WOMEN, WEALTH EFFECTS, AND SLOW RECOVERIES

Masao Fukui
Emi Nakamura
Jón Steinsson

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ABSTRACT

Business cycle recoveries have slowed in recent decades. This slowdown comes entirely from female employment: as women's employment rates converged towards men's over the course of the past half-century, the growth rate of female employment slowed. But does the slowdown in the growth of female employment rates translate into a slowdown for overall employment rates? The degree to which women "crowd out" men in the labor market is a sufficient statistic for this question. We estimate the extent of crowding out across states, and find that it is small. We then develop a general equilibrium model of the female convergence process featuring home production and show that our cross-sectional crowding out estimate provides a powerful diagnostic statistic for aggregate crowding out. Our model implies that 60-75% of the slowdown in recent business cycle recoveries can be explained by female con-vergence.

Masao Fukui
Department of Economics
Massachusetts Institute of Technology
77 Massachusetts Avenue, E52-301
Cambridge, MA 02139
fukuimasao@gmail.com

Emi Nakamura
Department of Economics
University of California, Berkeley 685
Evans Hall
Berkeley, CA 94720
and NBER
enakamura@berkeley.edu

Jón Steinsson
Department of Economics
University of California, Berkeley
671 Evans Hall
Berkeley, CA 94720
and NBER
jsteinsson@berkeley.edu

1 Introduction

A salient feature of recent business cycles has been the slow recovery of employment. Panel A of Figure 1 plots the employment-to-population ratio for prime-age workers around the last five recessions.[1] After the business cycle troughs in 1975 and 1982, the employment-to-population ratio rose rapidly—by roughly one percentage point per year (see Table 1). After more recent business cycle troughs, however, the employment-to-population ratio has risen much more slowly—by less than 1/2 a percentage point per year.[2]

Panel B of Figure 1 plots separately the evolution of the employment-to-population ratio around the last five recessions for men and for women. The contrast is striking. For men, recoveries have always been slow. For women, however, recoveries in the 1970s and '80s were very rapid, but have slowed sharply since. The 20th century saw a "Grand Gender Convergence" (Goldin, 2006, 2014). The speed of this gender convergence peaked for employment around 1975 and has slowed sharply since and virtually plateaued after 2000. The Grand Gender Convergence provides a simple explanation for slowing recoveries of female employment: If you superimpose a recovery on an upward trend, it will look fast; if you superimpose a recovery on a downward trend, it will look slow. As an accounting matter, therefore, much of the aggregate slowdown in recoveries can be attributed to a change in the trend growth of female employment (Juhn and Potter, 2006; Stock and Watson, 2012; Albanesi, 2019; Council of Economic Advisors, 2017).

An unsatisfying feature of this simple accounting exercise is that it requires a "no change" assumption for other groups in the economy aside from women. However, a dramatic increase in the employment rate of half of the population cannot be assumed to occur without implications for the other half of the population. The Gender Revolution was a large macro shock that likely had various general equilibrium effects on the economy. The magnitude of these general equilibrium effects matters crucially in determining the validity of the link between gender convergence and the slowing of overall recoveries.

Fortunately, it turns out that the degree to which women "crowd out" men when they enter the

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[1]For the overall population, aging of the population is part of the explanation for slower recoveries (Aaronson et al., 2006, 2014). However, as Figure 1 and Table 1 show, recoveries of employment have slowed even for prime-age workers.

[2]These facts point to *slow* recoveries from the last three recessions. Sometimes the alternative label of "jobless recoveries" is used, which is sometimes interpreted to mean that employment rises slowly relative to output—i.e., that labor productivity growth is high—or that the unemployment rate falls slowly. Table 1 reports the annual change in labor productivity and unemployment for the recoveries from the last five recessions. There is, in fact, scant evidence that the speed of recovery of labor productivity or unemployment has slowed following recent recessions. For this reason, we focus on explaining "slow" recoveries in this paper. See also Figures A.1 and A.2 in Appendix A.2.
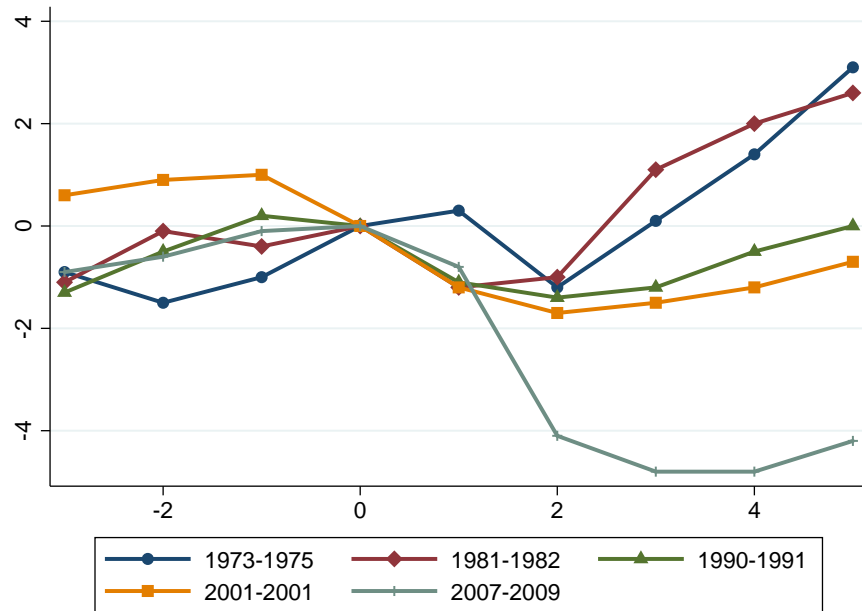
Panel A: Prime-Age Employment-to-Population Ratio
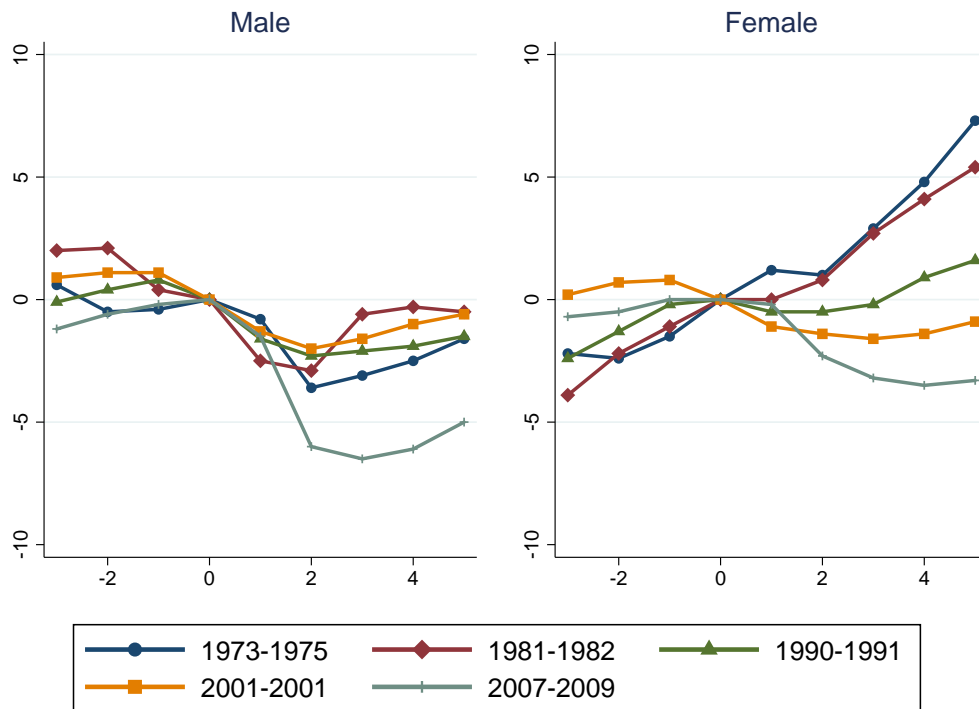
Panel B: Prime-Age Male and Female Employment-to-Population Ratio
Figure 1: Slowing Recoveries of the Employment Rate

Note: The figure plots the employment-to-population ratio for the prime-age population (aged 25-54) over the past five recessions and recoveries. We normalize each series to zero at the pre-recession business cycle peak (defined by the NBER): 1973, 1981, 1990, 2001 and 2007. We ignore the brief business cycle surrounding the 1979 recession.

Table 1: Employment, Productivity and Unemployment Following Business Cycle Troughs

	Panel A. Prime-Age Population				
	1973-1975	1981-1982	1990-1991	2001-2001	2007-2009
Employment-to-Population Ratio	1.32%	1.18%	0.48%	0.28%	0.40%
Labor Force Participation Rate	0.94%	0.61%	-0.04%	-0.07%	-0.40%
Unemployment Rate	-0.55%	-0.73%	-0.53%	-0.32%	-0.85%
Log Labor Productivity	1.18%	1.73%	1.17%	1.86%	0.77%
	Panel B. Prime-Age Men and Women				
	1973-1975	1981-1982	1990-1991	2001-2001	2007-2009
Employment-to-Population (Male)	0.52%	0.73%	0.28%	0.40%	0.65%
Employment-to-Population (Female)	2.00%	1.55%	0.68%	0.12%	0.18%
Unemployment (Male)	-0.58%	-0.80%	-0.62%	-0.38%	-1.03%
Unemployment (Female)	-0.57%	-0.65%	-0.40%	-0.25%	-0.62%

Note: The table reports annualized average growth rates over 4 years following each business cycle trough (defined as the year with the lowest employment rate): 1975, 1983, 1992, 2003, 2010. Labor productivity refers to real output divided by total employment in the non-farm business sector (BLS series PRS85006163).

labor force is a sufficient statistic for all these general equilibrium effects. Consider the identity $L = \frac{1}{2}L_f + \frac{1}{2}L_m$, where L denotes the overall employment rate, while L_f and L_m denote the female and male employment rates, respectively. Suppose a female-biased shock θ occurs—e.g., a reduction of discrimination against women. The effect of this θ shock on L depends on its effect on female employment and its effect on male employment: $dL/d\theta = \frac{1}{2}dL_f/d\theta + \frac{1}{2}dL_m/d\theta$. It is useful to scale this expression by the effect of the θ shock on female employment:

$$\frac{dL/d\theta}{dL_f/d\theta} = \underbrace{\frac{1}{2}}_{\text{Accounting}} + \frac{1}{2}\underbrace{\frac{dL_m/d\theta}{dL_f/d\theta}}_{\text{Crowding Out}} . \tag{1}$$

The left-hand-side of this equation is the scaled effect of the θ shock on total employment. The right-hand-side shows that the effect of the θ shock on total employment differs from what simple accounting would yield if and only if the θ shock affects male employment. We refer to $\frac{dL_m}{d\theta}/\frac{dL_f}{d\theta}$ as the degree of crowding out of men by women in the labor market. Equation (1) shows that crowding out of men by women in the labor market is a sufficient statistic for assessing the role of the Gender Revolution (a large female biased shock) on total employment and therefore on the slowdown of recoveries.

A simple minded proposal for estimating crowding out as defined in equation (1) would be to run a time-series regression of male employment on female employment. An important identifi-

cation challenge arises, however, from the presence of "gender neutral shocks," i.e., shocks that affect employment of both men and women symmetrically. For example, consider business cycle shocks. Over the business cycle, male and female employment comove positively, presumably because gender neutral shocks drive much of the business cycle. This kind of variation will bias estimates of crowding out and may even lead researchers to spuriously estimate crowding in.

To estimate the effects of female-biased (as opposed to gender neutral) shocks, we focus on convergence dynamics across US states in the gender gap during the Gender Revolution. In 1970, some US states had particularly low female employment rates (and particularly large gender gaps). These states experienced much more rapid growth in female employment rates. We ask to what extent these states exhibit systematic differences in male employment growth. Our baseline estimate is that a 1% increase in female employment in one state relative to other states leads to only a 0.18% decline in male employment in that state relative to other states. In other words, our estimate implies that there is very little crowding out of men by women in the labor market. We also consider a second identification strategy using states' initial exposure to industries with particularly high gender gaps, based on the "Job Opportunity Index" proposed by Nakamura, Nakamura, and Cullen (1979). This identification strategy indicates even less crowding out.

Our empirical finding is that *relative* crowding out is small (i.e., in the cross-section). However, relative crowding out does not give us a direct measure of the extent of aggregate crowding—which is what appears in equation (1)—since aggregate general equilibrium effects are "differenced out" in our cross-state panel regressions. To bridge this gap, we develop a quantitative theoretical model with multiple regions designed to capture the Gender Revolution. We show that in this model relative crowding out will equal aggregate crowding out when household preferences take the King, Plosser, and Rebelo (1988) form. For more general specifications of preferences, the difference between relative and aggregate crowding out is quantitatively small for plausible parameter values since these are relatively close to the King, Plosser, and Rebelo (1988) form.

We then use our model to consider a counterfactual where we "turn off" female convergence and ask what would have happened to recent business cycle recoveries in this case. Our conclusion is that without female convergence—i.e., if the growth rate of female employment had been as high in recent recoveries as in the 1970s—-recent recoveries would have looked dramatically different. For a conservative calibration, we find that 60% of the slowdown in recoveries since the early-1980s can be explained by the convergence of female to male employment rates. For a less conservative calibration, our model can explain 75% of the observed slowdown in recoveries.

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These results are insensitive to a wide variety of modifications to our model. So long as we ensure that alternative models fit our cross-state estimates of crowding out, the conclusions about aggregate recoveries are virtually unchanged. The reason for this is that our cross-state empirical estimate of crowding out is "almost" a sufficient statistic for the counterfactuals we wish to investigate. (It is an exact sufficient statistic in the King, Plosser, and Rebelo (1988) case, since in that case it equals aggregate crowding out.) In particular, our conclusions are insensitive to whether the Gender Revolution was driven by shocks to female labor demand or female labor supply.[3] Our results are also insensitive to alternative assumptions about the degree of substitutability between men and women in the production function. Of course, each parameter separately affects the degree of crowding out (although surprisingly little in some cases because relevant parameter values are close to the King, Plosser, and Rebelo (1988) case).[4] But together the parameters of our model are constrained to match our estimate of crowding out which is "almost" a sufficient statistic for our counterfactual.

We show furthermore that a broad class of simple macroeconomic models with balanced growth preferences—i.e., models designed to match the fact that aggregate labor supply has remained relatively stable despite huge increases in real wages over the past 200 years—cannot fit the facts we document about small relative crowding out.[5] The reason for this is that these simple models imply large wealth effects of women entering the labor force which induce men to work less. A crucial feature of our model, that allows us to fit our empirical estimate of crowding out, is that we allow for home production (building on earlier work by Benhabib, Rogerson, and Wright (1991), Greenwood and Hercowitz (1991) and others). Time-use data shows that the Gender Revolution was to a large extent a transition from work at home to market work for women, not from

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[3]There is a large literature on the causes and consequences of the Grand Gender Convergence of the 20th century. Proposed explanations differ as to whether the rise of female employment is due to factors affecting female labor demand or supply shocks. Our results are insensitive to which of these explanation is most important. Prominent explanations include the increasing availability of household appliances (Greenwood, Seshadri, and Yorukoglu, 2005), the birth-control pill (Goldin and Katz, 2002), changes in discrimination (Jones, Manuelli, and McGrattan, 2015), reductions in the costs of child care (Attanasio, Low, and Sánchez-Marcos, 2008), medical innovation (Albanesi and Olivetti, 2016), cultural changes (Antecol, 2000; Fernández, Fogli, and Olivetti, 2004; Fernández and Fogli, 2009), the role of learning (Fogli and Veldkamp, 2011; Fernández, 2013), skill-biased technological change (Beaudry and Lewis, 2014), and the rise of service sector (Ngai and Petrongolo, 2017; Rendall, 2017). A more recent literature studies potential explanations for why female employment rates have leveled off since 2000 (Blau and Kahn, 2013; Kubota, 2017; Goldin, 2014).

[4]For example, a low degree of substitutability of men and women in the productions function implies that the entry of women raises the marginal product of men and therefore their wages. With King, Plosser, and Rebelo (1988) preferences, however, their labor supply is unaffected.

[5]Models with "balanced growth preferences" feature offsetting income and substitution effects on labor supply (King, Plosser, and Rebelo, 1988). This implies that technical progress has no effect on aggregate labor supply. These models are popular in macroeconomics because they fit the fact that over the past 200 years, real wages have risen by roughly 1500% (Clark, 2005), while hours worked have been stable or trended slightly downward (Boppart and Krusell, 2016).

leisure to work. Intuitively, the switch from home to market work has much smaller wealth effects for a family than the switch from leisure to market work.[6]

Relative to earlier work that has analyzed the Gender Revolution using models featuring home production, the crucial feature of our analysis is that we force our model to match the small degree of crowding out we estimate empirically. In contrast, Jones, Manuelli, and McGrattan (2015) discuss how standard unitary household models with home production tend to yield large crowding out of men by women in response to gender convergence shocks. Knowles (2013) studies a model in which crowding out is large, but is offset by preference shocks that make both men and women more willing to work.[7] In these models, female convergence associated with the Gender Revolution has only modest effects on aggregate employment since crowding out is large. For this reason, it cannot explain the slowdown of recoveries we have seen over the past few decades.

The paper proceeds as follows. Section 2 describes the data we use. Section 3 discusses basic facts about the convergence of female to male employment rates. We show that this arose mostly from convergence within occupations rather than from shifting composition of occupations in the economy. Section 4 presents our empirical estimates of crowding out using cross-state data. Section 5 develops a simple version of the model we will use to carry out our counterfactual analysis. We use this simple model to introduce the distinctive features of our model and to build intuition about crowding out. Section 6 presents our full model, which incorporates business cycle fluctuations. Section 7 performs our counterfactual to assess the role of female convergence in explaining the slowdown of business cycle recoveries. Section 8 concludes.

Related Literature

Many recent papers have proposed sophisticated explanations for slow (or jobless) recoveries. These include structural change (Groshen and Potter, 2003; Jaimovich and Siu, 2020; Restrepo, 2015; Gaggl and Kaufmann, 2020), secular stagnation (Hall, 2016; Benigno and Fornaro, 2017), changing hiring or firing dynamics (Berger, 2016; Koenders and Rogerson, 2005), declining startup rates (Pugsley and Şahin, 2019), changing social norms (Coibion, Gorodnichenko, and Koustas, 2013), wage rigidities (Shimer, 2012; Schmitt-Grohe and Uribe, 2017), vanishing pro-criticality in labor productivity (Galí and Van Rens, 2021), and changing unemployment insurance policies

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[6]Our model also fits the empirical fact that women's leisure has increased substantially over the past 50 years (Aguiar and Hurst, 2016).

[7]Knowles (2013) emphasizes the role of bargaining in mitigating crowding out. Although bargaining plays some role, auxiliary preference shocks play a very important role in his model in canceling the effects of crowding out. Knowles acknowledges this when he writes "Bargaining is therefore an important component of the story, ... but there are also large effects that do not operate through bargaining." In fact, his model generates crowding out of -0.5 without preference shocks (see Table 6 of his paper).

(Mitman and Rabinovich, 2014). Our analysis suggests a simple explanation for slow recoveries based on an incontrovertible economic trend—gender convergence. There may have been rich interactions between some of these mechanisms for structural change described above and the gender revolution, as we discuss in Section 7.2.

Worries that women might crowd out men in the labor market are not new. Juhn and Murphy (1997) discuss this hypothesis and argue that it is inconsistent with the fact that married women with the largest increases in market hours are those with high-income and high-skilled husbands, who also experienced the largest increases in market hours. McGrattan and Rogerson (2008) extend and further develop this set of facts. An earlier literature estimates structural models of family labor supply that touch on some of the issues we discuss in this paper (e.g., Van Soest, 1995; Fortin and Lacroix, 1997; Blundell and MaCurdy, 1999). These papers rely on strong structural assumptions to identifying the behavior of family labor supply. A small number of more recent papers have taken a less structural approach to identifying the extent of crowding out. Blank and Gelbach (2006) finds that an increase in low-skilled female labor supply driven by welfare programs did not crowd out male employment, for men with similar skill levels. Acemoglu, Autor, and Lyle (2004) study the labor market effects of women entering the labor force associated with quasi-random variation in World War II mobilization rates across states, focusing mostly on wage effects. They estimate statistically insignificant effects on male employment (though the standard errors are large).

The motivation for our work is closely related to Albanesi (2019). She estimates a DSGE model that allows for female-biased shocks using aggregate data, and finds that the dynamics of these shocks have changed in recent years, suggesting that gender convergence has played an important role in jobless recoveries. In more recent work, Olsson (2019) studies the role of female labor force participation in explaining jobless recoveries. She builds a model that incorporates differences between men and women in the labor market as well as heterogeneity in marital status to explore the changes in employment dynamics. Our work is also closely related to Heathcote, Storesletten, and Violante (2017) who develop a model of the gender revolution driven by demand shocks (though they focus on income as opposed to employment rates). None of these papers estimate crowding out in the data, which we argue is crucial for understanding the role of the Gender Revolution for the changing speed of recoveries.

Finally, our paper is more tangentially related to the large literature on potential crowding out of native workers by immigrants (e.g., Card, 2001; Borjas, 2003; Card, 2005; Hong and McLaren,

2015; Dustmann, Schönberg, and Stuhler, 2017).[8] There is, however, an important conceptual difference between the effects of immigrants and those of women entering the labor force. In contrast to women entering the labor force, immigrants add to the population and, for the most part, form new independent households. Standard macroeconomic models with constant-returns-to-scale production functions imply that at the aggregate level the economy will expand one-for-one in response to an influx of immigrants in the long run, without any crowding out of natives. The fact that women entering the labor force share their income with their husbands can potentially cause sizable crowding out through wealth effects (though not according to our empirical estimates).

2 Data

Our estimates of crowding out are primarily based on data from the U.S. Census and American Community Survey (ACS).[9] We use these data to calculate employment-to-population ratios at the state level for prime-age workers (aged 25-54). We focus on the sample period 1970-2016. As is standard in the literature, we exclude people not living in regular housing units as defined by the Census.[10] We construct employment-to-population ratio, as the ratio of the total number of individuals recorded as "at work," divided by the population, using Census weights. Those who reported doing any work at all for pay or profit, or who reported working at least fifteen hours without pay in a family business or farm, are classified as "at work."Employment is defined based on a worker's activities during the preceding week of the interview.

Our baseline analysis is at the state level, as opposed to a finer level geographical disaggregation. We make this choice in order to minimize the regional interactions that drive a wedge between our regional estimates of crowd out and aggregate crowd out (the object of primary interest). However, in Section 4.1, we confirm that our main regressions yield similar results at the commuting zone level.

Our analysis of business cycles requires higher frequency data than are available from the Census (which are only available every 10 years before 2000). Our main business cycle analysis uses aggregate annual data on employment rates for prime age workers from the Current Population Survey (CPS). These data have the disadvantage that they have a smaller sample size. Hence they

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[8]Burstein, Hanson, Tian, and Vogel (2017) theoretically and empirically explore how the effects of immigration varies across industry and occupation depending on tradability.

[9]We downloaded these data from the IPUMS website (Flood et al., 2017).

[10]That is, people in prison, mental hospitals, military, etc. This makes our sample definition consistent with that of the Current Population Survey, which does not include these individuals in the sampling frame for the employment status question.

are less well-suited to the state-level analysis we describe above—for example, state-level data are available only back to 1978.

We use several other datasets in constructing controls for our main regressions. We make use of data on per capita real GDP at the aggregate and the state level from the Bureau of Economic Analysis (BEA). We construct the service employment share, skill premium, non-white population share at the state level from Census Data. The service sector is defined as sectors other than manufacturing, mining and agriculture. The skill premium is defined as the ratio between composition adjusted wages of college graduates to those of high-school graduates. We also construct a Bartik shock as the interaction of initial state-level industry shares with subsequent national industry employment growth. We describe the construction of composition adjusted wages and the Bartik shock in more detail in Appendix A.1.

3 The Gender Revolution in Employment

Figure 2 plots the employment rates and labor force participation rates of prime-age men and women in the US over the sample period 1970 to 2016. In 1970, there was a very large gender gap in employment. While 93% of prime-age men were employed in 1970, only 48% of prime-aged women were employed. Over our sample period, the employment rate of prime-aged women converged considerably towards prime-aged men, mostly driven by the rapid increase in the female employment rate. In 2016, the employment rate of prime-aged men had fallen to 85%, while the employment rate of prime-aged women had risen to 71%.[11] Figure 2 also shows that the convergence of female employment rates was driven entirely be convergence in labor force participation rates, rather than differential changes in unemployment.

It is easier to visualize the convergence of female employment towards male employment by plotting the gender gap in employment over time—i.e., the female employment rate less the male employment rate. We do this in Figure 3. In the 1970s, this gap was shrinking rapidly. Over time as the gap shrunk, convergence has slowed down. Since about 2000, the gender gap in employment has largely plateaued.

The evolution of the gender gap can be described quite well by a simple statistical model since

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[11]Figure A.3 extends Figure 2 back in time. It shows that the rate of convergence of female employment rates towards male employment rates was increasing in the 1950s and 60s and reached a maximum speed in the 1970s. Figure A.4 plots male employment rates including older workers. This figure shows a clear downward trend in male employment from 1950 onward.
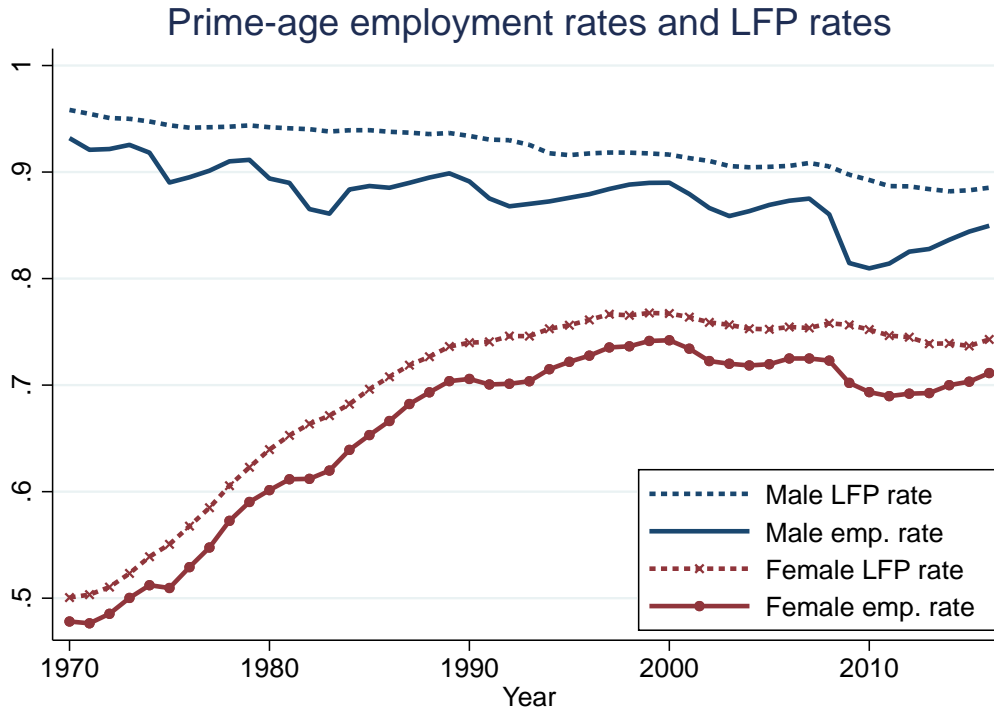
Prime-age employment rates and LFP rates

Figure 2: Convergence in Employment Rates

1980. Consider the following AR(1) process for convergence:

$$gap_t = \alpha + \beta gap_{t-1} + \epsilon_t, \tag{2}$$

where $gap_t \equiv epop_t^F - epop_t^M$ denotes the gap between the female and male employment rate at time t, and $epop_t^F$ and $epop_t^M$ are the employment rates of prime-aged women and men, respectively. Here, the AR(1) coefficient, β, governs the speed of convergence, and $\alpha/(1-\beta)$ can be interpreted as the long-run level that the gap is converging to.

The red solid line in Figure 3 plots the fitted value from this regression from 1980 to 2016. Before 1980, we plot a linear trend. Evidently, this simple statistical model performs well in explaining the evolution of the gender gap over the past several decades. This implies that the gender gap in employment rates has been declining approximately at a constant exponential rate since 1980. The estimated annual AR coefficient, β, is 0.88, which implies a half-life of roughly five and a half years. The estimated constant term, α, is -0.0165. These estimates imply that over this period, the gender gap has been converging to a long-run level of -13.5%.[12]

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[12] Among the many factors that may explain this long-run difference, Borella, De Nardi, and Yang (2018) emphasize that women often face high marginal tax rates as second earners.
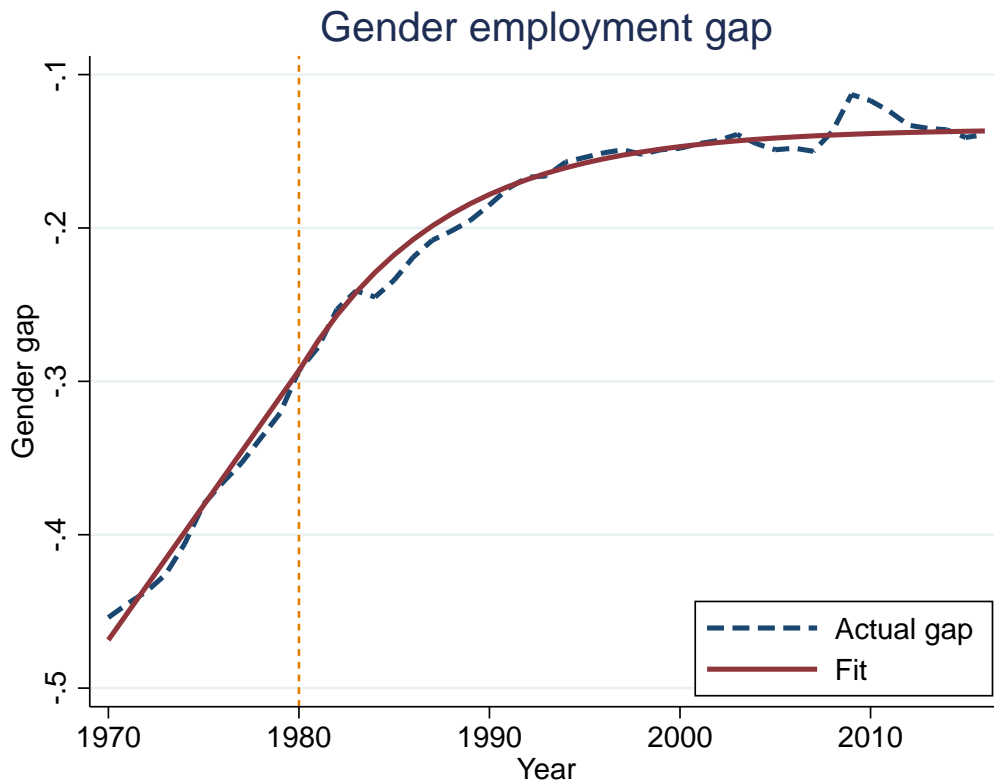
Figure 3: Convergence in Employment Rates

Figure 4 plots the employment rates of married and single men and women separately.[13] This figure shows the striking fact that the increase in female employment over our sample period comes entirely from married women. The employment rate of single women was comparable to that of single men in 1970 and follows a secular decline throughout our sample period similar to that of single (and married) men. These facts motivate our choice later in the paper to focus our model on married couples. Notice also that the employment rate of married men does not fall relative to that of single men despite the large increase in spousal income married men experience.

3.1   Decomposing the Rise in the Female Employment Share

The model of gender convergence that we present later in the paper does not require us to take a stand on the ultimate causes of the Gender Revolution. Our sufficient statistic argument for analyzing the impact of the gender revolution goes through regardless of its causes. Nevertheless, to gain some intuition, it is useful to carry out a shift-share decomposition of the rise in the female

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[13]We follow McGrattan and Rogerson (2008) in defining households as "married" when their marital status is "married with spouse present" and single when their marital status is "never married."
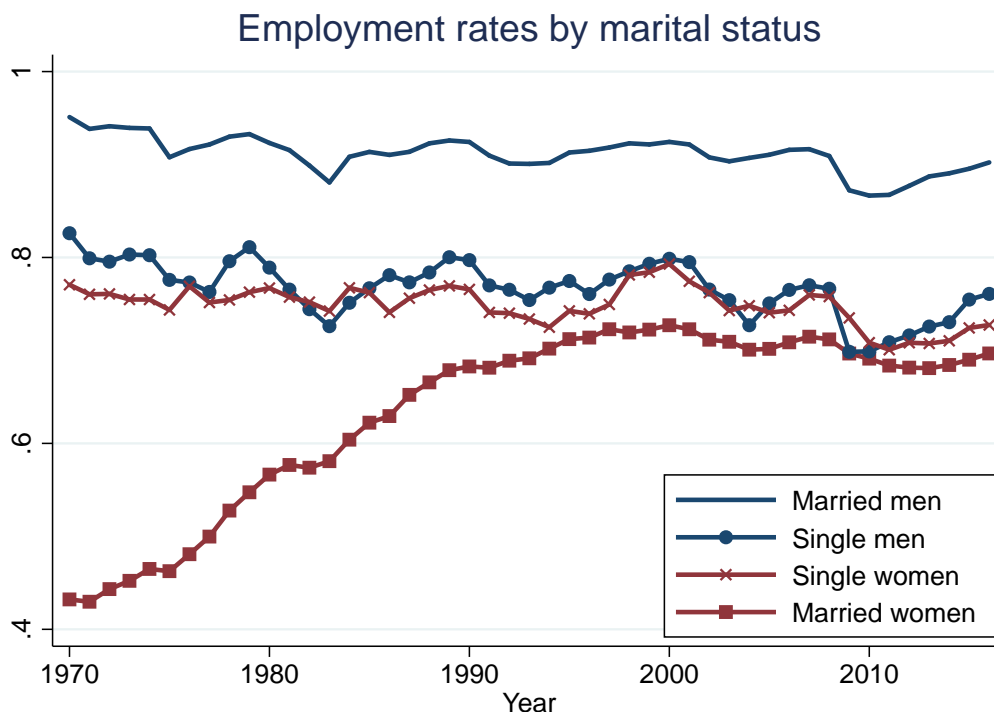
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Figure 4: Employment Rates by Marital Status

employment share over the course of the Gender Revolution. This exercise sheds light on the extent to which the Gender Revolution was associated with a sectoral shift toward jobs more likely to be performed by women, or a rise in the fraction of women within particular occupations?

Let $L_t(\omega)$ and $L_{ft}(\omega)$ denote total and female employment in occupation ω at time t. Let $\alpha_t(\omega) \equiv L_{ft}(\omega)/L_t(\omega)$ denote the female employment share in occupation ω, let $\alpha_t \equiv (\sum_\omega L_{ft}(\omega))/(\sum_\omega L_t(\omega))$ denote the aggregate female employment share at time t, and let $\pi(\omega) \equiv L_t(\omega)/(\sum_\omega L_t(\omega))$ denote the employment share of occupation ω. Now consider two time periods, $T > t$, and define $\Delta x \equiv x_T - x_t$ and $\bar{x} = (x_T + x_t)/2$, for any variable x. Then the aggregate change in the female employment share $\Delta\alpha$ can be decomposed into

$$\Delta\alpha = \underbrace{\sum_\omega \bar{\pi}(\omega) \Delta\alpha(\omega)}_{\text{within}} + \underbrace{\sum_\omega \Delta\pi(\omega) \bar{\alpha}(\omega)}_{\text{between}}.$$

The "between" component captures the rise in the aggregate female share of employment that would have occurred if only the employment shares across occupations had changed, but the female employment share in each occupation remained constant. The "within" component captures
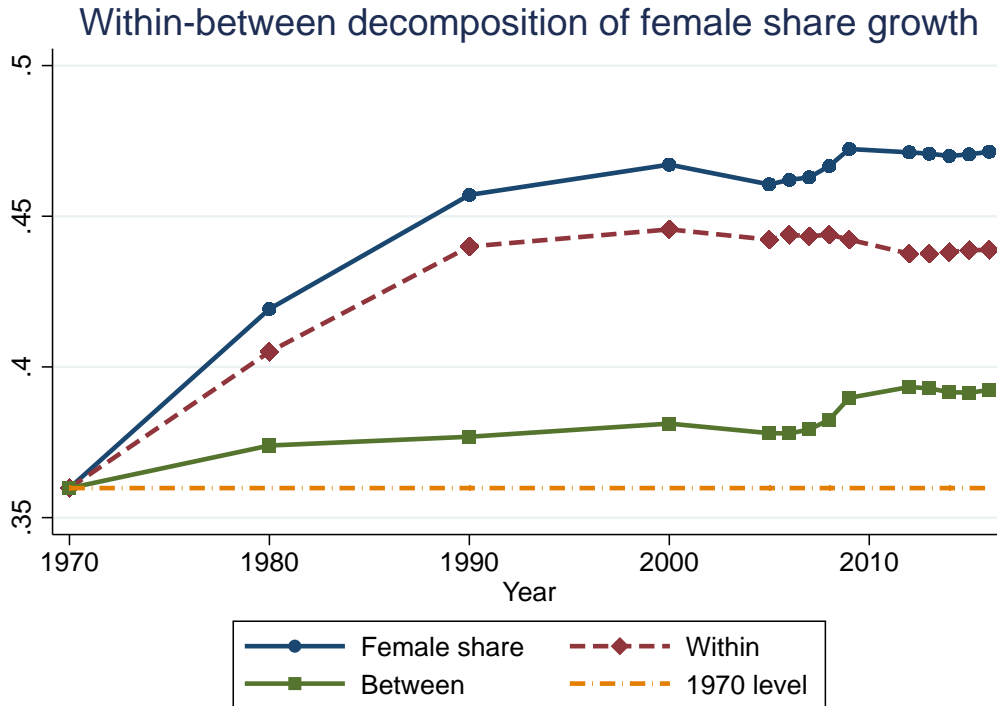
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Figure 5: Within and Between Decomposition of Female Share Growth

the rise in the aggregate female employment share that would have occurred if employment shares across occupations had remained constant, while the within-occupation female shares changed as they did in the data.

Figure 5 reports the results of this decomposition. To implement this decomposition over time, we take the base year to be $t = 1970$ while we vary T from 1980 to 2016. The figure shows clearly that most of the Gender Revolution comes from the "within" as opposed to the "between" component. The within component—arising from increases in female employment shares within occupations—accounts for nearly 80% of the rise in the total female share. In contrast, shifts in the economy toward occupations with higher female shares of employment are relatively unimportant. These reduced form facts do not, of course, settle the question of what caused the Gender Revolution. The shift-share decomposition we report above is a simple exercise that can't rule out richer interactions between occupational changes and gender shares, which could both be affected, for example, by a growing prevalence on female biased skills.[14]

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[14]Figure A.5 plots the service sector share and the skill premium over time. The dynamics of neither series line up well with the dynamics of the Gender Revolution. Figure A.6 shows that there is no relationship between either growth in the service share or growth in the skill premium and the change in the gender gap across U.S. states.

4 Cross-State Evidence on Crowding Out

We showed in the introduction that crowding out of men by women is a sufficient statistic for assessing the role of female-biased shocks (such as the shocks that caused the Gender Revolution) on total employment and therefore on the slowdown of recoveries. We defined crowding out as the response of male employment relative to the response of female employment to a female-biased shock: $\frac{dL_m}{d\theta} / \frac{dL_f}{d\theta}$, where θ denotes female-based shocks. Our goal in this section is to measure crowding out.

The central empirical challenge that we face in measuring crowding out is the presence of gender-neutral shocks. Male and female employment rates comove positively in response to gender-neutral shocks. A naive empirical strategy that regresses the change in male employment rates on the change in female employment rates will not yield a valid estimate of our concept of crowding out because the changes in male and female employment rates will be due to a mix of gender-neutral and female-biased shocks.[15] An unbiased estimate of crowding out requires us to identify a source of variation in female employment rates that is driven by female-biased shocks.

Notice that we don't care whether the female-biased shocks we identify are labor demand shocks or labor supply shocks. This distinction is important in many contexts, but not in our context. While female-biased labor demand shocks and labor supply shocks will not have identical consequences for all questions, we show in section 7.1 that these differences do not matter for the question we seek to answer.

4.1 Cross-Sectional Gender Convergence

The source of variation in female employment rates that we propose to use to estimate crowding out is cross-sectional. Specifically, we propose to use variation associate with gender convergence at the state level, which mirrors the convergence patterns we documented at the aggregate level in section 3. The top-left panel of Figure 6 plots the change in the gender gap for U.S. states from 1970 to 2016 against the initial gender gap in 1970. The figure shows strong evidence of cross-sectional convergence: states with an initially large gender gap experienced more rapid subsequent declines in the gender gap. The other three panels of Figure 6 plot the change in female, male, and total employment rates, respectively, against the initial gender gap in 1970. Together, these panels show that virtually all of the convergence across states arises from a more rapid increase in female

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[15]It is without loss of generality that we don't discuss male-biased shocks since these can be constructed as a combination of gender-neutral and negative female-biased shocks.
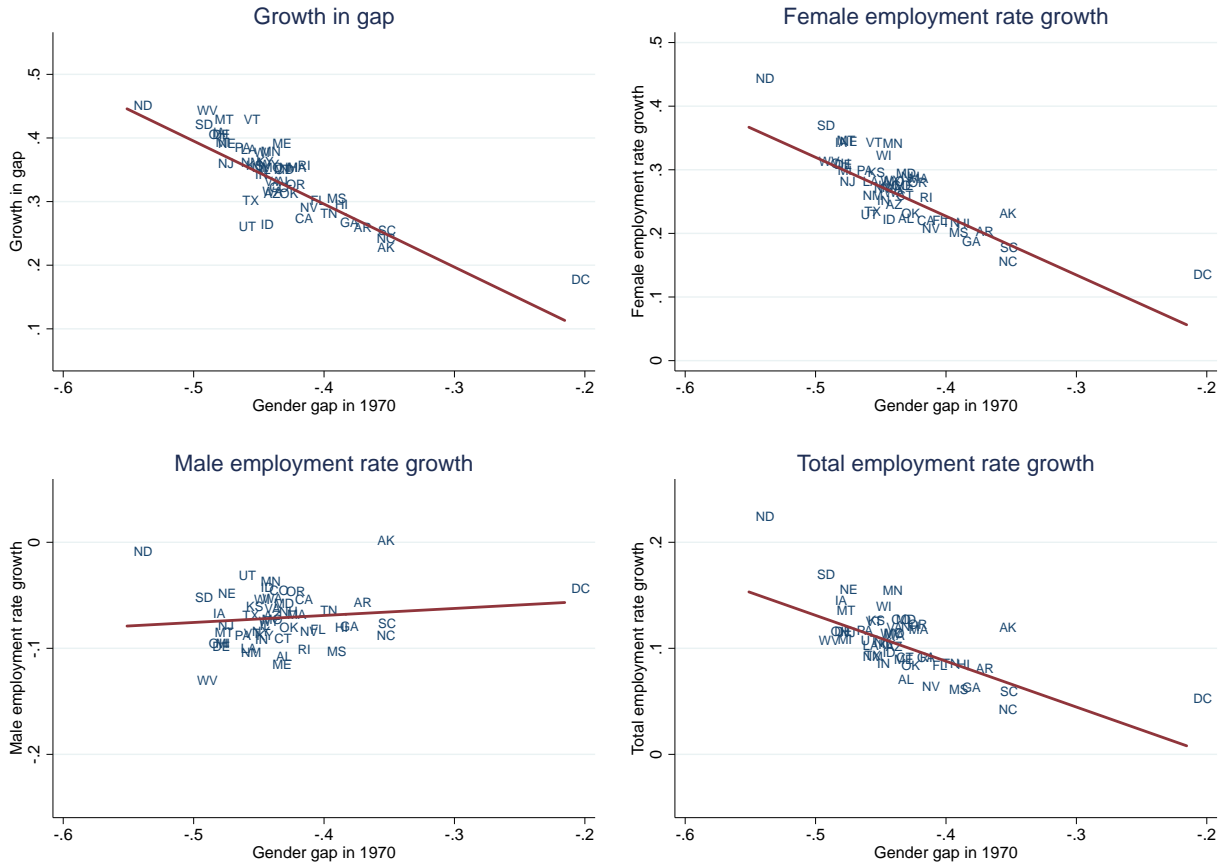
Figure 6: Gender Gap Convergence Across States

employment rates—i.e., women converging toward men. In sharp contrast, the change in male employment rates is not strongly related to the initial gender gap.

Figure 7 reports analogous results to those reported in Figure 6 for commuting zones.[16] The results are very similar to our state-level results: (i) commuting zones with initially large gender gaps tend to see larger reductions in the gender gap; (ii) the differential closing of the gender gap is mostly driven by faster growth in female employment; (iii) the change in male employment is not strongly related to the initial gender gap; and (iv) as a result, commuting zones with initially large gender gaps experienced faster total employment growth.

Motivated by Figures 6 and 7, we estimate the following convergence regression:

$$\Delta gap_i = \alpha + \beta gap_{i,1970} + \mathbf{X}_i' \gamma + \epsilon_i, \tag{3}$$

where i denotes state, $\Delta gap_i \equiv gap_{i,2016} - gap_{i,1970}$, and $\mathbf{X}_i$ is a vector of controls. A negative

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[16]We use definitions of commuting zones from Tolbert and Sizer (1996).

15
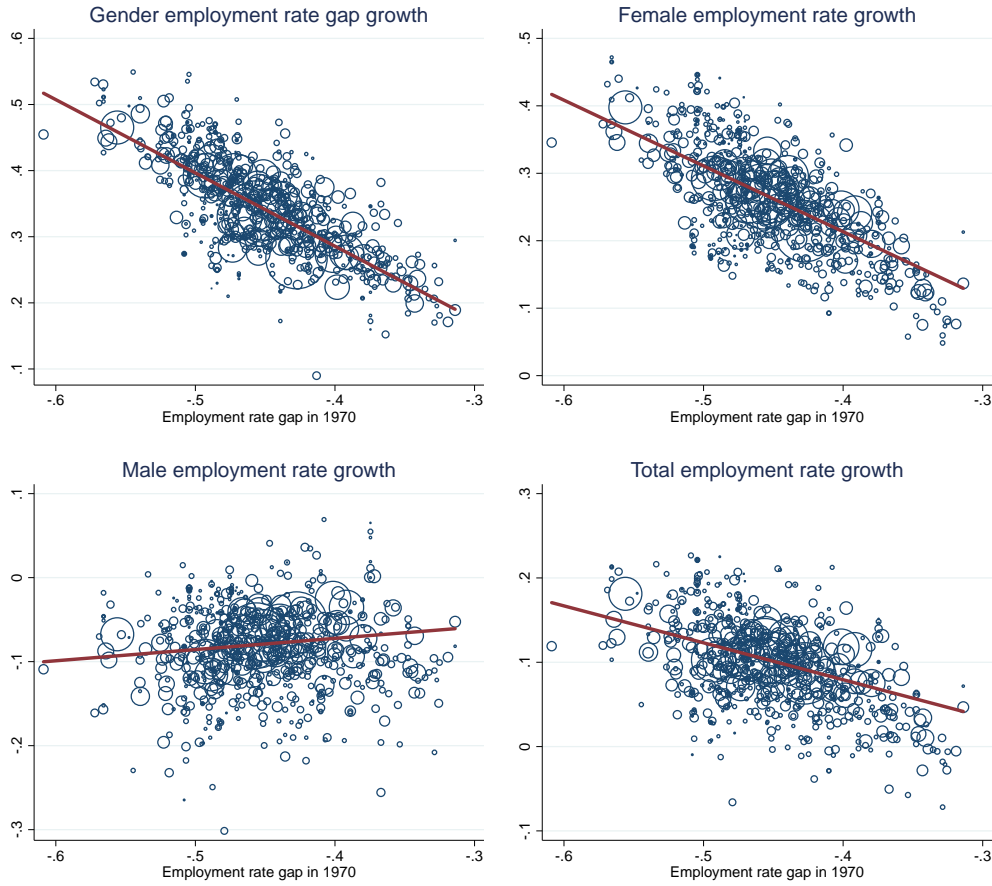
Figure 7: Gender Gap Convergence Across Commuting Zones

Note: Each circle corresponds to a commuting zone. The size of the circle represents the initial population size for that commuting zone. The line in each panel is from an OLS regression where observations are weighted by initial population size.

value of β indicates cross-state convergence. Column 1 of Table 2 presents the resulting estimates without controls. Despite having a small number of observations, we estimate β to be highly statistically significantly negative, indicating strong convergence. The point estimate is close to -1, indicating that over the period 1970-2016 the cross-state variation in the gender gap is completely eliminated on average. We have also run this type of analysis at the commuting zone level. This yields very similar results.

Table 2 also presents estimates of the relationship between the growth in the female employment-to-population ratio and the initial gender gap. The regression we run is

$$\Delta epop_i^F = \alpha + \beta gap_{i,1970} + \mathbf{X}_i'\gamma + \epsilon_i, \tag{4}$$

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Table 2: Gender Gap Convergence Across States

	Gender gap growth			Female emp. rate growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender gap in 1970	-0.991	-0.959	-1.060	-0.925	-0.893	-0.900
	(0.135)	(0.143)	(0.101)	(0.174)	(0.108)	(0.0834)
Skill premium in 1970			0.00402			-0.0483
			(0.0527)			(0.0411)
Log per-capita GDP in 1970			-0.0115			0.0156
			(0.0266)			(0.0271)
Non-white share in 1970			-0.0590			-0.120
			(0.0308)			(0.0292)
Bartik shock			0.0417			-0.0149
			(0.0896)			(0.0821)
Singles share in 1970			1.338			1.284
			(0.241)			(0.228)
Sectoral controls		✓	✓		✓	✓
Obervations	51	51	51	51	51	51
Adjusted R^2	0.687	0.677	0.789	0.652	0.724	0.837
F-stat	53.50	17.66	48.33	28.20	30.34	86.50

Note: The dependent variable in columns 1, 2, and 3 is the growth in the gender gap over the period 1970-2016. In columns 4, 5, and 6, the dependent variable is the growth of female employment-to-population ratio over the same time period. The sectoral controls are employment shares in agriculture, mining, manufacturing, and services in 1970. Robust standard errors are reported in parentheses.

where $\Delta epop_i^F \equiv epop_{i,2016}^F - epop_{i,1970}^F$ is the change in the female employment rate over the period 1970 - 2016 in state i. The coefficient we estimate on the initial gender gap in this regression—column 4 of Table 2—is virtually identical to the coefficient in the earlier regression (column 1). This shows that the gender gap fell more rapidly in states with a larger initial gap because of the differential behavior of female employment rates, not male employment rates.

Finally, the remaining columns of Table 2 present estimates for specifications that include various controls. These help assess whether the gender gap is picking up the effects of other prominent explanations for the rise of female employment such as the rise of the service sector, the increase in the skill premium, or other changes in industrial structure. To gauge the importance of these factors, we include as controls: the employment shares in agriculture, mining, manufacturing, and services in 1970, the skill premium in 1970, the share of singles in 1970, log per-capita GDP in 1970,

the non-white share of the population in 1970, and a Bartik shock (the construction of which we describe in more detail in Appendix A.1). The coefficient on the gender gap is unchanged when these controls are included. This suggests that the gender gap is an independent vector from these other prominent explanations for the rise of female employment.

4.2 Instrumental Variables Estimates of Crowding Out

We propose to estimate crowding out using the following cross-sectional specification:

$$\Delta epop_i^M = \alpha + \beta \Delta epop_i^F + \mathbf{X}_i' \gamma + \epsilon_i, \tag{5}$$

where θ_{fi}, where $\Delta epop_i^M \equiv epop_{i,2016}^M - epop_{i,1970}^M$ is the change in the male employment rate over the period 1970 - 2016, and $\mathbf{X}_i$ is a vector of controls. The coefficient of interest is β.

Two issues arise. First, since this specification focuses on cross-sectional variation, it can only yield an estimate of relative crowding out, not aggregate crowding out. Aggregate general equilibrium effects can result in aggregate crowding out deviating from relative crowding out. Since it is aggregate crowding out that is a sufficient statistic for our theoretical counterfactual, we need to pay special attention to how our empirical estimate of relative crowding out may differ from aggregate crowding out when we perform our counterfactual. We do this in sections 5.3 and 6.3.

The second issue is that equation (5) will only generate an unbiased estimate of crowding out if the variation in $\Delta epop_i^F$ used to estimate β arises from female biased shocks. If we use all the variation in $\Delta epop_i^F$, this will include both female biased shocks and gender-neutral shocks. Focusing on cross-sectional variation should help in this regard, since this differences out all aggregate shocks such as business cycle shocks and aggregate growth, much of which is gender neutral. But even some cross-sectional variation may be due to gender neutral shocks.

To address this issue, we propose two proxies for female-biased shocks over our sample period. The first is simply the gender gap in 1970. We have documented very strong cross-sectional convergence in the gender gap over our sample period. This suggests that the gender gap in 1970 is a good proxy for exposure to the Gender Revolution across states (a large female biased shock). The key identifying assumption is that the gender gap in 1970 is orthogonal to subsequent cross-state variation in gender-neutral shocks. One can also view the gender gap as conceptually similar to a "shift-share" instrument in the sense of Goldsmith-Pinkham, Sorkin, and Swift (2020). They formalize commonly used "shift-share" designs by treating initial shares as instruments. Since the

initial gender gap is very similar to the initial female share, our identification strategy is isomorphic to the one they describe.

The second proxy for female-biased shocks we propose is the "Job Opportunity Index" of Nakamura, Nakamura, and Cullen (1979). We construct this variable for each state i in 1970 according to the formula

$$JOI_{i,1970} = \sum_{\omega} \alpha_{-i,1970}(\omega)\pi_{i,1970}(\omega),$$

where ω denotes occupation, $\alpha_{-i,1970}(\omega)$ is the national prime-age female share in occupation ω (leaving out state i), and $\pi_{i,1970}(\omega)$ is the prime-age employment share of occupation ω in state i.[17] This variable captures state-level differences in demand for female labor arising from differences in occupational structure in 1970. In this case, the key identifying assumption is that the initial occupational share is orthogonal to subsequent gender neutral shocks. This again falls into the framework of Goldsmith-Pinkham, Sorkin, and Swift (2020). By applying their arguments, our estimator is equivalent to a GMM estimator where we use occupational shares as instruments with national female shares in each occupation as the weighting matrix.

We implement these empirical strategies by running instrumental variables regressions with these proxies for female biased shocks as instruments for the change in the female employment rate. We report the results of this analysis in panel A of Table 3. The first two columns present results using the gender gap in 1970 as an instrument, while the third and fourth columns present results using the JOI as an instrument. In both cases we present estimates with and without controls. The set of controls are the same as in Table 2. In all four cases, the first-stage regressions are strong as indicated by high first-stage F-statistics. When the gender gap in 1970 is used as an instrument, the first-stage regression is the cross-state convergence relationship reported in Table 2.

All four IV estimates of crowding out indicate that crowding out is minimal. The largest degree of crowding out across these four specifications is the specification in column 2—with the gender gap in 1970 serving as our proxy for female-biased shocks conditional on the controls we discuss above. But even in this case, the estimate of β indicates that a 1 percentage point increase in female employment rate due to female-biased shocks leads to only a 0.18 percentage point decrease

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[17]Our occupational measure is based on a classification scheme by Autor and Dorn (2013) ("occ1990dd") for the period 1980 - 2008. We manually aggregated this original scheme to 250 occupational categories to create a balanced occupational panel for the period 1970 - 2016.

Table 3: Estimates of Crowding Out: Effect on Male Employment

| | Panel A. Δ(Male Employment) | | | | | |
| | 2SLS (gap) | | 2SLS (JOI) | | OLS | |
	(1)	(2)	(3)	(4)	(5)	(6)
Δ(Female Employment)	-0.07	-0.18	0.04	0.06	0.06	-0.07
	(0.11)	(0.08)	(0.13)	(0.11)	(0.08)	(0.07)
Controls		✓		✓		✓
Observations	51	51	51	51	51	51
First-stage F stat	28.20	116.51	23.05	26.52		

| | Panel B. Δ(Total Employment) | | | | | |
| | 2SLS (gap) | | 2SLS (JOI) | | OLS | |
	(1)	(2)	(3)	(4)	(5)	(6)
Δ(Female Employment)	0.47	0.45	0.50	0.53	0.52	0.47
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.03)
Controls		✓		✓		✓
Observations	51	51	51	51	51	51
First-stage F stat	28.20	116.51	23.05	26.52		

Note: The dependent variable in panel A is the change in the male employment rate over the period 1970-2016, while in panel B it is the change in the total employment rate over this period. The main explanatory variable is the change in the female employment rate over the same time period. Columns 1 and 2 instrument for this explanatory variable using the 1970 gender gap in employment rates, while Columns 3 and 4 instrument using the Job Opportunity Index (JOI) described in the text. Controls refers to the full set of variables that we include in Table 2. Robust standard errors are reported in parentheses.

in male employment rate. The other specifications imply even less crowding out. All estimates except for the one in the second column are not statistically significantly different from each other or from zero.[18] In our theoretical analysis in sections 6 and 7, we take 0.18 as our baseline estimate for regional crowding out. We view this as a conservative choice, given that it is the upper envelope of the different estimates of crowding out we have obtained in our various empirical specifications. We also report counterfactual results for zero crowding out.

In Panel B of Table 3, we report results for a specification where the dependent variable is the change in the total employment rate, $\Delta epop_i^T$. If there were no crowding out, a 1 percentage point increase in the female employment rate would lead to a 0.5 percentage point increase in the total employment rate (since women account for half of the population). Our estimates are close to this no-crowd-out case: a 1 percentage point increase in female employment rate due to

[18] As can be seen in Figure 6, DC is an outlier. However, these results are robust to excluding DC. We have also conducted this analysis at the commuting zone level and this yields similar results (unreported).

female-based shocks translates into a 0.45-0.53 percentage point increase in the total employment rate depending on the specification. None of these estimates are statistically different from 0.50.

4.3 Threats to Identification

As we noted above, the key identifying assumption we are making is that our two instruments do not predict gender neutral shocks in the cross-section. If this assumption holds, our estimates indicate that crowding out is small. An alternative (more complicated) explanation of the data is that crowding out is actually large but the effect on male employment across states is offset by a roughly opposite pattern of gender neutral shocks. In this case, states that were particularly "behind" in terms of the gender gap also tended to experience positive employment shocks for men thereafter which offset the fact that men would otherwise have been crowded out.

While we cannot rule out this hypothesis, we can explore the plausibility of our identifying assumptions. One potential threat to identification is the worry that states that were "backward" in terms of the gender employment gap may also have been economically "backward" in other ways and therefore had lower male employment rates in 1970, which might have mean-reverted thereafter. In practice, however, states with a large (negative) gender gap in 1970 actually had higher average male employment rates in 1970 (the opposite from what this backwardness story suggests). A related concern is that there may have been differential pretrends. This is not the case. We show in Appendix A.5 that the gender gap in 1970 is uncorrelated with male and female employment growth rates in 1960s. Petterson et al. (2021) provide a related defense of our results based on the idea of placing bounds on the plausible size of shocks to male employment relative to female employment over our sample.

In Appendix A.5, we perform several additional diagnostic tests of the type recommended by Goldsmith-Pinkham, Sorkin, and Swift (2020) to assess our identifying assumptions. The "usual suspects" for factors that might have predicted overall employment growth are not correlated with the initial gender gap or the employment shares of occupations that receive large weights in JOI instrument. These include GDP per capita, the service sector employment share, the share of college graduates, the skill premium, and subsequent China shocks. We also analyze the relationship between our instruments and sectoral shares. The evidence favoring an important role for sectoral effects in driving crowding out appears weak, and is mostly driven by outliers. The most robust evidence for this type of correlation is with the non-white share, possibly reflecting variation across states in the overall degree of discrimination of multiple types (not only gender

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discrimination). We discuss this evidence in detail in Appendix A.5.

5 Crowding Out in a Simple Model

As a stepping stone towards developing a quantitative model in which we can conduct our main counter-factual, it is useful to consider a simple static model. This allows us to introduce the distinctive features of the model in as simple a setting as possible. It also allows us to derive analytical expressions for crowding out, which aid intuition. Finally, we can discuss the economics behind the difference between regional and aggregate crowding out. We then augment this simple model in section 6 to include additional features needed to match business cycle fluctuations.

5.1 A Simple Model without Home Production

Consider a model economy that consists of a representative firm and a large household made up of a continuum of men and women. The production technology used by the representative firm is linear in male and female labor:

$$y = A(L_m + \theta_f L_f), \tag{6}$$

where y denotes output produced, L_m denotes male labor, L_f denotes female labor, A denotes gender-neural aggregate productivity, and θ_f denotes female-specific productivity. All markets are competitive. The wages of men and women are equal to their marginal products: $w_m = A$ and $w_f = A\theta_f$, respectively, where the consumption good is taken to be the numeraire.

The large household maximizes a utility function that is given by the integral of the utility of each member. Household members derive utility from consumption and disutility from supplying labor. Consumption is shared among all members of the household. Each household member, however, faces a discrete choice regarding whether to supply labor or enjoy leisure. Furthermore, household members differ in their disutility of labor. The disutility of labor of household member $j \in [0,1]$ is given by $j^{\nu^{-1}}/\chi_g$ with $g \in \{m,f\}$. Here, χ_m and χ_f are gender specific labor supply parameters, and ν is the Frisch elasticity of labor supply. We assume that the Frisch elasticity ν is the same for men and women for simplicity.

Household members with low disutility of labor (low j) choose to work, while household members with high disutility of labor choose to enjoy leisure. The household's utility function can be written as

$$U = \frac{C^{1-\psi}}{1-\psi} - \frac{1}{\chi_m}\frac{(L_m)^{1+\nu^{-1}}}{1+\nu^{-1}} - \frac{1}{\chi_f}\frac{(L_f)^{1+\nu^{-1}}}{1+\nu^{-1}}, \tag{7}$$

where $\psi > 0$ governs the strength of the income effect on labor supply. Following Galí (2011), we have integrated over the disutility of labor of household members that choose to work.[19] In equation (7), L_m and L_f, therefore, denote the employment rate of men and women, respectively, as opposed to hours worked. Appendix B.1 provides more detail on how equation (7) is derived.

The household's budget constraint is

$$C = w_m L_m + w_f L_f. \tag{8}$$

Income by all household members is shared equally and, therefore, contributes to the consumption of all members. In particular, men share their labor earnings with women, and, conversely, increased labor earnings by women results in higher consumption by men.

Maximizing household utility and substituting $w_m = A$ and $w_f = A\theta_f$ yields equilibrium male and female employment rates of

$$L_m = A^{\frac{1-\psi}{\nu-1+\psi}}(\chi_m)^\nu((\chi_m)^\nu + (\chi_f)^\nu(\theta_f)^{\nu+1})^{\frac{-\psi\nu}{1+\nu\psi}}, \tag{9}$$

$$L_f = A^{\frac{1-\psi}{\nu-1+\psi}}(\theta_f)^\nu(\chi_f)^\nu((\chi_m)^\nu + (\chi_f)^\nu(\theta_f)^{\nu+1})^{\frac{-\nu\psi}{1+\nu\psi}}. \tag{10}$$

Suppose, for simplicity, that female convergence is driven by an increase in female-biased productivity θ_f. Increases in θ_f may be interpreted in several ways. The most straightforward interpretation is female-biased technical change (i.e., the rise of the service sector). But increases in θ_f may also be interpreted as resulting from a decrease in discrimination against women. If discrimination takes the form of men refusing to collaborate with women or promote them in the workplace, it will result in low productivity of women. Changes in the attitudes of men towards women in the workplace will then increase women's productivity.[20]

Increases in θ_f increase female labor *demand*. An alternative model of female convergence is that it resulted from an increase in female labor *supply*. If discrimination takes the form of men making employment unpleasant for women, it will result in low female labor supply. Cultural norms may also have discouraged women from entering the workplace or remaining employed after starting a family.

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[19]Gali's (2011) formulation is a generalization of the commonly used formulation of Hansen (1985) and Rogerson (1988) to allow for heterogeneity in disutility of labor. The degree of heterogeneity in disutility of labor across household members controls the labor supply elasticity at the aggregate level. As this heterogeneity falls to zero, the aggregate elasticity of labor supply converges to infinity as in Hansen (1985) and Rogerson (1988).

[20]Hsieh et al. (2019) model discrimination as a tax on female labor that accrues to firm owners. This formulation is isomorphic to our female-biased productivity shocks.

Our results are essentially invariant to whether we model the Gender Revolution as arising from labor demand or supply shocks, as we discuss in section 7.1. However, in our baseline case we model female convergence as an increase in female labor demand, because a demand-shock based explanation is more consistent with the fact that relative female wages have increased substantially over the course of the Gender Revolution (see Appendix A.4.2).[21]

Let us now consider how a change in θ_f affects male and female employment in this simple model. The log derivatives of male and female employment rates with respect to θ_f are given by

$$\frac{d \ln L_f}{d \ln \theta_f} = \underbrace{\nu}_{\text{substitution effect}} \underbrace{- \frac{\nu\psi}{1+\nu\psi}(\nu+1)\Lambda_f}_{\text{income effect}},$$

$$\frac{d \ln L_m}{d \ln \theta_f} = \underbrace{- \frac{\nu\psi}{1+\nu\psi}(\nu+1)\Lambda_f}_{\text{income effect}}$$

where $\Lambda_f \equiv \frac{(\chi_f)^\nu(\theta_f)^{\nu+1}}{(\chi_m)^\nu+(\chi_f)^\nu(\theta_f)^{\nu+1}}$ denotes the fraction of labor income earned by women. An increase in θ_f has two effects on female employment: a positive substitution effect and a negative income effect. For plausible parameter values, the substitution effect is stronger than the income effect—since women share their income with men within the household. An increase in θ_f, therefore, leads to an increase in female employment. For men, the change in θ_f does not have a substitution effect. The increased family income that results from the increase in female employment, however, leads men to decrease their employment. It is through this income effect that women crowd men out of the labor market in this basic model.

As we discuss in the introduction, we define crowding out of men by women in the labor market at the aggregate level as

$$\epsilon^{agg} \equiv \frac{\frac{dL_m}{d\theta_f}}{\frac{dL_f}{d\theta_f}} = \frac{\frac{d \ln L_m}{d \ln \theta_f}}{\frac{d \ln L_f}{d \ln \theta_f}} \frac{L_m}{L_f}. \tag{11}$$

ϵ^{agg} measures the change in male employment per unit increase in female employment in response to an economy-wide female-biased labor demand shock (θ_f). In the simple model we analyze in

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[21]Jones, Manuelli, and McGrattan (2015) show that in their quantitative model, supply side explanations for gender convergence have difficulty generating the magnitude of relative wage increases observed in the data. In addition to the basic features we consider, they also incorporate endogenous human capital accumulation, which implies that labor supply side shocks can induce women to invest more in human capital. This feature has the potential to generate relative wage increases of the type observed in the data. But Jones, Manuelli, and McGrattan find that it is not quantitatively strong enough to generate the size of the relative wage increases observed in the data.

this section, we can solve analytically for crowding out:

$$\epsilon^{agg} = \frac{\frac{-\nu\psi}{1+\nu\psi}(\chi_m)^\nu}{\frac{\nu}{(\nu+1)}\frac{1}{\theta_f}\left[(\chi_m)^\nu + (\chi_f)^\nu(\theta_f)^{\nu+1}\right] + \frac{-\nu\psi}{1+\nu\psi}(\theta_f)^\nu(\chi_f)^\nu}.$$ (12)

An important benchmark case is $\psi = 1$.[22] This is the "balanced growth preference" case highlighted by King, Plosser, and Rebelo (1988) and commonly used in the macroeconomics literature.[23] When $\psi = 1$, the above expression simplifies to

$$\epsilon^{agg} = -\theta_f = -\frac{w_f}{w_m}.$$

In this relatively standard case, therefore, crowding out is equal to the ratio of female-to-male wages; i.e., crowding out is very large. When women are exactly as productive as men, i.e., $\theta_f = 1$, crowding out is precisely one, and total employment is *unchanged* in response to a female-biased productivity shock. This result is a special case of the more general result that changes in productivity leave labor supply unchanged in the $\psi = 1$ case because the income and substitution effects of changes in wages exactly cancel out. In the present model, this result holds at the household level when men and women are equally productive.

We have made several stark simplifying assumptions above that help keep the model tractable but are not important for generating large crowding out. In Appendix B.2, we discuss several generalizations. First we relax the assumption that male and female labor are perfect substitutes. Instead, we consider a general production function $F(L_m, L_f; \theta)$ where F is constant returns to scale in male and female labor. This production function allows for arbitrary imperfect substitutability of male and female labor. Second, we consider a version of our model in which male and female leisure are complements. Third, we consider a version of our model in which income sharing between men and women within the household is imperfect. In all of these cases, crowding out is large when $\psi = 1$.

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[22]As is well known, the implications of our model when $\psi \to 1$ are the same as for a model with utility from consumption given by $\ln C$. What we refer to as the $\psi = 1$ case, is a model with utility from consumption given by $\ln C$.

[23]King, Plosser, and Rebelo (1988) show that for additively separable preferences to deliver constant labor along a balanced growth path utility from consumption must take the $\ln C$ form.

5.2 Adding Home Production

We now extend the model presented above to allow for home production by women. Each woman now chooses between three activities: working in the market, working at home, or enjoying leisure. There are now two dimensions to female heterogeneity. First, as before, women differ in their disutility of work, indexed by j. Second, women also differ in their productivity in home production, indexed by ω. We could alternatively have made women heterogeneous in their productivity in the market. This choice does not affect our results. Boerma and Karabarbounis (2017) provide estimates suggesting that heterogeneity in productivity at home is substantially larger than in the market. Female productivity in home production is distributed according to the distribution function $G(\omega)$ with support $[\underline{\omega}, \bar{\omega}]$.

We assume for simplicity that goods produced at home are perfect substitutes for goods produced in the market and that production at home is linear in labor, like market production. The wage of women working in the market is, as before, given by $w_f = A\theta_f$. The marginal product of women of type ω working at home is given by $A\omega$. Women self-select into the activity that yields the highest earnings. Conditional on working at all, women with $\omega \geq \theta_f$ choose to work at home, while women with productivity $\omega < \theta_f$ choose to work in the market.

Let $L_f(\omega)$ and $L_f^h(\omega)$ denote the female employment rate in the market and at home, respectively, as a function of ω. Output in home production is given by

$$y^h = A \int_H \omega L_f^h(\omega) dG(\omega),$$

where H is the set of women who choose to work at home conditional on choosing to work. The utility function for the representative household can be written as

$$U = \frac{(C)^{1-\psi}}{1-\psi} - v(L_m, \{L_f(\omega)\}, \{L_f^h(\omega)\}), \tag{13}$$

where

$$
\begin{aligned}
v(L_m, \{L_f(\omega)\}, \{L_f^h(\omega)\}) = & \frac{1}{\chi_m} \frac{(L_{mi})^{1+\nu^{-1}}}{1+\nu^{-1}} \\
& + \frac{1}{\chi_f} \left(\int_{\underline{\omega}}^{\theta_f} \frac{(L_f(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) + \int_{\theta_f}^{\bar{\omega}} \frac{(L_f^h(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) \right)
\end{aligned}
\tag{14}
$$

and $C = c + c^h$, the sum of the market-produced consumption good c and the home-produced

consumption good c^h. Female disutility of labor is the sum of disutility from work in the market and at home. Total female employment in the market is given by $L_f = \int_{\underline{\omega}}^{\theta_f} L_f(\omega) dG(\omega)$. We provide a more formal micro-foundation for these expressions in Appendix B.1. The amount of home production available to the household is

$$c^h = \int_{\theta_f}^{\bar{\omega}} A\omega L_f^h(\omega) dG(\omega). \tag{15}$$

The household's budget constraint is

$$c = w_m L_m + \int_{\underline{\omega}}^{\theta_f} w_f L_f(\omega) dG(\omega). \tag{16}$$

The household's problem is to maximize expression (13) subject to equations (15) and (16).

Given these assumptions, we can analytically solve for equilibrium male and female employment rates in market work:

$$L_m = A^{\frac{1-\psi}{\nu-1+\psi}} (\chi_m)^\nu \left((\chi_m)^\nu + (\chi_f)^\nu \int_{\underline{\omega}}^{\theta_f} (\theta_f)^{\nu+1} dG(\theta_f) + (\chi_f)^\nu \int_{\theta_f}^{\bar{\omega}} \omega^{\nu+1} dG(\omega) \right)^{\frac{-\nu\psi}{1+\nu\psi}},$$

$$L_f = G(\theta_f) A^{\frac{1-\psi}{\nu-1+\psi}} (\theta_f)^\nu (\chi_f)^\nu \left((\chi_m)^\nu + (\chi_f)^\nu \int_{\underline{\omega}}^{\theta_f} (\theta_f)^{\nu+1} dG(\theta_f) + (\chi_f)^\nu \int_{\theta_f}^{\bar{\omega}} \omega^{\nu+1} dG(\omega)) \right)^{\frac{-\nu\psi}{1+\nu\psi}}.$$

Taking log derivatives of these employment rates with respect to θ_f we then have

$$\frac{d\ln L_f}{d\ln \theta_f} = \underbrace{\nu}_{\text{substitution effect}} \underbrace{- \frac{\psi\nu}{1+\psi\nu}(\nu+1)\Lambda_f}_{\text{income effect}} \underbrace{+ \frac{g(\theta_f)}{G(\theta_f)}\theta_f}_{\text{switching effect}} \tag{17}$$

$$\frac{d\ln L_m}{d\ln \theta_f} = \underbrace{- \frac{\psi\nu}{1+\psi\nu}(\nu+1)\Lambda_f}_{\text{income effect}}, \tag{18}$$

where

$$\Lambda_f \equiv \frac{\int_{\underline{\omega}}^{\theta_f} (\theta_f)^{\nu+1}(\chi_f)^\nu dG(\omega)}{(\chi_m)^\nu + \int_{\underline{\omega}}^{\theta_f} (\theta_f)^{\nu+1}(\chi_f)^\nu dG(\omega) + \int_{\theta_f}^{\bar{\omega}} (\omega)^{\nu+1}(\chi_f)^\nu dG(\omega)}$$

is the share of female market work in total household income (including both market and home production).

Relative to the case without home production, there are two key differences. First, the income effect is smaller because female market work is a smaller fraction of total household income (in-
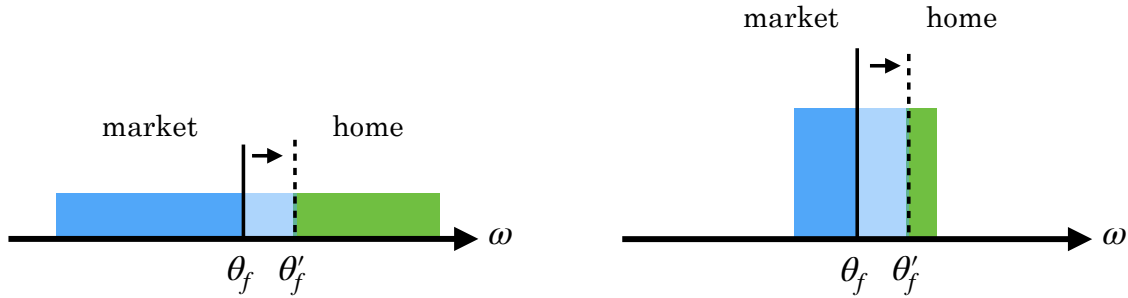
Figure 8: Illustration of Switching Effect

Notes: The figure plots the distribution of home productivity ω, which is assumed to be uniform distribution. The left panel shows a case where the distribution is concentrated, while the right panel shows a case where the distribution is dispersed. A change in θ_f leads a greater mass of women to switch from home production to market work in the former case than the latter case.

cluding both market and home production). That is, market work is a less important contributor to total household income (broadly defined) in the presence of home production. Hence, an increase in income from female market work leads to a smaller income effect on labor supply.

Second, there is a switching effect that increases the response of female employment relative to the response of male employment and therefore reduces crowding out. When θ_f increases, the wages women earn in the market increase relative to returns they earn from home production. This leads some women that were close to the margin of working in the market to switch from home production to market work. The strength of this switching effect depends on the degree of dispersion of the distribution of female productivity at home $g(\omega)$. This is illustrated in Figure 8. If $g(\omega)$ is very dispersed (as in the panel to the left in Figure 8), there will be relatively few women close to the margin and the switching effect will be small. If, however, $g(\omega)$ is concentrated close to θ_f (as in the panel to the right in Figure 8), even a small change in θ_f will lead the wage women earn in the market to sweep through a large mass of the distribution of female earnings at home. In this case, the switching effect will be large. Since we define crowding out to be the ratio of $dL_m/d\theta_f$ and $dL_f/d\theta_f$, a larger switching effect leads to less crowding out (a larger denominator).

We assume that the distribution of female productivity at home is uniform with support $[\bar{\omega} - \delta, \bar{\omega}]$. The parameter δ then controls the degree of dispersion of female productivity at home and, thereby, the strength of the switching effect. Table 4 presents results on crowding out for three different values of δ. We take $\delta = 0.88$ to be our benchmark value with $\bar{\omega} = 1.38$. (We provide a rationale for these choices in Section 6.3.) In this case, crowding out is 0.19. Evidently, introducing home production into the model dramatically lowers the magnitude of crowding out. For $\delta = 0.4$, crowding out is even smaller (it takes a value of 0.02) since the distribution of home production

is more concentrated and a larger mass of women are close to the margin of switching between working at home and working in the market. On the other hand, a larger value of δ implies a more dispersed distribution and larger crowding out. In the limit $\delta \to \infty$, we asymptote to the level of crowding out in the model with no home production. However, crowding out is moderate for a wide range of parameter values. Even with $\delta = 1.2$, crowding out is only 0.24.

We assume that only women can work at home, not men. This is clearly an extreme assumption. There is, however, strong evidence of asymmetry in the extent to which women and men engage in home production. Ramey (2009) estimates, based on time use data, that over our sample period, the average non-employed woman spent roughly 40 hours per week on home production, roughly 80% more than the average employed woman.[24] In contrast, the average non-employed man spent roughly 20 hours per week on home production, only about 30% more than the average employed man.

The historical evolution of time spent on home production as measured by time-use surveys is broadly consistent with our model. Both Ramey (2009) and Aguiar and Hurst (2016) document that average weekly hours spent on home production by women decreased by around 25% from the 1960s to 2000s.[25] Furthermore, Aguiar and Hurst (2016) show that time spent on leisure increased for both men and women over this period. This indicates that the Gender Revolution is not the result of women giving up leisure to work. Rather women have switched from working at home to working in the market.

The crowding out results for our model reported in Table 4 are for a specific calibration of the model: We assume $\psi = 1.12$, which we show below provides a parsimonious explanation for the trend decline in the male employment rate over the past several decades. We abstract from supply-side gender differences by setting $\chi_m = \chi_f = 1$ and set the Frisch elasticity of labor supply to $\nu = 1$, a relatively standard value in the macroeconomics literature.[26] We choose θ_f to match the female-to-male employment ratio of 0.7, which is the average value for this ratio over the period 1970-2016. The top row of Table 4 reports crowding out in our model without home production

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[24]We abstract from home production for women employed in the market. Allowing for some residual home production for such women would not affect our results in important ways as long as home production falls substantially when women enter the market sector.

[25]While Ramey (2009) and Aguiar and Hurst (2016) define home production somewhat differently (the main difference is the categorization of child care), both papers indicate that female hours spent on home production decreased from 1965 to 1985, the main period of the Gender Revolution. After 1985, Ramey's (2009) estimates suggest a smaller decrease in home production than Aguiar and Hurst (2016) because of an increase in time spent on child care during this time period.

[26]The finding of large crowding out for $\psi > 1$ is robust to smaller values of the Frisch elasticity. Actually, crowding out is even larger in our numerical experiments when we assume a lower Frisch elasticity.

Table 4: Crowding Out With and Without Home Production

	Aggregate Crowding Out	Regional Crowding Out
Without Home Production	-0.76	-0.76
With Home Production:		
$\delta = 0.4$	-0.02	-0.02
$\delta = 0.88$ (Baseline)	-0.19	-0.18
$\delta = 1.2$	-0.24	-0.23

Notes: The parameter values we used to arrive at these results are $\psi = 1.12, \nu = 1, \chi_m = \chi_f = \chi_f^h = 1, \eta = 5$, and $\bar{\omega} = 1.38$. The trade costs are set to $\tau_{ij} = \bar{\tau} = 2.88$ for $i \neq j$ and $\tau_{ii} = 1$. We explain the rationale for these parameter values in Section 6.3. We chose θ_f to match the male-to-female employment ratio of 0.7. We consider numerical derivatives around these values.

(equivalent to $\delta \to \infty$) for these same parameter values. The resulting degree of crowding out is 0.76, a slightly larger value than in the case of balanced growth preferences. Clearly, home production has a large effect on crowding out in our model.

5.3 Crowding Out in an Open Economy

Our empirical estimates of crowding out in section 4 are based on cross-sectional variation and therefore provide estimates of relative crowding out rather than aggregate crowding out. To understand the relationship between aggregate and relative crowding out, we next develop an open economy version of the model described above. We consider an economy consisting of n symmetric regions indexed by i. The population of each region has measure one and is immobile. (In Appendix A.5.5, we show that cross-state net migration is not correlated with our instruments.) The market sector in each region produces a differentiated traded good using the same technology as before: $y_i = A_i(L_{mi} + \theta_{fi}L_{fi})$, and trade across regions is subject to iceberg-type trade costs, τ_{ij}. In particular, in order to deliver one unit of good from region i to region $j \neq i$, region i must ship $\tau_{ij} \geq 1$ units of the good. Home production in each region is non-tradeable and is also produced using the same technology as before: $y_i^h = A_i \int_H \omega L_{fi}^h(\omega) dG(\omega)$. For simplicity, we assume that market and home goods in region i are perfect substitutes.

Let p_i denote the price of goods produced in region i. Firm optimization implies that $w_{mi} = p_i A_i$ and $w_{fi} = p_i A_i \theta_{fi}$. The price of region j's goods in region i is $p_{ij} = \tau_{ij} p_i$. Throughout the analysis, we assume that households consume a strictly positive amount of domestically produced market goods.[27] In this case, the perfect substitutability of tradable and non-tradable goods imply

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[27]This can always be guaranteed, so long as trade costs are sufficiently high or the productivity of home production is sufficiently low.

that the marginal product of home production is $p_i A_i \omega$.

The representative household in region i derives utility from consuming goods from all regions. The goods from different regions enter the household's utility function through a constant elasticity of substitution index:

$$C_i = \left((c_{ii} + c_i^h)^{\frac{\eta-1}{\eta}} + \sum_{j \neq i} (c_{ij})^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{19}$$

where $\eta > 1$ is the elasticity of substitution across different regional goods, and c_{ij} denotes region i's consumption of region j's goods. Each household in region i solves

$$\max_{\{c_{ij}\}, c_i^h, C_i, L_{mi}, \{L_{fi}(\omega), L_{fi}^h(\omega)\}} \frac{C_i^{1-\psi}}{1-\psi} - v(L_{mi}, \{L_{fi}(\omega)\}, \{L_{fi}^h(\omega)\}) \tag{20}$$

subject to

$$\sum_j p_{ij} c_{ij} = w_{mi} L_{mi} + \int_{\underline{\omega}}^{\theta_{fi}} w_{fi} L_{fi}(\omega) dG(\omega), \tag{21}$$

$$c_i^h = \int_{\theta_{fi}}^{\bar{\omega}} A_i \omega L_f^h(\omega) dG(\omega), \tag{22}$$

and (19), where $v(L_{mi}, \{L_{fi}(\omega)\}, \{L_{fi}^h(\omega)\})$ is given by equation (14).

The equilibrium of this economy consists of $\{w_{mi}, w_{fi}, p_{ij}, \{c_{ij}\}, c_{ii}^h, L_{mi}, \{L_{fi}(\omega), L_{fi}^h(\omega), \}\}$ such that: (i) given prices, $\{\{c_{ij}\}, c_{ii}^h, L_{mi}, \{L_{fi}(\omega), L_{fi}^h(\omega), \}\}$ solve the household's problem (20); (ii) firms optimize, $w_{fi} = \theta_{fi} w_{mi}, p_{ij} = w_{mi} \tau_{ij}/A_i$; and (iii) markets clear:

$$w_{mi} L_{mi} + \int_{\underline{\omega}}^{\theta_{fi}} w_{mi} \theta_{fi} L_{fi}(\omega) dG(\omega) + \int_{\theta_{fi}}^{\bar{\omega}} w_{mi} \omega L_f^h(\omega) dG(\omega) = \sum_j \frac{(\tau_{ij} w_{mi})^{1-\eta}}{P_j^{1-\eta}} P_j C_j, \tag{23}$$

where $P_j \equiv \left[(w_i \tau_{ij})^{1-\eta} \right]^{1/(1-\eta)}$ is the price index in region j.

To build intuition for how crowding out differs in this open economy setting from the closed economy model we discussed above, we consider the case where trade costs are zero, i.e., $\tau_{ij} = 1$ for all i, j. In this case, we can solve analytically for equilibrium L_{mi} and L_{fi} (see Appendix B.3). Using those expressions, we find that the log-derivatives of male and female employment rates

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with respect to θ_{fi} are given by:

$$\frac{d\ln L_{fi}}{d\ln\theta_{fi}} = \underbrace{\nu}_{\text{substitution effect}} \underbrace{-\frac{\psi\nu}{1+\psi\nu}(\nu+1)\Lambda_{fi}}_{\text{income effect}} + \underbrace{\frac{g(\theta_{fi})}{G(\theta_{fi})}\theta_{fi}}_{\text{switching effect}} + \underbrace{\frac{1-\psi}{1+\psi\nu}\frac{d\ln(p_i/P_i)}{d\ln\theta_{fi}}}_{\text{terms of trade effect}}, \quad (24)$$

$$\frac{d\ln L_{mi}}{d\ln\theta_{fi}} = \underbrace{-\frac{\psi\nu}{1+\psi\nu}(\nu+1)\Lambda_{fi}}_{\text{income effect}} + \underbrace{\frac{1-\psi}{1+\psi\nu}\frac{d\ln(p_i/P_i)}{d\ln\theta_{fi}}}_{\text{terms of trade effect}} \quad (25)$$

where Λ_{fi} is the share of female market wages in total household income, as before. The derivative $d\ln(p_i/P_i)/d\ln\theta_{fi}$ is a terms-of-trade effect. It is equal to

$$\frac{d\ln(p_i/P_i)}{d\ln\theta_{fi}} = -\frac{1+\nu}{(1-\psi)\nu+\eta+\psi\eta\nu}\Lambda_{fi}(1-\lambda_{ii}) < 0, \quad (26)$$

where $\lambda_{ii} \equiv p_i(c_{ii}+c_i^h)/(PC_i)$ denotes the expenditure share on domestic goods in region i.

Let us now define regional crowding out of men by women in the labor market as

$$\epsilon^{reg} \equiv \frac{\frac{d(L_{mi}-L_{mj})}{d\theta_{fi}}}{\frac{d(L_{fi}-L_{fj})}{d\theta_{fi}}}. \quad (27)$$

This simple definition depends on the regions in our economy being symmetric. A more general definition is $\epsilon^{reg} \equiv \text{cov}_J(dL_{mj}/d\theta_{fi}, dL_{fj}/d\theta_{fi})/\text{var}_J(dL_{fj}/d\theta_{fi})$, i.e., the regression coefficient in a cross-sectional regression of ΔL_{mj} on ΔL_{fj} where variation in these variables is driven by small changes in θ_{fi}.

Comparing expressions (24) and (25) with expressions (17) and (18) we see that the difference between aggregate and regional crowding out arises solely from the terms-of-trade effects in regions i and j.[28] In an open economy, an increase in a particular region's θ_{fi} relative to the θ_{fj} of other regions increases the relative supply of goods from region i and thereby worsens its terms-of-trade. In other words, $d\ln(p_i/P_i)/d\ln\theta_{fi} < 0$. This deterioration in the terms-of-trade, in turn, lowers wages in region i. The effect that this fall in wages has on labor supply depends on the relative strength of income and substitution effects. If the substitution effect dominates the income effect (i.e., $\psi < 1$), the fall in wages acts to decrease both male and female employment. In this case, male employment decreases by more than in the closed economy case, and female

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[28]To calculate regional crowding out, one also needs to know the effect of a change in θ_{fi} on employment in region j. The only effect is a terms-of-trade effect. The size of this effect is given by an expression identical to equation (26) expect that the sign is reversed and the factor $(1-\lambda_{ii})$ is replaced by λ_{ij}.

employment increases by less. Hence, regional crowding out is greater than aggregate crowding out.

However, if the income effect dominates the substitution effect ($\psi > 1$), the effect of the change in wages is reversed: the fall in wages acts to increase both male and female employment. In this case, regional crowding out is smaller (in absolute terms) than aggregate crowding out. With balanced growth preferences (i.e., $\psi = 1$), income and substitution effects exactly cancel each other out and the change in regional wages leaves regional employment rates unchanged. In this benchmark case, regional crowding out exactly equals aggregate crowding out.

Even away from balanced growth preferences, the difference between regional and aggregate crowding out is quantitatively small for plausible parameter values. To illustrate this numerically, we set $\eta = 5$, $n = 2$, and other parameters as before.[29] We set $\psi = 1.12$ implying that the income effect of a wage change on employment is slightly stronger than the substitution effect, consistent with the findings of Boppart and Krusell (2016).

We then calculate the response of the economy to a small variation in the θ_{fi} in one region, while holding θ_{fj} constant for the other regions. The second column in Table 4 shows the results of these calculations. Relative to the closed economy case we studied above, crowding out is smaller in magnitude. However, the differences are small. These calculations thus indicate that for plausible parameter values, estimates of regional crowding out are highly informative about the extent of aggregate crowding out. In other words, regional crowding out is almost a sufficient statistic for our counterfactuals since it is almost the same as aggregate crowding out for plausible parameter values.

6 Business Cycle Model

We are now ready to describe our full business cycle model. This model is somewhat more complex than the simple model described in section 5 and is designed to be able to match both the long-run properties of the data that we have emphasized so far, as well as business cycle features of the data. In section 7, we use this model to formally investigate the counterfactual of what would have happened if female employment rates had continued to increase as rapidly after recent recessions as they did after the recession of the 1970s and 80s.

We start from the n-region economy presented in section 5.3. As before, each region produces

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[29]Our calibration of the elasticity of substitution of goods produced in different regions of $\eta = 5$ is based on the results of Head and Mayer (2014).

a differentiated tradable good as well as non-tradable home production. We assume that time is discrete and the time horizon infinite. To be able to match business cycle fluctuations in employment, we assume preferences that are a hybrid of the preferences introduced by Galí, Smets, and Wouters (2012) and those studied by Boppart and Krusell (2016). This preference specification implies that, in the short-run, substitution effects dominate income effects as in Galí, Smets, and Wouters (2012) and Jaimovich and Rebelo (2009), but in the long-run, income effects dominate substitution effects, as in Boppart and Krusell (2016). This allows us to generate a positive correlation between employment and productivity over the business cycle but also a long-run decline in male employment rates in response to secular increases in productivity.[30]

The preferences of the representative household in region i are

$$U_i = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(C_{it})^{1-\psi}}{1-\psi} - \Theta_{it} v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{fit}^h(\omega)\}) \right], \tag{28}$$

where $\beta \in (0,1)$ is the household's subjective discount factor, and the preference shifter Θ_{it} is given by

$$\Theta_{it} = X_{it}^{\psi} C_{it}^{-\psi}, \quad \text{with} \quad X_{it} = (X_{it-1})^{1-\gamma}(C_{it})^{\gamma}, \tag{29}$$

where $\gamma \in [0,1]$ and $\psi > 0$ capture the strength of short-run and long-run wealth effects, respectively. Here, X_{it} is a "consumption habit" that affects the disutility of labor. As in Jaimovich and Rebelo (2009) and Galí, Smets, and Wouters (2012), higher consumption does not immediately raise the disutility of labor. Instead, the consumption habit accumulates slowly over time, generating a large income effect only in the long-run. We assume households do not internalize the effect of their consumption decisions on the preference shifter, Θ_{it}, following Galí, Smets, and Wouters (2012).[31] The consumption basket C_{it} is given by equation (19) as in section 5.3 and the function v is given by equation (14).

Several standard preference specifications are nested as special cases of the preferences above. Setting $\psi = 1$ yields the preference specification proposed by Galí, Smets, and Wouters (2012), which in turn builds on Jaimovich and Rebelo (2009). In this case, employment rates are constant along a balanced growth path. Setting $\psi = \gamma = 1$ yields KPR preferences (King, Plosser, and

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[30]Boppart and Krusell (2016) document that hours worked have been falling over the past century in essentially all developed countries, motivating a preference specification in which income effects dominate substitution effects in the long-run. Bick, Fuchs-Schündeln, and Lagakos (2018) present similar facts in the cross-section for a broad set of countries.

[31]In contrast, Jaimovich and Rebelo (2009) assume internal habits. We assume external habits purely for tractability.

Rebelo, 1988). Setting either $\psi = 0$ or $\gamma = 0$ yields GHH preferences (Greenwood, Hercowitz, and Huffman, 1988). If $\psi > 1$ and $\gamma = 1$, the preferences fall into the class of preferences discussed by Boppart and Krusell (2016) that generate falling labor along an otherwise balanced growth path. Also note that when $\gamma = 1$, the model is identical to the one we studied in section 5.3.

The equilibrium in this economy is defined as follows. (i) Given X_0, the path of $\{\Theta_{it}\}$, and prices $\{w_{mit}, w_{fit}, p_{ijt}\}$, households choose $\{c_{ijt}, C_{it}, L_{mit}, L_{fit}(\omega), L^h_{fit}(\omega)\}$ to maximize expression (28) subject to equations (19), (21) and (22) for each period t; (ii) firm optimization implies $w_{fit} = \theta_{fit} w_{mit}$ and $p_{ijt} = w_{mit} \tau_{ij} / A_i$; (iii) markets clear (equation (23)); and (iv) the path of preference shifter $\{\Theta_{it}\}$ is given by (29).

6.1 Long-run Characterization

We first characterize the balanced growth path when gender-neutral productivity is assumed to grow at the constant rate $g_A > 0$ in all regions, i.e., $A_{it} = A_i e^{g_A t}$, and θ_f, is assumed to be constant. Along such a balanced growth path, consumption grows at rate g_C and labor supply grows at rate g_L, where

$$g_C = g_A \frac{1 + \nu}{1 + \nu\psi}, \tag{30}$$

$$g_L = g_A \frac{(1 - \psi)\nu}{1 + \nu\psi}. \tag{31}$$

The role of ψ can be seen from equation (31). When $\psi = 1$, labor supply is a constant along the balanced growth path as in King, Plosser, and Rebelo (1988) and Jaimovich and Rebelo (2009). When $\psi > 1$, the wealth effect dominates the substitution effect, and steady positive growth in productivity yields a long-run decline in the employment rate as in Boppart and Krusell (2016).

Given the growth rates in equations (30) and (31), we can detrend consumption and labor as follows: $c_i = \frac{C_{it}}{\exp(g_C t)}$, $x_i = \frac{X_{it}}{\exp(g_C t)}$, $l_{mi} = \frac{L_{mit}}{\exp(g_L t)}$, $l_{fi}(\omega) = \frac{L_{fit}(\omega)}{\exp(g_L t)}$, and $l^h_{fi}(\omega) = \frac{L^h_{fit}(\omega)}{\exp(g_L t)}$. Detrended total female employment in the market sector is then $l_{fi} = \int_{\underline{\omega}}^{\theta_f} l_{fi}(\omega) dG(\omega)$. Because every region experiences the same growth rate, there is no borrowing or lending in equilibrium along the balanced growth path. Along the balanced growth path, the detrended solutions are identical to those in section 5.3.

6.2 Business Cycles and Gender Convergence

We next introduce business cycles and gender convergence into the model. We assume that business cycles arise due to stochastic variation in gender-neutral productivity, A_t. Specifically, $A_t = A_0 e^{g_A t} \tilde{A}_t$, where $g_A > 0$ is the trend productivity growth, and $\tilde{A}_t$ denotes detrended productivity shocks. Since the households decision problems are static, we do not need to take a stand on the stochastic process of $\{\tilde{A}_t\}$.

We assume that female-biased productivity, $\theta_{f,t}$ evolves according to the dynamics we estimated in section 3:

$$\theta_{f,t+1} = \rho_f \theta_{f,t} + (1 - \rho_f)\bar{\theta}_f$$

from 1980 onward, and follows a linear trend in the 1970s, $\theta_{f,t+1} = \theta_{f,t} + \Delta_{\theta,70s}$. This process for female-biased productivity—a form of structural change—is what yields gender convergence in our model.

6.3 Calibration

Table 5 presents a summary of our calibration of the parameters of our full model. For expositional simplicity, we discuss the calibration of several sets of parameters separately even though the calibration of different groups of parameters interacts, which means that, in practice, we calibrate these groups jointly and the calibration involves an iterative process.[32]

Crowding Out As in section 5, we assume that productivity in home production is distributed according to a uniform distribution, i.e., $\omega \sim U[\bar{\omega} - \delta, \bar{\omega}]$. The key parameter determining the extent of crowding out in our model is δ. This parameter determines how many women are on the margin between home production and market work, and therefore how many women switch to market work when female market wages rise. We choose δ to match the extent of regional crowding out in the data, which we show in section 5.3 is a powerful diagnostic for the amount of aggregate crowding out generated by the model. To determine the model's predictions for regional crowding out, we calculate the response of the economy to shocks to θ_{fi} of a magnitude

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[32]The process we use is as follows: We begin by setting values for (ν, η, γ). Then we make a guess of δ. Conditional on δ, we choose $\theta_{f,1970}$ and $\bar{\omega}$ so that the model matches the ratio of male to female employment and the home production to GDP ratio in 1970. Then we calibrate $\{\rho_f, \bar{\theta}_f, \Delta_{\theta,70s}\}$ by solving the problem (33). Next, we choose $\{g_A, \psi\}$ to match the trend in male employment growth and the trend of per-capita GDP growth. We then set $\bar{\tau}$ to match the domestic expenditure share. Finally, we compute regional crowding out by running regression (32). We iterate on the guess for δ until we match the regional crowding out estimates.

Table 5: Calibration

Parameters	Description	Values	Targets
δ	Support of home productivity	0.88	Regional crowding out estimates
$\bar{\omega}$	Upper bound of home productivity	1.38	Home production to GDP ratio
ν	Frisch elasticity of labor supply	1	Standard
η	Trade elasticity	5	Head and Mayer (2014)
$\bar{\tau}$	Trade costs	2.88	Domestic expenditure share 70%
$(\rho_f, \bar{\theta}_f, \Delta_{\theta,70s})$	Female-biased shocks	(0.89,1.15,0.0102)	Female to male labor ratio
g_A	Gender-neutral productivity growth	0.014	Per-capita real GDP growth
ψ	Long-run wealth effect	1.12	Trend male labor growth
γ	Short-run wealth effect	0.1	Jaimovich and Rebelo (2009)

that plausibly occurred during the Gender Revolution.[33] We then run the following cross-sectional regression on the model-generated data

$$\Delta L_{mi} = \alpha + \epsilon^{reg} \Delta L_{fi} + \epsilon_i, \tag{32}$$

where ΔL_{gi} is the employment growth in region i for $g \in \{m, f\}$ and ϵ^{reg} is regional crowding out. We choose $\delta = 0.88$ so that ϵ^{reg} in our model matches our cross-state estimate of regional crowding out, including controls, of -0.18. This calibration yields aggregate crowding out of -0.19. The upper bound of home productivity, $\bar{\omega}$ is chosen to be 1.38 to match the ratio of home production to GDP in 1970, which was 40% according to BEA estimates.

Standard Parameters   A time period in the model is meant to represent a year. We set the Frisch elasticity of labor supply to one, $\nu = 1$. We set the elasticity of substitution of goods produced in different regions to $\eta = 5$, as in, e.g., Head and Mayer (2014). The number of regions is $n = 51$, corresponding to the 50 states plus the District of Columbia. We set the strength of short-run wealth effects to $\gamma = 0.1$, which lies in the middle of the values explored in Jaimovich and Rebelo (2009). The trade cost is assumed to be $\tau_{ij} = \bar{\tau}$ for $i \neq j$ and $\tau_{ii} = 1$ for all i. We choose $\bar{\tau}$ so that the domestic expenditure share on market goods is 70%, as reported in Nakamura and Steinsson (2014).

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[33]We use the observed male-to-female employment ratio in each state in 1970 to back out initial values for $\{\theta_{fi,1970}\}$. To do this, we use the expression for the female-to-male employment ratio from the balanced growth path of our model: $\frac{L_{fi}}{L_{mi}} = G(\theta_{fi}) \left(\frac{\theta_{fi}\chi_{fi}}{\chi_{mi}} \right)^{\nu}$ and, for simplicity, assume that $\chi_{fi} = \chi_{mi}$. We back out $\{\theta_{fi,2016}\}$ in an analogous way, assuming the economy has converged to a new balanced growth path in 2016. We calculate the changes in the endogenous variables of the model economy assuming that the economy starts off in a steady state with $\{\theta_{fi,1970}\}$ and ends up in a steady state with $\{\theta_{fi,2016}\}$.

Female Biased Shocks   We choose the process for female-biased productivity, $(\rho_f, \bar{\theta}_f, \Delta_{\theta,70s})$, to replicate the observed dynamics of the female-to-male employment rate ratio at the aggregate level:

$$(\rho_f, \bar{\theta}_f, \Delta_{\theta,70s}) = \arg\min \sum_{t=1970}^{2016} ((L_f/L_m)_{t,data} - (L_f/L_m)_{t,model})^2, \tag{33}$$

where $(L_f/L_m)_{t,model} = G(\theta_{fi}) \left(\frac{\theta_{fi}\chi_{fi}}{\chi_{mi}}\right)^\nu$. We assume $\chi_f = \chi_m = 1$. These assumptions imply that female convergence arises from labor demand shocks.

Wealth Effects and Gender-Neutral Shocks   We choose g_A to match the growth rate of per-capita real GDP over the period 1970-2016. We choose ψ to match the trend growth rate of the male employment rate over the period 1970-2016. We set the realized path of gender-neutral productivity, $\{\tilde{A}_t\}_{t=1970}^{2016}$, so as to exactly match the observed path of the male employment rate. As a robustness exercise in section 7.1, we also consider a calibration where we set the growth rate of gender neutral productivity g_A to match the growth rate of real median family income (deflated by the growth in the PCE deflator), which yields similar results to our baseline analysis.

Our calibration procedure leads to $\psi > 1$, which implies that the wealth effect of a change in wages on labor supply dominates the substitution effect in the long-run, as in Boppart and Krusell (2016). The role of wealth effects in generating a long-run decline in male employment rates in our model should not be taken too literally. We do not wish to claim that prime-age men are working less than before primarily because they themselves are wealthier. Rather, our preferred interpretation involves a broader set of wealth effects. One potentially important channel is that prime-aged men have wealthier parents that can support them to a greater extent than before, lessening their need to work. Figure A.10 in the appendix shows that the fraction of prime-age men and women living with their parents doubled during the past 40 years.[34] Moreover, Figure A.10 also shows that almost all of the increase in co-habitation with parents comes from the non-employed. Related to this, Austin, Glaeser, and Summers (2018) document that the expenditures of non-employed men are at similar levels to low-income employed men despite the non-employed having significantly lower income. Sacerdote (2017) emphasizes that median household income, deflated using the more theoretically appealing PCE deflator, has risen substantially in the past several decades,

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[34]This exercise is similar to evidence presented in Aguiar et al. (2017). They document that young men (aged 21-30) increasingly live with their parents starting in 2001. We show that this pattern also holds for the prime-age population, and the trend goes back to 1970.

Figure 9: Model Fit: Simulated versus Actual Data

as we discuss in Appendix A.7. Sacerdote (2017) also documents a steady increase in various metrics of household consumption, including number of bedrooms, bathrooms, and cars per household, despite falling household size. Larger houses and more cars may have made remaining at home, and out of the labor force, more feasible than it once was for many young men.

6.4 Model Fit

The top two panels of Figure 9 compare simulated data from our model to the corresponding time series for the US economy, for male and female employment rates. The top-left panel shows that we perfectly match the time series for the male employment rate over our sample. This is a mechanical consequence of our calibration procedure. The same panel also shows a nearly perfect fit to female employment dynamics. This reflects two factors: first, male and female employment rates share similar business cycle dynamics; and second, female employment rates have been converging to male employment rates roughly according to an AR(1) process since 1980. However, since male employment rates are somewhat more cyclical than female employment rates, as documented in Albanesi and Şahin (2018), our model slightly overstates the cyclicality of female employment. The upper-right panel of Figure 9 plots the fit of our model to the female-to-male employment ratio. The bottom panels of Figure 9 plot the time series of gender-neutral and female-biased productivity that we feed into the model in carrying out this simulation.

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7 A Counterfactual: No Female Convergence

Let us now return to answering the question we started out with: How different would recent business cycle recoveries have looked if female convergence had not caused female employment growth to slow down? We do this by conducting the following counterfactual experiment: for each recession since 1970, we "turn off" the convergence in female employment, by assuming that female-biased productivity, $\theta_{f,t}$, grows at the speed it did in the 1970s as opposed to the slower rate our AR(1) convergence model implies. That is, we assume the following counterfactual path for $\theta_{f,t}$,

$$\theta^{cf}_{f,t+1} = \theta^{cf}_{f,t} + \Delta_{\theta,70s}.$$

In calculating the counterfactual path, we add back the "model error" for the female employment rate, i.e., the difference between the actual and the simulated employment rates. Figure 9 shows that this model error is generally quite small.

The results of this counterfactual experiment for the last five recessions are presented in Figure 10. The left panel plots the the evolution of the actual prime-age employment rate, while the right panel plots the counterfactual where we have turned off female convergence. The contrast is striking. Take, for example, the 1990 and 2001 recessions. In the left panel, there is a clear slowdown versus the two prior recessions. However, in the counterfactual in the right panel, the recoveries after these two recessions are virtually identical to the previous two. Turning to the Great Recession, we see a much larger initial drop in employment, even in the counterfactual. However, the speed of recovery in the counterfactual for the Great Recession is roughly similar to earlier recessions, once female convergence has been accounted for.

Figure 11 presents analogous results to those presented in Figure 10 but for female employment. Again the left panel plots the actual female employment rate, while the right panel plots our counterfactual without convergence. The left panel shows a pronounced slowdown. In the right panel, however, this fanning down of the time series for different recessions is almost completely gone.

Table 6 quantifies the effect of female convergence on the slowdown of recoveries, by reporting average growth rates of actual and counterfactual prime-aged employment rates over the four years following the trough of each of the last five recessions.[35] Panel A reports these statistics for

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[35]We define the employment rate trough as the year with the minimum value of the employment rate in the five

Figure 10: Counterfactual Results: Total

Note: Employment rates are normalized to zero at the peak of each recession (1973, 1981, 1990, 2001 and 2007).

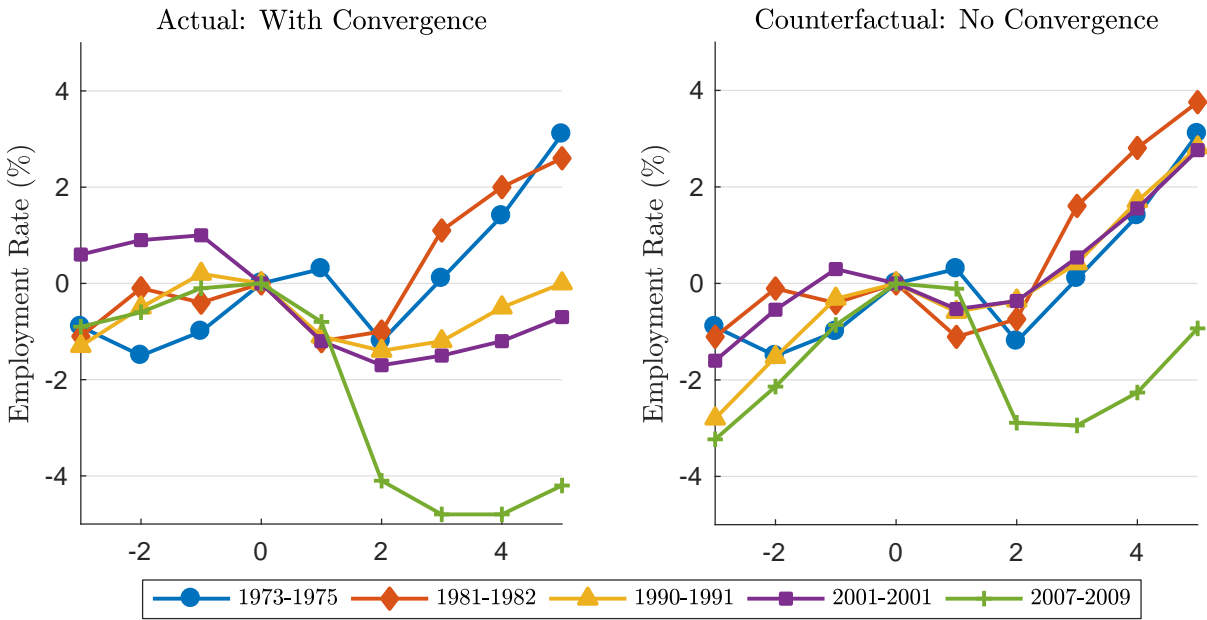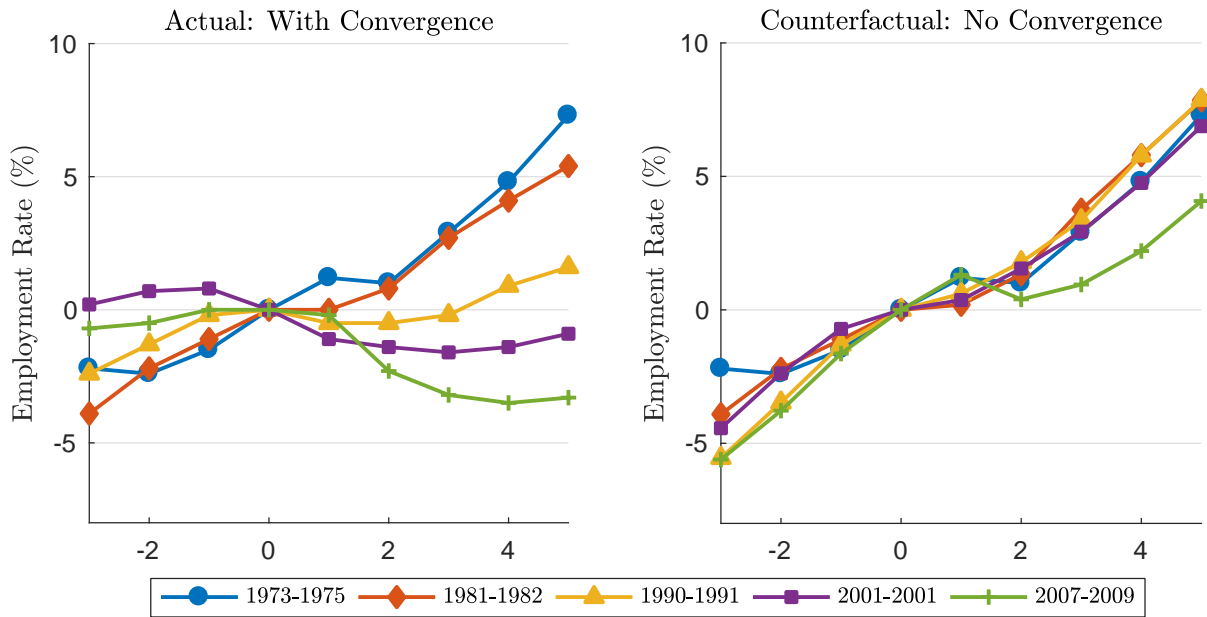

Figure 11: Counterfactual Results: Female

Note: Employment rates are normalized to zero at the peak of each recession (1973, 1981, 1990, 2001 and 2007).

overall prime-aged employment, while Panels B and C report them for women and men, respectively. Actual recoveries of the total prime-aged employment rate after the last three recessions slowed to 36%, 21%, and 30% of the recovery rate following the 1973 recession. In contrast, our counterfactual implies recoveries that were 73%, 65%, and 74% of the recovery rate following the 1973 recession. Accounting for female convergence therefore largely eliminates the slowdown in recoveries. In the actual data, recoveries from the last three recessions were on average only 29% as fast as for the 1973 recession. In our counterfactual, however, the average speed of recoveries in these recent recessions was 71% as fast as for the 1973 recession. This implies that female convergence explains roughly 60% ((71-29)/(100-29) ≈ 60%) of the recent slowdown in recoveries.

The counterfactual that we report results for in Figures 10 and 11 and Table 6 uses our most conservative point estimate of crowding out from section 4. Our other estimates indicate even less crowding out. If we instead assume zero crowding out in the counterfactual, we find that female convergence explains 75% of the slowdown in recent recoveries.

We see from panels Panel B and C of Table 6 that the counterfactual scenario almost exclusively affects the female employment rate, but leaves the male employment rate relatively unaffected. When we turn off female convergence, the growth in the female employment rate during recoveries is much more rapid in recent business cycles. In the counterfactual scenario, male employment growth is slightly slower because of crowding out associated with the much more rapid increase in female employment. However, our model implies that crowding out is relatively small. This is in line with our empirical evidence.

7.1 Robustness: "Almost" a Sufficient Statistic

We have emphasized throughout the paper that aggregate crowding out is a sufficient statistic for our counterfactual exercise and that relative crowding out is "almost" a sufficient statistic since it differs very little from aggregate crowding out for reasonable parameter values. In Table 7, we demonstrate this by presenting counterfactuals for several alternative models and alternative calibrations of our model. Importantly, in all these alternative cases we recalibrate the model to match our estimate of relative crowding out. We do this by varying the parameter δ which governs the degree of dispersion of female productivity at home (and therefore the strength of the switching effect we discuss earlier in the paper). Table 7 shows clearly that for all of these alternative cases we get very similar results as in our baseline model: the counterfactual explains

year period following each NBER business cycle peak. This differs slightly from the NBER business cycle trough dates because in some cases, the employment rate continues to decrease even after the NBER trough date.

Table 6: Employment Following Business Cycle Troughs

	Panel A. Employment Rate Growth in Recovery				
	1973-1975	1981-1982	1990-1991	2001-2001	2007-2009
Actual	1.33%	0.95%	0.48%	0.28%	0.40%
Relative to 1973 Recession	100%	72%	36%	21%	30%
Counterfactual	1.32%	1.16%	0.97%	0.86%	0.98%
Relative to 1973 Recession	100%	88%	73%	65%	74%
	Panel B. Employment Rate Growth in Recovery (Female)				
	1973-1975	1981-1982	1990-1991	2001-2001	2007-2009
Actual	2.00%	1.35%	0.68%	0.13%	0.18%
Relative to 1973 Recession	100%	67%	34%	6%	9%
Counterfactual	2.00%	1.88%	1.92%	1.61%	1.66%
Relative to 1973 Recession	100%	94%	96%	80%	83%
	Panel C. Employment Rate Growth in Recovery (Male)				
	1973-1975	1981-1982	1990-1991	2001-2001	2007-2009
Actual	0.52%	0.50%	0.28%	0.40%	0.65%
Relative to 1973 Recession	100%	95%	52%	76%	124%
Counterfactual	0.52%	0.39%	0.01%	0.08%	0.33%
Relative to 1973 Recession	100%	74%	1%	15%	63%

Note: The "Actual" and "Counterfactual" statistics are for annualized average growth rates. Troughs are defined as years in which the employment rate reaches a minimum over the five years following an NBER business cycle peak. These trough years are 1975, 1982, 1992, 2003, 2010.

the vast majority of the slowdown of recoveries.

The first two rows in Table 7 reproduce the actual and baseline counterfactual employment growth in the four years after each business cycle trough relative to employment growth after the 1973 recession from Table 6. The remaining columns report this same statistic for alternative cases. In the first row of panel A, we present results for a version of our model in which female convergence occurs due to increases in female labor supply rather than increases in female labor demand. This modification to our baseline model is described in Appendix B.4.1. In the second and third rows of panel A, we present results for a version of our model in which male and female labor are imperfect substitutes in production and home and market goods are imperfect substitutes in consumption. These extensions are presented in Apendix B.4.2. Fourth, we consider a case where the leisure of men and women are complements (see Appendix B.4.3). Fifth, we consider a non-unitary household model, where men and women share income imperfectly (see Appendix B.4.4). Sixth, we analyzed an alternative model with a task-based production function, following Acemoglu and Autor (2011). In this framework, we model the gender revolution as an expansion

Table 7: Different Counterfactuals

	Employment Growth Relative to 1973 Recession				
	1973-75	1981-82	1990-91	2001-01	2007-09
Actual	100%	72%	36%	21%	30%
Benchmark Counterfactual	100%	88%	73%	65%	74%
A. Model extensions					
Female Labor Supply Shocks	100%	89%	77%	69%	79%
Male & Female Labor Imperfect Sub.	100%	87%	71%	63%	72%
+ Home & Market Goods Imperfect Sub.	100%	84%	65%	56%	65%
Leisure Complementarity	100%	88%	74%	66%	76%
Non-Unitary Household	100%	86%	73%	66%	76%
Task-based model	100%	92%	81%	74%	83%
Gender-specific labor supply elasticity	100%	90%	72%	64%	74%
B. Alternative Parameterization					
Balanced Growth Preferences	100%	88%	73%	65%	75%
Weak Income Effects	100%	89%	75%	68%	77%
Low labor supply elasticity	100%	86%	71%	62%	72%
No Habit	100%	88%	73%	65%	74%
Median Income Instead of GDP	100%	88%	73%	65%	74%

Note: The "Actual" and "Counterfactual" statistics are for annualized average growth rates over four years following business cycle troughs. Troughs are defined as years in which the employment rate reaches a minimum over the five years following an NBER business cycle peak. These trough years are 1975, 1982, 1992, 2003, 2010. The remaining rows report these same statistics for alternative versions of the model described in the text.

of tasks that can be performed by women (see Appendix B.4.5). As a consequence, mens' labor demand can be negatively affected in contrast to the prediction of models with neoclassical production functions. Seventh, we allow women to have a higher Frisch elasticities of labor supply than men (1.5 for women and 1 for men), consistent with the micro evidence as surveyed in Keane (2011) (see Appendix B.4.6).

We also consider several changes to our baseline calibration. First, we consider as case with balanced growth preferences ($\psi = 1$). Second, we consider a case where income effects are weak ($\psi = 0.5$). Third, we consider a case with a smaller labor supply elasticity ($\nu = 0.5$). Fourth, we assume no habit ($\gamma = 1$). Fifth, we consider a case where the model is calibrated to fit median family income growth rather than growth in GDP (see Figure A.11 in the appendix). With this alternative calibration, productivity growth is $g_A = 0.009$, which results in a slightly larger calibrated value for ψ (1.20 versus our baseline calibration of 1.12).

Table 7 shows that all of these different models yield very similar predictions for our counterfactual about the effects of female convergence on aggregate employment rate. In this sense, our

results are highly robust. The intuition for this robustness is simple. Aggregate crowding out is a sufficient statistic for the counterfactual exercise, as we show in equation (1). Regional crowding out is closely related to aggregate crowding out for the reasons we describe in section 5.3. The regional crowding out statistic we estimate in section 4 tightly constrains our predictions about aggregate crowding out, within the range of models we consider.

7.2 Further Discussion

7.2.1 The Role of Family Structure

Our theoretical analysis abstracts from the role of single people and instead considers an economy consisting only of married couples. In thinking about how the addition of single people might affect our conclusions, it is important what one assumes about the connection between single people and other people in the economy. On the one end of the spectrum, single men could be totally disconnected (in terms of their budget constraints) from women entering the labor force. In this case, if preferences are close to KPR preferences, single households would exhibit no crowding out.

At the other end of the spectrum, one might argue that even if a man is single, his budget constraint nevertheless depends on the labor market outcomes of women. Clearly, this is the case for men who—though not married—have a female partner that they share a substantial amount of their income with (and may even be cohabiting with). Also, if a single man's mother enters the labor force, this may affect his budget constraint. Furthermore, increased female labor supply may also lead to greater tax revenues that could affect a single man's budget constraint through social programs. These types of linkages can implicitly be accommodated in a representative family framework.

As an intermediate case between these two extremes, we also analyze the case of non-unitary households, in which men and women share their income imperfectly (Appendix B.4.4). Ultimately, because of the sufficient statistic argument we have made throughout the paper, the key question is whether the presence of *either* single or married households drives a wedge between regional and aggregate estimates of crowding out. Table 7 shows that the sufficient statistic argument holds in the non-unitary household case as in other cases we consider.

As we discussed earlier in the paper, the increase in female employment rates comes entirely from married women (see the left panel of Figure 4). Focusing on married women's employment rates, thus, captures the main features of the Gender Revolution. We have redone our main crowd-

ing out analysis for married couples, and the results are essentially unchanged (Table A.5 in the appendix).

The time series patterns for married and single men are also supportive of our empirical finding that crowding out is low. If crowding out were large, one would expect to see greater declines in the employment rates of married relative to single men. Figure 4 shows that, if anything, the employment rate of single men decreased faster than the employment rate of married men.

7.2.2 Hours versus Employment

A second important issue is that our model focuses on the discrete choice of whether to work or not, rather than the continuous choice of how many hours to work, which is more common in the existing literature.[36] This issue turns out to be relatively unimportant in practice. Figure 12 plots per-capita hours worked based on the CPS, and compares them with employment rates. Both measures are normalized to one in 1970. We see that per capita hours worked display very similar patterns to employment rates. The gender convergence patterns we emphasize are slightly amplified for per-capita hours relative to employment rates, since hours per week tend to adjust (by a small amount) in the same direction as the employment rate. Clearly, the patterns we emphasize in our analysis are, however, essentially preserved.

7.2.3 Heterogeneity in Skills

Our model also abstracts from heterogeneity in skills. Figure 13 plots the evolution of the gender gap within skill groups, based on employment rates from the March CPS. As is standard in the literature, we divide workers into skilled versus unskilled based on whether they have a college degree. The figure also plots the fitted value of an AR(1) process after 1980 and a linear trend before 1980. Again, the basic patterns we aim to capture in our model are preserved. The evolution of the gender gap for each skill group is well approximated by an AR(1) process since 1980, as in our baseline analysis.

7.2.4 Relationship to Other Work

Our explanation for recent slow recoveries relies on a slowdown in the growth of θ_f associated with the convergence of female employment towards male employment. This certainly does not rule out rich theories of interaction between the evolution of θ_f and other structural changes in the

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[36]See, e.g., McGrattan and Rogerson (2008), Heathcote, Storesletten, and Violante (2017), and Knowles (2013).
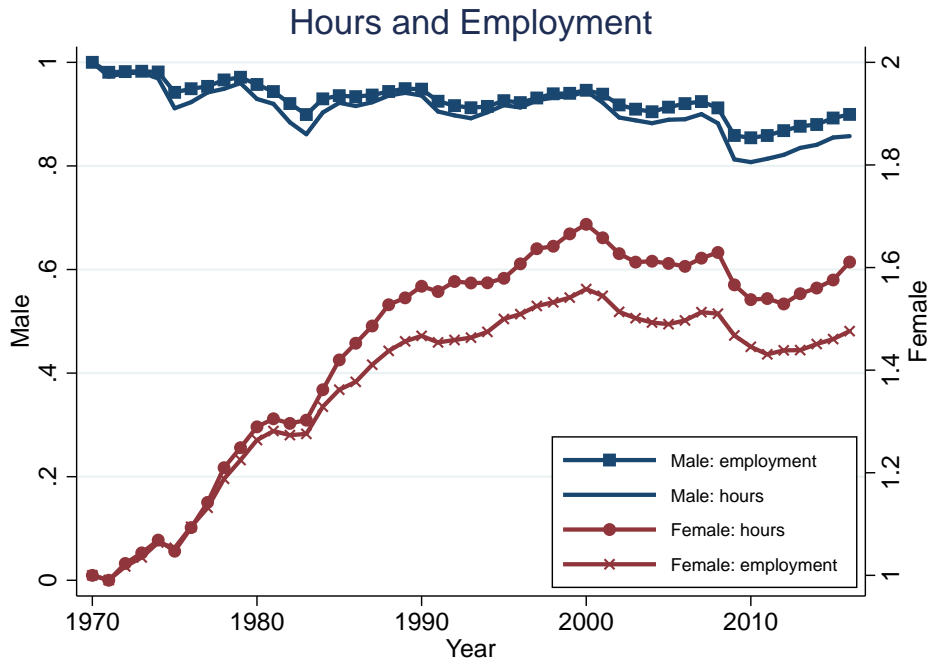
Hours and Employment

Figure 12: Employment Rates vs. Hours: Males and Females

Note: Hours come from "hours worked last week" recorded in the CPS. All the values are normalized to one in 1970. The left scale is for men, and the right scale is for women.
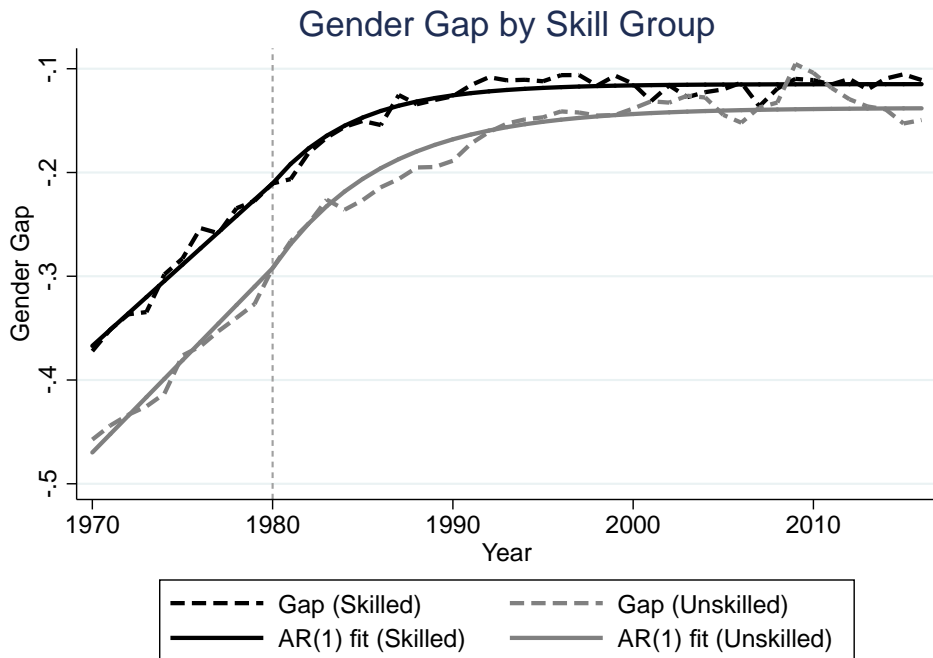
Gender Gap by Skill Group

Figure 13: Actual Employment Gap and Simulated Employment Gap within Skill Group

economy. For example, Pugsley and Şahin (2019) attribute jobless recoveries to the declining trend of startup rate. As Karahan, Pugsley, and Şahin (2021) show, the startup rate is strongly influenced by labor force growth in a canonical model of firm dynamics. A substantial slowdown in female labor force participation growth through a decline in the growth rate of θ_f would naturally lead to the declining startup rate. Hence, we view the mechanism we document, and the one documented in Pugsley and Şahin (2019) as highly complementary.

We do wish to distinguish our explanation—which focuses on a slowdown in the the trend growth of labor force participation—from explanations that focus on changes in the *cyclical* properties of the economy. Table 1 of our paper shows that the key change driving slow recoveries have been a slowdown in the growth rate of labor force participation (in particular, female labor force participation), as opposed to a slowdown in the recovery of unemployment or labor productivity following recessions. The findings of Gaggl and Kaufmann (2020) appear consistent with this narrative: they find a structural break in the growth rate of both routine and non-routine employment rates around 1990.

8 Conclusion

The Gender Revolution led to a dramatic increase in the female employment rate over the past half century. The speed of this convergence peaked in the 1970's and has since slowed considerably. We present new evidence on the role of female convergence in explaining slow recoveries after the last three recessions in the US, based on cross-state estimates of the magnitude of "crowding out" of male employment in response to female-biased shocks. We show that this is close to being a sufficient statistic for estimates of the aggregate effects of the Gender Revolution on total employment. Our model, when calibrated to match estimates of regional crowding out—which we show is highly informative about aggregate crowding out—implies that female convergence explains 60-75% of the slowdown of the recovery in employment rates in recent business cycles. In contrast, most existing models of the Gender Revolution, generate large crowding out and little role for the Gender Revolution in explaining aggregate employment trends.

Appendix

A Empirical Appendix

A.1 Data construction

Occupational Classification In our analysis of between versus within-occupation variation, we use an occupational measure that is based on a version of the 1990 Census Bureau occupational classification scheme modified by IPUMS. We aggregated this original scheme to 180 occupational categories to create a balanced occupational panel for the period 1970-2016.

Bartik Shocks We make use of Bartik shocks as a control variable in our crowding out regressions (Bartik, 1991). We construct these shocks as follows. For state i over the time period between t and $T > t$,

$$\text{Bartik}_{i,t,T} = \sum_\omega \pi_{i,t}(\omega) \frac{v_{-i,T}(\omega) - v_{-i,t}(\omega)}{v_{-i,t}(\omega)},$$

where $\pi_{i,t}(\omega)$ is the local employment share of industry ω in state i at time t, and $v_{-i,t}(\omega)$ is the national employment share of industry ω excluding state i at time t. Industries are defined by the IPUMS (variable "ind1990"), which is quite similar to 3 digit SIC codes. We extend the "Time-Consistent Industry Codes for 1980-2005" constructed by Autor, Dorn, and Hanson (2013) to the period 1970-2016. We compute employment shares using Census and ACS data.

State-Level Wage Indexes Using Census and ACS data, we calculate composition-adjusted state-level wage indexes separately for both men and women. In doing this, we restrict the sample to individuals who (1) are currently employed, (2) report working usually more than 30 hours per week, and (3) report working at least 40 weeks during the prior year (as is standard in the literature). These restrictions select workers with a strong attachment to labor force, for whom hours variation is likely to be small. We compute the hourly wage by dividing total pre-tax wage and salary income by total hours worked in the previous year. We construct a composition-adjusted wage by regressing the resulting hourly wage of individual i of gender $g \in \{m, f\}$ on individual

characteristics:

$$\ln(w_{git}) = \alpha_{gt} + \beta_{gt} X_{git} + \epsilon_{git}, \tag{34}$$

where X_{it}^g is a set of dummy variables for education, hours worked, race, whether the worker was born in a foreign country.[37] The state-level wage index in state s for each gender, denoted by W_{gst}, is then constructed by calculating the average value of $\exp(\alpha_{gt} + \epsilon_{git})$, using population weights. The state-level gender wage gap is defined as $\ln(W_{fst}/W_{mst})$. The aggregate counterparts of these objects are calculated by taking an average at the national level, using population weights.

In our analysis of the skill-premium, we compute the composition adjusted wage separately for college graduates and high-school graduates as in Katz and Murphy (1992), and aggregate this to the state-level. We adjust for composition in an analogous manner as in equation (34). Let W_{cst} and W_{hst} denote the state-level wage index for college graduates and high-school graduates, respectively. The skill premium is defined as $\ln(W_{cst}/W_{hst})$.

A.2   Unemployment and Labor Force Participation During Recoveries

Figure A.1 plots the unemployment rate for prime-age men and women around the last five recessions. This figure is analogous to Panel B of Figure 1 in the main text but for unemployment rather than the employment-to-population ratio. Analogously, Figure A.2 plots the labor force participation rate for prime-age men and women around the last five recessions. The data used in these figures are from the BLS. These figures make it clear that the slowdown in the pace of employment recoveries in recent recessions has come almost entirely from a slowdown in the growth rate of labor force participation rate, not from changing dynamics in unemployment.

A.3   Employment and Labor Force Participation Rate Over a Longer Horizon

Figure A.3 plots the employment rate and labor force participation rate for prime-age men and women over the time period 1948-2016. The figure shows that growth in the employment rate of prime-aged women was increasing from 1950 until the 1970s and then decreasing after that. In sharp contrast, the employment rate of prime-aged men was roughly constant from 1950 to 1970 and has been falling at a roughly constant rate since 1970.

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[37]The dummies for education are: a dummy for high school dropouts, high school graduates, college dropouts, college graduates, and higher degrees. The dummies for age are: a dummy for the age groups, 25-29, 30-34, 35-39, 40-44, 45-49, and 50-54. The dummies for hours worked are: a dummy for the categories 30-39 hours, 40-49 hours, 50-59 hours, and more than 60 hours. The dummies for race are: black, white, Hispanic, and other races.
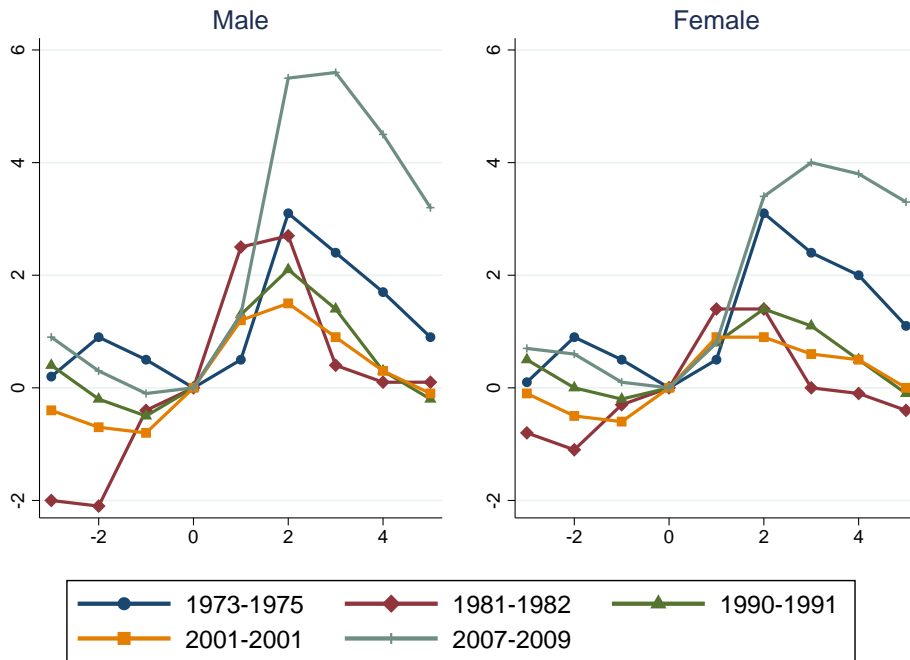
Figure A.1: Unemployment Rate in Recessions by Gender

Note: The figure shows the unemployment rate of prime age (25-54) workers, for males and females separately. We normalize the graph at zero at pre-recession business cycle peaks: 1973, 1981, 1990, 2001 and 2007.
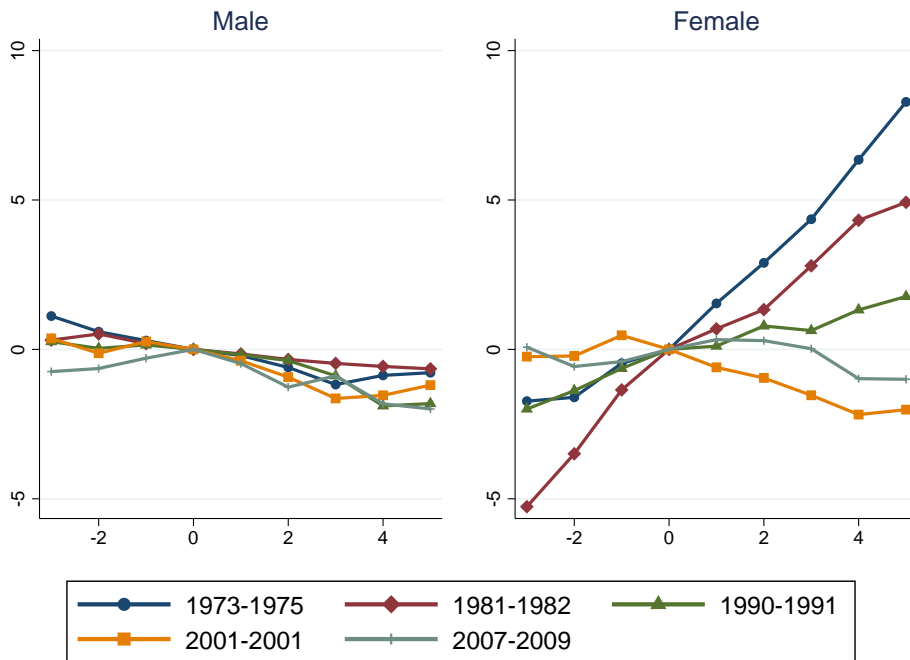

Figure A.2: Labor Force Participation Rate in Recessions by Gender

Note: The figure shows the labor force participation rate of prime age (25-54) males and females separately. We normalize the graph to zero at pre-recession business cycle peaks: 1973, 1981, 1990, 2001 and 2007.
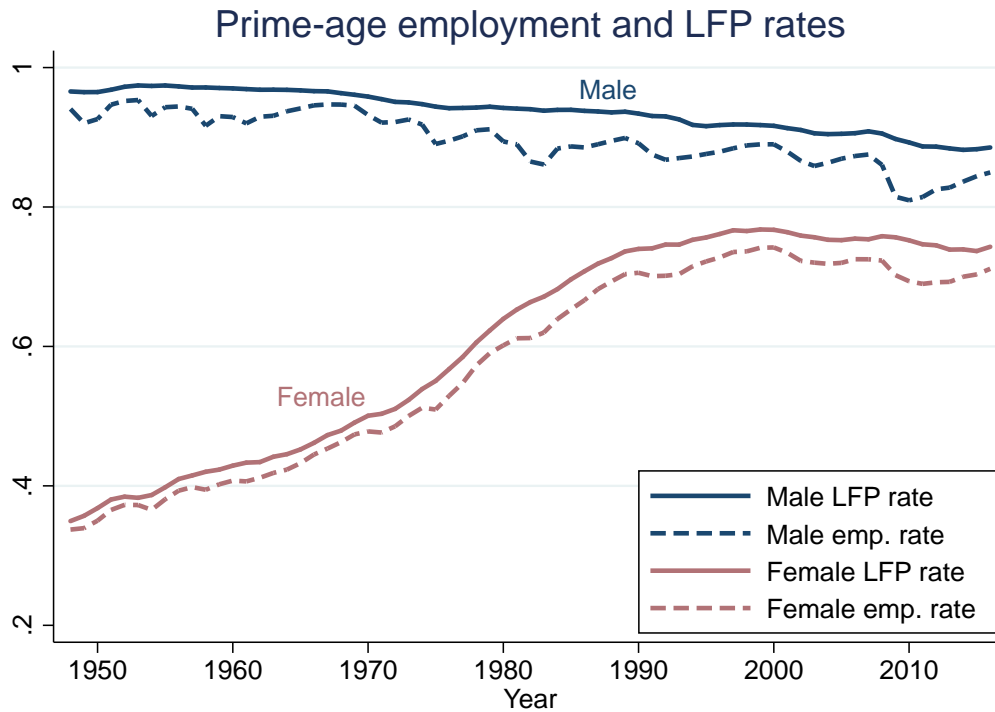
Figure A.3: Prime-age Employment and Labor Force Participation Rates over 1948-2016

The left panel of Figure A.4 plots the employment rate of men over the age of 24 (including those older than 55). For this group, the trend decline in employment extends all the way back to 1948. We plot a linear trend line through the data to illustrate that the downward trend has been roughly constant over this 70 year period. The right panel of Figure A.4 plots the employment rate for prime-aged men and men older than 55. This panel shows that the decline in the employment rate of men older than 24 comes from men older than 55 in the early part of this sample period—in other words, the retirement margin contributed disproportionately to the declining male employment rate between 1950 and 1970—while the decline came from prime-aged men in the latter part of the sample period.

A.4 Correlates of the Gender Revolution Over Time and Space

A.4.1 Variation in the Skill Premium and the Service Share Over Time and Space

Figure A.5 plots the skill premium (left panel) and the employment share of the service sector over the period 1970-2016. Appendix A.1 provides a description of how we constructed these variables. Neither of these variables has the same time pattern of change as the gender gap. The skill premium is falling (or flat) between 1970 and 1990, but then rises rapidly from 1990 to 2005.
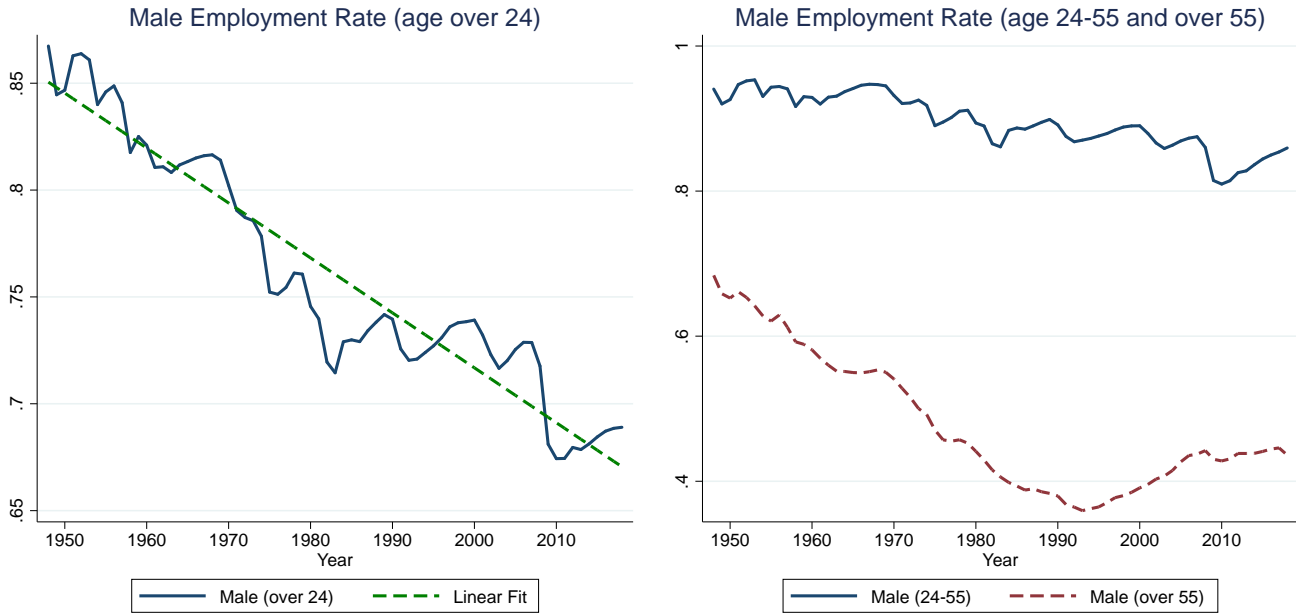
Figure A.4: Employment Rates: Age over 24

This time pattern contrasts sharply with the convergence dynamics of the gender gap. The service sector employment share has risen steadily over the entire sample period. Again, this contrasts with the dynamics of the gender gap, which has essentially plateaued in recent decades.

Figure A.6 considers cross-state variation in the skill premium and the service share. The left panel shows a scatter plot with the growth in the skill premium on the vertical axis and the growth in the gender employment gap ($\Delta(L_{fi} - L_{mi})$) on the horizontal axis. The right panel shows a scatter plot with the growth in the service sector employment share ($\Delta(L_{service,i}/(L_{service,i} + L_{non-service,i}))$) on the vertical axis and the growth in the gender employment gap on the horizontal axis. In both panels, the growth rates are calculated over the time period 1970-2016. In both cases, the relationship between the two variables is weak and statistically insignificant. The p-values for the coefficients on the skill premium and service share being different from zero are 0.51 and 0.64, respectively. The R-squared in these regressions are 0.03 and 0.005, respectively.[38]

A.4.2 Variation in the Gender Wage Gap Over Time and Space

The left panel of Figure A.7 plots the evolution of real wages for men and women over the period 1970 to 2016. The right panel of Figure A.7 plots the real wage of women relative to the real wage

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[38]Rendall (2017) shows that the growth in female market hours and the growth in service sector are positively correlated at MSA-level. Although we confirm this relationship at MSA-level in our data, the correlation disappears (it becomes slightly negative) at the state-level.
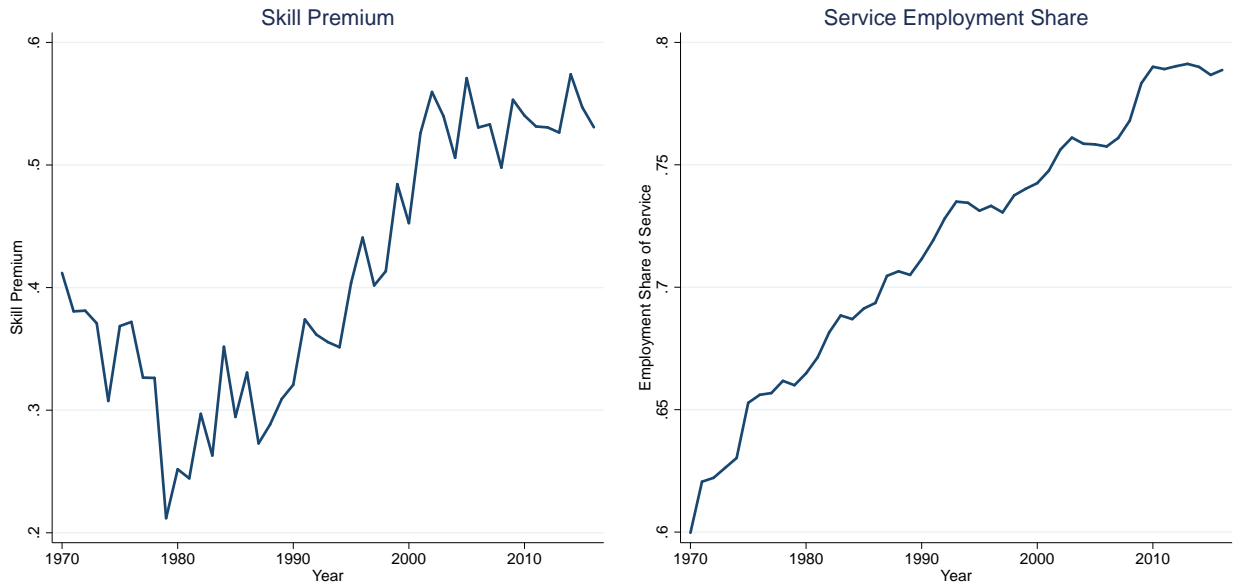
Figure A.5: Skill premium (left) and employment share of the service sector (right)

Figure A.6: Cross-sectional correlation of relative female labor growth and growth in skill premium (left) and service sector employment share (right)

of men. The wages plotted in this figure are the composition adjusted wage series described in Appendix A.1. The gender wage gap has declined substantially over our sample period in spite of the large increase in female employment. This suggests that increasing demand for female labor played an important role in the Gender Revolution.

Figure A.8 considers cross-state variation in the gender wage gap. It plots the change in the female-to-male wage ratio ($w_{f,2016}/w_{m,2016} - w_{f,1970}/w_{m,1970}$) against growth in the gender gap in employment rates for U.S. states. These variables are positively correlated. The correlation is 0.27 and the p-value for rejecting a correlation of zero is 5.5%. Once Washington, D.C. (an outlier) is removed, the correlation is 0.32, which is statistically significant with a p-value of 2.2. Again, this relationship suggests that increased demand for female labor was important over our sample period.

A.5 Diagnostic Tests for Cross-Sectional Identification

We now explore several diagnostic tests designed to shed light on the source of identification for our gender gap and JOI instruments. These tests are recommended by Goldsmith-Pinkham, Sorkin, and Swift (2020).

A.5.1 Correlates of the Instruments

We first we explore how the gender gap in 1970 and JOI in 1970 are correlated with observable state characteristics. We do this by regressing our instruments on various characteristics one at a time. The characteristics we consider are the agricultural, mining, manufacturing, and service sector employment shares in 1970, log GDP per capita in 1970, the college share in 1970, the skill wage premium in 1970, the share of single in 1970, the non-white population share in 1970, the China shock, and a Bartik shock. We construct a state-level version of China shock, following Autor, Dorn, and Hanson (2013). In particular, we interact the initial industry employment share for each state with the increase in Chinese exports to non-US advanced countries for each industry, for the period 1990-2007.

The results of this analysis are reported in Table A.1. The first column of Table A.1 reports the coefficient from regressions of the gender gap in 1970 on various state-level characteristics. The second column reports the coefficient from regressions of JOI in 1970 on various state-level characteristics. The correlation of the gender gap in 1970 with most of these variables is not statistically significantly different from zero, but some are. Places with a larger non-white population share
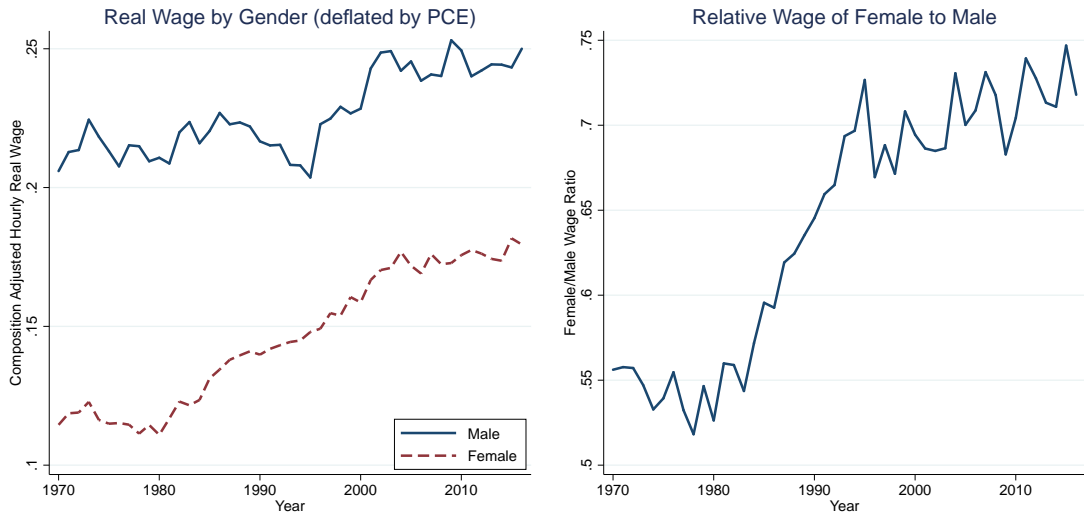
Figure A.7: Real Wage by Gender and Relative Wage: Time-series
Note: Wages are hourly and composition adjusted (age, education, race, whether the worker is foreign-born).
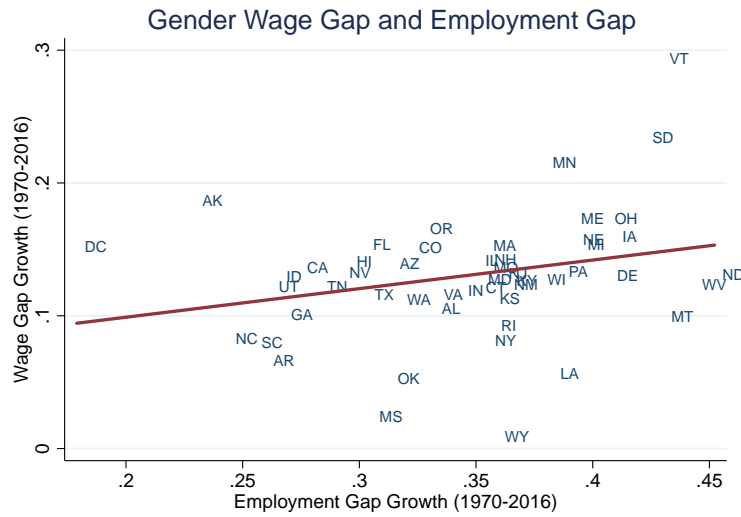

Figure A.8: Gender Gap in Employment Rate and Relative Wages: Cross-section

Table A.1: Correlations with the Instruments

	Gender gap in 1970	JOI in 1970
	(1)	(2)
Agricultural employment share in 1970	-0.41	-0.24
	(0.13)	(0.05)
Mining employment share in 1970	-0.21	-0.23
	(0.31)	(0.12)
Manufacturing employment share in 1970	-0.01	0.01
	(0.11)	(0.04)
Service employment share in 1970	0.19	0.10
	(0.19)	(0.07)
log GDP per capita in 1970	0.10	0.05
	(0.06)	(0.02)
College share in 1970	0.16	0.19
	(0.38)	(0.14)
Skill wage premium in 1970	0.00	0.06
	(0.08)	(0.03)
Singles share in 1970	1.10	0.60
	(0.40)	(0.08)
Non-white population share in 1970	0.26	0.11
	(0.07)	(0.03)
China shock (1990-2007)	0.00	0.00
	(0.01)	(0.00)
Bartik shock	0.12	0.07
	(0.11)	(0.04)
Observations	51	51

Note: In column (1), we report the coefficients from univariate regressions of the gender gap in 1970 on each of the variables listed to the left. In column (2), we report the coefficients from univariate regressions of the JOI in 1970 on these same variables. Robust standard errors are reported in parenthesis.

tended to have a smaller gender gap (in absolute value). Whether this represents a threat to our research design depends on whether it is likely that the non-white share in 1970 is correlated with gender-neutral shocks over our sample period. It is not clear why this would be the case. While the non-white share certainly affects the *level* of male employment, the key question is whether it predicts future *changes* in male employment, as discussed in Goldsmith-Pinkham, Sorkin, and Swift (2020). In fact, the employment gap between white and non-white men has been stable over time, suggesting that this may not be an important concern.

Some of the other correlations are driven by outliers. There is a statistically significant negative correlation with the agricultural employment share (i.e., states with larger gender gaps in

employment had higher agricultural shares), but not with the other sectoral shares. The correlation between the gender gap and the agricultural employment share is driven by three outliers: D.C., South Dakota, and North Dakota. If we remove these three observations, the coefficient becomes statistically insignificant (coefficient of -0.12, standard error of 0.13). Dropping these three states from our crowding out regressions does not significantly change our estimates of crowding out. Furthermore, even if a robust negative relationship were present, this correlation would lead us to overstate the magnitude of crowding out, since states with a higher than average agricultural employment share would have been expected to face negative employment shocks (for other reasons than crowding out) over this period, given the overall decline in the agricultural sector. This would make our (already small) estimates of crowding out *conservative*—i.e., the adjusted estimates would be even smaller. Ultimately, the evidence for an important role for sectoral effects in driving crowding out appears weak. Nevertheless, to be conservative on this front, we control for agricultural, manufacturing, mining and service employment shares in our main analysis in the paper.

Finally, there is a statistically significant correlation between the gender gap and the singles share. However, this correlation is driven by a single outlier, D.C. Once D.C. is removed, this correlation becomes statistically insignificant.

A.5.2   Pre-Trends and the Gender Gap

Next we consider whether male and female employment rates exhibit pre-trends. Figure A.9 plots the relationship between male and female employment growth in the pre-period 1960-1970 and the gender gap in 1970. The left panel shows that there is no association between pre-period male employment growth and the initial gender gap (regression point estimate is 0.01 with a standard error of 0.06). The right panel likewise shows that there is no correlation between pre-period female employment growth and the initial gender gap (regression point estimate is 0.004 with a standard error of 0.1). These results are reassuring that our results are not driven by systematic difference in prevailing employment growth rates.

A.5.3   A Decomposition of the Variation in the JOI using Rotemberg Weights

As explained in the main text, our JOI instrument is a particular type of shift-share instrument and our key identifying assumption for this instrument is that the initial occupational shares are orthogonal to subsequent gender-neutral shocks. Goldsmith-Pinkham, Sorkin, and Swift (2020)
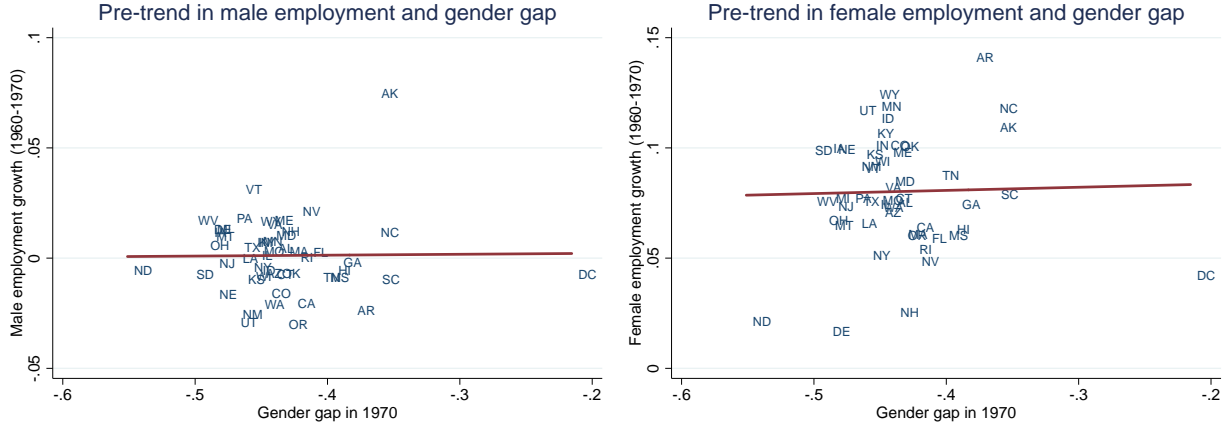
Figure A.9: Pre-trend and Initial Gender Employment Gap

Note: The left panel plots male employment growth during 1960-1970 against the gender gap in 1970. The right panel plots female employment growth during 1960-1970 against the gender gap in 1970.

point out that in this type of setting it can be useful to understand which occupations are driving the results. To assess this, we follow their analysis and that of Rotemberg (1983) in decomposing our IV estimator ($\hat{\beta}$ in equation (5)) into

$$\hat{\beta} = \sum_{\omega} \hat{\gamma}(\omega)\hat{\beta}(\omega), \tag{35}$$

where

$$\hat{\beta}(\omega) = \left(\sum_{i} \pi_{i,1970}(\omega)\widetilde{\Delta epop}_i^F\right)^{-1} \sum_{i} \pi_{i,1970}(\omega)\widetilde{\Delta epop}_i^M,$$

$$\hat{\gamma}(\omega) = \left(\sum_{\omega}\sum_{i} \alpha_{-i,1970}(\omega)\pi_{i,1970}(\omega)\widetilde{\Delta epop}_i^F\right)^{-1} \sum_{i} \alpha_{-i,1970}(\omega)\pi_{i,1970}(\omega)\widetilde{\Delta epop}_i^F.$$

In these expressions, $\widetilde{\Delta epop}_i^F$ and $\widetilde{\Delta epop}_i^M$ are residualized $\Delta epop_i^F$ and $\Delta epop_i^M$ with respect to the full set of controls X_i that we include in column (4) of Table 3, $\pi_{i,1970}(\omega)$ is the 1970 employment share of occupation ω in state i, and $\alpha_{-i,1970}(\omega)$ is the 1970 female share of employment in occupation ω in the US leaving out state i. Here, $\hat{\beta}(\omega)$ corresponds to a just-identified estimator when only the occupation share for occupation ω is used as an instrument, and $\hat{\gamma}(\omega)$ corresponds to the "Rotemberg weight" on each occupation ω.

Table A.2 reports $\hat{\gamma}(\omega)$ and $\hat{\beta}(\omega)$ for the 10 occupations that have the largest Rotemberg weights. Two observations stand out. First, while there are 255 occupations, the top few occu-

Table A.2: Occupations with the Largest Rotemberg Weights

Occupation	$\hat{\gamma}(\omega)$	$\hat{\beta}(\omega)$	$\alpha(\omega)$	$\pi(\omega)$
Textile sewing machine operators	0.461	-0.076	0.938	1.015
Housekeepers, maids, butlers, and cleaners	0.301	0.212	0.856	1.823
Winding and twisting textile and apparel operatives	0.230	-0.243	0.626	0.330
Miscellanious textile machine operators	0.153	-0.177	0.465	0.261
Knitters, loopers, and toppers textile operatives	0.098	-0.210	0.635	0.113
Bookkeepers and accounting and auditing clerks	0.079	-0.100	0.833	2.016
Personal service occupations, n.e.c	0.077	0.496	0.640	1.109
Farm workers, incl. nursery farming	0.065	0.159	0.210	1.198
Hairdressers and cosmetologists	0.053	0.107	0.873	0.535
Child care workers	0.052	-0.127	0.963	0.416

Notes: The table reports the decomposition of our IV estimator using the JOI instrument into Rotemberg weights $\hat{\gamma}(\omega)$ and just-identified IV estimators $\hat{\beta}(\omega)$ as in equation (35) for the 10 occupations with largest Rotemberg weights. We also report the national female share in occupation ω denoted $\alpha(\omega)$ and the mean employment share of occupation ω denoted $\pi(\omega)$, both in 1970. We report $\pi(\omega)$ in percent.

pations receive a hugely disproportionate weight in $\hat{\gamma}$. Several of these occupations are in textiles. Second, it appears that our finding of low crowding out does not seem to be driven by any particular occupation. While the coefficients from the just-identified regressions ($\hat{\beta}(\omega)$) vary a lot among these top few occupations, they tend to be centered around our point estimates in Table 4.

A.5.4 Correlates of Initial Occupational Employment Shares

Finally, we can explore whether local characteristics are correlated with the initial employment share of particular occupations across states for the occupations that receive high Rotemberg weights. These results are reported in Table A.3. Each element of the table reports the coefficient from a univariate regression. In each column, the dependent variable in the regression is the employment share of the occupation listed at the top of the column. The independent variable in each regression is the variable listed at the left of the row. The occupations for which we report results are the five occupations with the largest Rotemberg weights for the JOI instrument. The states with higher employment shares for these occupations tend to be manufacturing oriented, have a smaller share of college educated people, and have a higher skill premium. There is no significant association between pre-1970 male and female growth rates and occupational shares.

Table A.3: Corrlation between Female Occupation Shares and State Characteristics

	Textile sewing operators	Housekeepers & maids	Winding operators	Misc. Textile operators	Knitters operators
Agricultural share	-0.054	-0.021	-0.019	-0.016	-0.008
	(0.015)	(0.021)	(0.006)	(0.005)	(0.003)
Mining share	-0.033	0.069	-0.047	0.046	-0.081
	(0.030)	(0.061)	(0.034)	(0.036)	(0.043)
Manufacturing share	0.057	-0.013	0.032	0.026	0.012
	(0.011)	(0.017)	(0.012)	(0.010)	(0.005)
Service share	-0.069	0.022	-0.043	-0.035	-0.016
	(0.016)	(0.032)	(0.018)	(0.015)	(0.007)
log GDP per capita	-0.020	0.001	-0.009	-0.008	-0.003
	(0.006)	(0.015)	(0.005)	(0.004)	(0.002)
College share	-0.179	-0.054	-0.104	-0.089	-0.040
	(0.040)	(0.068)	(0.045)	(0.037)	(0.017)
Skill premium	0.037	0.017	0.018	0.016	0.008
	(0.014)	(0.012)	(0.008)	(0.007)	(0.004)
Singles share	-0.004	0.139	-0.010	-0.006	-0.002
	(0.048)	(0.081)	(0.015)	(0.013)	(0.006)
Non-white share	0.012	0.050	0.007	0.007	0.003
	(0.014)	(0.017)	(0.009)	(0.007)	(0.003)
China shock	0.005	-0.001	0.002	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
Bartik shock	-0.042	0.007	-0.024	-0.021	-0.009
	(0.010)	(0.020)	(0.011)	(0.009)	(0.004)
Past $\Delta epop^M$	-0.017	-0.041	0.010	0.013	0.006
	(0.074)	(0.055)	(0.040)	(0.034)	(0.016)
Past $\Delta epop^F$	0.021	-0.069	0.009	0.012	0.004
	(0.052)	(0.054)	(0.031)	(0.026)	(0.014)

Notes: Each element of Table A.3 reports the coefficient from the univariate regression of column variable on the row variable. The first eight row variables are same as in Table A.1. The first five columns are top 5 Rotemberg weight occupations, and the last column is the JOI instrument. Past $\Delta epop^M$ ($\Delta epop^F$) is the male (female) employment rate growth during 1960-1970. Robust standard errors are reported in parenthesis.

Table A.4: Our Instruments do not Predict Cross-state Migration

	All		Men		Women		Married	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender gap in 1970	0.0511		0.0438		0.0575		0.358	
	(0.251)		(0.245)		(0.257)		(0.393)	
JOI in 1970		0.223		0.191		0.254		0.947
		(0.552)		(0.542)		(0.561)		(0.887)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Obervations	153	153	153	153	153	153	153	153
Adjusted R^2	0.0101	0.0165	0.0105	0.0150	0.00925	0.0180	0.0847	0.106

Note: The dependent variable in columns 1 and 2 are net migration rate of entire state population over 1975-1980, 1985-1990, and 1995-2000. The dependent variable in columns 3 and 4 are that of men. The dependent variable in columns 5 and 6 are that of women. The dependent variable in columns 7 and 8 are that of married households. Robust standard errors are clustered at the state-level and reported in parentheses.

A.5.5 Cross-State Migration

Our baseline model abstracts for simplicity from cross-state migration. In this section, we analyze the relationship between our instruments and state-level net migration flows (and show they are not statistically significant). We calculate state-level net migration using census data. The census records a person's current state of residence. The 1980, 1990, and 2000 Censuses asked respondents where they lived five years earlier. This question was not asked in the 2010 Census. Using this information, we construct gross inflows and outflows as well as cross-state net migration at the state-level. We compute the cross-state net migration rate as the difference between the total inflow and the total outflow divided by the population. As in our main analysis, we focus on the prime-age population. We also repeat the same analysis by further limiting the sample only to men, women, and married households.

Table A.4 shows the results of regressions of the cross-state net migration rate during 1975-1980, 1985-1990 and 1995-2000 on our two instrumental variables, the gender gap and the JOI in 1970. All regressions include year fixed effects to account for the declining trend of cross-state migration. A positive estimates indicates that states with relatively more women working ("higher" gender gap) had larger net migration inflow. In all cases, the correlation is weakly positive, but not statistically different from zero. Hence, we do not find evidence that our instruments predict cross-state migration.
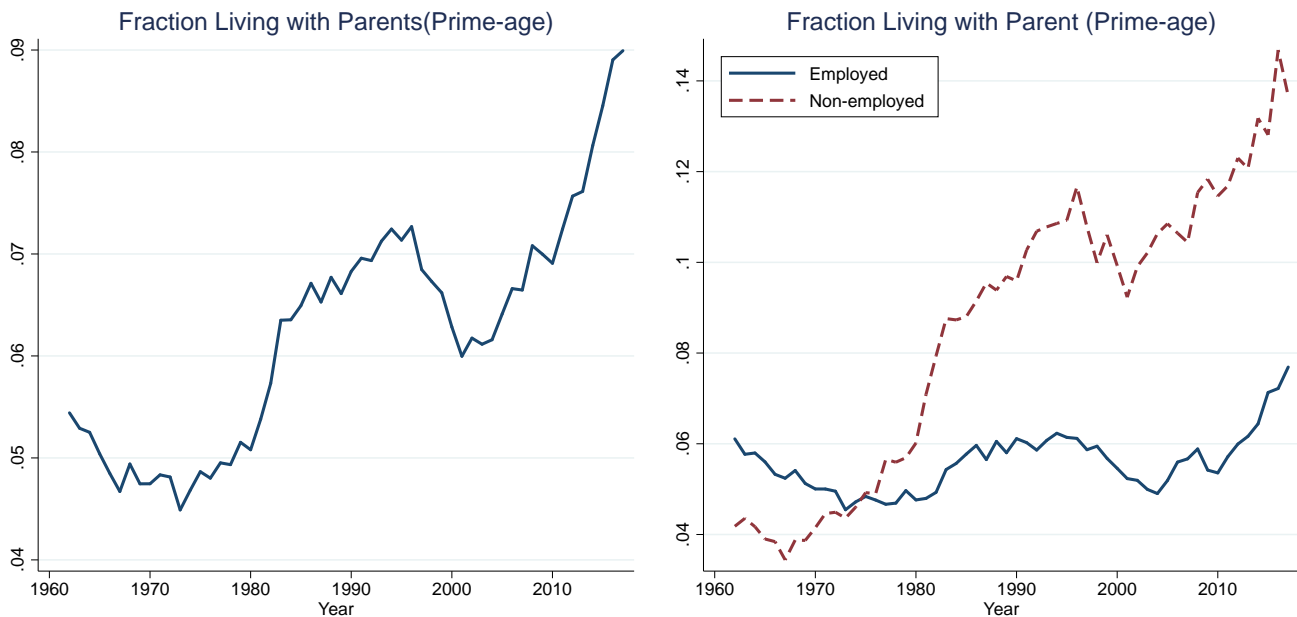
Figure A.10: Fraction of Prime-Age Living with Parents

Note: Figure shows the fraction of prime-age people cohabiting with their parents or step-parents. Data are from the March CPS.

A.6 Trends in Cohabitation with Parents

The left panel of Figure A.10 documents cohabitation patterns of prime-age people over the period 1962-2016 using March CPS. Following Aguiar et al. (2017), a person is defined to be living with parents when the household head is a parent or step-parent. The fraction of prime-aged people cohabiting with their parents has almost doubled over the past 50 years. We show that this is true for all prime-age people, while Aguiar et al. (2017) focus on young men. The right panel of Figure A.10 plots the rate of cohabitation with parents among employed and non-employed prime-aged people. It shows that the increase in cohabitation arises almost entirely from the non-employed. The possibility of living with one's parents when one is out of work is an important form of wealth transfer from parents to their adult children, that has become more prevalent in recent years.

A.7 Alternative Measures of Real Income

Figure A.11 presents a time series plot of real median family income deflated alternatively by the CPI and the PCE deflator, as well as a plot of real GDP. Real median family income deflated by the CPI grows much more slowly than real GDP. But half of this difference disappears once we deflate median family income by the PCE deflator, as emphasized by Sacerdote (2017). The PCE deflator
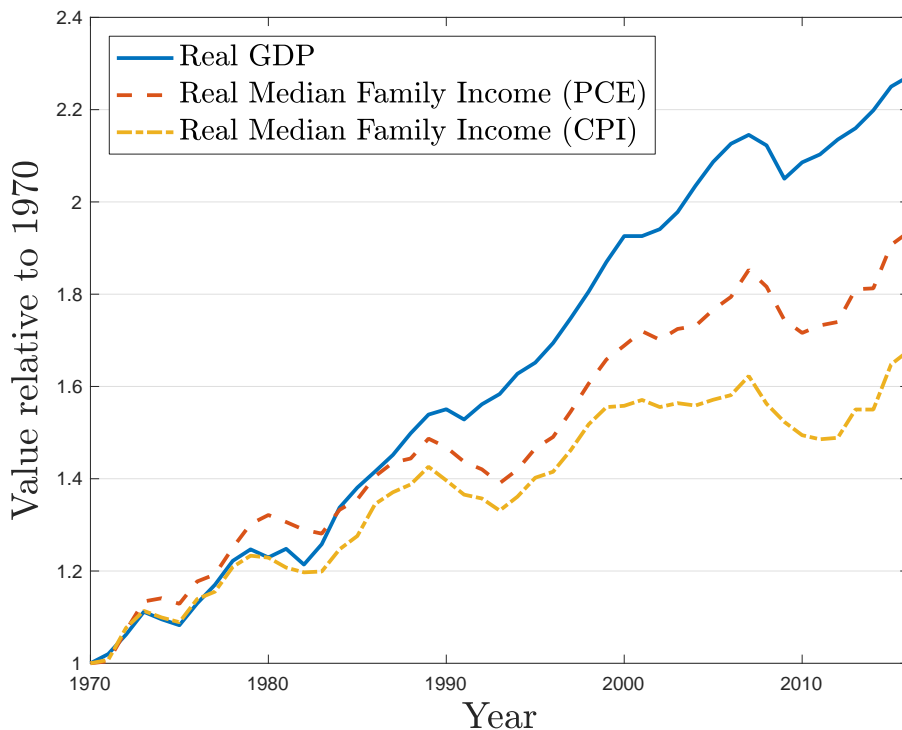
Figure A.11: Real GDP and Real Median Family Income

Note: Values are normalized by their 1970 level. Both family income series are normalized by household size.

yields a lower inflation rate (and therefore a higher growth rate in real median family income) mostly because it is based on a Fisher index that accounts for substitution bias, and weights that derive from production information rather than consumer surveys. The U.S. Federal Reserve Board has typically viewed the PCE deflator is its preferred inflation measure for these reasons.

A.8 Family Structure

Table A.5 estimates crowding out for single men and married men separately. The table shows that crowding out is not statistically different from zero in any of these specifications. This finding is consistent with the result that, with balanced growth preferences, the employment of single men is not affected by the Gender Revolution. Married men are not affected much because of the home production channel that we highlight in our paper. As a consequence, crowding out is small for both groups.

Figure A.12 further decomposes employment rates of married men by the employment status of their wives. The figure shows that the employment rate of married men with non-working wives declined more quickly than the employment rate of those with working wives. These facts are consistent with minimal crowding out though it is hard to draw definitive conclusions, given

Table A.5: Estimates of Crowding Out: Effect on Married and Single Male Employment

	Δ(Male Employment)							
	2SLS (gap)				2SLS (JOI)			
	Married		Single		Married		Single	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ(Female Employment)	-0.05	-0.08	-0.06	-0.32	-0.00	0.08	0.24	0.09
	(0.09)	(0.08)	(0.17)	(0.18)	(0.12)	(0.13)	(0.12)	(0.18)
Controls		✓		✓		✓		✓
Observations	51	51	51	51	51	51	51	51

Note: The dependent variables in columns (1), (2), (5), (6) are the change in the married male employment rate over the period 1970-2016, while in columns (1), (2), (5), (6), they are the change in the single male employment rate over this period. The main explanatory variable is the change in the female employment rate over the same time period. Columns (1)-(4) instrument for this explanatory variable using the 1970 gender gap in employment rates, while columns (5)-(8) instrument using the Job Opportunity Index (JOI) described in the paper. Robust standard errors are reported in parentheses.

Figure A.12: Employment Rates by Marital Status

the changing selection into marriage over time.

B Theory Appendix

B.1 Large Representative Household

Following Galí (2011), we assume that the representative household consists of a continuum of men and women. Each man is indexed by $j \in [0, 1]$, which determines his disutility of working. The disutility of labor of a member j is given by $j^{\nu^{-1}}/\chi_m$, where ν governs the elasticity of labor supply and χ_m is the male-specific labor supply shifter. The total disutility of labor for men is

$$\int_0^{L_m} \frac{j^{\nu^{-1}}}{\chi_m} dj = \frac{1}{\chi_m} \frac{(L_m)^{1+\nu^{-1}}}{1+\nu^{-1}}. \tag{36}$$

where L_m is the fraction of men that choose to work.

In our more general model with home production, each woman is indexed by a pair (ω, j). The first dimension, ω, denotes productivity in the home production sector. The second dimension, $j \in [0, 1]$, determines disutility of labor, which is given by $j^{\nu^{-1}}/\chi_f$, where χ_f is a female-specific labor supply shifter. We assume that these two dimensions of heterogeneity are independent. The distribution function of womens' productivity at home is $G(\omega)$. Each woman can choose to (i) work at home, (ii) work in the market, or (iii) enjoy leisure. Conditional on deciding to work, a woman with $\omega > \theta_f$ chooses to work at home, while a woman with $\omega \leq \theta_f$ chooses to work in the market, as described in the main text. The total disutility of labor for women of type $\omega \leq \theta_f$ when $L_f(\omega)$ fraction of them work in the market is

$$\int_0^{L_f(\omega)} \frac{j^{\nu^{-1}}}{\chi_f} dj = \frac{1}{\chi_f} \frac{(L_f(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}}. \tag{37}$$

Similarly, the total disutility of labor for women of type $\omega > \theta_f$ when $L_f^h(\omega)$ fraction of them work at home is

$$\int_0^{L_f^h(\omega)} \frac{j^{\nu^{-1}}}{\chi_f} dj = \frac{1}{\chi_f} \frac{(L_f^h(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}}. \tag{38}$$

The total disutility of work in a large household is the sum of expressions (36), (37), and (38):

$$\frac{1}{\chi_m} \frac{(L_m)^{1+\nu^{-1}}}{1+\nu^{-1}} + \frac{1}{\chi_f} \left(\int_{\underline{\omega}}^{\theta_f} \frac{(L_f(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) + \int_{\theta_f}^{\bar{\omega}} \frac{(L_h(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) \right).$$

B.2 Robustness of Crowding Out Under "Balanced Growth Preferences"

In section 5, we show that under "balanced growth preferences," aggregate crowding out is given by the relative productivity of women to men. In this section, we show that the finding that crowding out is large in models with balanced growth preferences does not depend on the simplifying assumptions of perfect substitutability between male and female labor, additive separability of the disutility of male and female labor, or the unitary household assumption.

Constant Returns to Scale Production   First, in section 5, we assumed a linear production function. Suppose instead that the production function is $F(L_m, L_f; \theta)$, where F is any constant returns to scale function in male and female labor, and θ is an exogenous parameter. Male and female wages are given by $w_m = F_m(L_m, L_f; \theta)$ and $w_f = F_f(L_m, L_f; \theta)$, where $F_g(L_m, L_f; \theta) \equiv \frac{\partial F(L_m, L_f; \theta)}{\partial L_g}$ for $g \in \{m, f\}$. The household's problem under balanced growth preferences is given by

$$
\max_{C, L_m, L_f} \ln C - \frac{1}{\chi_m} \frac{L_m^{1+\nu^{-1}}}{1+\nu^{-1}} - \frac{1}{\chi_f} \frac{L_f^{1+\nu^{-1}}}{1+\nu^{-1}}
$$
$$
C = w_m L_m + w_f L_f.
$$

The solution to this problem is given by

$$
L_m = (w_m \chi_m)^\nu \left((w_m)^{\nu+1}(\chi_m)^\nu + (w_f)^{\nu+1}(\chi_f)^\nu \right)^{\frac{-\nu}{1+\nu}}
$$
$$
L_f = (w_f \chi_f)^\nu \left((w_m)^{\nu+1}(\chi_m)^\nu + (w_f)^{\nu+1}(\chi_f)^\nu \right)^{\frac{-\nu}{1+\nu}}
$$

Taking derivatives with respect to θ, we have

$$
\frac{dL_m}{d\theta} = \nu \left((w_m)^{\nu+1}(\chi_m)^\nu + (w_f)^{\nu+1}(\chi_f)^\nu \right)^{\frac{-1-2\nu}{1+\nu}}
$$
$$
\times \left((w_m)^{\nu-1}(\chi_m)^\nu \frac{dw_m}{d\theta} (w_f)^{\nu+1}(\chi_f)^\nu - (w_m \chi_m)^\nu (w_f \chi_f)^\nu \frac{dw_f}{d\theta} \right)
$$
$$
\frac{dL_f}{d\theta} = \nu \left((w_m)^{\nu+1}(\chi_m)^\nu + (w_f)^{\nu+1}(\chi_f)^\nu \right)^{\frac{-1-2\nu}{1+\nu}}
$$
$$
\times \left((w_f)^{\nu-1}(\chi_f)^\nu \frac{dw_f}{d\theta} (w_m)^{\nu+1}(\chi_m)^\nu - (w_f \chi_f)^\nu (w_m \chi_m)^\nu \frac{dw_m}{d\theta} \right).
$$

From the above expressions, we thus arrive at the following proposition.

Proposition 1. *If the utility function is given by*

$$U(C, L_m, L_f) = \ln C - \frac{1}{\chi_m} \frac{L_m^{1+\nu^{-1}}}{1+\nu^{-1}} - \frac{1}{\chi_f} \frac{L_f^{1+\nu^{-1}}}{1+\nu^{-1}},$$

and the production function features constant returns to scale in male and female labor, aggregate crowding out from any technology shock such that $dL_f/d\theta \neq 0$ is given by the relative wage of women to men:

$$\epsilon^{agg} \equiv \frac{\frac{dL_m}{d\theta}}{\frac{dL_f}{d\theta}} = -\frac{w_f}{w_m}.$$

This result also holds when the production function features decreasing returns to scale, as long as the production function is Cobb-Douglas in the labor composite (i.e., $F(L_m, L_f; \theta) = L(L_m, L_f; \theta)^\alpha$ with $\alpha < 1$ for some constant returns to scale function L). In this case, one can show that household income is proportional to labor income: $\frac{1}{\alpha}(w_m L_m + w_f L_f)$. The labor supply conditions in this model are scaled by the factor $1/\alpha$ relative to those in in the constant return to scale model, but otherwise unchanged. As a consequence, the derivation above goes through.

Leisure Complementarity Second, in section 5, we assume additive separability in the disutility of male and female labor. One might worry that leisure complementarity might overturn our results. In fact, this is not the case. When male and female leisure are complementary, it is tempting to think that as women work more, men will also wish to work more—reducing crowding out. This intuition is not correct. Raising the degree of leisure complementarity does not, in general, lower the degree of crowding out in a model with balanced growth preferences. The intuition is that leisure complementarity not only reduces the degree to which male employment responds to a female-biased technology shock—it also weakens the response of female employment to the same shock. When male and female leisure are complements, neither men nor women wish to consume leisure alone. This implies that increasing leisure complementarity leaves the relative response of females to males (crowding out) unchanged. We establish this analytically below.

Suppose the household utility function is given by $U(C, L_m, L_f) = \ln C - v(L_m, L_f)$ for some function v. The production function has constant returns to scale in male and female labor: $Y =$

$F(L_m, L_f; \theta)$. The household's problem is

$$\max_{C, L_m, L_f} \ln C - v(L_m, L_f)$$

$$\text{s.t.} \quad C = w_m L_m + w_f L_f.$$

The first order conditions are

$$w_m = (w_m L_m + w_f L_f) v_m(L_m, L_f) \tag{39}$$

$$w_f = (w_m L_m + w_f L_f) v_f(L_m, L_f). \tag{40}$$

An analytical solution is not available at this level of generality. We therefore derive comparative statics with respect to θ around a point where men and women are symmetric. First order expansions of equations (39) and (40) around $L_m = L_f = L$, $w_m = w_f = w$, $v_m = v_f$ and $v_{mm} = v_{ff}$ give

$$(wv_m + 2wLv_{mm})\frac{dL_m}{d\theta} = -(wv_m + 2wLv_{mf})\frac{dL_f}{d\theta} - Lv_m\frac{dw_f}{d\theta} + (1 - Lv_m)\frac{dw_m}{d\theta}$$

$$(wv_f + 2wLv_{ff})\frac{dL_f}{d\theta} = -(wv_f + 2wLv_{mf})\frac{dL_m}{d\theta} - Lv_m\frac{dw_m}{d\theta} + (1 - Lv_f)\frac{dw_f}{d\theta}.$$

Combining these two equations and after some algebra, we obtain

$$\frac{dL_m}{d\theta} = \frac{1}{4wL(v_{mm} - v_{mf})}\frac{dw_m}{d\theta} - \frac{1}{4wL(v_{mm} - v_{mf})}\frac{dw_f}{d\theta}$$

$$\frac{dL_f}{d\theta} = -\frac{1}{4wL(v_{mm} - v_{mf})}\frac{dw_m}{d\theta} + \frac{1}{4wL(v_{mm} - v_{mf})}\frac{dw_f}{d\theta}.$$

This leads to the following proposition.

Proposition 2. *Suppose the utility function is given by*

$$U(C, L_m, L_f) = \ln C - v(L_m, L_f),$$

for some v, and the production function features constant returns to scale in male and female labor. Around an allocation where men and women are symmetric ($L_m = L_f$, $w_m = w_f$, $v_m = v_f$ and $v_{mm} = v_{ff}$), the aggregate crowding out from any technology shock such that $dL_f/d\theta \neq 0$ is one:

$$\epsilon^{agg} = -1.$$

Notice that we did not put any restrictions on the cross-partial derivative of the disutility function, v_{mf}. This implies that when men and women are symmetric, women perfectly crowd out men regardless of what we assume about the extent of leisure complementarity. Intuitively, leisure complementarity weakens the level of the response, but not the relative response of female labor to male labor.

In reality, men and women are not completely symmetric in the labor market. However, this results is nevertheless a useful benchmark showing that leisure complementarity does not necessarily lower crowding out. Since male and female labor are smooth functions of the underlying parameters, we conjecture that crowding out is still large even away from, but in the vicinity of, the exact symmetric case we analyze.

Non-Unitary Household   So far, we have assumed a unitary household, where men and women perfectly share income. Although this assumption is standard in the literature, there is evidence against the unitary household assumption (e.g., Cesarini et al., 2017). One might worry that the unitary household assumption is crucial for generating large crowding out. This turns out to not necessarily be the case. We present a stylized model to illustrate that crowding out can remain large even if men and women share income imperfectly. Intuitively, while imperfect income sharing reduces the income effect on men, it increases the income effect on women. The resulting effect on the response of men relative to women is ambiguous.

Suppose that men share a fraction $1 - \alpha_m$ of their income with women, and women share a fraction $1 - \alpha_f$ of their income with men. Each gender $g \in \{m, f\}$ solves the following problem:

$$\max_{L_g, C_g} \ln C_g - \frac{1}{\chi_g} \frac{(L_g)^{1+\nu^{-1}}}{1 + \nu^{-1}}$$

$$\text{s.t.} \quad C_g = \alpha_g w_g L_g + (1 - \alpha_{-g}) w_{-g} L_{-g},$$

where we have assumed balanced growth preferences and $-g$ denotes the opposite gender from g. Utility maximization yields the following labor supply curves for women and men, respectively:

$$\alpha_f w_f = \frac{1}{\chi_f} L_f^{\nu^{-1}} \left((1 - \alpha_m) w_m L_m + \alpha_f w_f L_f \right)$$

$$\alpha_m w_m = \frac{1}{\chi_m} L_m^{\nu^{-1}} \left(\alpha_m w_m L_m + (1 - \alpha_f) w_f L_f \right).$$

Consider a shock to technological parameter θ starting from an allocation where men and women

are symmetric, i.e., $\chi_m = \chi_f \equiv \chi, \alpha_m = \alpha_f \equiv \alpha, w_m = w_f \equiv w$ and thus $L_m = L_f \equiv L$. In this case, the response of male and female labor are given by

$$\frac{dL_m}{d\theta} = \frac{1}{((\alpha + \nu^{-1})^2 - (1-\alpha)^2) \, wL^{\nu^{-1}}} \alpha\chi(1+\nu^{-1})(1-\alpha) \left[\frac{dw_m}{d\theta} - \frac{dw_f}{d\theta} \right]$$

$$\frac{dL_f}{d\theta} = \frac{1}{((\alpha + \nu^{-1})^2 - (1-\alpha)^2) \, wL^{\nu^{-1}}} \alpha\chi(1+\nu^{-1})(1-\alpha) \left[\frac{dw_f}{d\theta} - \frac{dw_m}{d\theta} \right].$$

This implies that

$$\epsilon^{agg} = -1.$$

In other words, crowding out is precisely one despite the imperfect income sharing in this model.

B.3   Derivation of Expressions in Section 5

Here we derive expressions (24) and (25). The corresponding expressions for the closed economy model with or without home production are special cases of these expressions.

Firm optimization yields:

$$w_{mi} = p_i A_i \tag{41}$$

$$w_{fi} = p_i A_i \theta_f. \tag{42}$$

Household optimization yields:

$$(L_{mi})^{\nu^{-1}} = \chi_{mi} w_{mi} \lambda \tag{43}$$

$$(L_{fi})^{\nu^{-1}} = \chi_{fi} w_{fi} \lambda \tag{44}$$

$$(L_{fi}^h(\omega))^{\nu^{-1}} = \chi_{fi} A \omega \lambda^h, \tag{45}$$

where λ and λ^h are Lagrangian multipliers on the budget constraint and home production constraint, respectively. Household optimization—first order conditions with respect to c_{ii} and c_i^h—furthermore, implies that $\lambda^h = p_i \lambda$.

Since market produced goods and home produced goods are perfect substitutes, there is a

single market clearing condition:

$$A_i \left[L_{mi} + \int^{\theta_f} \theta_f L_{fi} dG(\omega) + \int_{\theta_f} \omega L_f^{hi}(\omega) dG(\omega) \right]$$

$$= \sum_j \left(\frac{p_i}{P} \right)^{-\eta} \frac{1}{P} \left[w_{mj} L_{mj} + \int^{\theta_{fj}} w_{fj} L_{fj} dG(\omega) + \int_{\theta_{fj}} w_{fj}^h(\omega) L_{fj}^h(\omega) dG(\omega) \right] \tag{46}$$

Combining these conditions we obtain closed form expressions for equilibrium employment:

$$L_{mi} = \left(\frac{p_i}{P} \right)^{\frac{1-\psi}{\nu-1+\psi}} (A_i)^{\frac{1-\psi}{\nu-1+\psi}} (\chi_{mi})^\nu \left((\chi_{mi})^\nu + (\chi_{fi})^\nu (\theta_{fi})^{\nu+1} G(\theta_{fi}) + \int_{\theta_{fi}} \omega dG(\omega) \right)^{\frac{-\nu\psi}{1+\nu\psi}},$$

$$L_{fi} = G(\theta_{fi}) \left(\frac{p_i}{P} \right)^{\frac{1-\psi}{\nu-1+\psi}} (A_i)^{\frac{1-\psi}{\nu-1+\psi}} (\theta_{fi})^\nu (\chi_{fi})^\nu \left((\chi_{mi})^\nu + (\chi_{fi})^\nu (\theta_{fi})^{\nu+1} G(\theta_{fi}) + \int_{\theta_{fi}} \omega dG(\omega) \right)^{\frac{-\nu\psi}{1+\nu\psi}},$$

with

$$\frac{p_i}{P} = \frac{\Gamma_i^{-1}}{\left(\sum_j \Gamma_j^{-(1-\eta)} \right)^{\frac{1}{1-\eta}}},$$

and

$$\Gamma_i = \left[(A_i)^{1+\nu} \left((\chi_{mi})^\nu + (\theta_{fi})^{\nu+1} (\chi_{fi})^\nu G_f(\theta_{fi}) + \int_{\theta_{fi}} \omega^{\nu+1} (\chi_{fi})^\nu dG(\omega) \right) \right]^{\frac{1}{\eta(1+\nu)-(\eta-1)\nu(1-\psi)}}.$$

These same equations hold in the closed economy version of the model with $p^i/P = 1$ and in the model without home production if the mass of women with productivity at home above θ_f^i is set to zero.

B.4 Robustness: Alternative Specifications

Next, we describe the alternative model specifications for which we calculate counterfactuals in Table 7.

B.4.1 Gender Revolution through Female Labor Supply Shocks

Our baseline model assumes that female convergence occurs due to increases in demand for female labor. This choice was motivated by the fact that the composition-adjusted gender wage gap and the gender employment gap are positively correlated across states and over time (see Appendix A.4.2). We do not, however, wish to suggest that labor supply shocks were unimpor-

tant during the Gender Revolution. The development of birth control, child care, technological progress in home production, and changes in norms regarding the role of women were likely important factors in driving gender convergence by increasing female labor supply (e.g., Goldin and Katz, 2002; Fernández, Fogli, and Olivetti, 2004; Greenwood, Seshadri, and Yorukoglu, 2005; Attanasio, Low, and Sánchez-Marcos, 2008; Fernández and Fogli, 2009; Albanesi and Olivetti, 2016). The observed correlation between the growth in relative female wages and employment rates is likely due to a combination of labor demand and labor supply shocks.

To assess crowding out in response to female-biased labor supply shocks, consider a model in which female convergence arises from a reduction in the disutility women experience from market work (i.e., a reduction in gender-biased workplace harassment by men). In this case, rather than differing in productivity at home, we assume that women differ in their disutility from working at home. This version of our model is, therefore, isomorphic to our benchmark model with home production except that in this case, both heterogeneity and shocks are modeled as affecting labor supply rather than labor demand.

Women are heterogeneous along two dimensions. First, they differ in the extent to which they dislike working whether at home or in the market. This factor is indexed by j, as before. Second, they differ in their special disutility of working at home, indexed by ω. Specifically, the disutility of labor of women of type (ω, j) is $\frac{1}{\chi_f} j^\nu$ for market work and $\frac{1}{\omega} j^\nu$ for work at home. We assume that ω and j are independent, ω is distributed according to the CDF $G(\omega)$ with support $[\underline{\omega}, \bar{\omega}]$, and j is uniformly distributed between 0 and 1. In this version of the model, we abstract from heterogeneity in productivity between home and market work and assume that the productivity of women relative to men is θ_f both in market work and home production.

We can divide the labor market choices women face into two separate choices. First, women of type j, conditional on working at all, choose to work in the market if and only if $\omega > \chi_f$. Second, women of type j must decide whether to work or enjoy leisure. The utility function of the representative household is given by

$$
\begin{aligned}
&U(C, L_m, \{L_f(\omega)\}, \{L_f^h(\omega)\}) \\
&= \frac{(C)^{1-\psi}}{1-\psi} - \Theta_t \left(\frac{1}{\chi_m} \frac{(L_m)^{1+\nu^{-1}}}{1+\nu^{-1}} + \int_{\underline{\omega}}^{\chi_f} \frac{1}{\chi_f} \frac{(L_f(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) + \int_{\chi_f}^{\bar{\omega}} \frac{1}{\omega} \frac{(L_f^h(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) \right),
\end{aligned}
$$

where $C = c + c^h$. The rest of the models are unchanged.

B.4.2 Imperfect Substitutability

Next, we consider a case where we relax the assumptions of perfect substitutability of men and women in production:

$$y_i = A_i \left((L_{mi})^{\frac{\kappa-1}{\kappa}} + (\theta_{fi} L_{fi})^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}},$$

where κ is the elasticity of substitution between male and female labor. We also relax the perfect substitutability of market and home goods in the consumption basket:

$$C_i = \left[\sum_j (c_{ji})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta-1}{\eta}}, \quad c_{ii} = \left((c_i^m)^{\frac{\xi-1}{\xi}} + (c_i^h)^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}}.$$

Our benchmark model is the special case with $\kappa = \xi = \infty$. In this case, we instead set $\kappa = 5$ and $\xi = 10$.

B.4.3 Leisure Complementarity

In the benchmark model, disutility from labor for men and women were additively separable. Here, we instead assume that the men and women's leisure are complements. In particular, we assume that disutility of labor is

$$
\begin{aligned}
&v(L_m, \{L_f(\omega)\}, \{L_f^h(\omega)\}) \\
&= \left[\left(\frac{1}{\chi_m} \frac{(L_{mi})^{1+\nu^{-1}}}{1+\nu^{-1}} \right)^{1+\mu} + \left(\frac{1}{\chi_f} \left(\int_{\underline{\omega}}^{\theta_f} \frac{(L_f(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) + \int_{\theta_f}^{\bar{\omega}} \frac{(L_f^h(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) \right) \right)^{1+\mu} \right]^{\frac{1}{1+\mu}},
\end{aligned}
$$

where $\mu > -1$ controls the degree of leisure complementarity. When $\mu < 0$, $\frac{\partial^2 v}{\partial L_m \partial L_f(\omega)} < 0$, capturing the idea that additional work by men is less costly when women also work more. With $\mu = 0$, we recover the benchmark case. We set $\mu = -0.5$.

B.4.4 Non-Unitary Household Model

In our baseline model, we assume that income sharing between male and female is perfect. Here we relax this assumption. In particular, men retain a share $\alpha \in [0, 1]$ of their own earnings while they give a share $1 - \alpha$ to women. The same is true of women, including earnings from home

production. The household problem of men is

$$\max_{\{c_{mij},c^h_{mii}\},L_{mi}} \frac{C_{mi}^{1-\psi}}{1-\psi} - \Theta_{it}\frac{1}{\chi_m}\frac{L_{mi}^{1+\nu^{-1}}}{1+\nu^{-1}}$$

$$\text{s.t.}\quad \sum_j p_{ij}c_{mij} = \alpha w_{mi}L_{mi} + (1-\alpha)\int_{\underline{\omega}}^{\theta_{fi}} w_{fi}L_{fi}(\omega)dG(\omega),$$

$$c_{mi}^h = (1-\alpha)\int_{\theta_{fi}}^{\bar{\omega}} A_i\omega L_f^h(\omega)dG(\omega),$$

where C_m is the CES basket defined as in equation (19). Similarly, the problem of women is

$$\max_{\{c_{fij},c^h_{fii}\},\{L_{fi}(\omega)\},\{L^h_{fi}(\omega)\}} \frac{C_{fi}^{1-\psi}}{1-\psi} - \Theta_{it}\frac{1}{\chi_f}\left(\int_{\underline{\omega}}^{\theta_{fi}} \frac{(L_{fi}(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}}dG(\omega) + \int_{\theta_{fi}}^{\bar{\omega}} \frac{(L^h_{fi}(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}}dG(\omega)\right)$$

$$\text{s.t.}\quad \sum_j p_{ij}c_{fij} = (1-\alpha)w_{mi}L_{mi} + \alpha\int_{\underline{\omega}}^{\theta_{fi}} w_{fi}L_{fi}(\omega)dG(\omega),$$

$$c_{fi}^h = \alpha\int_{\theta_{fi}}^{\bar{\omega}} A_i\omega L_f^h(\omega)dG(\omega).$$

With $\alpha = 1/2$, the model is isomorphic to the benchmark model. We set $\alpha = 2/3$.

B.4.5 Task-Based Model

A common intuition is that women crowd out men in the labor market by increasing competition for jobs, which reduces labor demand for men. However, with a neoclassical production function, an increase in female-biased productivity, θ_f, can never decrease male labor demand, as long as there is no fixed factor, as shown by Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018). In contrast, the task-based production function of Acemoglu and Autor (2011) allows for the possibility that an increase in female labor productivity reduces males labor demand.

In this model, aggregate output is produced from a unit mass of tasks $x \in [0, 1]$ combined via a CES aggregator:

$$Y = A\left(\int_0^1 y(x)^{\frac{\lambda-1}{\lambda}}dx\right)^{\frac{\lambda}{\lambda-1}},$$

where $\lambda \geq 0$ is the elasticity of substitution between tasks. Similarly to Acemoglu and Restrepo (2018) in the context of automation, we assume tasks $x \in [0, \theta_f]$ can be performed by both men

and women, and tasks $x \in [\theta_f, 1]$ can only be performed by men. Specifically,

$$y(x) = \begin{cases} l_m(x) + \gamma_f l_f(x) & \text{if } x \in [0, \theta_f] \\ l_m(x) & \text{if } x \in [\theta_f, 1] \end{cases},$$

where γ_f is the relative productivity of women, which we assume is constant across tasks. We focus on the portion of the parameter space where $w_f/\gamma_f \leq w_m$, which implies that tasks $x \in [0, \theta_f]$ are performed by women. Consequently, the aggregate production function can be derived to be

$$Y = A \left((1 - \theta_f)(L_m)^{\frac{\lambda-1}{\lambda}} + \theta_f (\gamma_f L_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}.$$

This implies that an increase in θ_f may well decrease the male labor demand. In our numerical simulation, we set $\lambda = 10$ and $\gamma_f = 1$.

B.4.6 Gender Specific Frisch Elasticity of Labor Supply

In our baseline model, we assume that the elasticity of labor supply for men and women is equal. A large literature in labor economics estimates a larger labor supply elasticity for women. We can capture this in our model by assuming that the disutility of labor is given by

$$v(L_m, \{L_f(\omega)\}, \{L_f^h(\omega)\}) = \frac{1}{\chi_m} \frac{(L_{mi})^{1+\nu_m^{-1}}}{1 + \nu_m^{-1}}$$
$$+ \frac{1}{\chi_f} \left(\int_{\underline{\omega}}^{\theta_f} \frac{(L_f(\omega))^{1+\nu_f^{-1}}}{1 + \nu_f^{-1}} dG(\omega) + \int_{\theta_f}^{\bar{\omega}} \frac{(L_f^h(\omega))^{1+\nu_f^{-1}}}{1 + \nu_f^{-1}} dG(\omega) \right),$$

where $\nu_f > \nu_m$. We set $\nu_m = 1$ and $\nu_f = 1.5$ in simulating this version of the model.

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