Online Appendix to
"Women, Wealth Effects, and Slow Recoveries"

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A Empirical Appendix

A.1 Data construction

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

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

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

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

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

characteristics:

$$\ln(w_{git}) = \alpha_{gt} + \beta_{gt}X_{git} + \epsilon_{git}, \tag{1}$$

where X_{it}^g is a set of dummy variables for education, hours worked, race, whether the worker was born in a foreign country.[1] The state-level wage index in state s for each gender, denoted by W_{gst}, is then constructed by calculating the average value of $\exp(\alpha_{gt} + \epsilon_{git})$, using population weights. The state-level gender wage gap is defined as $\ln(W_{fst}/W_{mst})$. The aggregate counterparts of these objects are calculated by taking an average at the national level, using population weights.

In our analysis of the skill-premium, we compute the composition adjusted wage separately for college graduates and high-school graduates as in Katz and Murphy (1992), and aggregate this to the state-level. We adjust for composition in an analogous manner as in equation (1). Let W_{cst} and W_{hst} denote the state-level wage index for college graduates and high-school graduates, respectively. The skill premium is defined as $\ln(W_{cst}/W_{hst})$.

A.2 Unemployment and Labor Force Participation During Recoveries

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

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

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

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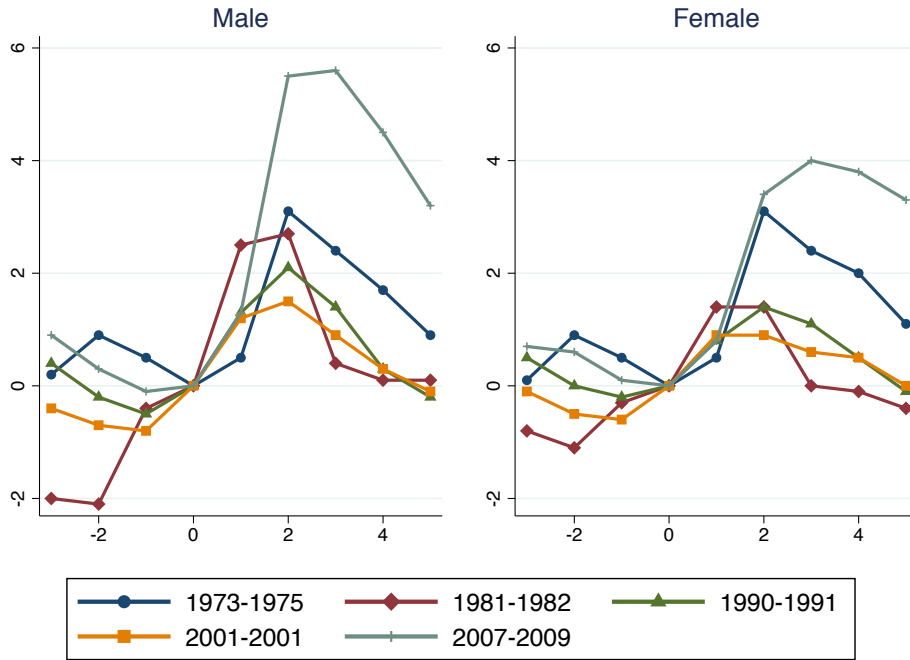
Figure A.1: Unemployment Rate in Recessions by Gender

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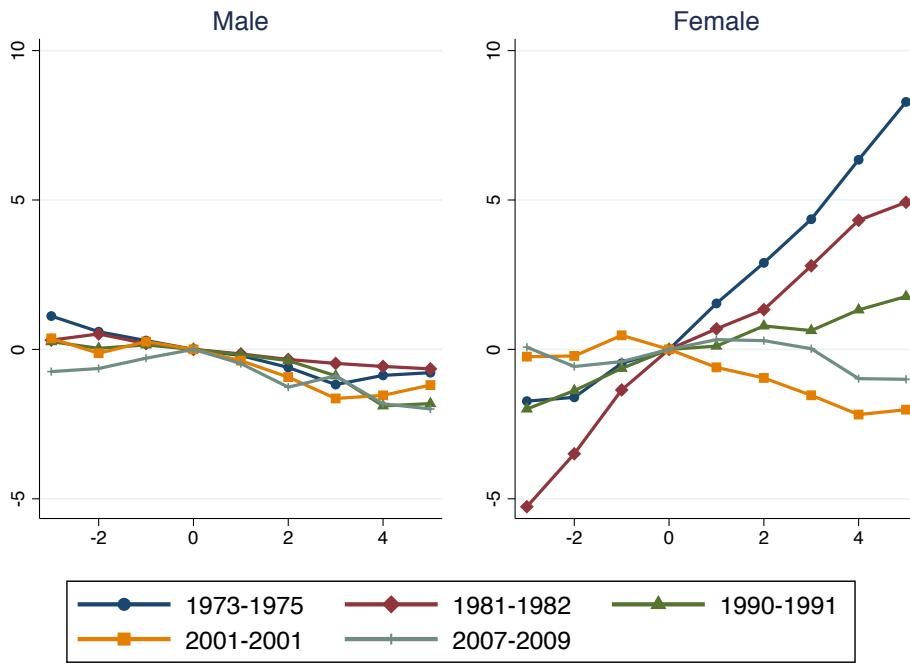

Figure A.2: Labor Force Participation Rate in Recessions by Gender

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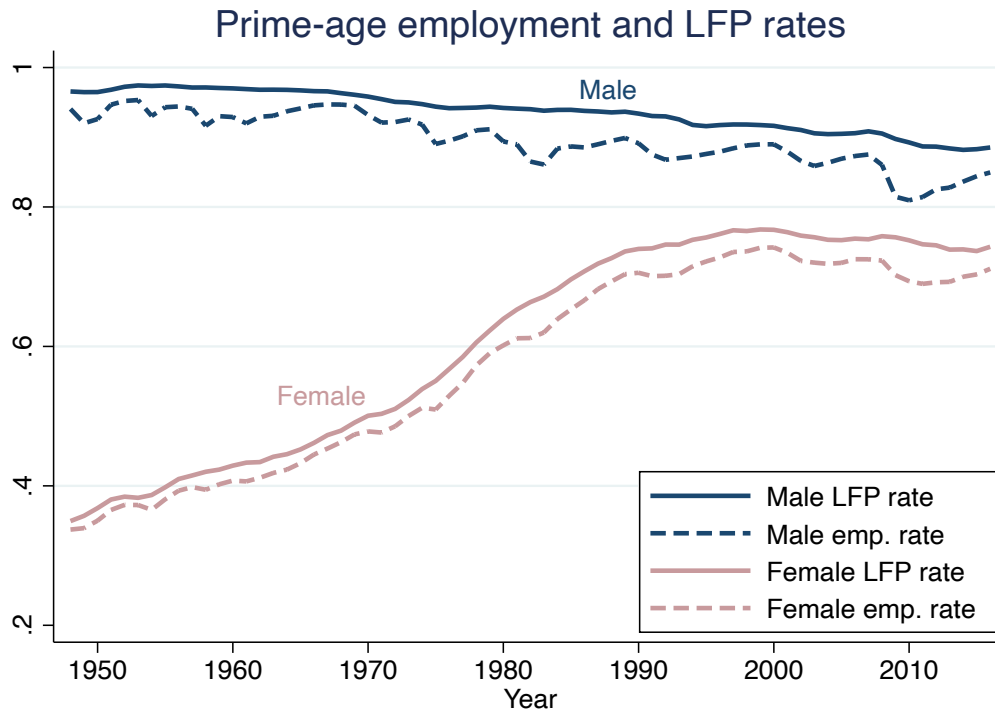
Figure A.3: Prime-age Employment and Labor Force Participation Rates over 1948-2016

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

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

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

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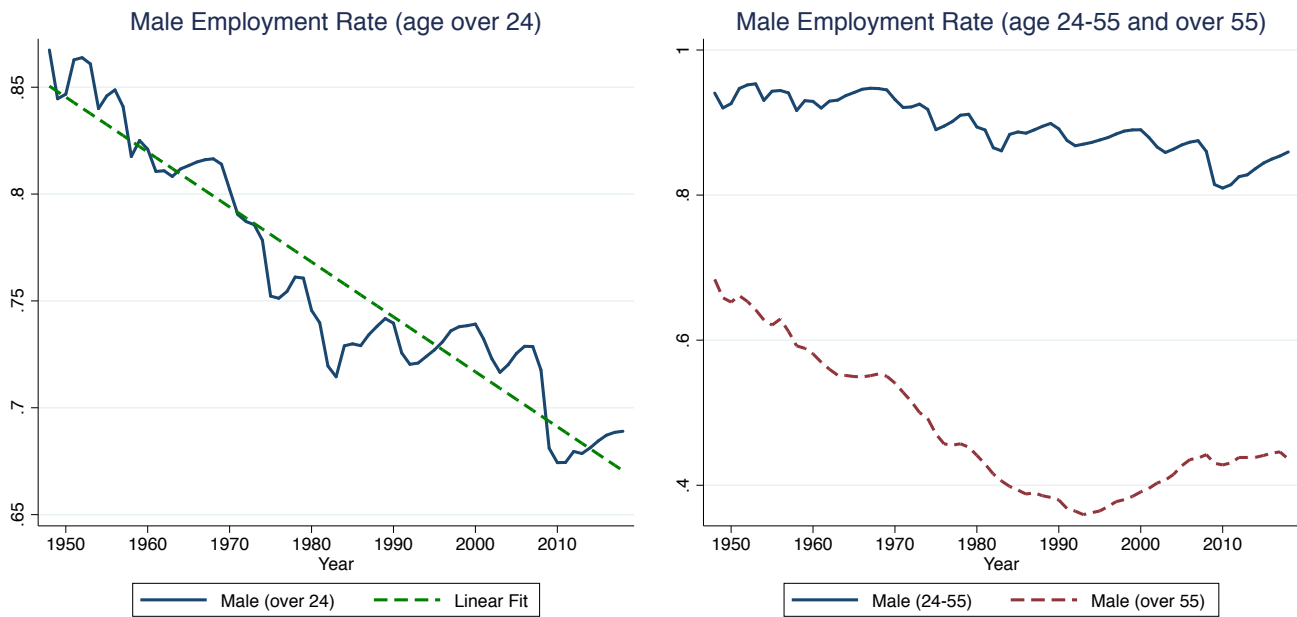
Figure A.4: Employment Rates: Age over 24

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

Figure A.6 considers cross-state variation in the skill premium and the service share. The left panel shows a scatter plot with the growth in the skill premium on the vertical axis and the growth in the gender employment gap ($\Delta(L_{fi} - L_{mi})$) on the horizontal axis. The right panel shows a scatter plot with the growth in the service sector employment share ($\Delta(L_{service,i}/(L_{service,i} + L_{non-service,i})$)) on the vertical axis and the growth in the gender employment gap on the horizontal axis. In both panels, the growth rates are calculated over the time period 1970-2016. In both cases, the relationship between the two variables is weak and statistically insignificant. The p-values for the coefficients on the skill premium and service share being different from zero are 0.51 and 0.64, respectively. The R-squared in these regressions are 0.03 and 0.005, respectively.[2]

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

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

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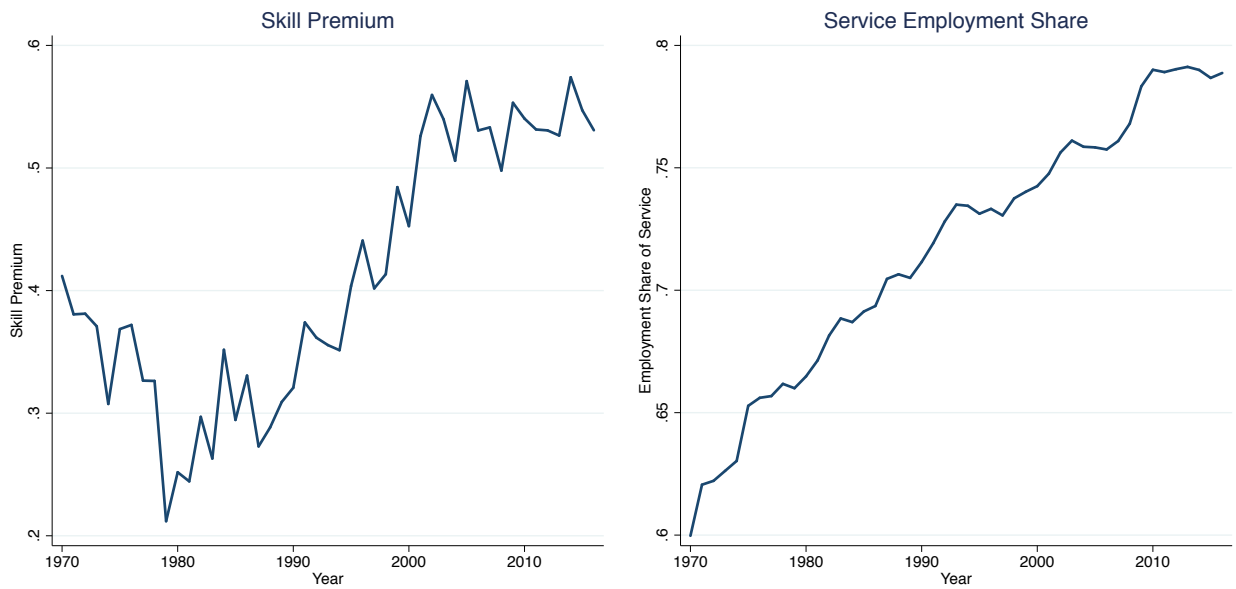
Figure A.5: Skill premium (left) and employment share of the service sector (right)
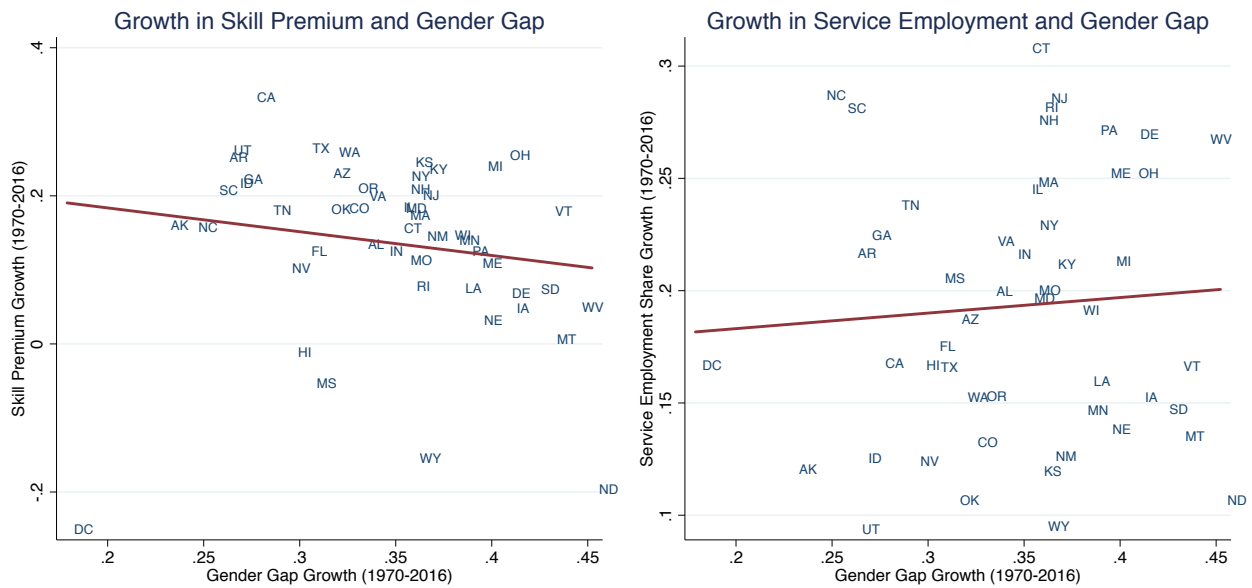

Figure A.6: Cross-sectional correlation of relative female labor growth and growth in skill premium (left) and service sector employment share (right)

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

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

A.5   Diagnostic Tests for Cross-Sectional Identification

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

A.5.1   Correlates of the Instruments

We first we explore how the gender gap in 1970 and JOI in 1970 are correlated with observable state characteristics. We do this by regressing our instruments on various characteristics one at a time. The characteristics we consider are the agricultural, mining, manufacturing, and service sector employment shares in 1970, log GDP per capita in 1970, the college share in 1970, the skill wage premium in 1970, the share of single in 1970, the non-white population share in 1970, the China shock, and a Bartik shock. We construct a state-level version of China shock, following Autor, Dorn, and Hanson (2013). In particular, we interact the initial industry employment share for each state with the increase in Chinese exports to non-US advanced countries for each industry, for the period 1990-2007. TO construct employment share, we use county business data from Guren et al. (2021).

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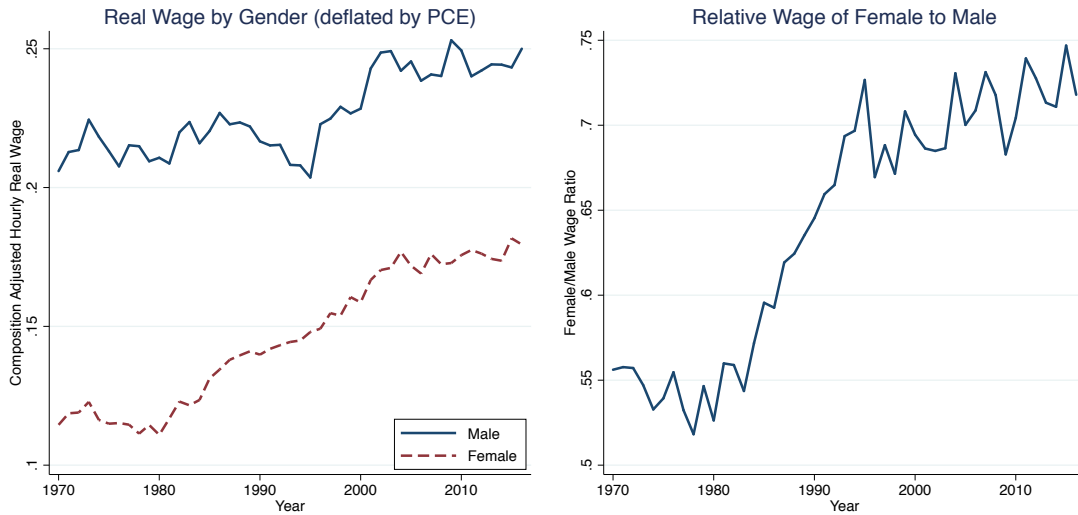
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Figure A.7: Real Wage by Gender and Relative Wage: Time-series
Note: Wages are hourly and composition adjusted (age, education, race, whether the worker is foreign-born).
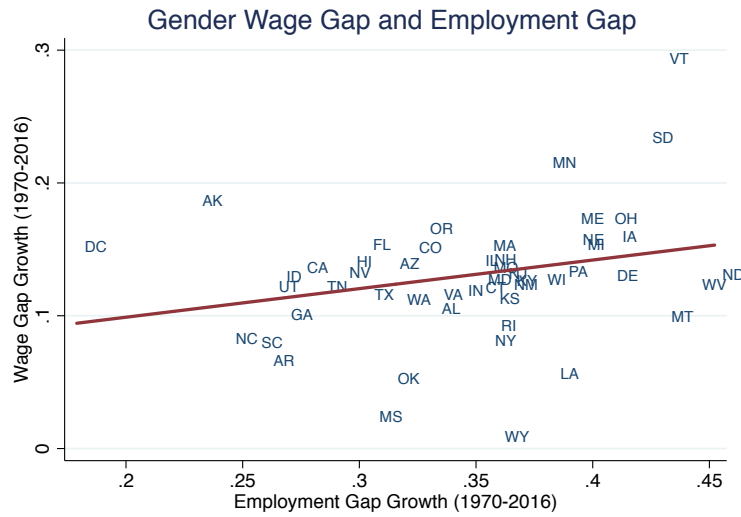

Figure A.8: Gender Gap in Employment Rate and Relative Wages: Cross-section

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Table A.1: Correlations with the Instruments

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

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

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

Some of the other correlations are driven by outliers. There is a statistically significant neg-

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

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

A.5.2   Pre-Trends and the Gender Gap

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

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

As explained in the main text, our JOI instrument is a particular type of shift-share instrument and our key identifying assumption for this instrument is that the initial occupational shares are
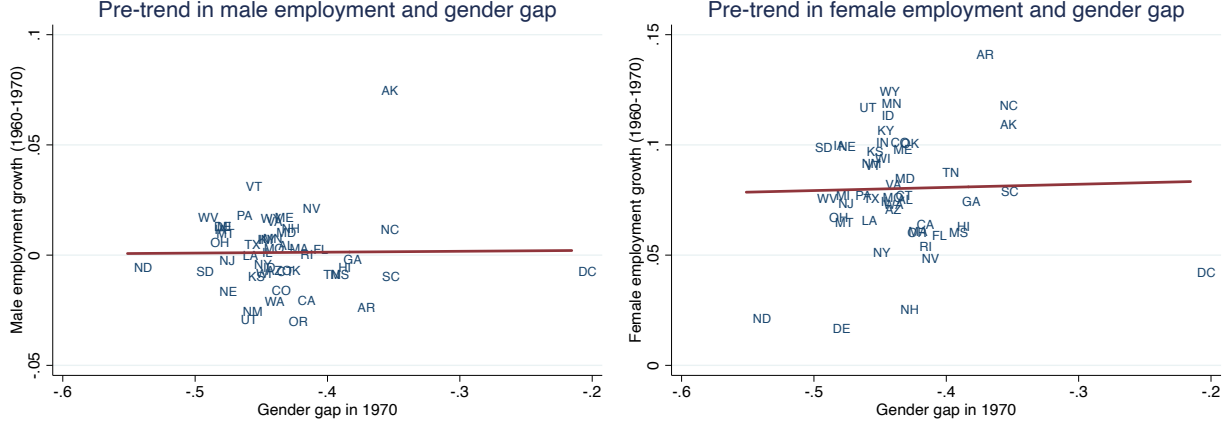
Figure A.9: Pre-trend and Initial Gender Employment Gap

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

orthogonal to subsequent gender-neutral shocks. Goldsmith-Pinkham, Sorkin, and Swift (2020) point out that in this type of setting it can be useful to understand which occupations are driving the results. To assess this, we follow their analysis and that of Rotemberg (1983) in decomposing our IV estimator ($\hat{\beta}$ in equation (5)) into

$$\hat{\beta} = \sum_{\omega} \hat{\gamma}(\omega)\hat{\beta}(\omega), \tag{2}$$

where

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

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

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

Table A.2 reports $\hat{\gamma}(\omega)$ and $\hat{\beta}(\omega)$ for the 10 occupations that have the largest Rotemberg

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Table A.2: Occupations with the Largest Rotemberg Weights

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

Notes: The table reports the decomposition of our IV estimator using the JOI instrument into Rotemberg weights $\hat{\gamma}(\omega)$ and just-identified IV estimators $\hat{\beta}(\omega)$ as in equation (2) for the 10 occupations with largest Rotemberg weights. We also report the national female share in occupation ω denoted $\alpha(\omega)$ and the mean employment share of occupation ω denoted $\pi(\omega)$, both in 1970. We report $\pi(\omega)$ in percent.

weights. Two observations stand out. First, while there are 255 occupations, the top few occupations receive a hugely disproportionate weight in $\hat{\gamma}$. Several of these occupations are in textiles. Second, it appears that our finding of low crowding out does not seem to be driven by any particular occupation. While the coefficients from the just-identified regressions ($\hat{\beta}(\omega)$) vary a lot among these top few occupations, they tend to be centered around our point estimates in Table 4.

A.5.4 Correlates of Initial Occupational Employment Shares

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

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

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

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

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

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

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

A.5.5 Cross-State Migration

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

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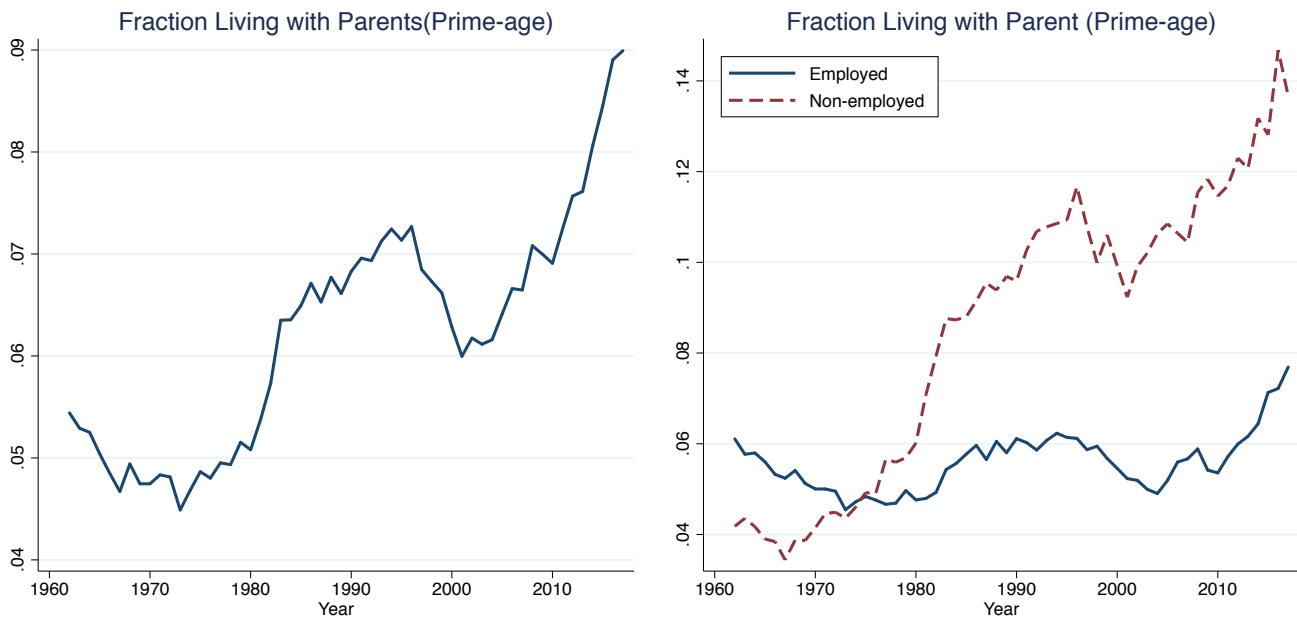
Figure A.10: Fraction of Prime-Age Living with Parents

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

A.6 Trends in Cohabitation with Parents

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

A.7 Alternative Measures of Real Income

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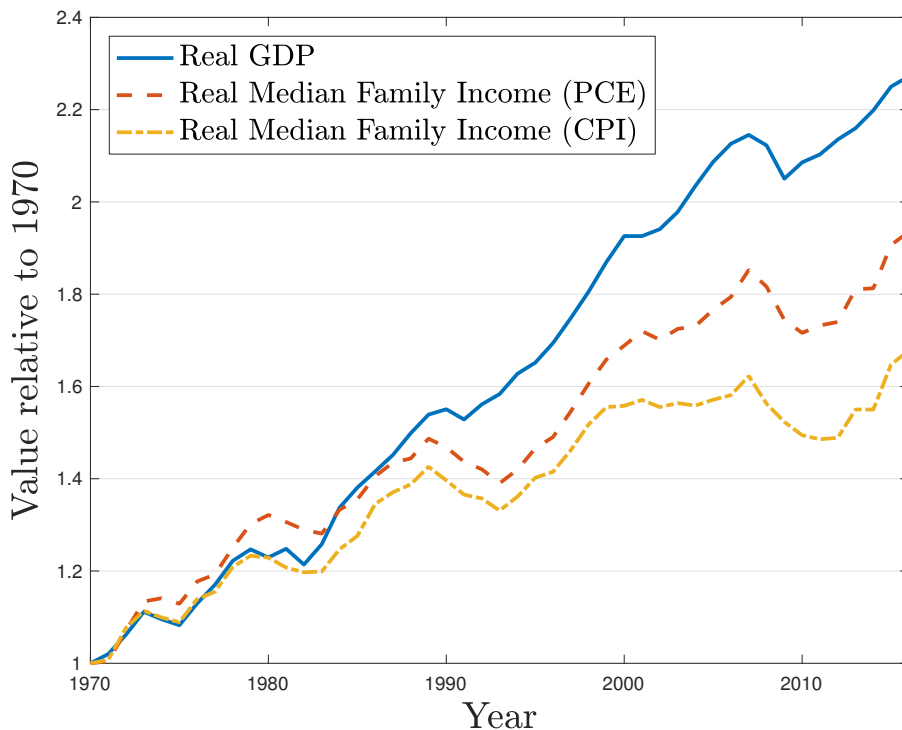
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Figure A.11: Real GDP and Real Median Family Income

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

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

A.8 Family Structure

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

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

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

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

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

Figure A.12: Employment Rates by Marital Status

the changing selection into marriage over time.

B Theory Appendix

B.1 Large Representative Household

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

$$\int_0^{L_m} \frac{j^{\nu^{-1}}}{\chi_m} dj = \frac{1}{\chi_m} \frac{(L_m)^{1+\nu^{-1}}}{1 + \nu^{-1}}. \tag{3}$$

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

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

$$\int_0^{L_f(\omega)} \frac{j^{\nu^{-1}}}{\chi_f} dj = \frac{1}{\chi_f} \frac{(L_f(\omega))^{1+\nu^{-1}}}{1 + \nu^{-1}}. \tag{4}$$

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

$$\int_0^{L_f^h(\omega)} \frac{j^{\nu^{-1}}}{\chi_f} dj = \frac{1}{\chi_f} \frac{(L_f^h(\omega))^{1+\nu^{-1}}}{1 + \nu^{-1}}. \tag{5}$$

The total disutility of work in a large household is the sum of expressions (3), (4), and (5):

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

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

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

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

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

$$C = w_m L_m + w_f L_f.$$

The solution to this problem is given by

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

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

Taking derivatives with respect to θ, we have

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

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

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

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

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

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

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

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

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

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

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

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

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

The first order conditions are

$$w_m = (w_m L_m + w_f L_f) v_m(L_m, L_f) \tag{6}$$

$$w_f = (w_m L_m + w_f L_f) v_f(L_m, L_f). \tag{7}$$

An analytical solution is not available at this level of generality. We therefore derive comparative statics with respect to θ around a point where men and women are symmetric. First order expansions of equations (6) and (7) around $L_m = L_f = L$, $w_m = w_f = w$, $v_m = v_f$ and $v_{mm} = v_{ff}$ give

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

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

Combining these two equations and after some algebra, we obtain

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

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

This leads to the following proposition.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

This implies that

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

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

B.3 Derivation of Expressions in Section 5

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

Firm optimization yields:

$$w_{mi} = p_i A_i \tag{8}$$

$$w_{fi} = p_i A_i \theta_f. \tag{9}$$

Household optimization yields:

$$(L_{mi})^{\nu^{-1}} = \chi_{mi} w_{mi} \lambda \tag{10}$$

$$(L_{fi})^{\nu^{-1}} = \chi_{fi} w_{fi} \lambda \tag{11}$$

$$(L_{fi}^h(\omega))^{\nu^{-1}} = \chi_{fi} A \omega \lambda^h, \tag{12}$$

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

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

single market clearing condition:

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

$$= \sum_j \left(\frac{p_i}{P} \right)^{-\eta} \frac{1}{P} \left[w_{mj} L_{mj} + \int^{\theta_{fj}} w_{fj} L_{fj} dG(\omega) + \int_{\theta_{fj}} w_{fj}^h(\omega) L_{fj}^h(\omega) dG(\omega) \right] \qquad (13)$$

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

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

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

with

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

and

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

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

B.4 Robustness: Alternative Specifications

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

B.4.1 Gender Revolution through Female Labor Supply Shocks

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

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

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

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

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

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

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

B.4.2 Imperfect Substitutability

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

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

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

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

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

B.4.3 Leisure Complementarity

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

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

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

B.4.4 Non-Unitary Household Model

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

production. The household problem of men is

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

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

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

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

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

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

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

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

B.4.5 Task-Based Model

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

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

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

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

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

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

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

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

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

B.4.6 Gender Specific Frisch Elasticity of Labor Supply

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

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

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

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