Women, Wealth Effects, and Slow Recoveries

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Abstract

We study how the “Grand Gender Convergence” of the past half-century has affected the speed of US business cycle recoveries. As women’s employment has converged towards men’s, the growth rate of female employment has slowed. Whether this means that female convergence has caused aggregate business cycle recoveries to become slower depends on the extent to which women “crowd out” men in the labor market. We use state-level panel data to estimate this crowd-out: States with larger initial gender gaps in employment see both larger convergence of women and larger overall growth in employment. Our estimates imply minimal crowding out of men by women in the labor market. We use a multi-region general equilibrium business cycle model—calibrated to match our cross-sectional estimate of crowd-out—to show that 70% of the slowdown in recent business cycle recoveries can be explained by female convergence. Home production plays a key role in our model. In standard models with “balanced growth preferences” and without home production, the entrance of women into the labor force has small effects on aggregate employment because income effects from rising female earnings causes men to exit the labor force.

JEL Classification: E24, E32, J21

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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. 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.

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. 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; Albanesi, 2017; Krueger, 2017; Council of Economic Advisors, 2017).

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. One way in which increased female employment may have affected men’s employment is through income effects within families. 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). These facts have lead macroeconomists to favor “balanced growth preferences” in which income and substitution effects are equally strong (King, Plosser, and Rebelo, 1988) and technical progress has no effect on aggregate labor supply. One simple way to model gender convergence is as a particular form of technological change—female biased technological change. With balanced

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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 The recoveries from the last three recessions are often described as “jobless.” This label 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 of a change in these features of recoveries over this time period.

3 We discuss in more detail below how various potential explanations for gender convergence—such as reduced discrimination, changing views about gender roles, and changes in the sectoral composition of the economy—can be mapped into female biased technological change. We also consider a model in which gender convergence is modeled as a change in female labor supply. This yields similar results.
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

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Prime-Age Population</th>
<th>Panel B. Prime-Age Men and Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment-to-Population Ratio</td>
<td>1.32% 1.18% 0.48% 0.28% 0.40%</td>
<td>0.52% 0.73% 0.28% 0.40% 0.65%</td>
</tr>
<tr>
<td>Labor Force Participation Rate</td>
<td>0.94% 0.61% -0.04% -0.07% -0.40%</td>
<td>2.00% 1.55% 0.68% 0.12% 0.18%</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>-0.55% -0.73% -0.53% -0.32% -0.85%</td>
<td>-0.58% -0.80% -0.62% -0.38% -1.03%</td>
</tr>
<tr>
<td>Log Labor Productivity</td>
<td>1.18% 1.73% 1.17% 1.86% 0.77%</td>
<td>-0.57% -0.65% -0.40% -0.25% -0.62%</td>
</tr>
</tbody>
</table>

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).

growth preferences (and no home production), female-biased technological change yields very large “crowding out” of men when women enter the labor force, as we show in section 4. In other words, the standard model implies almost no effect of female convergence on aggregate employment rates.\(^4\)

To assess the role of female convergence in causing a slowdown of economic recoveries over the past few decades, it is, therefore, crucial to have estimates of the extent to which female-biased shocks crowd out men in the labor market. We present new evidence on the extent of such crowd out. An important empirical challenge in producing these estimates is the presence of gender-neutral shocks. Aggregate (gender-neutral) shocks will typically yield positive comovement of male and female employment rates. Such shocks are clearly important. For example, business cycles yield strong positive comovement of male and female employment rates. The presence of such gender neutral shocks will bias simple OLS estimates of the crowding out towards finding less crowding out, or even to finding crowding in.

We address this issue by exploiting a state-level analog to the aggregate gender convergence facts we describe above: States with a particularly large gap between female and male employment-to-population ratios in 1970 experienced much more rapid growth in female employment rates.

\(^4\)The reason why the effect is not exactly zero is that women’s wages are lower than men’s implying that a unit increase in women’s employment does not generate enough income to compensate for a unit decrease in men’s employment.
over the subsequent four decades. This source of variation in female employment rates “differences out” aggregate (gender-neutral) shocks driving business cycles and long-run growth and is therefore likely to be dominated by female-biased shocks.

Did more rapid growth in female employment rates “pass through” into more rapid growth in aggregate employment rates? The discussion above makes clear that this is by no means guaranteed, at least in standard macroeconomic models. Our empirical analysis shows that it did. States with larger gender gaps in employment in 1970 not only had much more rapid growth in female employment rates over the subsequent decades, they also had much more rapid growth in aggregate employment rates.

We quantify these effects by running instrumental variables regressions. We use the gender gap in employment-to-population ratios in 1970 as an instrument for subsequent changes in female employment. We find that increases in female employment translate almost one-for-one into increases in total employment. The response of male employment to an increase in female employment is negative but small and statistically insignificant. In other words, we estimate that female biased shocks cause little crowding out of men in the labor market.

These empirical results suggest that the Grand Gender Convergence over the past half-century may have had important implications for aggregate employment rates and the speed of recovery after recessions in the US. We investigate these questions formally, using a multi-region general equilibrium model. As we discuss above, standard models with balanced growth preferences imply much more crowding out than we find in the data. To match our empirical estimates on crowding out, we augment the standard model to allow for home production by women along the lines of Benhabib, Rogerson, and Wright (1991), Greenwood and Hercowitz (1991), and others. In this model, the entrance of women into the market sector has much smaller income effects on men since the fruits of women’s home production had been shared within the family before they switched to market work.

A second important aspect of our model is that it is a multi-region model. Our empirical evidence on crowding out is based on regional variation. We use our multi-region model to infer aggregate crowding out from our estimates on regional crowding out. One reason aggregate crowding out may differ from crowding out in the cross section is terms-of-trade effects: local female biased shocks may cause variation in the relative price of local output. We show that the difference between aggregate crowding out and regional crowding out is small if household preferences are not too far from the King, Plosser, and Rebelo (1988) case in which changes in real
wage leave labor supply unchanged (because income and substitution effects cancel out).

We show that convergence of the aggregate gender gap in the employment-to-population ratio is almost perfectly described by a simple AR(1) model with an intercept term since 1980 (see Figure 2). Gender convergence in employment was very rapid in the 1970’s and early 80’s, but has virtually ceased since 2000 with the gender gap in the employment-to-population ratio converging to roughly 13.5 percentage points. Using the general equilibrium model described above, we ask how this slowdown in the growth of female employment has affected the speed of recoveries after recessions. We do this by considering the following counterfactual question: How would recent business cycle recoveries have looked different if the growth in female employment had remained at the level its was at in the 1970s.

We find that roughly 70% of the slowdown in recoveries since the early-1980s can be explained by the slowdown in the growth of female employment. The fact that our model matches our cross-sectional estimates of crowding out greatly disciplines the aggregate implications of the model. We also take care to match the pro-cyclicality of aggregate employment as well as the secular decline in the employment-to-population ratio of men observed in the data. To jointly match these aspects of the data with pro-cyclical productivity shocks we extend the preference specification developed by Jaimovich and Rebelo (2009) to allow the strength of the long-run income effect on labor supply to dominate the the long-run substitution effect—as in Boppart and Krusell (2016). We emphasize, however, that our main points about the effect of gender convergence are orthogonal to the specifics of our model for the long-run trend decline in male employment rates.

Relationship to Prior Work

There are few previous empirical estimates of the extent to which female-biased shocks “crowd out” men in the labor market. But those that exist are broadly consistent with our empirical findings. Blank and Gelbach (2006) find 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). Our finding that crowding out of men by women is rel-

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5Boppart 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 the income effect dominates the substitution effect in the long-run. Bick, Fuchs-Schündeln, and Lagakos (2018) present similar facts in the cross-section for a broad set of countries.
atively small is also consistent with descriptive facts in Juhn and Murphy (1997) and McGrattan and Rogerson (2008). They document that the 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.

The spirit of our exercise is closely related to ongoing work by Albanesi (2017), which 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. It 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). Our focus on empirically estimating crowding out using cross-state data, as well as on home production, which mitigates the extent of crowding out, differs importantly from these papers.6

Our theoretical analysis is related to models of family labor supply such as Jones, Manuelli, and McGrattan (2015) and Heathcote, Storesletten, and Violante (2017). Previous models in this literature have tended to yield large crowding out of men by women in response to gender convergence shocks. These papers incorporate offsetting shocks to explain why this large amount of crowding out does not lead to a larger decline in male employment (which is not observed empirically). Knowles (2013) presents a model with home production, and argues that in this context, a change in intra-household bargaining is necessary to explain the observed dynamics of male and female employment. In particular, the increase in female employment is accompanied by an increase in the wife’s bargaining power, leading to a smaller income effect and less crowding out. One might wonder why this feature is necessary. Why does home production not itself limit crowding out, as it does in our model? The key difference between our model and Knowles’ in this regard is that we allow for heterogeneity in women’s productivity. As a consequence, while female biased shocks lead to large changes in the propensity of women to work in the market, the women most likely to switch are those whose productivity at home is similar to their productivity in the market. Hence, the income effect of women entering the labor force is smaller in our model than in the representative agent model that Knowles considers.

Our paper is also related to the large literature on the effects of immigration on the native workforce. The empirical evidence on whether increased immigration crowds out native employment is mixed, with estimates ranging from substantial crowding out (Borjas, 2003; Dustmann,
Schönberg, and Stuhler, 2017, among others), to no significant effects (Card, 2001, 2005, among others), to substantial crowding in (Hong and McLaren, 2015). There is, however, an important conceptual difference between the effects of immigrants and those of women entering the labor force. Immigrants add to the population and, for the most part, consume their own income. Standard macroeconomic models with constant-returns-to-scale production functions imply that the economy will expand one-for-one with in the influx of immigrants in the long run, without any crowding out of natives. In contrast, women that enter the labor force were part of the economy before they entered the labor force. They typically cohabit with men and share their income and their spouses income within the family. Their entrance to the labor force, therefore, can have an important income effect on their spouses, potentially leading to substantial crowding out of their spouses labor supply.

There is a large literature on the causes and consequences of the Grand Gender Convergence of the 20th century. Many explanations have been proposed for the rise of female employment. These 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-M Marcos, 2008), medical innovation (Albanesi and Olivetti, 2016), cultural changes (Fernández, Fogli, and Olivetti, 2004; Fernández and Fogli, 2009; Antecol, 2000), 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). These explanations differ as to whether the rise of female employment is due to factors affecting female labor supply or labor demand. Our model yields similar implications about the role of female convergence in explaining the slowdown in recent recoveries from recession whether we model gender convergence as arising from changes in female labor supply or demand.

Many recent papers have proposed sophisticated explanations for slow (or jobless) recoveries. These including structural change (Groshen and Potter, 2003; Jaimovich and Siu, 2012; Restrepo, 2015), secular stagnation (Hall, 2016; Benigno and Fornaro, 2017), changing hiring or firing dynamics (Berger, 2016), changing social norms (Coibion, Gorodnichenko, and Koustas, 2013), wage rigidities (Shimer, 2012; Schmitt-Grohe and Uribe, 2017), and changing unemployment insurance policies (Mitman and Rabinovich, 2014). Our analysis suggests a simple explanation for these

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

8 A more recent literature studies potential explanations for why female employment rates have leveled off recently (Blau and Kahn, 2013; Kubota, 2017; Goldin, 2014).
Structure of the Paper

The paper proceeds as follows. Section 2 describes the data we use. Section 3 presents simple time-series and cross-sectional evidence on gender convergence in employment. Section 4 presents a simple model and derives results about aggregate and local crowding out with and without home production. Section 5 presents our main empirical results on crowding out in response to female biased shocks. Section 6 presents our full model. Section 7 performs our main theoretical counter-factual exercise. Section 8 concludes.

2 Data

Our estimates of crowding out from cross-state evidence primarily uses data from the U.S. Census and American Community Survey (ACS).\(^9\) We use this dataset 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.\(^10\) 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, we have conducted the analysis at the commuting zone level and confirmed that our main results are unchanged.

We calculate employment-to-population ratios in the following way. Employment is defined based on a worker’s activities during the preceding week of the interview. Those who reported doing any work at all for pay or profit, or working at least fifteen hours without pay in a family business or farm, are classified as “at work.” We then define the “employment-to-population ratio” by aggregating the total number of individuals recorded as “at work,” and dividing this by the population, using Census weights.

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

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\(^9\)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.
Survey (CPS). These data have the disadvantage that they have a smaller sample size. Hence they are less well-suited to the state-level analysis we describe above—for example, state-level data are available only back to 1978. In our analysis of employment rates within skill groups, we construct our own aggregates of employment rates from the March CPS.

We also 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. We use these variables as controls in our analysis. 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 B.1.

3 Convergence of Female Employment Rates

The left panel of Figure 2 plots the employment-to-population ratio for prime-age men and women 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, 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%. The right panel of Figure 2 plots the gender gap in employment over time. In the 1970s, this gap was shrinking rapidly. Since then, the pace of convergence has slowed, and the gap has plateaued after 2000.

The evolution of the gender gap can be described quite well by a simple statistical model since 1980. Consider the following AR(1) process for convergence:

\[ gap_t = \alpha + \beta gap_{t-1} + \epsilon_t, \]  

where \( gap_t \equiv e_{pop}^F_t - e_{pop}^M_t \) denotes the gap between the female and male employment-to-population ratio at time \( t \), and \( e_{pop}^F_t \) and \( e_{pop}^M_t \) are the employment-to-population ratios of prime-aged women and men, respectively. Here, the AR(1) coefficient, \( \beta \), 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 the right panel of Figure 2 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, $\beta$, is 0.88, which implies a half-life of roughly five and a half years. The estimated constant term, $\alpha$, is -0.0165. These estimates imply that over this period, the gender gap has been converging to a long-run level of -13.5%.

### 3.1 Cross-State Evidence

We next consider whether the same type of gender convergence in employment rates has occurred across states in the U.S. The top-left panel of Figure 3 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 3 plot the change in female, male, and total employment rates, respectively, against the initial gender gap in 1970. These figures show that virtually all of the convergence across states arises from a more rapid increase in female 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.

Motivated by Figure 3, we estimate the following convergence regression:

\[
\Delta \text{gap}_i = \alpha + \beta \text{gap}_{i,1970} + X_i' \gamma + \epsilon_i,
\]  

(2)

where \(i\) denotes state, \(\Delta \text{gap}_i \equiv \text{gap}_{i,2016} - \text{gap}_{i,1970}\), and \(X_i\) is a vector of controls. A negative value of \(\beta\) indicates cross-state convergence. Table 2 presents the resulting estimates. Despite having a small number of observations, our estimate of \(\beta\) is both economically and statistically significantly negative, indicating strong convergence.

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

\[
\Delta \text{epop}^F_i = \alpha + \beta \text{gap}_{i,1970} + X_i' \gamma + \epsilon_i,
\]  

(3)
Table 2: Gender Gap Convergence Across States

<table>
<thead>
<tr>
<th></th>
<th>Gender Gap Growth</th>
<th>Female Emp. Rate Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Gender Gap in 1970</td>
<td>-0.991***</td>
<td>-0.972***</td>
</tr>
<tr>
<td></td>
<td>(0.135)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>Service Employment Share in 1970</td>
<td>-0.0630</td>
<td>-0.144</td>
</tr>
<tr>
<td></td>
<td>(0.0659)</td>
<td>(0.127)</td>
</tr>
<tr>
<td>Skill Premium in 1970</td>
<td>0.0855</td>
<td>0.0609</td>
</tr>
<tr>
<td></td>
<td>(0.0548)</td>
<td>(0.0481)</td>
</tr>
<tr>
<td>Log Per-capita GDP in 1970</td>
<td>0.0327</td>
<td>0.0577*</td>
</tr>
<tr>
<td></td>
<td>(0.0220)</td>
<td>(0.0292)</td>
</tr>
<tr>
<td>Non-white Share in 1970</td>
<td>0.0420</td>
<td>-0.0283</td>
</tr>
<tr>
<td></td>
<td>(0.0356)</td>
<td>(0.0374)</td>
</tr>
<tr>
<td>Bartik Shock</td>
<td>0.0103</td>
<td>-0.0799</td>
</tr>
<tr>
<td></td>
<td>(0.0745)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>Observations</td>
<td>51</td>
<td>51</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.687</td>
<td>0.706</td>
</tr>
<tr>
<td>$F$-stat</td>
<td>53.50</td>
<td>41.57</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

where $\Delta e_{p,F,i} = e_{p,F,i,2016} - e_{p,F,i,1970}$. The coefficients we estimate on the initial gender gap in this regression are virtually identical to those further to the left in the table where the change in the gender gap is the dependent variable. This shows that the gender gap fell because female employment rates rose, not because male employment rates fell.

Finally, Table 2 presents 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. We include as controls the employment share in 1970, the skill premium in 1970, log per-capita GDP in 1970, the non-white share of the population in 1970, and a Bartik shock (described in more detail in Appendix B.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.

A corollary of the convergence dynamics we establish above is that the cross-sectional standard deviation of the gender gap in employment rates has collapsed over time. Figure 4 shows the
standard deviation of gender gap in employment-to-population ratios across US states over time. This cross-sectional dispersion declined dramatically from 1970 to 2000, but has stabilized since.

![Standard Deviation of Gender Gap across US States](image)

**Figure 4: Dispersion in Gender Gap Across States**

### 3.2 Inspecting the Sources of Convergence

As we note above, several prominent explanations for the rise in female employment focus on structural change in the economy that may have disproportionately benefited women. To better assess the role of these potential explanations, we present several decompositions of the rise of female employment in Appendix B. First, we carry out a simple shift-share decomposition of the growth in female employment rates into “within” versus “between” occupation variation. We find that the vast majority of the increase in female employment occurred within occupation (see Figure B.5). Second, we assess convergence of female employment within skill groups. We find similar convergence within skill groups as in the aggregate (see Figure B.6).

Third, the aggregate convergence dynamics we describe above cannot be explained as a straightforward consequence of service sector growth or the rising skill premium. Figure B.7 presents the aggregate skill premium and service employment shares over our sample period.\(^{11}\) The service

\(^{11}\)The skill premium is defined as the ratio of the composition-adjusted hourly wages of college graduates to non-college graduates. The service employment share is defined as the share of all employed workers who are employed in the service sector based census data. See appendix B.1 for a detailed description of how we construct composition-adjusted wages.
employment share has grown almost linearly over our sample period. The skill premium was flat in the 1970s and early 1980s, but then grew rapidly in the late 1980s and early 1990s. Neither pattern resembles the AR(1) convergence dynamics we documented above for the gender gap in employment rates. Similarly, the cross-state convergence patterns we document do not arise from cross-state differences in growth in the service share or the skill premium. Figure B.8 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. state.\textsuperscript{12}

4 Crowding Out: Theory

We have documented that the growth in female employment has slowed sharply over the past few decades. What implications this has for aggregate employment rates depends crucially on how an increase in female employment rates affects male employment, i.e., how much women crowd out men in the labor market. We begin our analysis of this question by showing that crowding out is very large in standard macroeconomic models. We then show how allowing for home production can yield a model with much less crowding out. Finally, we assess the degree to which cross-sectional estimates of crowding out may differ from crowding out at the aggregate level.

4.1 Crowding Out in a Standard Macroeconomic Model

Consider a simple static model 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:

\[
y = A(L_m + \theta_f L_f),
\]

where \( y \) denotes output produced, \( L_m \) denotes male labor, \( L_f \) denotes female labor, \( A \) denotes gender-neutral aggregate productivity, \( \theta_f \) 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

\textsuperscript{12}Rendall (2017) shows that growth in female market hours and growth in service sector are positively correlated at MSA-level. Although we confirm this relationship at MSA-level in our data, the correlation becomes slightly negative once we aggregate to state-level, suggesting the importance of migration or other agglomeration forces at finer geographical units.
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, \( \chi_m \) and \( \chi_f \) are gender specific labor supply parameters, and \( \nu \) is the Frisch elasticity of labor supply. 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

\[
U(C, L_m, L_f) = \frac{C^{1-\psi}}{1-\psi} - \frac{1}{\chi_m} \left( \frac{(L_m)^{1+\nu-1}}{1+\nu-1} \right) - \frac{1}{\chi_f} \left( \frac{(L_f)^{1+\nu-1}}{1+\nu-1} \right),
\]

where \( \psi > 0 \) governs, among other things, 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. In equation (5), \( L_m \) and \( L_f \), therefore, denote the employment-to-population ratio of men an women, respectively, as opposed to hours worked. Appendix A.1 provides more detail on how equation (5) is derived.

The household’s budget constraint is

\[
C = w_m L_m + w_f L_f.
\]

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, converseley, increased labor earnings by women results in higher consumption by men.

Maximizing household utility yields equilibrium male and female employment rates of

\[
L_m = A^{\frac{1}{\nu+\psi}} \frac{(\chi_m)^\nu((\chi_m)^\nu + (\chi_f)^\nu(\theta_f)^{\nu+1}1)}{1+\nu+\psi},
\]

\[
L_f = A^{\frac{1}{\nu+\psi}} \frac{(\theta_f)^\nu((\chi_m)^\nu + (\chi_f)^\nu(\theta_f)^{\nu+1}1)}{1+\nu+\psi}.
\]

Our baseline assumption is that female convergence is driven by an increase in female-biased productivity \( \theta_f \). Increases in \( \theta_f \) 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 \( \theta_f \) 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.

Increases in \( \theta_f \) 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. The main reason why we model female convergence as an increase in female labor demand is that relative female wages have increased substantially over the course of the Gender Revolution (see Appendix B.8). However, we discuss the robustness of our results to a labor supply interpretation of gender convergence in section 4.4.

We next consider how a change in \( \theta_f \) affects male and female employment. The log derivatives of male and female employment rates with respect to \( \theta_f \) are given by

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

\[
\frac{d \ln L_m}{d \ln \theta_f} = -\frac{\nu \psi (\nu + 1) \Lambda_f}{1 + \nu \psi}
\]

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 \( \theta_f \) 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 \( \theta_f \), therefore, leads to an increase in female employment. For men, the change in \( \theta_f \) 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.

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

\[ \epsilon^{agg} \equiv \frac{dL_m}{d\theta_f} = \frac{d}{d\ln \theta_f} \frac{L_m}{L_f}. \]

\( \epsilon^{agg} \) measures the change in male employment per unit increase in female employment in response to an economy-wide female-biased labor demand shock \((\theta_f)\). In the simple model we analyze in this section, we can solve analytically for crowding out:

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

(9)

An important benchmark case is \( \psi = 1 \).\(^{14}\) This is the “balanced growth preference” case highlighted by King, Plosser, and Rebelo (1988) and commonly used in the macroeconomics literature.\(^{15}\) When \( \psi = 1 \), the above expression simplifies to

\[ \epsilon^{agg} = -\theta_f. \]

In this relatively standard case, therefore, crowding out is equal to the ratio of female-to-male wages. Crowding out is, therefore, 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 substitutions 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. It provides a stark illustration of just how inaccurate the “accounting” approach to calculating the contribution of gender convergence to aggregate employment is in benchmark macroeconomic models.

When women are less productive than men, e.g., due to discrimination, crowding out is smaller than one. Intuitively, a unit increase in female labor is not enough to compensate for a unit decrease in male labor in this case. Hence, male labor falls less than one-for-one with an increase in female labor. Crowding out nevertheless remains large in magnitude for realistic values of the

\(^{14}\)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 \( \ln C \).

\(^{15}\)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.
### Table 3: Crowding Out With and Without Home Production

<table>
<thead>
<tr>
<th></th>
<th>Aggregate Crowding Out</th>
<th>Regional Crowding Out</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Home Production</td>
<td>-0.80</td>
<td>-0.75</td>
</tr>
<tr>
<td>With Home Production:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \delta = 0.25 )</td>
<td>-0.10</td>
<td>-0.09</td>
</tr>
<tr>
<td>( \delta = 0.5 )   (Baseline)</td>
<td>-0.19</td>
<td>-0.18</td>
</tr>
<tr>
<td>( \delta = 1.0 )</td>
<td>-0.33</td>
<td>-0.31</td>
</tr>
</tbody>
</table>

**Notes:** The parameter values are \( \psi = 1.2, \nu = 1, \chi_m = \chi_f = \chi_h = 1, \eta = 2 \), and we chose \( \theta_f \) to match the male-to-female employment ratio of 0.7. We consider numerical derivatives around these values.

relative productivity of women to men.

In Appendix A.2, we consider several extensions of the model presented above: We consider a model in which male and female labor are imperfect substitutes in production, a model in which male and female leisure are complements, and a model in which income sharing between men and women within the household is imperfect. Perhaps surprisingly, in all cases, we show that crowding out is large when households have balanced growth preferences.

Next, we consider a numerical example in which we deviate from balanced growth preferences: We assume \( \psi = 1.2 \), which we show below provides a parsimonious explanation for the trend decline in the male employment-to-population ratio 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.\(^{16}\) Because \( \theta_f \) corresponds to the female-to-male employment ratio with \( \chi_m = \chi_f \), we set \( \theta_f = 0.7 \), which is the average value for this ratio over the period 1970-2014.

Given these assumptions, we compute the degree of crowding out directly from equation (9). The resulting degree of crowding out is 0.8—a slightly larger value than in the case of balanced growth preferences. We report this result in the top row of the left-most column of Table 3.

#### 4.2 Crowding Out with 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 \( \omega \). We could alternatively have made women heterogeneous in their pro-

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\(^{16}\)In our numerical experiments with \( \psi > 1 \), crowding out is even larger for lower values of the Frisch elasticity.
ductivity in the market. This choice does not affect our results. Female productivity in home production is distributed according to the distribution function $G(\omega)$ with support $[\omega, \bar{\omega}]$.

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

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

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

$$U(C, L_m, \{L_f(\omega)\}, \{L^h_f(\omega)\}) = \frac{(C)^{1-\psi}}{1-\psi} - \frac{1}{\chi_m} \frac{(L_m)^{1+\nu^{-1}}}{1+\nu^{-1}} \int \frac{\omega}{1+\nu^{-1}} dG(\omega) - \frac{1}{\chi_f} \int_{\omega}^{\theta_f} \frac{(L^h_f(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega),$$

where $C \equiv c + c^h$, 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 $L_f = \int_{\omega}^{\theta_f} L_f(\omega) dG(\omega)$. We provide a more formal micro-foundation for these expressions in Appendix A.1. The amount of home production available to the household is $c^h = \int_{\omega}^{\theta_f} A\omega L^h_f(\omega) dG(\omega)$. The household’s budget constraint is

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

Given these assumptions, we can analytically solve for male and female employment rates in
Taking log derivatives of male and female employment rates with respect to $\theta_f$ we then have

$$\frac{d\ln L_f}{d\ln \theta_f} = \nu - \frac{\psi\nu}{1 + \psi}(\nu + 1)\Lambda_f + \frac{g(\theta_f)}{G(\theta_f)} \frac{1}{\theta_f},$$

(10)

$$\frac{d\ln L_m}{d\ln \theta_f} = -\frac{\psi\nu}{1 + \psi}(\nu + 1)\Lambda_f,$$

(11)

where

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

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 (including 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 $\theta_f$ 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 5. If $g(\omega)$ is very dispersed (as in the panel to the left in Figure 5), 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 $\theta_f$ (as in the panel to the right in Figure 5), even a small change in $\theta_f$ 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.

We assume that the distribution of female productivity at home is uniform with support \([1 - \delta, 1]\). The parameter \(\delta\) then controls the degree of dispersion of female productivity at home and, thereby, the strength of the switching effect. Table 3 presents results on crowding out for three different values of \(\delta\). We take \(\delta = 0.5\) to be our benchmark value. (We provide a rationale for this choice below.) In this case, crowding out is 0.19. Evidently, introducing home production into the model dramatically lowers the magnitude of crowding out. For \(\delta = 0.25\), crowding out is even smaller at 0.10 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. Even with \(\delta = 1\), crowding out is only 0.33.

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. 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 spend 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. 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.

4.3 Crowding Out in an Open Economy

The evidence we present on crowding out in sections 3 and 5 is based on cross-sectional variation. To understand how cross-sectional crowding out may differ from aggregate crowding out, we next develop an open economy version of the model described above. The economy consists of \( n \) regions indexed by \( i \). The population of each region has measure one and is immobile. The market sector in each region produces a differentiated traded good using the same technology as before:

\[
y_i = A_i (L_{mi} + \theta_{fi} L_{fi}).
\]

Home production in each region is non-tradeable and also produced using the same technology as before:

\[
y^h_i = A_i \int H \omega L^{h}_{fi}(\omega) dG(\omega).
\]

Let \( p_i \) denote the price of goods produced in region \( i \). Firm optimization implies that

\[
w_{mi} = p_i A_i, \quad w_{fi} = p_i A_i \theta_{fi}.
\]

The marginal product of home production is \( p_i A_i \omega \) (recall that tradeable and non-tradeable goods are perfect substitutes and, therefore, have the same price).

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:

\[
C_i = \left( (c_{ii} + c^h_i) \frac{\eta-1}{\eta} + \sum_{j \neq i} (c_{ij}) \frac{\eta-1}{\eta} \right)^{\frac{\eta}{\eta-1}},
\]

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.

In Appendix A.3, we present analytical expressions for \( L_{mi} \) and \( L_{fi} \). The log-derivatives of male and female employment rates with respect to \( \theta_{fi} \) are given by:

\[
\frac{d \ln L_{fi}}{d \ln \theta_{fi}} = \nu \frac{\psi \nu}{1 + \psi \nu} (\nu + 1) \Lambda_{fi} + \frac{g(\theta_{fi})}{G(\theta_{fi})} \frac{1}{\theta_{fi}} + \frac{1 - \psi}{1 + \psi} \frac{d \ln (p_i/P)}{d \ln \theta_{fi}},
\]

\[
\frac{d \ln L_{mi}}{d \ln \theta_{fi}} = -\frac{\psi \nu}{1 + \psi \nu} (\nu + 1) \Lambda_{fi} + \frac{1 - \psi}{1 + \psi} \frac{d \ln (p_i/P)}{d \ln \theta_{fi}},
\]

where \( P \equiv \left( \sum_j (p_j)^{1-\eta} \right)^{1/\eta} \) and \( \Lambda_{fi} \) is the share of female market wages in total household in-
come, as before. The derivative \( d \ln(p_i/P)/d \ln \theta_{fi} \) is a terms-of-trade effect. It is equal to

\[
\frac{d \ln(p_i/P)}{d \ln \theta_{fi}} = -\frac{1 + \nu}{(1 - \psi)\nu + \eta + \psi\nu} \Lambda_{fi}(1 - \lambda_{ii}) < 0, \quad (15)
\]

where \( \lambda_{ii} \equiv p_i(c_{ii} + c_i^h)/(PC_i) \) denotes the expenditure share on domestic goods in region \( i \).\(^{17}\)

Comparing expressions (13) and (14) with expressions (10) and (11) we see that the difference between aggregate and regional crowding out arises solely from the terms-of-trade effect. In an open economy, an increase in a particular region’s \( \theta_{fi} \) relative to the \( \theta_{fj} \) of other regions increases the relative supply of goods from region \( i \) and thereby worsens its terms-of-trade. In other words, \( d \ln(p_i/P)/d \ln \theta_{fi} < 0 \). 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 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 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 \( \eta = 2 \), \( n = 2 \), and other parameters as before.\(^{18}\) In particular, we set \( \psi = 1.2 \) implying that the income effect of a wage change on employment is slightly stronger than the substitution effect. We then calculate the response of the economy to small variation in the \( \theta_{fi} \) in one region, while holding \( \theta_{fj} \) constant for the other region, and estimate regional crowding out \( \epsilon_{reg} \) by running the regression

\[
\Delta L_{mi} = \alpha + \epsilon_{reg} \Delta L_{fj} + \varepsilon_i, \quad (16)
\]

\(^{17}\)The fact that the terms-of-trade effect can be expressed as a combination of expenditure shares and several elasticities builds on the insights from Arkolakis, Costinot, and Rodríguez-Clare (2012), in the context of exogenous labor supply, and Adao, Arkolakis, and Esposito (2018) in the context of endogenous labor.

\(^{18}\)Our parameterization of \( \eta = 2 \) follows Obstfeld and Rogoff (2005). The trade literature often assumes higher values of \( \eta \) (around 5), which would imply smaller terms-of-trade effects and hence a smaller difference between regional and aggregate crowding out.
This is the same specification that we use when analyzing data from the US economy in the empirical part of the paper.

The second column in Table 3 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.

4.4 Synthesis and Robustness

Let us synthesize the main points we have made in this section. First, crowding out of male employment in response to female-biased shocks is large in standard macroeconomic models with balanced growth preferences and without home production. Second, this conclusion changes dramatically when we allow for home production. Together these results imply that a simple “accounting” analysis that implicitly assumes that female convergence has no effect on male employment rates may be very wrong, but me also be close to correct (depending on which model is more realistic). We have also seen that regional crowding out differs from aggregate crowding out by only a modest amount for plausible parameter values.

In the analysis above, we have made several modeling choices and simplifying assumptions. In the remainder of this section, we study how various alternative assumptions affect these conclusions about crowding out. The results are reported in Table 4. In some cases, we consider the alternative assumptions in the model without home production, for simplicity. Panel A of Table 4 reports cases with home production, while Panel B reports cases without home production.

**Strength of Income Effects** The parameter $\psi$ governs the strength of the income effect on labor supply. Our baseline value is $\psi = 1.2$. Table 4 reports results for two alternative values: $\psi = 1$ and $\psi = 0$. The former of these values corresponds to the usual balanced growth preferences (King, Plosser, and Rebelo, 1988). In the latter case, there is no income effect on labor supply. Smaller values of $\psi$ yield less crowding out. Aggregate crowding out falls more rapidly as $\psi$ falls than regional crowding out. In the case of small income effects, regional crowding out provides an upper bound on the magnitude of aggregate crowding out.

**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 fact that the composition-adjusted gender wage gap and the gender employment gap are positively correlated across states
Table 4: Crowding Out: Robustness

<table>
<thead>
<tr>
<th></th>
<th>Aggregate Crowding Out</th>
<th>Regional Crowding Out</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Home Production Models</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benchmark ($\psi = 1.2$)</td>
<td>-0.19</td>
<td>-0.18</td>
</tr>
<tr>
<td>Balanced growth Preferences ($\psi = 1$)</td>
<td>-0.17</td>
<td>-0.17</td>
</tr>
<tr>
<td>No Income Effect ($\psi = 0$)</td>
<td>0.00</td>
<td>-0.11</td>
</tr>
<tr>
<td>Female Labor Supply Shocks ($\psi = 1.2$)</td>
<td>-0.09</td>
<td>-0.09</td>
</tr>
<tr>
<td><strong>Panel B. No Home Production</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benchmark ($\psi = 1.2$)</td>
<td>-0.80</td>
<td>-0.75</td>
</tr>
<tr>
<td>Benchmark ($\psi = 0$)</td>
<td>0.00</td>
<td>-0.40</td>
</tr>
<tr>
<td>Female Labor Supply Shocks ($\psi = 1.2$)</td>
<td>-0.41</td>
<td>-0.39</td>
</tr>
<tr>
<td>Female Labor Supply Shocks ($\psi = 0$)</td>
<td>0.00</td>
<td>-0.23</td>
</tr>
<tr>
<td>Imperfect Substitutes ($\psi = 1.2$)</td>
<td>-0.91</td>
<td>-0.80</td>
</tr>
<tr>
<td>Imperfect Substitutes ($\psi = 0$)</td>
<td>0.35</td>
<td>-0.18</td>
</tr>
<tr>
<td>With Fixed Factor ($\psi = 1.2$)</td>
<td>-0.77</td>
<td>-0.73</td>
</tr>
<tr>
<td>With Fixed Factor ($\psi = 0$)</td>
<td>-0.29</td>
<td>-0.51</td>
</tr>
</tbody>
</table>

Notes: The parameter values are $A = 1, \nu = 1, \chi_m = \chi_f = 1, \alpha = 0.66$ (for fixed factor), $\kappa = 3$ (for imperfect substitutes), and we chose $\theta_f$ to match male to female employment ratio of 0.7. The choice of $\kappa = 3$ comes from the empirical estimates in Acemoglu, Autor, and Lyle (2004). For the model with supply shock, we set $A = 1, \nu = 1, \theta_f = 1, \chi_m = 1$, and we chose $\chi_f$ to match male to female employment ratio of 0.7.

and over time (see appendix B.8). We do not, however, wish to suggest that labor supply shocks were unimportant 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). The observed correlation between the growth in relative female wages and the growth in female relative 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, we also alter the model such that women differ in the disutility they experience from home production (instead of having differing productivity in home production). 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. Appendix A.4 provides more detail about this version of the model.
The bottom row of panel A and the third and fourth rows of panel B of Table 4 present estimates of aggregate and regional crowding out in response to female-biased labor supply shocks. The magnitude of crowding out in this case is smaller than in the baseline model in which gender convergence is driven by an increase in female labor demand. The intuition is that labor-supply driven increases in female employment result in a fall in female wages and therefore a smaller income effect than labor-demand driven increases in female employment. The difference between the aggregate and the regional crowding out also tends to be smaller in the female labor supply shock case. This is because female labor supply shocks tend to increase the supply of regional goods less (because there is no increase in productivity).

**Imperfect Substitutability between Men and Women** We have so far assumed, for simplicity, that male and female labor are perfect substitutes in production. However, Acemoglu, Autor, and Lyle (2004) provide direct estimates of such substitutability, finding that male and female labor are imperfectly substitutable with an elasticity of substitution of around 3. We next consider how our conclusions about crowding out change if we allow for imperfect substitutability between male and female labor. In this case, we abstract from home production to maintain tractability. We assume that the production technology is

\[
y_i = A_i \left( (L_{mi})^{\kappa-1} + (\theta f_i L_{fi})^{\kappa-1} \right)^{\frac{1}{\kappa-1}},
\]

where \(\kappa\) is the elasticity of substitution between male and female labor. Imperfect substitutability implies that an increase in female labor raises the marginal product of male labor, all else equal. In an open economy, the terms-of-trade effect counteracts this. The overall effect on mens’ wages depends on the relative magnitude of the elasticity of substitution between male and female labor in production and the elasticity of substitution between goods from different regions. The consequences of these movements in male wages for crowding out then depend on the balance between income and substitution effects on labor supply.

The fifth and sixth rows of Panel B of Table 4 presents results with \(\kappa = 3\). Since we calibrate \(\eta = 2\), this means that \(\kappa > \eta\) (male and female labor are more substitutable than goods from

19Similarly, substitutability between natives and immigrants is thought to be a key factor in determining the labor market effects of immigration (e.g., Ottaviano and Peri, 2012). Intuitively, when immigrants and natives are less substitutable, the crowding out effect of immigrants will be lower.

20The importance of the difference in these elasticities in determining crowding out is emphasized in Burstein, Hanson, Tian, and Vogel (2017), in the context of crowding out effects associated with immigration. If men and women are sufficiently complementary in production (\(\kappa < \eta\)), and there is no income effect, then the entry of women can crowd in men (the Rybczynski effect).
different regions). In this case, an increase in female employment increases the wages of men more than in the baseline case. For $\psi > 1$, this yields slightly larger crowding out, but with $\psi < 1$ it yields slightly less crowding out. The relationship between aggregate and regional crowding out is similar to the baseline model for $\psi$ close to one.

**A Fixed Factor of Production**  Our baseline model does not capture the idea that new workers might lower the employment of incumbent workers as a consequence of downward-sloping labor demand, an idea that has been emphasized in the immigration literature (Borjas, 2003). In our baseline model, output is linear in labor. This yields a horizontal labor demand curve. Labor demand is also horizontal in a model with several factors of production if all factors of production are able to adjust proportionately with labor (as is reasonable to assume for capital in the long run). In contrast, labor demand is downward sloping if some factors of production are fixed and the production function has diminishing returns to scale in the remaining factors. Consider a version of the model with the production technology

$$y = A_i(L_{mi} + \theta f_i L_{fi})^\alpha,$$

with $\alpha \in (0, 1]$. For simplicity, we again consider this modification in the model without home production.

With this production technology, an increase in female labor supply lowers the marginal product of male labor all else equal. As before, whether this reduces male employment depends on the relative magnitude of income and substitution effects on labor supply. If the former dominate ($\psi > 1$), lower male wages increase male employment, while the opposite occurs if $\psi < 1$. The final two rows of Panel B in Table 4 reports results for $\alpha = 0.66$. For $\psi > 1$, crowding out is slightly smaller than in the baseline case, while with $\psi < 1$ crowding out is slightly larger. The relationship between aggregate and regional crowding out is again similar to the baseline model for $\psi$ close to one.

**Wealth Effect and Terms-of-Trade Effect**  There are a few cases in Table 4 in which regional crowding out is substantially larger in magnitude than aggregate crowding out. This arises from the combination of two deviations from our baseline case: no wealth effect and no home production. What is the intuition for this? First, differences between aggregate and regional crowding out arise due to terms-of-trade effects. But these only affect crowding out if income and substitu-
tion effects on labor supply differ. Second, the absence of home production is important because the magnitude of the terms-of-trade effect also depends on how large female market output is as a fraction of total household income (see equation (15)). Without home production, this fraction is larger implying that the terms-of-trade effect is larger. In these cases, as we noted earlier, regional crowding out provides an upper bound on aggregate crowding out.

5 Cross-State Evidence on the Impact of Female Convergence

We now turn to estimating the extent of regional “crowding out” $\epsilon_{reg}$ in the data, —a statistic we have shown is informative about the impact of female convergence on the aggregate labor market. We defined this parameter as the elasticity of male employment with respect to an increase in female employment induced by an increase in $\theta_j$, in our baseline case. We calculated this elasticity numerically as the parameter $\epsilon_{reg}$ in the regression (16).

Consider a slightly more general version of this regression that also allows for additional controls,

$$\Delta \text{epop}_i^M = \alpha + \beta \Delta \text{epop}_i^F + X_i' \gamma + \epsilon_i,$$  

(17)

where $\Delta \text{epop}_i^M \equiv \text{epop}_i^{M,2016} - \text{epop}_i^{M,1970}$ is the change in the male employment rate over the period 1970-2016, $\Delta \text{epop}_i^F$ is the analogous statistic for the female employment rate, and $X_i$ is a vector of controls. Suppose we were to estimate this regression in the data. Would our estimate of $\beta$ recover the true value of $\epsilon_{reg}$?

The answer is no. Recall that in our theoretical analysis, we assumed that all of the variation in $\Delta \text{epop}_i^F$ arose from female-biased shocks, i.e., variation in $\theta_j$ in our baseline case. This is very unlikely to be true in the data. Male and female employment rates are positively correlated over time, suggesting an important role for gender neutral shocks in explaining the time series variation in female employment rates. In other words, there is an obvious endogeneity issue in identifying $\epsilon_{reg}$. Estimates of $\beta$ using OLS will be upward biased relative to $\epsilon_{reg}$ because gender neutral shocks induce a correlation between variation in female employment rates and the error term in equation (17).

We wish to study the response of $\Delta \text{epop}_i^M$ to the variation in $\Delta \text{epop}_i^F$ associated with female-biased (not gender-neutral) shocks. To isolate this component of the variation, we propose to use the cross-sectional variation in convergence dynamics that we documented in section 3, as a
source of variation. Specifically, we instrument for female employment growth $\Delta e_{\text{pop}}_{t}^F$ with the initial gender gap. The first stage regression in this IV regression is

$$\Delta e_{\text{pop}}_{t}^F = \alpha + \beta \text{gap}_{t,1970} + X_t' \gamma + \epsilon_t.$$  \hspace{1cm} (18)

The first-stage relationship in this IV regression is equivalent to the convergence regressions we estimated in section 3 with the left-hand side variable being the growth in the female employment-to-population ratio. Estimates of this relationship are reported in last three columns of table 2. This convergence relationship—which now serves as our first-stage equation—has strong predictive power: states with a larger gender employment gap in 1970 experienced much more rapid growth in the female employment rate over the next several decades.

Panel A in Table 5 presents estimates of equation (18). The first two columns present estimates based on IV regression, using the gender gap in 1970 as an instrument for the growth in female employment, as we discuss above. The results are presented both with and without controls.\textsuperscript{21} The estimated value of $\beta$ in column 1 implies that a 1 percentage point increase in female employment rate leads to 0.07 percentage point decrease in male employment rate. When we add controls, we find that a 1 percentage point increase in female employment rate leads to 0.15 percentage point decrease in male employment rate (with slightly larger standard errors). Neither estimate is statistically significantly different from zero, or from each other. There is no evidence from this analysis that more rapid female employment growth crowds out male employment.\textsuperscript{22} We take -0.15 as our baseline estimate for regional crowding out.

We also consider a specification where the dependent variable is total employment rate growth, $\Delta e_{\text{pop}}_{t}^T$. 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). Panel B of Table 5 presents the coefficient estimates from this specification, which are close to the benchmark of no crowding out. According to these estimates, a 1 percentage point increase in female employment rate translates into 0.45-0.47 percentage point increase in the total employment rate.

The third and forth columns of Table 5 (Panel A and B) present OLS estimates of equation (18). Were we to take these estimates literally, they would suggest that an increase in female employment due to a female-biased shock leads to “crowding in” of male employment, instead

\textsuperscript{21}The set of controls are same as in Table 5: the skill premium in 1970, the service employment share in 1970, log per capita GDP in 1970, the non-white share in 1970, and Bartik shocks.

\textsuperscript{22}As can be seen in Figure 3, DC is an outlier. However the results are robust to excluding DC.
Table 5: Estimates of Crowding Out: Effect on Male Employment

<table>
<thead>
<tr>
<th>Panel A. Male Employment</th>
<th>2SLS</th>
<th>OLS</th>
<th>2SLS (using JOI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Δ(Female Employment)</td>
<td>-0.07</td>
<td>-0.15</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.13)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>51</td>
<td>51</td>
<td>51</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>.</td>
<td>0.042</td>
<td>-0.005</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B. Total Employment</th>
<th>2SLS</th>
<th>OLS</th>
<th>2SLS (using JOI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Δ(Female Employment)</td>
<td>0.47***</td>
<td>0.46***</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>51</td>
<td>51</td>
<td>51</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.850</td>
<td>0.877</td>
<td>0.858</td>
</tr>
</tbody>
</table>

**Note:** The dependent variable in all specifications is the growth in the male employment-to-population rate over the period 1970-2016. The main explanatory variable is the growth in the female employment-to-population rate over the same time period. Columns 1 and 2 instrument for this variable using the 1970 gender gap in employment rates, while Columns 5 and 6 use the Job Opportunity Index (JOI) described in the text. * p < 0.10 ** p < 0.05 *** p < 0.01

...of the small amount of “crowding out” we estimate using our IV strategy. The fact that the OLS estimates imply less crowding out than the IV estimates is consistent with the logic we describe above for the implications of gender-neutral shocks.

To interpret our IV estimate of $\beta$ as $\epsilon_{reg}$, a requirement is that the initial gender gap is orthogonal to subsequent gender neutral shocks. One obvious concern regarding this identifying assumption is that perhaps states that were “backward” in terms of the gender employment gap were also “backward” in other ways—so they not only had larger initial gender gaps, they also had low male employment. These gender-neutral factors that might be expected to mean revert over subsequent years, biasing our estimates of crowding-out. In practice, however, the correlation goes (weakly) in the opposite direction. Figure B.11 presents a scatter plot of the male employment rate in 1970 versus the gender gap in 1970. The figure implies that the male employment rate was slightly higher in 1970 in states that were more “backward” in terms of the gender gap.
5.1 Estimates using the Job Opportunity Index Instrument

We explore the robustness of these estimates of crowding-out using an alternative instrument: the “Job Opportunity Index” proposed by Nakamura, Nakamura, and Cullen (1979), which we construct for each state $i$ in 1970 according to the formula,

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

where $\omega$ denotes occupation, $\alpha_{-i,1970}(\omega)$ is the national prime-age female share in occupation $\omega$ (leaving out state $i$), and $\pi_{i,1970}(\omega)$ is the prime-age employment share of occupation $\omega$ in state $i$. This instrument captures state-level differences in demand for female labor arising from differences in occupational structure in 1970. The instrument has a strong first-stage: the initial JOI index strongly predicts subsequent female employment growth with an F-stat exceeding 15.

The last two columns in Table 5 present estimates of equation (18) using the $JOI_{i,1970}$ as an instrument. As in our baseline specification, our estimates suggest minimal crowding out. The main identifying assumption here is that the predicted female share based on initial industrial structure is orthogonal to subsequent gender neutral shocks.

6 Business Cycle Model

This section extends the model we present in Section 4.3 into a dynamic, infinite-horizon business cycle setting. We calibrate the model to match our estimates of regional crowding out from the previous section, as well as features of the aggregate time series data. We use the calibrated model to quantify the importance of female convergence as an explanation for the emergence of slow recoveries in recent business cycles.

As in our previous open economy model, there are $n$ regions in the economy. Time is discrete and the time horizon is infinite. Each region produces tradable goods that are differentiated by origin as well as non-tradable home production goods. However, we assume a slightly more general preference specification, that is a hybrid of the preferences introduced by Jaimovich and Rebelo (2009) and those studied by Boppart and Krusell (2016). The hybrid preference specification implies that, in the short-run, substitution effects dominate income effects as in Jaimovich and

---

20Our 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.
Rebelo (2009), but in the long-run, income effects dominate substitution effects, as in Boppart and Krusell (2016). This allows us to generate both procyclical fluctuations in employment over the business cycle, and the long-run decline in the male employment rate that has occurred over the past several decades (and the international patterns for longer periods documented by Boppart and Krusell (2016)). The preferences we assume in this section imply an equilibrium that is isomorphic (up to a multiplicative constant) to the equilibrium implied by the preferences assumed in Section 4 for the case of $\gamma = 1$ (see Appendix A.5).

The preferences of a representative household in region $i$ are defined over a sequence of consumption baskets, $C_{it}$, and labor supply realizations as,

$$U_i = E_0 \sum_{t=0}^{\infty} \beta^t \left( \frac{(C_{it}) - (X_{it})^\psi v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{hf}(h)\})}{1-\sigma} - 1 \right),$$

with $X_{it} = (C_{it})^\gamma (X_{it-1})^{1-\gamma}$, where $\beta \in (0, 1)$ is the discount factor, $\sigma > 0$ is the intertemporal elasticity of substitution (IES), and $\gamma \in [0, 1]$ and $\psi > 0$ capture the strength of short-run and long-run wealth effect, respectively. Here, $X_i$ is the expression for the “consumption habit” that feeds into the disutility of labor. As in Jaimovich and Rebelo (2009), higher consumption does not immediately raise the disutility of work, which depends on the level of the consumption habit, but the habit accumulates slowly over time, generating a large income effect in the long-run. The consumption basket $C_{it}$ is defined, as before, as a CES aggregator over regional goods with an elasticity of substitution of $\eta > 1$, where local market goods and home production goods are assumed to be perfect substitutes, as described by equation (12).

The function $v$ specifies the total disutility of work in market and home production, and remains the same as in Section 4.3:

$$v(L_{mi}, \{L_{fi}(\omega)\}, \{L_{hf}(h)\}) = \frac{1}{\chi_m} \left( \frac{(L_{mi})^{1+\nu^{-1}}}{1+\nu^{-1}} \right) + \frac{1}{\chi_f} \left( \int_{\omega}^{\theta_{fi}} \frac{(L_{hf}(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) + \int_{\theta_{fi}}^{\omega} \frac{(L_{hf}(\omega))^{1+\nu^{-1}}}{1+\nu^{-1}} dG(\omega) \right),$$

where $L_f(\omega)$ denotes the fraction of females that choose to work among each type $\omega$, as before. Furthermore, we assume that productivity in home production is distributed according to the uniform distribution, i.e., $\omega \sim U[1-\delta, 1]$.

Several standard preference specifications obtain as special cases of the preferences above.
Jaimovich-Rebelo preferences are the special case with $\psi = 1$, which ensures the constant labor along balanced growth path. If we impose $\psi = \gamma = 1$, we obtain KPR preferences (King, Plosser, and Rebelo, 1988). If $\psi = 0$ (or $\gamma = 0$), the preferences reduce to GHH preferences (Greenwood, Hercowitz, and Huffman, 1988). If $\psi > 1$ and $\gamma = 1$, the preferences fall into the class of preferences that generate falling labor in the long-run described by Boppart and Krusell (2016).

### 6.1 Long-run Characterization

We first characterize the balanced growth path, along which gender-neutral productivity is assumed to grow at the constant rate $g_A > 0$ in all regions, i.e., $A_{it} = A_t e^{g_A t}$, and $\theta_f$ is assumed to be constant. In Appendix A.5, we show that along such balanced growth path, consumption grows at rate $g_C$ and labor supply grows at rate $g_L$, where

$$g_C = g_A \frac{1 + \nu}{1 + \nu \psi},$$  \hspace{1cm} (19) $$g_L = g_A \frac{(1 - \psi) \nu}{1 + \nu \psi}. \hspace{1cm} (20)$$

The role of $\psi$ can be seen from equation (20). When $\psi = 1$, labor supply is a constant along the path, which is the case of balanced growth path preferences as in Jaimovich and Rebelo (2009). When $\psi > 1$, the wealth effect dominates the substitution effect, and we have a long-run decline in labor, as in Boppart and Krusell (2016). Given these growth rates, we detrend consumption and labor by defining:

$$c_i = \frac{C_{it}}{\exp(g_C t)}, \quad x_i = \frac{X_{it}}{\exp(g_C t)}, \quad l_{mi} = \frac{L_{mit}}{\exp(g_L t)}, \quad l_{fi} = \frac{L_{fit} \omega}{\exp(g_L t)}, \quad \text{and} \quad l_{hi} = \frac{L_{hit} \omega}{\exp(g_L t)}.$$  

The detrended total female employment in the market sector is $l_{fi} = \int \theta_f l_{fi}(\omega) dG(\omega)$. Because every region experiences the same growth rate, there is no borrowing or lending in equilibrium. Therefore, the budget constraint in each region is given by

$$\sum_j p_{ij} c_{ij} = w_{mi} l_{mi} + \int \theta_f w_{fi} l_{fi}(\omega) dG(\omega),$$

where $w_{ki}$ is the wage for each type of labor. XXX The home production constraint is $c_i^h = \int \omega \ A_t \omega l_{fi} dG(\omega)$. XXX In Appendix A.5, we analytically solve for male and female labor and show that exactly the same comparative statics as in Section 4.3 apply along the balanced growth path.\(^{24}\)

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\(^{24}\)The solutions here and those in Section 4.3 differ only by multiplicative constants.
6.2 Aggregate Business Cycle Characterization

We next introduce business cycles into the model, by assuming that gender-neutral productivity, $A_t$, is stochastic and follows a log-AR(1) process with a trend component. That is, $A_t = A_0 e^{g_A t} \hat{A}_t$ with

$$\ln \hat{A}_{t+1} = \rho_A \ln \hat{A}_t + \epsilon_{t+1},$$

where $g_A > 0$ is the trend productivity growth, $\epsilon_{t+1} \sim N(0, \sigma_A^2)$ and $\hat{A}_t$ denotes detrended productivity.

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

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

since 1980, and a linear trend before that, $\theta_{f,t+1} = \theta_{f,t} + \Delta \theta_{70s}$. Households form rational expectation about gender-neutral productivity. However, we assume that the gender revolution was unanticipated and households cannot insure against it. Moreover, we assume that at each point in time, households expect no change in $\theta_{f,t}$—as opposed to foreseeing the whole future path of convergence. While we cannot know for sure how much people anticipated, we believe this assumption is closer to reality than assuming the full path of $\theta_{f,t}$ was anticipated in 1970. In practice, this makes little difference: both sets of assumptions yield similar quantitative results for our counterfactual analysis.\textsuperscript{25}

Given these assumptions, it is possible to characterize the aggregate business cycle dynamics of the detrended economy by the following Bellman equation, which corresponds to the social planner’s problem:

$$W(x, \hat{A}) = \max_{x', l_m, \{l_f(\omega)\}, \{l_{h_f}(\omega)\}} \left( \left( c - (x')^\psi \nu(l_m, \{l_f(\omega)\}, \{l_{h_f}(\omega)\}) \right)^{1-\sigma^{-1}} - 1 \right) + \beta \mathbb{E} W(x', \hat{A}')$$

s.t. $c = \hat{A} \left( l_m + \int^\omega_{\theta_f} l_f(\omega) dG(\omega) + \int^\omega_{\theta_f} \omega l_{h_f}(\omega) dG(\omega) \right)$

$$x' = c^\gamma x^{1-\gamma}.$$

\textsuperscript{25}If we assumed that households anticipated the whole figure path of $\theta_{f,t}$ on arrival of the first shock in 1970, the crowding out would be larger in 1970 than in our baseline model. However, the differences are quantitatively small, since our parameterization implies very little crowding out to begin with.
where $\hat{\beta} \equiv \beta e^{\frac{gA e^{-1+1+1}}{1+1} (1-\sigma^{-1})}$ and the presence of expectations reflects uncertainty over the stochastic gender-neutral productivity process (see Appendix A.6 for a detailed derivation). For the counterfactual experiment we wish to conduct, it suffices to characterize only aggregate (as opposed to regional) business cycle dynamics, because the implications we focus on at the regional level are for the long-run features of the model.

6.3 Calibration: Crowding Out

The key parameter determining the extent of "crowding out" in our model is $\delta$ which determines how many women are on the margin between home production and employment (as opposed to employment versus leisure). The larger is the value of $\delta$, the smaller the degree of crowding out (because a higher $\delta$ implies a more concentrated distribution for female productivity at home production, and hence more switching versus home production, as opposed to leisure). We choose $\delta$ to match the extent of regional crowding out, which we showed in section 4.3 was a powerful diagnostic for the amount of aggregate crowding out generated by the model.

To determine the model’s predictions for the extent of regional crowding out, we numerically calculate the response of the male employment rate to shocks to $\theta_f$, for a given value of $\delta$, by estimating the following regression,

$$\Delta L_{mi} = \alpha + \epsilon_{reg} \Delta L_{fi} + \epsilon_i,$$

where $\Delta L_{gi}$ is the employment growth in region $i$ over the period 1970-2016 for gender $g \in \{m,f\}$, and $\epsilon_{reg}$ is regional crowding out. We choose $\delta = 0.45$ so that $\epsilon_{reg}$ in our model matches our cross-state estimate of regional crowding out, including controls, of -0.15.

It is worth mentioning a few details of this procedure. First, simulating the model to carry out the procedure above requires us to condition on several other parameters, which we describe below (and report in Table 6). Second, to account for possible non-linearities in the extent of regional crowding out as a function of the size of the structural shock to $\epsilon_{reg}$ we do the calculations above for $\theta_f$ shocks of a magnitude that plausibly occurred during the gender revolution.26

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26Specifically, we calibrate the shocks to $\theta_f$ for each of the states in the following way. We assume that each of the 51 states had initial values of $\{\theta_{fi,1970}\}$, which we back out from observed male to female employment ratio in each state in 1970, using the following expression for the female-to-male employment ratio from the balanced growth path of the model, $\frac{L_{fi}}{L_{mi}} = G(\theta_{fi}) \left( \frac{\theta_{fi} X_f}{X_m} \right)^{\nu}$, where we assume for simplicity that men and women share the same preferences for leisure, $X_f = X_m$. We choose $\{\theta_{fi,2016}\}$ in an analogous way, assuming the economy has converged to a new balanced growth path in 2016.
6.4 Other Parameters

Let us now describe our remaining parameter choices, which are summarized in Table 6.

**Standard Parameters**  The time frequency is annual. We set the discount factor to \(\beta = 0.96, \sigma = 1\) (i.e., log-utility) and \(\nu = 1\). The elasticity of substitution across the regional goods is \(\eta = 2\), as in e.g., Obstfeld and Rogoff (2005).\(^{27}\) The number of regions is \(n = 51\), corresponding to the 50 states plus Washington D.C. The strength of short-run wealth effect, \(\gamma\), is set to \(\gamma = 0.1\), which is in the middle of the values explored in Jaimovich and Rebelo (2009).\(^{28}\)

**Labor Supply**  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. That is,

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

where \((L_f/L_m)_{t, model} = G(\theta_f) \left(\frac{\theta_f \chi_{f}}{\chi_m}\right)^\nu\). We assume \(\chi_f = \chi_m = 1\) (implying that female convergence arises from labor demand shocks).

**Gender-Neutral Shocks**  We choose \(g_A\) to match that the growth rate of per-capita real GDP over the period 1970-2016. We parameterize \(\psi\) to match the trend growth rate of the male employment rate over the period 1970-2016. The parameters of the stochastic process for gender neutral productivity shocks, \((\rho_A, \sigma_A^2)\) are chosen to match the persistence and standard deviation of the detrended male employment rate. We approximate this process using the Rouwenhorst (1995) method with 5 grid points in computing expectations. 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. Note that our calibration procedure leads to \(\psi > 1\), which implies that the wealth effect dominates substitution effect in the long-run, as in Boppart and Krusell (2016).\(^{29}\)

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\(^{27}\)As we describe earlier, the international trade literature sometimes assumes larger values for the elasticity of substitution which would lessen the difference between regional and aggregate crowding out by diminishing the terms-of-trade effect (in absolute terms).

\(^{28}\)The quantitative results are very similar even if we set \(\gamma = 1\). However, with \(\gamma = 1\), productivity must be countercyclical to generate procyclical employment rates.

\(^{29}\)To be clear, conditional on exogenously set values for \((\beta, \sigma, \nu, \eta, \gamma)\), the parameters \(\{\psi, g_A, (\rho_f, \bar{\theta}_f, \Delta_{\theta, 70s}), \delta\}\) are jointly calibrated. These parameters either relate exclusively to the model’s long-run properties (and can be calculated from the balanced growth path) or, in the case of \((\rho_f, \bar{\theta}_f, \Delta_{\theta, 70s})\), it is possible to calibrate them based only on observable data conditional on \(\delta\), without solving for the model’s short-run dynamics. Finally, we calibrate the remaining
Table 6: Parameter Values and Moments

<table>
<thead>
<tr>
<th>Panel A. Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Discount factor</td>
<td>0.96</td>
<td>Standard</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>IES</td>
<td>1</td>
<td>Standard</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Frisch elasticity of labor supply</td>
<td>1</td>
<td>Standard</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Trade elasticity</td>
<td>2</td>
<td>Obstfeld and Rogoff (2005)</td>
</tr>
<tr>
<td>$(\rho_f, \theta_f, \Delta \theta, \gamma)$</td>
<td>Female-biased shocks</td>
<td>(0.89, 0.95, 0.0069)</td>
<td>Female to male labor ratio</td>
</tr>
<tr>
<td>$\gamma_A$</td>
<td>Gender-neutral productivity growth</td>
<td>0.016</td>
<td>Per-capita real GDP growth</td>
</tr>
<tr>
<td>$\psi$</td>
<td>Long-run wealth effect</td>
<td>1.14</td>
<td>Trend male labor growth</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Short-run wealth effect</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>Distribution of home productivity</td>
<td>0.45</td>
<td>Regional crowding out estimates</td>
</tr>
<tr>
<td>$(\rho_A, \sigma_A)$</td>
<td>Gender-neutral productivity shocks</td>
<td>(0.50, 0.016)</td>
<td>Detrended male labor dynamics</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B. Moments</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\epsilon^{reg}$</td>
<td>Regional crowding out</td>
<td>-0.15</td>
<td></td>
</tr>
<tr>
<td>$\epsilon^{agg}$</td>
<td>Aggregate crowding out</td>
<td>-0.16</td>
<td></td>
</tr>
</tbody>
</table>

XXX The role of wealth effect in generating long-run decline in male employment rates should not be interpreted too literally. We do not claim that prime-age men are working less than before because they themselves are richer. Rather, our preferred interpretation is that their parents are richer so prime-age men need not to work as much as before. Consistent with this interpretation, Appendix B.11 shows that fraction of prime-age men and women living with parents doubled during the past 40 years. Moreover, almost all of the increase comes from the non-employed person. Consistent with this view, Hall and Petrosky-Nadeau (2016) show that decline among prime-age workers can be attributed in large part to lower participation from among the higher-income half of U.S. households. Austin, Glaeser, and Summers (2018) document that expenditure of non-employed men is at the similar level to low-income employed men despite non-employed have significantly lower income.

7 A Counterfactual: No Female Convergence

We wish to use our calibrated model to ask what would have happened if there was no slowdown in the female employment growth rates, associated with the plateauing of the gender revolution.

parameters $(\rho_A, \sigma_A^2)$, that relate to the short-run properties of the model, and require that we solve the aggregate Bellman equation described above. Specifically, in choosing $(\rho_A, \sigma_A^2)$, we simulate 1000 artificial datasets for 1970-2016 and compute the average persistence and standard deviation of the detrended male employment rate and calibrate the value of $(\rho_A, \sigma_A^2)$ that match the counterpart in the data.

30 This exercise follows Aguiar et al. (2017), which document young men (aged 21-30) increasingly live with parents starting in 2001. We show pattern also holds among prime-age, and the trend goes back to 1970.
7.1 Model Fit: Simulated vs. Actual Data

Figure 6 shows the simulated data, for the parameterization we described in the previous section. The upper left-hand graph shows that we perfectly match the male employment rate. This is a mechanical consequence of our calibration procedure. Recall that we backed out gender-neutral shocks to exactly match this series.

What is not mechanical in this graph is the fit to female employment rates. This reflects the combination of two facts: first, male and female employment rates largely share the same business cycle dynamics, and second, female employment rates have been converging to male employment rates at roughly an AR(1) rate since 1980. The upper-right hand panel of Figure 6 directly shows the fit of our model to the female-to-male employment ratio. The bottom left and right panels of the figure show the time series of gender-neutral and female-biased shocks that we feed into the model in carrying out this simulation.31

At a conceptual level, our model is able to generate two predictions that might a priori seem to be at odds with one another. On the one hand, long run increases in aggregate (gender-neutral)
productivity do not raise employment rates in the long-run (they actually reduce them somewhat). On the other hand, female-biased shocks do lead to long-run increases in employment rates. The crucial assumption we are making is that the female-biased shocks behind the gender revolution led women to work more in the market sector (relative to the home sector). These female-biased shocks therefore differ fundamentally from gender-neutral productivity shocks that do not lead to such switching.

7.2 Counterfactual “Experiment”

The recovery of the employment-to-population rate of prime age workers has slowed dramatically in recent recessions, as we showed in Figure 1. How much of this slow-down can be accounted for by female convergence? To investigate this, we conduct the following counterfactual experiment: for each recession, we “turn off” the convergence in female labor supply, by assuming that female-biased productivity, \( \theta_{f,t} \), grows at the speed it did in the 1970s.\(^{32}\) That is, we assume the following counterfactual path for \( \theta_{f,t} \),

\[
\theta_{f,t+1}^{cf} = \theta_{f,t}^{cf} + \Delta \theta_{70s}.
\]

Figure 7 plots the employment rates for prime age workers in the last five recessions. The left panel shows the actual employment rate, and the right panel shows the counterfactual case where we turn off female convergence. The figure suggests that much of the slowdown in recent recoveries can be accounted for by female convergence. Looking at the actual data, the Great Recession (2007-2009) appears not only to involve a particularly large initial decline in employment, but is also associated with a particularly slow recovery. Once we account for the slowdown in gender convergence, the Great Recession continues to start with a bang, but the subsequent recovery appears roughly in line with previous business cycles.

Table 7 quantifies these patterns. The first two rows of Panel A report the average change in the employment rate during each of the last five business cycle recoveries. Specifically, we calculate growth during the recovery as the average growth over the 4 years the employment rate trough.\(^{33}\)

\(^{32}\)We start the experiment for each recession three years before the business cycle peak. In practice, however, the state variables do not matter much so long as \( \theta_{f,t} < 1 \). Also, in calculating the counterfactual path, we add back in the “model error” in matching actual employment dynamics (i.e., the difference between actual and simulated employment rates in Figure 6, which is generally quite small.)

\(^{33}\)We define the employment rate trough as the year with the minimum value of the employment rate in the five 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.
Figure 7: Counterfactual Results: Total


Figure 8: Counterfactual Results: Female

The table illustrates how recoveries in the employment rate have slowed substantially in recent recessions. The average growth in the employment rate during the recoveries from the 1981-1982, 1990-1991, 2001 and 2007-2009 recessions was 72%, 36%, 21%, and 30% respectively of the rate during the recovery from the 1973-1975 recession.

The second two rows of Panel A report the results of our counterfactual analysis, where we turn off female convergence. In this counterfactual scenario, recent recoveries look similar to earlier ones. The growth in the employment rate during the recoveries implied by the counterfactual is 91%, 81%, 74%, and 83% of the rate during the 1973-1975 recession. If we divide the average average fraction of the 1973 recovery in the actual data by the same statistic in the counterfactual data, we conclude that female convergence explains about 70% of the slowdown in the recovery of the employment rate in recent recessions.34

Panel B and C of Table 7 decompose these findings into their components for female and male employment rates respectively. The effects of the counterfactual scenario are concentrated almost entirely on the female employment rate. When we turn off female convergence, the growth in the female employment rate during recoveries is much more rapid in recent business cycles than in the actual data. In the counterfactual scenario, male employment growth would have been slightly slower due to the crowding out associated with female-based shocks. However, our model implies this crowding out is small.

In the analysis above, we used average real GDP growth rate to infer the income growth. One might worry, given the substantial increase in inequality that we have observed over the past decades, that this calibration might overstate the magnitude of the income effect for the typical household. We consider an alternative calibration where we calibrate 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).35 In this case, productivity growth is given by \( g_A = 0.010 \), which is lower than the value of 0.016 assumed in the baseline calibration. This implies that a larger value of the long-run wealth effect parameter, \( \psi \), is needed to match long-run decline in male employment rates (since the assumed income growth is smaller). However, it turns out that \( \psi \) need only be slightly larger, 1.22, versus our baseline calibration of 1.14. The results of the counterfactual analysis presented above are essentially unchanged versus our baseline calibration.

---

34This statistic is based on the following calculation. The average speed of the recovery in the last three recessions relative to the 1973-1975 recession is 29%, while the average in the counterfactual data is 79%. The fraction of the slowdown explained by female convergence is, therefore, \((79 - 29)/(100 - 29) \approx 70\%\).

35See Appendix B.10 for a time series plot of this alternative income measure.
Table 7: Employment Following Business Cycle Troughs

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Employment Rate Growth in Recovery</th>
<th>Panel B. Employment Rate Growth in Recovery (Female)</th>
<th>Panel C. Employment Rate Growth in Recovery (Male)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>1.33% 0.95% 0.48% 0.28% 0.40%</td>
<td>2.00% 1.35% 0.68% 0.13% 0.18%</td>
<td>0.52% 0.50% 0.28% 0.40% 0.65%</td>
</tr>
<tr>
<td>Relative to 1973 Recession</td>
<td>100% 72% 36% 21% 30%</td>
<td>100% 67% 34% 6% 9%</td>
<td>100% 95% 101% 86% 89%</td>
</tr>
<tr>
<td>Counterfactual</td>
<td>1.33% 1.20% 1.08% 0.98% 1.10%</td>
<td>2.00% 1.91% 2.02% 1.73% 1.77%</td>
<td>0.52% 0.44% 0.13% 0.22% 0.45%</td>
</tr>
<tr>
<td>Relative to 1973 Recession</td>
<td>100% 91% 81% 74% 83%</td>
<td>100% 95% 101% 86% 89%</td>
<td>100% 84% 25% 41% 86%</td>
</tr>
</tbody>
</table>

Note: The “Actual” and “Counterfactual” statistics are for annualized average growth rates. Troughs are defined as the year with the minimum employment rate over the five years following an NBER business cycle peak: 1975, 1982, 1992, 2003, 2010.

8 Conclusion

The “Grand Gender Revolution” led to a dramatic increase in the female employment rate over the past four decades. We present new evidence on the role of female convergence in explaining the slowdown of the recovery of the employment rate in recent business cycles. A key input into this calculation is the extent of “crowding out” of male employment in response to female-biased shocks.

We show, that a class of benchmark models in macroeconomics implies that crowding out is large. We present new empirical evidence on the impact of regional shocks to female employment, and develop a theoretical framework to interpret this evidence. Based on this evidence, we parameterize an open economy model with home production and show that implies that gender convergence explains roughly 70% of the slowdown of the recovery in employment rates in recent business cycles.
Appendix

A Theory Appendix

A.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 $\nu$ governs the elasticity of labor supply and $\chi_m$ is the male-specific labor supply shifter. The total disutility of labor for men is

$$\int_0^{L_m} \frac{j^{\nu - 1}}{\chi_m} dj = \frac{1}{\chi_m} \frac{(L_m)^{1+\nu - 1}}{1 + \nu - 1}. \quad (21)$$

where $L_m$ is the fraction of man that choose to work.

In our more general model with home production, each woman is indexed by a pair $(\omega, j)$. The first dimension, $\omega$, 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 $\chi_f$ is a female-specific labor supply shifter. The distribution function of women’s 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 women of type $\omega \leq \theta_f$ when $L_f(\omega)$ fraction of them work in the market is

$$\int_0^{L_f(\omega)} \frac{j^{\nu - 1}}{\chi_f} dj = \frac{1}{\chi_f} \frac{(L_f(\omega))^{1+\nu - 1}}{1 + \nu - 1}. \quad (22)$$

Similarly, the total disutility of women of type $\omega > \theta_f$ when $L_h^b(\omega)$ fraction of them work at home is

$$\int_0^{L_h^b(\omega)} \frac{j^{\nu - 1}}{\chi_f} dj = \frac{1}{\chi_f} \frac{(L_h^b(\omega))^{1+\nu - 1}}{1 + \nu - 1}. \quad (23)$$

The total disutility of work in a large household is the sum of (21), (22) and (23),

$$\frac{1}{\chi_m} \frac{(L_m)^{1+\nu - 1}}{1 + \nu - 1} + \frac{1}{\chi_f} \left( \int_{\theta_f}^{\omega} \frac{(L_f(\omega))^{1+\nu - 1}}{1 + \nu - 1} dG(\omega) + \int_{\theta_f}^{\omega} \frac{(L_h(\omega))^{1+\nu - 1}}{1 + \nu - 1} dG(\omega) \right).$$
A.2 Robustness of Crowding Out Under “Balanced Growth Preferences”

In Section 4.1, we showed 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 that male and female labor are perfect substitutes in production, additive separability in the disutility of male and female labor, or the unitary household assumption that we make in Section 4.1.

Constant Returns to Scale Production  
First, in Section 4.1, we assumed a linear production function. Suppose instead that the production function is $F(L_m, L_f; \theta)$, where $F$ is constant returns to scale in male and female labor, and $\theta$ 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

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

$$C = \frac{w_m L_m}{\chi_m} + \frac{w_f L_f}{\chi_f}.$$

The solutions to this problem are 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 $\theta$, we have

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

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

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

$$\times \left((w_f)^{\nu-1} (\chi_f)^{\nu} \frac{dw_f}{d\theta} (w_m)^{\nu+1} (\chi_m)^{\nu} - (w_f \chi_f)^{\nu} (w_m \chi_m)^{\nu} \frac{dw_m}{d\theta}\right).$$
Therefore crowding out, $\epsilon_{agg} \equiv \frac{dL_m}{dL_f}$ is

\[
\frac{dL_m}{dL_f} = \frac{(w_m)^{\nu-1}(\chi_m)^{1+\nu}d\omega_m(w_f)^{\nu+1}(\chi_f)^{1+\nu}d\omega_f}{(w_f)^{\nu-1}(\chi_f)^{1+\nu}d\omega_f(w_m)^{\nu+1}(\chi_m)^{1+\nu}d\omega_m} = \frac{dw_m(w_f)^2 - w_m w_f d\omega_f}{dw_f(w_m)^2 - w_f w_m d\omega_m} = \frac{w_f}{w_m}
\]

We thus arrive at the following proposition.

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

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

and the production function features constant returns to scale in male and female labor, aggregate crowding out from any technology shock is given by the relative wage of females to males:

\[
\epsilon_{agg} = -\frac{w_f}{w_m}.
\]

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, household income is proportional to labor income: $\frac{1}{\alpha}(w_m L_m + w_f L_f)$, and the analysis above goes through.

**Leisure Complementarity** Second, in Section 4.1, 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 of 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 is constant returns to scale in male and female labor: \( Y = F(L_m, L_f; \theta) \). The household’s problem is

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

s.t. \( C = w_m L_m + w_f L_f \).

The first order conditions are

\[
w_m = (w_m L_m + w_f L_f) v_m(L_m, L_f) \tag{24}
\]
\[
w_f = (w_m L_m + w_f L_f) v_f(L_m, L_f). \tag{25}
\]

An analytical solution is not available at this level of generality. We therefore derive comparative statics with respect to \( \theta \) around a point where men and women are symmetric. First order expansions of (24) and (25) around \( L_m = L_f = L, w_m = w_f = w, v_m = v_f \) and \( v_{mm} = v_{ff} \) give

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

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 is one:

\[ \epsilon^{agg} = -1. \]

Notice that we did not put any restriction 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 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 (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 the 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 \( \alpha_m \) of their income with women, and women share a fraction \( \alpha_f \) of their income with men. Each gender \( g \in \{m, f\} \) solves the following problem:

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

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

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:

\[
\begin{align*}
\alpha w_f &= \frac{1}{\alpha f} L_f^{\nu-1} \left((1 - \alpha_m) w_m L_m + \alpha w_f L_f\right) \\
\alpha w_m &= \frac{1}{\alpha m} L_m^{\nu-1} \left((\alpha w_m L_m + (1 - \alpha f) w_f L_f)\right).
\end{align*}
\]

Consider a shock to technological parameter \( \theta \) 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 \( L_m \equiv L_f \). In this case, the response of male and female labor are given by

\[
\begin{align*}
\frac{dL_m}{d\theta} &= \frac{1}{((\alpha + \nu^{-1})^2 - (1 - \alpha)^2)} w L^{-\nu} \alpha \chi (1 + \nu^{-1})(1 - \alpha) \left[ \frac{dw_f}{d\theta} - \frac{dw_m}{d\theta} \right] \\
\frac{dL_f}{d\theta} &= \frac{1}{((\alpha + \nu^{-1})^2 - (1 - \alpha)^2)} w L^{-\nu} \alpha \chi (1 + \nu^{-1})(1 - \alpha) \left[ \frac{dw_f}{d\theta} - \frac{dw_m}{d\theta} \right].
\end{align*}
\]

This implies that

\[
\epsilon^{agg} = -1.
\]

In other words, crowding out is precisely one despite the imperfect income sharing. Although this is a stylized example, it is a useful reminder that non-unitary household assumption does not necessarily lower crowding out.

**A.3 Derivations**

**A.3.1 Derivation of Equation (9)**

\[
\epsilon^{agg} = \frac{\frac{d\ln L_m}{d\ln \theta_f}}{\frac{d\ln L_f}{d\ln \theta_f}} \times \frac{L_m}{L_f}
\]

\[
= \frac{-\nu \psi (\nu + 1)(\chi_m)^{\nu}(\theta_f)^{\nu+1}}{\nu + \nu \psi (\chi_m)^{\nu} + (\chi_f)^{\nu}(\theta_f)^{\nu+1}} \times \frac{L_m}{L_f}
\]

\[
= \frac{-\nu \psi \frac{(\chi_m)^{\nu} + (\chi_f)^{\nu}(\theta_f)^{\nu+1}}{\nu + 1 + \nu \psi}}{(\nu + 1)(\chi_f)^{\nu}(\theta_f)^{\nu+1}} + \frac{-\nu \psi \frac{(\chi_m)^{\nu}}{\nu + 1 + \nu \psi}}{(\chi_f)^{\nu}(\theta_f)^{\nu}}
\]

\[
= \frac{-\nu \psi \frac{1}{\nu + 1}}{\theta_f} \left[ (\chi_m)^{\nu} + (\chi_f)^{\nu}(\theta_f)^{\nu+1} \right] + \frac{-\nu \psi \frac{1}{\nu + 1}}{\theta_f} (\chi_f)^{\nu}(\theta_f)^{\nu}
\]
A.3.2 Derivation of Expressions in Section 4

Here we derive expressions (14) and (13). The corresponding expressions for the closed economy model with or without home production are special cases of these expression.

Firm optimization yields:

\[ w_{mi} = p_i A_i \]  
\[ w_{fi} = p_i A_i \theta_f. \]  

Household optimization yields:

\[ (L_{mi})^{\nu-1} = \chi_{mi} w_{mi} \lambda \]  
\[ (\tilde{L}_{fi})^{\nu-1} = \chi_{fi} w_{fi} \lambda \]  

(34)

where \( \lambda \) and \( \lambda^h \) are Lagrangian multipliers on the budget constraint and home production constraint, respectively. Household optimization—first order conditions with respect to \( c_{ii} \) and \( c^h_{fi} \)—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:

\[
A_i \left[ L_{mi} + \int_{\theta_f}^{\theta_f} \theta_f L_{fi} dG(\omega) + \int_{\theta_f}^{\theta_f} \omega \tilde{L}_{fi}^h(\omega) dG(\omega) \right] = \sum_j \left( \frac{p_j}{P} \right)^{-\eta} \left[ w_{mi} L_{mi} + \int_{\theta_f}^{\theta_f} w_{fi} L_{fi} dG(\omega) + \int_{\theta_f}^{\theta_f} \tilde{w}_{fi}^h(\omega) \tilde{L}_{fi}^h(\omega) dG(\omega) \right]
\]

(35)

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

\[
L_{mi} = \left( \frac{p_i}{P} \right)^{1+\psi} \left( A_i \right)^{1-\psi} \left( \chi_{mi} \right)^{\nu} \left( \chi_{mi} \right)^{\nu} + \left( \chi_{fi} \right)^{\nu} \left( \theta_f \right)^{\nu+1} G(\theta_f) + \int_{\theta_f}^{\theta_f} \omega dG(\omega) \right) \right]^{\frac{-\psi}{1+\nu\psi}}.
\]

\[
L_{fi} = G(\theta_f) \left( \frac{p_i}{P} \right)^{1+\psi} \left( A_i \right)^{1-\psi} \left( \theta_f \right)^{\nu} \left( \chi_{fi} \right)^{\nu} \left( \chi_{mi} \right)^{\nu} + \left( \chi_{fi} \right)^{\nu} \left( \theta_f \right)^{\nu+1} G(\theta_f) + \int_{\theta_f}^{\theta_f} \omega dG(\omega) \right) \right]^{\frac{-\psi}{1+\nu\psi}}.
\]

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with
\[
\frac{p_i}{P} = \frac{\Gamma_i^{-1}}{\left(\sum_j \Gamma_j^{-(1-\eta)}\right)^{1/\eta}},
\]
and
\[
\Gamma_i = \left[ \left( A_i \right)^{1+\nu} \left( \chi_mi \right)^{\nu} + \left( \theta_{fi} \right)^{\nu+1} \left( \chi_{fi} \right)^{\nu} G_f(\theta_{fi}) + \int_{\theta_{fi}} \omega^{\nu+1} \left( \chi_{fi} \right)^{\nu} dG(\omega) \right]^{\frac{1}{\eta(1+\nu)-(\eta-1)(\nu+1)}}.
\]

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 \( \theta_{fi} \) is set to zero.

### A.4 Female Labor Supply Shocks and Supply Side Heterogeneity

We now consider a model in which the two dimensions of female heterogeneity are disutility of labor in the market, indexed by \( j \) as before, and disutility of labor at home, indexed by \( \omega \). Specifically, the disutility of labor of women of type \( (\omega, j) \) is \( \frac{1}{\chi_f}j^\nu \) for market work and \( \frac{1}{\omega}j^\nu \) for work at home. We assume that \( \omega \) and \( j \) are independent, \( \omega \) is distributed according to the CDF \( G(\omega) \) with support \([\underline{\omega}, \bar{\omega}]\), and \( j \) is uniformly distributed between 0 and 1. We abstract from heterogeneity in productivity between home and market work and assume that the productivity of women relative to men is \( \theta_f \) 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, chooses 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

\[
U(C, L_m; \{L_f(\omega)\}, \{L_h^h(\omega)\}) = \frac{(C)^{1-\psi}}{1-\psi} - \frac{1}{\chi_m} \left( \frac{L_m}{1+\nu} \right)^{1+\nu-1} + \int_{\chi_f}^{\chi_f} \frac{1}{\chi_f} \left( \frac{L_f(\omega)}{1+\nu} \right)^{1+\nu-1} dG(\omega) + \int_{\chi_f}^{\bar{\omega}} \frac{1}{\omega} \left( \frac{L_h^h(\omega)}{1+\nu} \right)^{1+\nu-1} dG(\omega),
\]

where \( C = c + c^h \). The technology for production is given by \( y = A(L_m + \theta_f \int_{\chi_f} L_f(\omega)dG(\omega)) \) and \( y^h = A\theta_f \int_{\chi_f} L_h^h(\omega)dG(\omega) \). We can solve the model in the same manner as the baseline model to
obtain

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

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

The log-derivatives with respect to female disutility of market work $\chi_f$ are then given by

\[
\frac{d\ln L_f}{d\ln \chi_f} = \nu - \frac{\nu\psi^2}{1+\psi} \Lambda_f + \frac{g(\chi_f)}{G(\chi_f) \chi_f},
\]

\[
\frac{d\ln L_m}{d\ln \chi_f} = -\frac{\nu\psi^2}{1+\psi} \Lambda_f,
\]

where

\[
\Lambda_f \equiv \frac{\int_{\omega_f}^{\chi_f} (\theta_f)^{\nu+1} (\chi_f)^\nu dG(\omega) + \int_{\chi_f}^{\omega} (\theta_f)^{\nu+1} (\omega)^\nu dG(\omega)}{(\chi_m)^\nu + \int_{\omega_f}^{\chi_f} (\theta_f)^{\nu+1} (\chi_f)^\nu dG(\omega) + \int_{\chi_f}^{\omega} (\theta_f)^{\nu+1} (\omega)^\nu dG(\omega)}
\]

is the share of female market work in total household income (including both market and home production). These expressions are similar to those in our benchmark models, (11) and (10), except that the coefficients on the income effects are smaller in this version of the model. This difference arises because positive female labor supply shocks result in lower equilibrium female wages and therefore a smaller increase in income than positive female-biased productivity shocks.

We can easily extend this version of the model to allow for multiple regions in an analogous way as with our benchmark model. In this case, labor supply is given by

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

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

where

\[
p_i = \frac{1}{\eta^2} \frac{\Gamma_i^{-\frac{1}{\eta(1+\nu)-(\eta-1)\nu(1-\psi)}}}{\sum_j \Gamma_j^{-\frac{1}{\eta(1+\nu)-(\eta-1)\nu(1-\psi)}}}^{-\frac{1}{1+\psi}},
\]
\[ \Gamma_i = (A_i)^{1+\nu} \left( \left( \chi_{fi} \right)^{\nu} + \int_{\omega}^\chi_{fi} (\theta_{fi})^{\nu+1} (\chi_{fi})^{\nu} dG(\omega) + \int_{\theta_{fi}}^{\omega} (\theta_{fi})^{\nu+1} (\omega)^{\nu} dG(\omega) \right). \]

The comparative statics with respect to \( \chi_{fi} \) give the regional responses to a female labor supply shock:

\[
\begin{align*}
\frac{d \ln L_{fi}}{d \ln \theta_{fi}} &= \nu \left( -\psi \nu \frac{\Lambda_{fi}}{1+\psi \nu} \text{ substitution effect} \right) + \frac{g(\chi_{fi})}{G(\chi_{fi}) \chi_{fi}} \frac{1}{1+\psi \nu} \text{ income effect} + \frac{1-\psi}{1+\psi \nu} \frac{d \ln (p_{i}/P)}{d \ln \chi_{fi}} \text{ terms of trade effect}, \\
\frac{d \ln L_{mi}}{d \ln \theta_{fi}} &= \nu \left( -\psi \nu \frac{\Lambda_{fi}}{1+\psi \nu} \text{ income effect} \right) + \frac{1-\psi}{1+\psi \nu} \frac{d \ln (p_{i}/P)}{d \ln \chi_{fi}} \text{ terms of trade effect},
\end{align*}
\]

(36) (37)

where

\[
\frac{d \ln (p_{i}/P)}{d \ln \chi_{fi}} = -\nu \frac{1}{1-\psi} + \psi \eta \Lambda_{fi}(1-\lambda_{ii}) < 0.
\]

### A.5 Characterization of the Balanced Growth Path

The representative household in each region solves

\[
\max_{\{C_{it}, L_{mit}, \{L_{fit}(\omega)\}, \{L_{li}(\omega)\}, X_{it}\}} E_0 \sum_{t=0}^{\infty} \beta^t \left( C_{it} - (X_{it})^\gamma v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{li}(\omega)\}) \right)^{1-\sigma} - 1, \]

s.t. \( X_{it} = (C_{it})^\gamma (X_{i,t-1})^{1-\gamma} \)

\[
\sum_j p_{ij} c_{ij} = w_{mit} L_{mit} + \int_{\theta_{fi}}^{\omega} w_{fit}(\omega) L_{fit}(\omega) dG(\omega)
\]

\[
c^h_i = \int_{\theta_{ji}}^{\omega} A_{it} \omega L_{fit}(\omega) d\omega
\]

where

\[
C_{it} = \left( c_{it} + c^h_i \right)^{\frac{\eta-1}{\eta}} + \sum_{j \neq i} \left( c_{ij} \right)^{\frac{\eta-1}{\eta}}.
\]

We wish to characterize the balanced growth path, on which all regions grow at the same rate, \( g_A \), and female biased productivity remains constant over time. We will guess and verify that consumption grows at the constant rate, \( g_C \), along the balanced growth path, which implies that the habit stock also grows at the same rate, \( X_{it} = XC_{it} \) for some \( X > 0 \). The problem then reduces
\[
\max_{\{C_{it}, L_{mit}, \{L_{fit}(\omega)\}, \{L_{hfit}(\omega)\}\}} \sum_{t=0}^{\infty} \beta^t \left( C_{it} - (X C_{it})^{\psi} v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{hfit}(\omega)\}) \right)^{1-\sigma^{-1}} - 1 \\
\text{s.t.} \sum_j p_{ij} c_{ij} = w_{mit} L_{mit} + \int_{\bar{\omega}} w_{fit}(\omega) dG(\omega) \\
c_{ih}^h = \int_{\theta_f} A_{it} \omega L_{hfit}(\omega) d\omega
\]

The first-order conditions with respect to \(L_{mit}, L_{fit}(\omega), L_{hfit}(\omega)\) are

\[
\left( C_{it} - X^{\psi}(C_{it})^{\psi} v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{hfit}(\omega)\}) \right)^{-\sigma^{-1}} X^{\psi}(C_{it})^{\psi} (L_{mit})^{\nu} = \lambda_t w_{mit} \chi_m \tag{38}
\]

\[
\left( C_{it} - X^{\psi}(C_{it})^{\psi} v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{hfit}(\omega)\}) \right)^{-\sigma^{-1}} X^{\psi}(C_{it})^{\psi} (L_{fit}(\omega))^{\nu} = \lambda_t w_{fit} \chi_f \tag{39}
\]

\[
\left( C_{it} - X^{\psi}(C_{it})^{\psi} v(L_{mit}, \{L_{fit}(\omega)\}, \{L_{hfit}(\omega)\}) \right)^{-\sigma^{-1}} X^{\psi}(C_{it})^{\psi} (L_{hfit}(\omega))^{\nu} = \lambda_t^h A_{it} \omega \chi_f, \tag{40}
\]

where \(\lambda_t\) and \(\lambda_t^h\) are the Lagrange multipliers on the budget constraint and the home production constraint, respectively. The first order conditions with respect to \(c_{it}\) and \(c_{ih}^h\) imply that \(\lambda_t = \lambda_t^h p_{it}\) because goods produced in the market and at home are perfect substitutes. Profit maximization, along with a linear production technology imply that wages are equal to the marginal product of labor:

\[
w_{mit} = A_{it} p_{it}
\]
\[
w_{fit} = A_{it} \theta_f p_{it}
\]

Using these conditions, we can express consumption as

\[
C_{it} = \frac{p_{it}}{P_{it}} A_{it} \chi_m^{-\nu} \pi(\theta_{fit}) L_{mit}, \tag{41}
\]
where \( \pi(\theta_f) \equiv (\chi_m)^\nu + (\chi_f)^\nu(\theta_f)^{\nu+1}G(\theta_f) + (\chi_f)^\nu \int_{\theta_f}^\omega \omega^{\nu+1}dG(\omega) \). Thus the problem simplifies to

\[
\max_{\{C_{it}, L_{mit}\}} \sum_{t=0}^{\infty} \beta^t \left( C_{it} - (XC_{it})^{\frac{1}{1+\psi}}(\chi_m)^{-1(1+\nu)}\pi(\theta_f_i)(L_{mit})^{1+\nu-1} \right)^{1-\sigma^{-1}} - 1,
\]

s.t. \( C_{it} = \frac{p_{it}}{P_t} A_{it} \chi_m^{-\nu} \pi(\theta_f_i)L_{mit} \).

The solution is

\[
L_{mit} = \left( \frac{p_{it}}{P_t} A_{it} \right)^{\frac{1-\psi}{\psi+\nu-1}} \pi(\theta_f_i) \frac{-\psi}{\psi+\nu-1} X^{\frac{-\psi}{\psi+\nu-1}}(\chi_m)^\nu \left( \frac{1+\nu^{-1}}{\psi+1+\nu^{-1}} \right)^{\frac{1}{\psi+\nu-1}}. \tag{42}
\]

Using (39) and (40), we have

\[
L_{fit}(\omega) = (\theta_f_i)^\nu \left( \frac{p_{it}}{P_t} A_{it} \right)^{\frac{1-\psi}{\psi+\nu-1}} \pi(\theta_f_i) \frac{-\psi}{\psi+\nu-1} X^{\frac{-\psi}{\psi+\nu-1}}(\chi_m)^\nu \left( \frac{1+\nu^{-1}}{\psi+1+\nu^{-1}} \right)^{\frac{1}{\psi+\nu-1}} \tag{43}
\]

\[
L_{jit}^{h_i}(\omega) = \omega^{\nu} \left( \frac{p_{it}}{P_t} A_{it} \right)^{\frac{1-\psi}{\psi+\nu-1}} \pi(\theta_f_i) \frac{-\psi}{\psi+\nu-1} X^{\frac{-\psi}{\psi+\nu-1}}(\chi_m)^\nu \left( \frac{1+\nu^{-1}}{\psi+1+\nu^{-1}} \right)^{\frac{1}{\psi+\nu-1}} \tag{44}
\]

The market clearing condition for goods produced in region \( i \) is

\[
A_{it} \left( L_{mit} + \int_{\omega}^{\theta_f} \theta_f L_{fit}(\omega)dG(\theta_f) + \int_{\theta_f}^{\omega} \omega L_{jit}^{h_i}(\omega)d\omega \right) = \left( \frac{p_{it}}{P_t} \right)^{-\eta} \sum_{s} C_{it}^{s}
\]

This implies that the relative prices between goods produced in region \( i \) and \( j \) must satisfy

\[
\left( \frac{p_{it}}{p_{jt}} \right)^{-\eta} = \frac{A_{it} \left( L_{mit} + \int_{\omega}^{\theta_f} \theta_f L_{fit}(\omega)dG(\theta_f) + \int_{\theta_f}^{\omega} \omega L_{jit}^{h_i}(\omega)d\omega \right)}{A_{jt} \left( L_{mit} + \int_{\omega}^{\theta_f} \theta_f L_{fit}(\omega)dG(\theta_f) + \int_{\theta_f}^{\omega} \omega L_{jit}^{h_i}(\omega)d\omega \right)}
\]

Plugging in the labor supply functions, (42), (43) and (44), we have closed form solutions for the relative prices:

\[
\frac{p_{it}}{p_{jt}} = \left( \frac{(A_{jt})^{1+\nu} \pi(\theta_f_j)}{(A_{it})^{1+\nu} \pi(\theta_f_i)} \right)^{\frac{1}{(1-\psi)\nu+\psi+\eta}}
\]

Thus, the terms of trade are given by

\[
\frac{p_i}{P} = \frac{\Pi(\theta_f_i, A_{it})^{-\frac{1-\eta}{(1-\psi)\nu+\psi+\eta}}}{\left( \sum_{j} \Pi(\theta_f_j, A_{jt})^{-\frac{1-\eta}{(1-\psi)\nu+\psi+\eta}} \right)^{\frac{1}{1-\eta}}}
\]

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where $\Pi(\theta_{fj}, A_{jt}) \equiv (A_{jt})^{1+\nu} \pi(\theta_{fj})$. From this expression, it is clear that if all the countries grow at the same rate, then the terms of trade are constant over time. Given that $p_t/P_t$ is constant, equation (42) implies that labor grows at the rate

$$g_L = g_A \frac{1 - \psi}{1 + \nu \psi}.$$  

Because the budget constraint implies $g_L + g_A = g_C$, we also have

$$g_C = g_A \frac{1 + \nu}{1 + \nu \psi}.$$  

Thus, we confirm our initial guess that consumption grows at a constant rate. Because $\bar{L}_{fit}$ were expressed in per-capita terms, the regional male labor supply and the female labor supply in the market are

$$L_{mit} = \left( \frac{p_t A_t}{P_t} \right)^{\frac{1 - \psi}{\psi + \nu - 1}} \pi(\theta_{fi})^{\frac{-\psi}{\psi + \nu - 1}} X^{\frac{-\psi}{\psi + \nu - 1}} (X_m)^{\nu} \left( \frac{1 + \nu^{-1}}{\psi + 1 + \nu^{-1}} \right)^{1 - \frac{1}{\psi + \nu - 1}}.$$  \hspace{1cm} (45)

$$L_{fit} = G(\theta_{fi}) (\theta_{fi})^\nu \left( \frac{p_t}{P_t} A_t \right)^{\frac{1 - \psi}{\psi + \nu - 1}} \pi(\theta_{fi})^{\frac{-\psi}{\psi + \nu - 1}} X^{\frac{-\psi}{\psi + \nu - 1}} (X_m)^{\nu} \left( \frac{1 + \nu^{-1}}{\psi + 1 + \nu^{-1}} \right)^{1 - \frac{1}{\psi + \nu - 1}}.$$  \hspace{1cm} (46)

These expressions complete the characterization of the regional balanced growth path equilibrium. Note that these expressions differ from the ones in section 4 only by multiplicative constants. Therefore, exactly the same comparative statics apply as in Section 4.

The aggregate balanced growth path equilibrium can be obtained by setting $p_t/P_t = 1$ in the expression (45) and (46).

### A.6 Characterization of Business Cycles

The original Bellman equation is

$$\hat{W}_t(X, A_t) = \max_{C, X', C_t, \{L_m\}, \{L_f(\omega)\}, \{L_f(\omega)\}} \frac{(C - (X')^\psi v(L_m, \{L_f(\omega)\}, \{L_f(\omega)\}))^{1-\sigma^{-1}}}{1-\sigma^{-1}} + \beta \mathbb{E} \hat{W}_{t+1}(X', A_{t+1})$$

s.t. $C = A_t \left( L_m + \int_0^{\theta_f} \theta_f L_f(\omega) dG(\omega) + \int_{\theta_f}^{\bar{\omega}} \omega L_f^h(\omega) dG(\omega) \right)$

$$X' = C^\gamma X^{1-\gamma}.$$
Let $\tilde{A}_t$ denote the trend component of productivity, so that $\tilde{A}_{t+1} = \tilde{A}_t \tilde{A}_{t}$ and $\tilde{A}_t = \tilde{A}_0 e^{\gamma \tilde{A}_t}$. We will guess and verify that solution takes the form $\tilde{W}_t(X, A) = (\tilde{A}_0 e^{\gamma \tilde{A}_t})^{\nu - 1 + 1} W(x, \tilde{A})$ with some $W(x, \tilde{A})$ that does not depend on time. Define $L_g = A^{\nu - 1 + \psi} l_g$ for $g \in \{m, f\}$, $L_f^h(\omega) = A^{\nu - 1 + \psi} l_f^h(\omega)$, $C = A^{\nu - 1 + \psi} c$ and $X = A^{\nu - 1 + \psi} x$. Plugging in this guess,

$$W(X, \tilde{A}) = \max_{c, x', l_m, \{l_f(\omega)\}, \{l_f^h(\omega)\}} \frac{(c - (x')^{\psi} v(l_m, \{l_f(\omega)\}, \{l_f^h(\omega)\}))^{1-\sigma}}{1 - \sigma^{-1}} + \beta e^{\gamma A^{\nu - 1 + \psi} (1 - \sigma^{-1})} E W(X', \tilde{A}')$$

subject to

$$c = \tilde{A} \left( l_m + \int_{\theta}^{\theta_f(\omega)} \omega l_f(\omega) dG(\omega) + \int_{\theta_f}^{\omega} \omega l_f^h(\omega) dG(\omega) \right)$$

and

$$x' = c^{\gamma} x^{1-\gamma}.$$
B Empirical Appendix

B.1 Data construction

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 $\omega$ in state $i$ at time $t$, and $v_{-i,t}(\omega)$ is the national employment share of industry $\omega$ 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:

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

where $X_{git}^g$ is a set of dummy variables for education, hours worked, race, whether the worker was born in a foreign country.\footnote{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.} 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.
Figure B.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.

The state-level gender wage gap is defined as $\ln(\frac{W_{fst}}{W_{mst}})$. The aggregate counterparts of these objects are calculated by taking an average at the national level, using the 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 (47). 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 $\ln(\frac{W_{cst}}{W_{hst}})$.

**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.

**B.2 Unemployment and Labor Force Participation During Recoveries**

Figure B.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 B.2 plots the labor force participation rate for prime-age men and women around the last five recessions. The data used in these figures is 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.

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

Figure B.3 plots the employment rate (left panel) and labor force participation rate (right panel) for prime-age men and women over the time period 1948-2016. The figure shows that the growth in 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.

The left panel of Figure B.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 B.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.

**B.4 Shift-Share Decomposition of Aggregate Gender Employment Convergence**

We next perform a shift-share decomposition of the rise in the female employment share, into “within” and “between” occupation variation. Let $L_t(\omega)$ and $L_{ft}(\omega)$ denote total and female employment in occupation $\omega$ at time $t$. Let $\alpha_t(\omega) \equiv L_{ft}(\omega)/L_t(\omega)$ denote the female employment share in occupation $\omega$, $\bar{\alpha}_t \equiv (\sum_{\omega} L_{ft}(\omega))/(\sum_{\omega} L_t(\omega))$ denote the aggregate female employment share at time $t$, and $v(\omega) \equiv L_t(\omega)/(\sum_{\omega} L_t(\omega))$ denote the employment share of occupation $\omega$. 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 $\Delta \alpha$ can be decomposed into

$$\Delta \alpha = \sum_{\omega} \bar{\nu}(\omega) \Delta \alpha(\omega) + \sum_{\omega} \Delta v(\omega) \bar{\alpha}(\omega),$$

where
where the “within” effect captures 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. The “between” effect captures the rise that would have occurred if only the employment shares across occupations changed, but the female employment share in each occupation remained constant.

Figure B.5 plots this decomposition for several years. We set the base year $t = 1970$ and vary $T$ from 1980 to 2016. The figure shows clearly that most of the “Grand Gender Convergence” comes from increases in female employment shares within occupation.

B.5 Convergence within Skill Groups

Figure B.6 plots the evolution of the gender gap within skill groups. 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. The figure shows that 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.
Figure B.5: Within and Between Decomposition of Female Share Growth

Figure B.6: Actual Employment Gap and Simulated Employment Gap within Skill Group
Figure B.7 plots the skill premium (left panel) and the employment share of the service sector over the period 1970-2016. Appendix B.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 actually falling (or flat) between 1970 and 1900, but then rises rapidly from 1990 to 2005. 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 sharp slowdown in the change of the gender gap.

B.7 Cross-State Variation in the Skill Premium and the Service Share

Figure B.8 considers cross-state variation in the skill premium and the service share. The left panel shows a scatter plot of the growth in the skill premium as a function of the growth in gender employment gap ($\Delta(L_{f_i} - L_{m_i})$) over the time period 1970-2016. The right panel shows a scatter plot of the growth in service sector employment share ($\Delta(L_{service,i}/(L_{service,i} + L_{non-service,i}))$) as a function of the growth in gender employment gap over the same time period. In both cases, the relationship between the two variables is weak and statistically insignificant. The p-value for the coefficient on the skill premium and service share being different from zero are 0.51 and 0.64, respectively. The R-squared in these regression are 0.03 and 0.005, respectively.
Figure B.8: Cross-sectional correlation of relative female labor growth and growth in skill premium (left) and service sector employment share (right)

B.8 The Gender Wage Gap vs. the Gender Employment Gap

The left panel of Figure B.9 plots the evolution of real wages for men and women over the period 1970 to 2016. The right panel of Figure B.9 plots the real wage of women relative to the real wage of men. The wages plotted in this figure are the composition adjusted wage series described in Appendix B.1. The gender wage gap has declined substantially over our sample period in spite of the large increase in female employment. This suggests that increased demand for female labor played a large role in the Grand Gender Convergence.

Figure B.10 considers cross-state variation in the gender wage gap. It plots the change in the female-to-male wage ratio \( \left( \frac{w_{f,2016}}{w_{m,2016}} - \frac{w_{f,1970}}{w_{m,1970}} \right) \) against growth in the gender gap in employment rates for U.S. state. 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 and 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.
Figure B.9: Real Wage by Gender and Relative Wage: Time-series
*Note:* Wages are hourly and composition adjusted (age, education, race, whether born in foreign).

Figure B.10: Gender Gap in Employment Rate and Relative Wages: Cross-section
B.9 Mean Reversion and the China Shock

Our identifying assumption in our empirical analysis is that the initial gender gap in employment—and associated subsequent convergence dynamics—are orthogonal to subsequent gender neutral shocks. One potential concern is that the states that had the largest gender gap in 1970 also had low male employment rates because they were generally economically depressed or “backwards” at the time. If this were the case, the subsequent growth in female employment may have been correlated with differential gender neutral shocks as these states converged overall to the rest of nation. To assess whether this is the case, the left panel of Figure B.11 presents a scatter plot of the male employment rate in 1970 against the gender employment gap. The relationship is actually slightly negative, i.e., states that were originally more “backward” in terms of the gender employment gap actually had slightly higher initial male employment rates, though it is statistically insignificant if one outlier (AK) is dropped.

Another variable that has been shown to have substantial explanatory power for local employment growth is the “China shock,” constructed by Autor, Dorn, and Hanson (2013). The China shock is intended to capture changes in labor demand associated with competition from Chinese imports. To investigate whether this factor plays a role in our results, we have constructed a state-level version of the China shock, by interacting the initial industry employment share for each
state with the increase in Chinese exports to non-US advanced countries for each industry (as in Autor, Dorn, and Hanson (2013)), for the period 1990-2007. The right panel of Figure B.11 presents a scatter plot of the China shock versus the gender gap in 1970. As the figure shows, the exposure to Chinese imports is uncorrelated with the initial gender gap in 1970. The correlation is 0.019 and is not statistically different from zero.

### B.10 Alternative Measures of Real Income

Figure B.12 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 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.
B.11 Trends in Cohabitation with Parents

The left panel of Figure B.13 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 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 B.13 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. This is suggestive that the long-term decline in prime-age male employment reflects the fact that their parents are becoming richer and therefore providing a more appealing alternative to employment and self-sufficiency.

B.12 Employment Rates vs. Hours

Much of the existing literature has focused on per-capita hours worked as opposed to employment rates (e.g., McGrattan and Rogerson, 2008; Heathcote, Storesletten, and Violante, 2017; Knowles, 2013). Figure B.14 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 a very similar patterns to employment rates. The convergence pattern we emphasize are
Figure B.14: 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.

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.
References


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