \log\beta_{16\text{–}19,f,t} + e_{16\text{–}19,f,t}$$

$$\log LFPR_{20\text{–}24,f,t} = \log \alpha_{20\text{–}24,f} + \lambda_{20\text{–}24,f} \log X + \frac{1}{n_{20\text{–}24,f}} * GI * \log\beta_{20\text{–}24,f,t} + e_{20\text{–}24,f,t}$$

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$$\log LFPR_{55+,f,t} = \log \alpha_{55+,f} + \lambda_{55+,f} \log X + \frac{1}{n_{55+,f}} * GI * \log\beta_{55+,f,t} + e_{55+,f,t}$$

$$\log LFPR_{16\text{–}19,m,t} = \log \alpha_{16\text{–}19,m} + \lambda_{16\text{–}19,m} \log X + \frac{1}{n_{16\text{–}19,m}} * GI * \log\beta_{16\text{–}19,m,t} + e_{16\text{–}19,m,t}$$

--------------------------------

$$\log LFPR_{55+,m,t} = \log \alpha_{55+,m} + \lambda_{55+,m} \log X + \frac{1}{n_{55+,m}} * GI * \log\beta_{55+,m,t} + e_{55+,m,t}$$

Where: *m = male, f = female*

We run two separate versions of the model: the basic model and the augmented model. The basic version (**Equation A3**) excludes the structural variables denoted by *X* and only includes dummies for the generations.

Equation A3

$$\log LFPR_{g,t} = \log \alpha_g + \frac{1}{n_g} * Generation\ indicator\ (GI) * \log\beta_{g,t} + e_{g,t}$$

In the basic model, we are able to capture age effect ($\alpha$) and generation effect ($\beta$), which can be combined to calculate the trend participation rate (**Equation A4**).

Equation A4

$$Trend\ LFPR_{t,i} = \alpha_{i,t} * \left(\prod_{j=1}^{k} \beta_{t,i}^{\frac{1}{n_g}}\right)$$

The augmented model includes the age and generation effect, along with other structural variables in vector *X*. In this framework we continue to assume that the age and cohort effect are constant across time. However, now, in addition to these two factors, participation will also be partly explained by the variables in *X*. Thus, it is no longer possible to separate out the trend in participation due to disjointed age and generation components. The variables in *X* vary across both age and time.

Once we obtain the estimates from the model, we are able to construct the trend labor force participation rate (**Equation A5**).

Equation A5

$$Trend\ LFPR_{t,i} = \alpha_{i,t} * \left(\prod_{j=1}^{k} \beta_{t,i}^{\frac{1}{n_g}}\right) * X_{t,i}^{\lambda}$$

Where:
*k = total number of generations at time t in age cohort i, t = time, i = age cohort, j = generation indicator at time t in age cohort i, λ = coefficient estimate of socioeconomic variables*

The model thus helps us obtain a trend-cycle decomposition that is a better alternative to an aggregate time series model or other smoothing algorithms. In the model, we are able to observe the behavior of different cohorts over business cycles and use that information to project future labor force attachment. Also, the trends are directly interpretable in an economic context, as we are able to distinguish between effects of demographics and cohorts.

### *2. Results*

The estimates that we get from the model (Figure 2) represent the elasticity of a variable; i.e., by what percentage participation for that age and gender cohort would change if the variable changes by 1%.
The negative sign on the coefficient indicates the direction of the impact.

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