Convergence Almost Nowhere: Employment Volatility and the Family Channel (Preliminary)

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September 23, 2023

Abstract

Countries with high female labor force participation exhibit larger differences in cyclical labor volatility for men and women. While gender convergence occurs across many dimensions, such as hours and pay, the cyclicality of employment and hours diverges. We model this fact as the result of a within-family insurance mechanism: men and women sort into jobs with different business cycle risks in order to smooth out family consumption over the business cycle. Calibrating the model, we estimate the contribution of this insurance mechanism to the gender pay gap and household consumption volatility over the business cycle.

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1 Introduction

Over the past 50 years, gender convergence has occurred along many dimensions including employment, hours, occupational choice, and pay in the United States (Goldin 2014). However, there is significant heterogeneity across developed countries in terms of the level and the growth rate of female labor force participation (Olivetti and Petrongolo (2016)). In this paper, we show that although gender convergence occurs along many dimensions, men and women's cyclical volatility of employment diverge from each other over time, where the cyclical volatility of employment is measured as in Doepke and Tertilt (2016). We observe larger gender differences in cyclical volatility of employment in countries with low gender hours gap (that is, the difference between average female hours per capita and average male hours per capita).

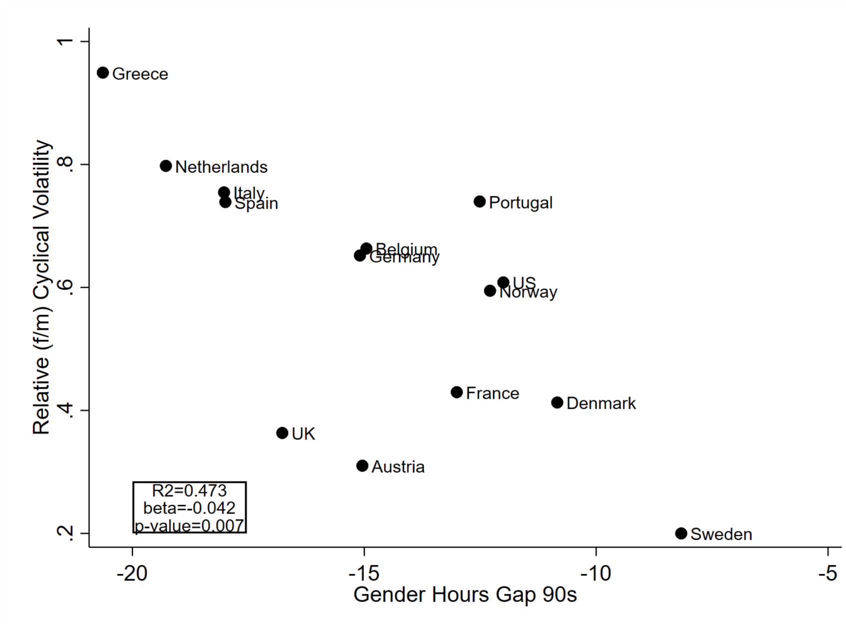
We argue that this observation stems from an active family insurance mechanism. As noted earlier by Lundberg (1985) and more recently by Ellieroth (2019), married women act as family insurers by either entering the labor market when their husbands lose jobs, or by increasing their hours if already working. Bardóczy (2020) shows that this type of spousal insurance substantially mitigates the volatility of aggregate consumption. We argue that this type of insurance through labor supply adjustment becomes less relevant in countries with low gender gaps in employment because many women are already working full time. Hence, women instead sort into safer, less cyclical jobs in order to stabilize household income in economic downturns. In this paper, we show that part of the differences in the gender pay gap across countries can be explained by this sorting. We also show that this mechanism smooths aggregate consumption relative to an economy where gender sorting does not increase as female labor force participation rises.

Our paper uncovers a new mechanism of family insurance through gender differences in the cyclical properties of labor supply. We also contribute to the literature by highlighting cross-country differences in gender gaps and showing how these differences result in different types of family insurance: added worker effect vs. industry sorting and how sorting in turn contributes to the persistence of the gender pay gap in many countries that otherwise appear highly gender-equal.

2 Facts

In Figure 1, we show that countries like Sweden which had low levels of the gender hours gap in the 1990s exhibited larger gender differences in cyclical volatility of hours over the period 1995-2019.[1] We further show that the cross-country fact is primarily driven by the behavior of married women. Figure 2 shows that gender differences in cyclical volatility among married people are correlated with the gender hours gap but gender differences among single people are not. In other words, it is mostly married women who sort into safe jobs, pointing towards a family insurance motive for sorting. Coskun and Dalgic (2023) shows that in the US, industry sorting is pronounced among couples too; the majority of couples are working in industries with different cyclical properties. Moreover, Figure 2 shows that overall cyclical volatility of married couples is lower in countries with low gender hours gap whereas the cyclical volatility of unmarried people is not correlated with gender hours gap.

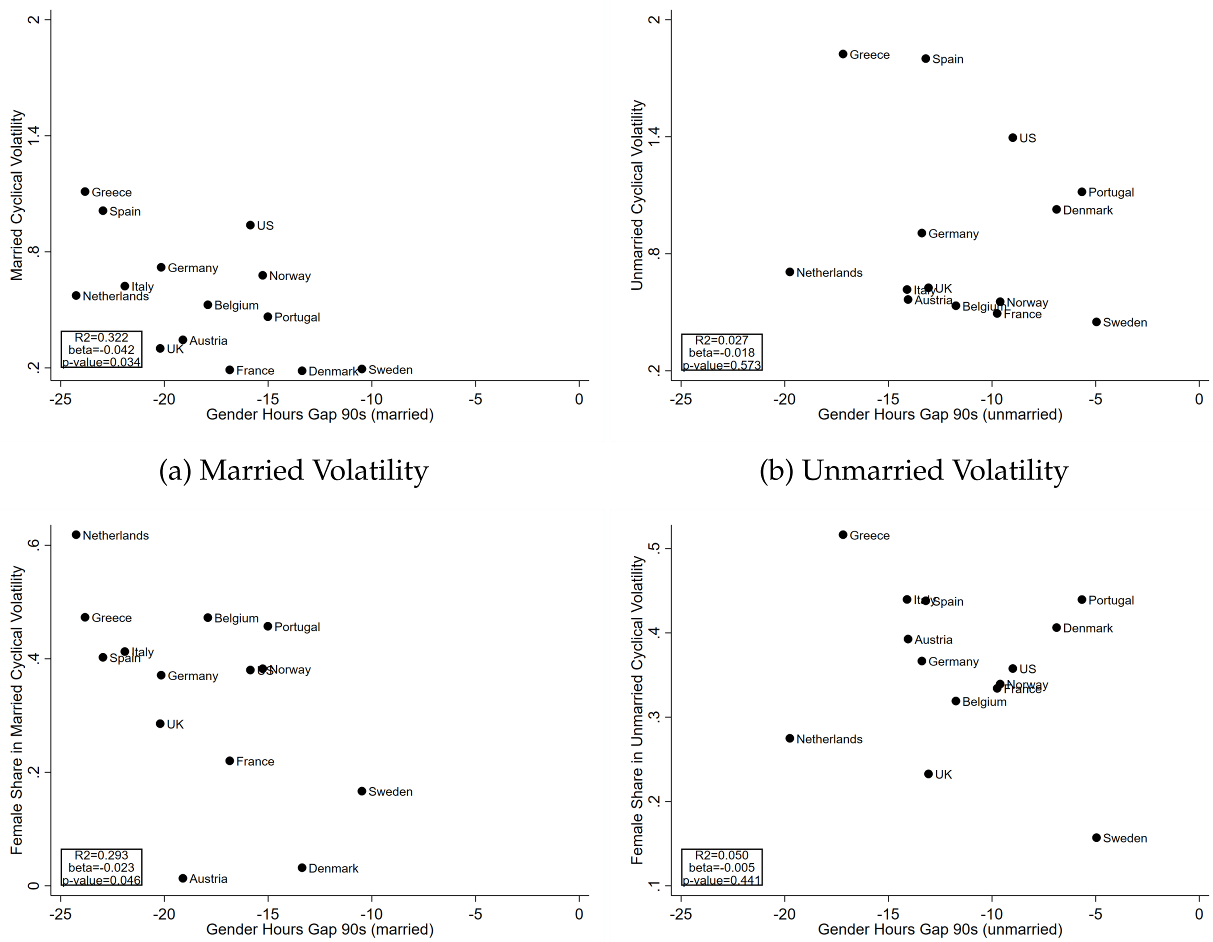
Figure 1: Relative Cyclical Volatility



Notes: Data source is EU-LFS, all individuals between age 25-54. Gender hours gap is defined as the difference between average female hours (per capita) and average male hours (per capita) over the period 1995-1999. Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual of men's and women's hours on the HP-residual of GDP over the period 1995-2019.

[1] See Figure 15 for the evolution of gender gap in these countries.

Figure 2: Marital Status and Cyclical Volatility



(a) Married Volatility

(b) Unmarried Volatility

(c) Married Women's Volatility

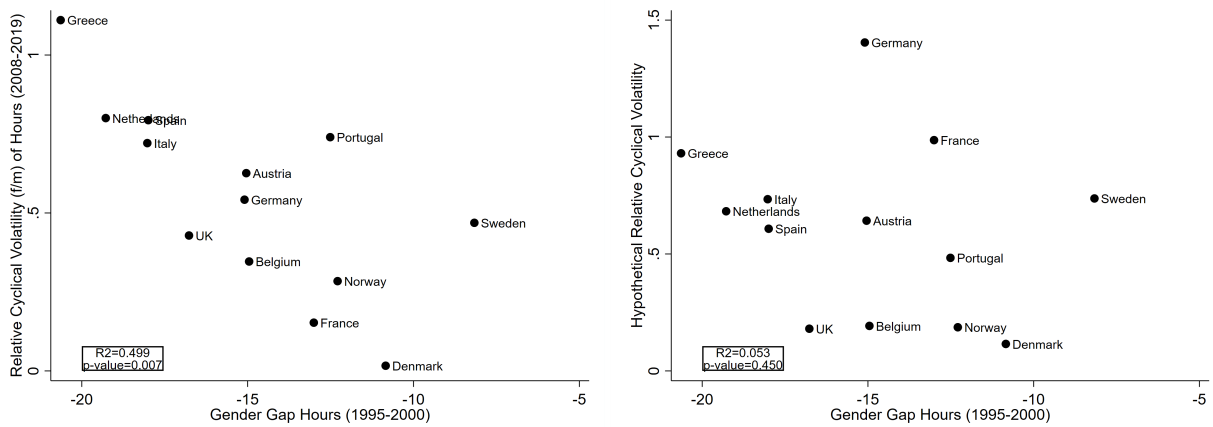
(d) Unmarried Women's Volatility

Notes: Data source is EU-LFS, all individuals between age 25-54. Gender hours gap is defined as the difference between average female hours (per capita) and average male hours (per capita) over the period 1995-1999. Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual of men's and women's hours on the HP-residual of GDP over the period 1995-2019.

We next analyze how men and women sort into different industries in different countries. The importance of industry composition in determining the cyclicality of the gender unemployment gap is previously noted by Albanesi and Şahin (2018). We then calculate a hypothetical relative cyclical volatility assuming the same fraction of women in each industry across countries to understand if the relationship in Figure 1 is driven by differences in the cyclicality of different industries across countries. We follow the aggregate industry classification as in Alon et al. (2021) and calculate the female share of hours in each industry and country over the period 2008-2019. We then recalculate the aggregate male and female hours as the sum of industry hours where the female shares are replaced by EU-average shares rather than country-specific ones.

In Figure 3, we show that the relationship between gender differences in cyclical volatility and the gender hours gap disappears completely when we assign the same gender industry sorting to all countries. In other words, if all countries had the same gender sorting across industries, relative cyclical volatility would not be correlated with the gender hours gap, showing that gender industry sorting is the driving mechanism of the observed fact.[2]

Figure 3: Role of Industry Gender Shares



(a) Data

(b) Composition Adjusted Data

Notes: Data source is EU-LFS, all individuals between age 25-54. Gender hours gap is defined as the difference between average female hours (per capita) and average male hours (per capita). Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual of men's and women's hours on the HP-residual of GDP over the period 2008-2019.

We then ask to what extent women's sorting into safer jobs can explain the differences in the gender pay gap across countries. We investigate the lifetime income profiles of safer and riskier jobs using the EU Labor Force Survey. We expect that safer jobs pay less because one amenity of these jobs is lower income risk and less correlation with the business cycle. It is perhaps surprising that countries like Italy, with a large gender gap in hours that might suggest lingering gender norms around work and the division of household duties, have some of the smallest gender pay gaps in Europe, while countries like Denmark and Sweden have comparatively large gender pay gaps (Olivetti and Petrongolo (2008)). Sorting into safe jobs is one way to rationalize this fact.

[2]See Figure 18 for additional measures of industry sorting.

We also analyze if low relative cyclical volatility in low gender gap countries is driven by men or women; i.e. whether sorting is solely driven by men or women or both. Figure 17 shows that both women's and men's cyclicality relative to total cyclicality is correlated with the gender gap: negatively for women and positively for men. This observation tells us that the sorting happens jointly by men and women. In low gender gap countries, not only do women sort into safe jobs, but also men sort into riskier jobs.

Additionally, we ask if our main fact is driven by motherhood. It is possible that mothers sort into jobs with better amenities like parental leave and hours flexibility which happen to have lower cyclicality (e.g. the government sector). Figure 16[3] shows that we do not find any evidence supporting this hypothesis. Although, nonmothers have higher cyclicality than mothers in many countries, our main correlation holds true especially for relative cyclical volatility of nonmothers to men.

Finally, by using the longitudinal dimension of the CPS data, we look at the relationship between riskiness of a job and returns to experience as a potential mechanism explaining the existing gender wage gap. Indeed, Figure 19 verifies that returns to experience is higher in industry-occupation pairs which exhibit higher riskiness measured by coefficient of variation of earnings and probability of being fired. Women who sort into safe jobs cannot benefit from high returns to experience and this can partially explain gender differences in earnings.

3 Model

To answer these questions, we build a model similar to Alon et al. (2020) but with endogenous industry choice over two industries, one safe and one risky, with different expected income profiles and risk. The model features singles and married couples. Each period agents receive at most one job offer and decide whether to reject the offer, accept and work part time, or accept and work full time. Married couples make labor supply and consumption decisions to maximize joint utility. Gender differences in labor supply occur for three reasons. First, there is an exogenous gender pay gap that can capture things like gender discrimination in the labor market. Second, men and women differ in the amount of disutility they get from working. Third, there can potentially be systematic gender differences in human capital across sectors in the model.

[3]EU-LFS does not allow us to identify motherhood for many of the countries (especially Nordic countries) in our sample. Hence, the correlations we document here are suggestive with available countries.

Agents differ in terms of gender, marital status, wealth, and human capital in the two sectors. In recessions, job finding rates and layoffs in the risky sector fall more than in the safe sector. We then study how gender sorting between the two sectors varies as the steady state level of the female labor force participation rate rises because of either reduced discrimination (smaller exogenous gender pay gap) or changes in social norms that reduce women's disutility from working. Because human capital accumulation is endogenous and occurs more quickly in the riskier sector (Figure 19), this can have counterintuitive effects on the observed gender pay gap. Marginal women who are induced to work because of these changes sort into safer jobs, so the gender pay gap conditional on working can actually grow even as discrimination falls. We then use the model to explore a counterfactual where industry sorting remains the same as women's labor force participation rate increases and quantify how much smaller the gender pay gap would be in this case. We will also explore how important this gender sorting into industries is for the stabilization of household consumption to quantify the importance of this insurance. Finally, we do policy counterfactuals to explore how greater generosity of unemployment insurance impacts gender industry sorting and ultimately the gender pay gap and consumption volatility.

3.1 Simple Model

In the simple static model, we show why it makes sense for couples to sort into different type of jobs (safe and risky) and how these choice will change along the dimension of female labor force participation.

Consider the simple household model

$$V(h^m, h^f) = \max_{\ell^g, s^g, c^g} \ \mathbb{E}\ \left[(1-\lambda)u(c^m) + \lambda u(c^f) - \phi\, \ell^f\right] \tag{1}$$

subject to:

$$\begin{aligned} c^f + c^m &= y(h^m, \ell^m, s^m) + y(h^f, \ell^f, s^f) \\ y(h^g, \ell^g, s^g) &= \ell^g \cdot (\omega^g h^g_s \epsilon_s) \\ \ell^g &\in \{0, 1\} \\ s^g &\in \{S, R\} \end{aligned}$$

where sector of employment differs only by the riskiness of income. Specifically, we assume sector shocks are independent with $\mathbb{E}(\epsilon_s) = 1$ and $\text{Var}(\epsilon_s) = \sigma_s^2$ where $\sigma_R^2 > \sigma_S^2$. ω_m is normalized to one so that ω_f captures a female-specific wage penalty relative to men. In this model, men always work but women may or may not participate. There is also a utility cost (ϕ) associated with female participation.

Order of events:

1. Households born with iid human capital $h_s^m \sim F$, $h_s^f \sim F$
2. Make labor supply and sector of employment choices
3. Realize earnings shocks, make consumption decision.

Let $Y(s^m, s^f, \ell^f)$ denote household income for couple with sector of employment choices s^f and s^m, with mean and variance given by

$$\mathbb{E}\left[Y(s^m, s^f, \ell^f)\right] = h_s^m + \omega^f \ell^f h_s^f \tag{2}$$

$$\text{Var}\left[Y(s^m, s^f, \ell^f)\right] = (h_s^m)^2 \sigma_{s^m}^2 + \ell^f \cdot \left[(\omega^f h_s^f)^2 \sigma_{s^f}^2 + 2(\omega^f h_s^f)(h_s^m)\text{cov}\left(\epsilon_{s^f}, \epsilon_{s^m}\right)\right] \tag{3}$$

In this framework, even if it is always individually optimal to work in the safe sector, due to the covariance term, households might prefer to send one person to the risky sector if the incremental increase in the variance coming from being employed in the risky sector is smaller than the incremental increase in the covariance term. However, it is not clear why it should be the men who go to the risky sector.

Assume gender wage gap $\omega^f < 1$ and one-dimensional heterogeneity in individual human capital, $h^g \sim F$ (e.g. the same in both sectors, no comparative advantage). The human capital distribution are also iid across gender, so men and women are inherently the same. The household member that enters the risky sector will be the one with lower human capital, since they add less volatility.

With a utility cost on female participation, it will be generally the men who adds less volatility *endogenously* through female selection into work. In other words, while in the population men and women are the same, among working couples the women will generally have more human capital than the men because of the participation cost. Furthermore, women with low human capital husbands are more likely to enter since the marginal utility of increasing family income through wife working is greater. Hence in our model, among working couples, it will generally *endogenously* be the case that $h_m/h_f < 1$ within the couple, and so men will select into the risky sector rather than their wives.

Of course, there can also be some couples where both are working, but the husband's human capital is sufficiently high relative to his wife that they choose $\{S, R\}$. In this case, if we raise the exogenous gender wage gap, female earnings will rise relative to their husband and some of these $\{S, R\}$ couples will reallocate to $\{R, S\}$ couples. (The first one denotes the sector choice of husband and the second one is for wife).

Figure 4 below demonstrate the economic relationships when we vary the exogenous gender wage gap, ω^f, to generate different participation levels across countries.

In particular, we use a CRRA utility function

$$u(c) = \frac{c^{1-\rho} - 1}{1 - \rho}$$

and assume sectoral shocks are multivariate lognormal,

$$\epsilon \sim \text{LN}\left(\begin{bmatrix} -\frac{\sigma_R^2}{2} \\ -\frac{\sigma_S^2}{2} \end{bmatrix}, \begin{bmatrix} \sigma_R^2 & 0 \\ 0 & \sigma_S^2 \end{bmatrix}\right)$$

so that $\mathbb{E}(\epsilon_s) = 1$ and $\text{Var}(\epsilon_s) = \sigma_s^2$, where $\sigma_R^2 > \sigma_S^2$.

The parameters used in the calibration are in Table 1.

Table 1: Parameters for Simple Model Simulation

Parameter	Value
λ	0.50
ϕ	1.00
ρ	1.80
σ_R^2	0.25
σ_S^2	0.15
h^g	$\sim \text{LN}(-\frac{1}{2}\sigma_h^2, \sigma_h^2) \quad \sigma_h^2 = 1$
ω_f	$\in [0.25, 0.90]$

.

Figure 4: Female Labor Force Participation

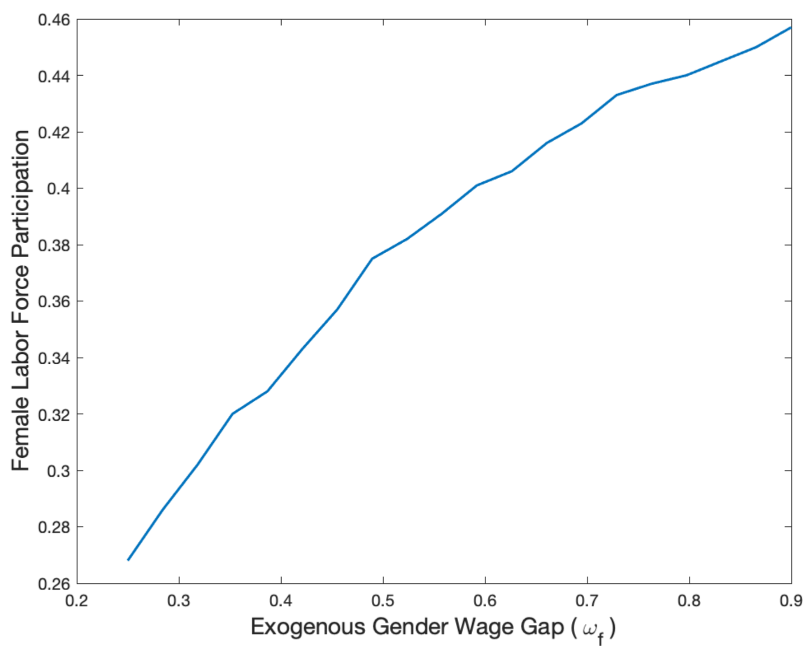
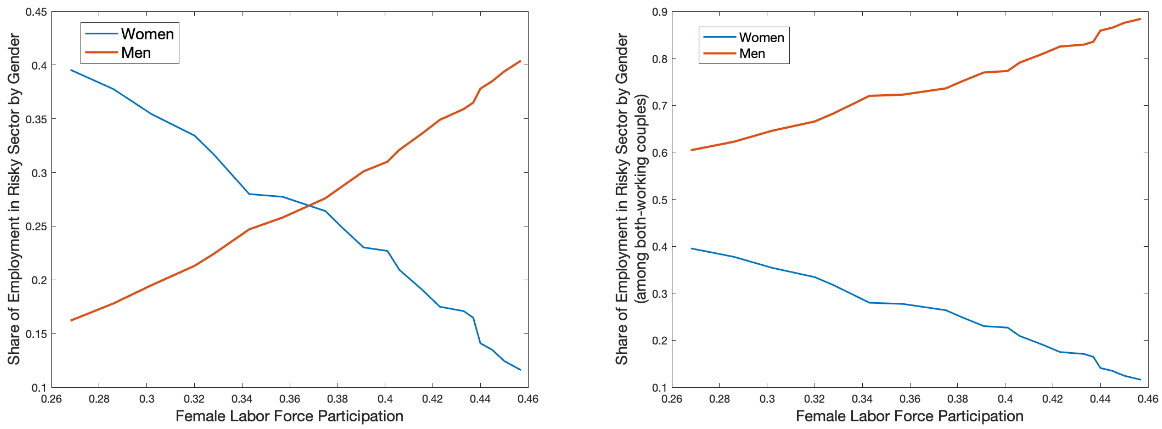


Figure 5 shows that when we raise the exogenous gender wage gap (ω_f), the fraction of men who work in the risky sector increases as opposed a decrease in fraction of women who work in the safe sector. Among both working couples, it is always the case that there are more men who work in the risky sector even at low female participation levels. Women who work even when the gender wage gap is large (small ω_f) are the ones with high human capital hence who adds higher earnings volatilty if they worked in the risky sector.

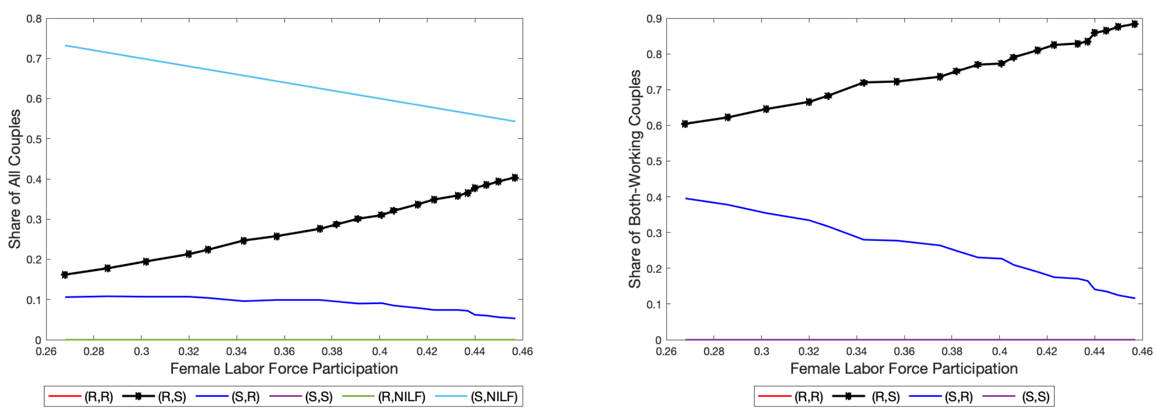
Figure 5: Share of Workers by Gender



(a) All Couples (b) Both Working

Figure 6 shows the share all couple types in the economy. Note that there are no couples where both are in the risky or both are in the safe sector. As discussed above, it always makes sense to diversify sector choices as long as the sector shocks are not perfectly correlated.

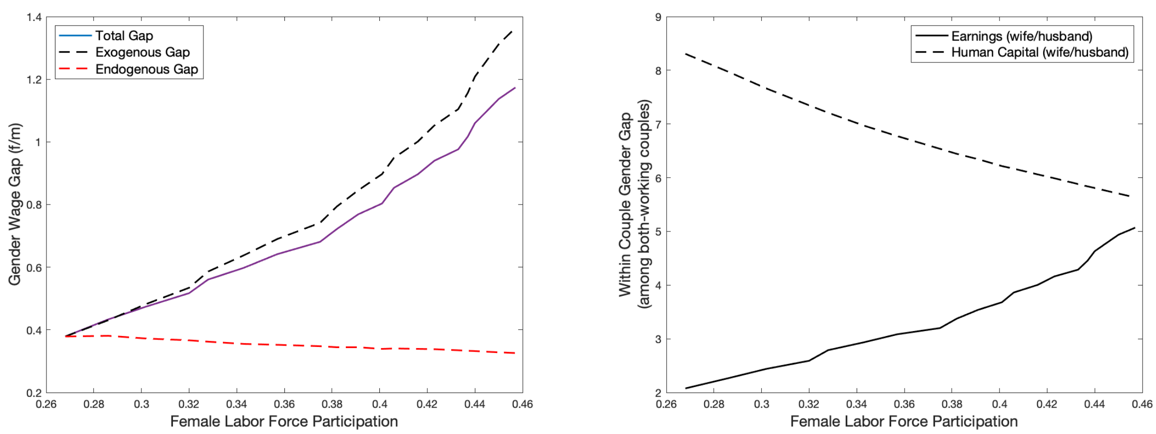
Figure 6: Share of each HH Configuration



(a) All Couples (b) Both Working

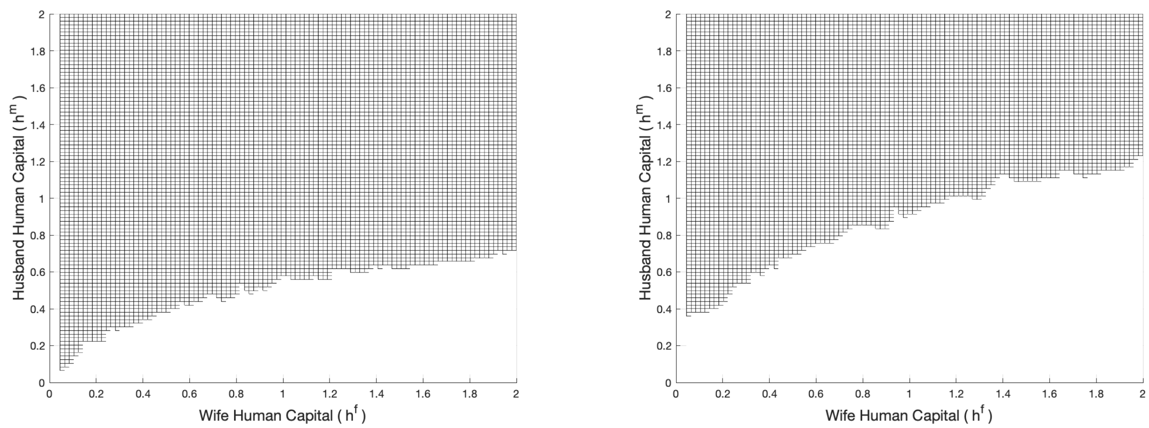
Figure 7 shows the evolution of gender wage gap with female participation. The left panel of Figure 7 is mechanical as the way that we increase female participation is through decreasing the exogenous gender wage gap (increasing ω_f). However, the right panel of Figure 7 is interesting. Note that among both working couples, within couple earnings ratio (wife/husband) is larger than 1 and it is increasing with the increase in female participation. At high gender wage gap levels, women who work are the ones with high human capital and/or the poorest husbands. In other words, the wives of rich men do not participate in the labor market. Due to this selection into work, within couple earnings ratio (wife/husband) is larger than 1, in line with Alon, Coskun, and Doepke (2020). Figure 8 shows the selection in a more clear way. Women who participate in the labor market are the ones with high human capital and a poor husband. However, the decrease in the exogenous gender wage gap changes the decision threshold of women by inducing marginal women to enter into the labor market. However, on average wife's human capital is larger than husband's human capital and this gap is shrinking when participation rises and earnings gap increases.

Figure 7: Gender Wage Gap



(a) All Couples (b) Both Working

Figure 8: Selection into Female Labor Force Participation, by Family Type



(a) Lower Female Participation (b) Higher Female Participation

Notes: White shaded areas correspond to households where wives are participating in the labor market. Dark shaded areas are households where women are not in the labor force. Comparing panel (b) to panel (a) captures changes in participation following a rise in the exogenous component of the gender wage gap.

3.2 Extension: Sector Specific Human Capital (SSHC)

In the current model, some household types never occur, like $\{R, R\}$ couples or $\{R, NILF\}$ couples, etc. This is by design to highlight our main mechanism.

To show our mechanism is still consistent with a model in which all types occur, we introduce sector specific human capital. In particular, we assume human capital has a general component–as in the simple model above–and a sector specific component, $z \sim \mathcal{G}$, such that an individual's human capital in sector s is given by

$$h_s = h \cdot z_s$$

where $\mathbb{E}[z_s] = 1$ and $\text{Var}(z_s) = \sigma^2$. Note that sector specific human capital is also symmetric and iid across sectors and genders. As the simple model above, the only inherent difference between the sectors is riskiness (volatility) of income.

For our result to be preserved, we need the common individual-specific component of human capital, $h \sim F$, to be the dominant source of variation in human capital. This insure the dynamics discussed in earlier sections are preserved. Without the common, selection on women into employment will strongly favor those who enter the safe sector. As a consequence, as participation rises, subsequent cohorts of women favor risky employment and hence do not favor the rise of $\{R, S\}$ households, as we see in the data. Rather, there is a rise in $\{S, R\}$ households, as the last women to enter employment are those with comparative advantage in risky employment and husbands and lower income husbands in safe employment.

One way this strong selection on female comparative advantage could be moderated is if human capital variation is predominantly in the individual component common to both sectors. This is what we do here. The presence of the sector specific comparative advantage is just strong enough to allow some individuals to accept the additional volatility of income and select into risky employment. This is what allows all households types to exist in equilibrium and still preserve our main mechanism.

Another way we could moderate the strong selection on female comparative advantage (in the absence of a common component of human capital) is by having a wage premium in the risky sector. This would also induce more men into the risky sector. While such a wage premium for risky employment seems reasonable (and is something we allow for in our quantitative and empirical work below), we have shown that such a feature is not necessary for our mechanism to operate.

Finally, note that rather than modelling the log-linear function of a general and sector-specific component of human capital, we could have just generated two draws of human capital which were highly correlated. In other words, generate sector specific human capital with a correlation. In this case, the correlation would serve the role of the common component h in the formulation above. While the two approaches are virtually equivalent, the advantage of the one above is that it will give rise to log-linear earnings functions in our model that can be used to calibrate things. More on this below.

The new parameter to be set is σ_z. Table 2 lists parameters for these simulations. Figures 10 through 14 shows the counterparts of Figure 4 through Figure 7 when we introduce sector-specific human capital in the simple model. In this version of the model, we can observe all household types (Figure 12) including (S,S) and (R,NILF).

3.3 Quantitative Dynamic Model

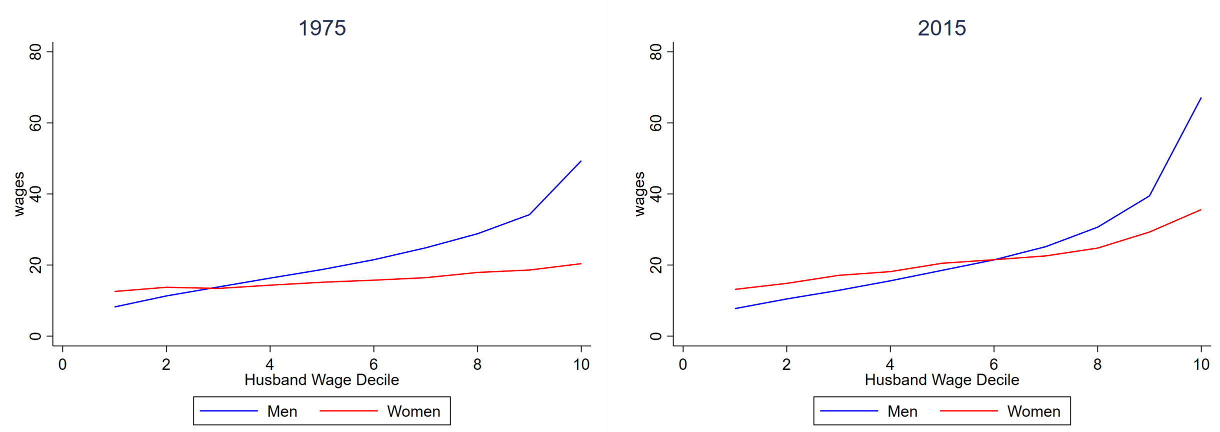
There are several possible ways that household can insure themselves against business cycle shocks. In the simple model, we only considered job choice as the possible insurance mechanism. However, precautionary savings and human capital accumulation are also potentially important channels through which household can insure themselves. In order to understand the role of job choice as opposed other possible mechanisms, we build a dynamic model. In the quantitative model, we include idiosyncratic earnings volatility as well as aggregate recession risk. Moreover, we incorporate search frictions together with the job choice. We allow households to accumulate assets and life cycle human capital. Finally, we also include government transfers as a potential mechanism which can be important in cross-country comparison. The questions that we answer in the quantitative model are as follows. First of all, we quantify the role of family insurance mechanism through job choice in explaining cross-country differences in relative cyclical volatility. Second, we quantify the importance of this channel for consumption smoothing in different countries. Third, we quantify the endogenous gender wage gap due to pay differences and differences in returns to experience across different sectors. Finally, we analyze the role of unemployment insurance for determining the job mix of couples.

4 Model Fit

Using CPS data, we identify two groups of industries, which we classify as safe or risky based on their cyclical volatility of employment as in Coskun and Dalgic (2023). We then measure the composition of couples across types of jobs (Figure 13). Consistent with the predictions of the static model (Figure 12), the share of "Husband risky, wife safe" couples rises as female labor force participation rises. This is now the largest of the six main couple types at around 30% of all couples, whereas the share of "Husband risky, wife not in the labor force" couples has fallen from around 45% of all couples to 20%.

Additionally, we look at the within family gender wage gap following Alon, Coskun, and Doepke (2020) and show that the fraction of couples where the wife outearns her husband increased over time (Figure 9). On average, among couples who are both working, the gender wage ratio is above 1, indicating the sorting of women into the labor force consistent with Figure 8. That is, women with higher human capital than their husbands tend to select into the labor force.

Figure 9: Within Family Relative Wages



(a) 1975 (b) 2015

Notes: Data source is CPS, all matched couples between age 25-54 who work fulltime. Wages represents hourly levels in 2015 $.

The current model specification of the wage also gives rise to a tractable earnings function. In the full model with sector specific human capital (and adding sector-specific wages, w_s) we get for an individual i of gender g in sector s

$$ln(y_{i,t}) = w_s + \omega^g + h_i + z_{is} + \epsilon_{st}$$

where the sectoral components are subject to selection, as per the model above. We will estimate such a specification from microdata to complement our model.

5 Conclusion

In this paper, we show a novel fact that men and women diverge from each other in terms of cyclical volatility of employment as female labor force participation rises. We show that this pattern is particularly pronounced among married people and cannot be explained by differences in industry cyclicality across countries. We provide an explanation for this fact, arguing that it stems from a family insurance mechanism. Individuals in couples insure one another through job segregation. As female earnings go up, women entering the workforce sort more into safe jobs. We argue that this mechanism sheds light on the discussion about "gender convergence". If women give up higher earnings to provide insurance, there are implications for the aggregate, endogenous gender wage gap. Furthermore, cross-country variation in employment and consumption volatility can be explained by the extent of this family insurance mechanism.

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A Appendix

Table 2: Parameters for All HH Types Model Simulation

Parameter	Value
λ	0.50
ϕ	0.25
ρ	1.80
σ_R^2	0.20
σ_S^2	0.15
h^g	$\sim \text{LN}(-\frac{1}{2}\sigma_h^2, \sigma_z^2, \sigma_h^2) \quad \sigma_h^2 = 1$
z_s^g	$\sim \text{LN}(-\frac{1}{2}\sigma_z^2, \sigma_z^2) \quad \sigma_z^2 = 0.022$
ω_f	$\in [0.25, 0.90]$

.

Figure 10: Female Labor Force Participation with SSHC

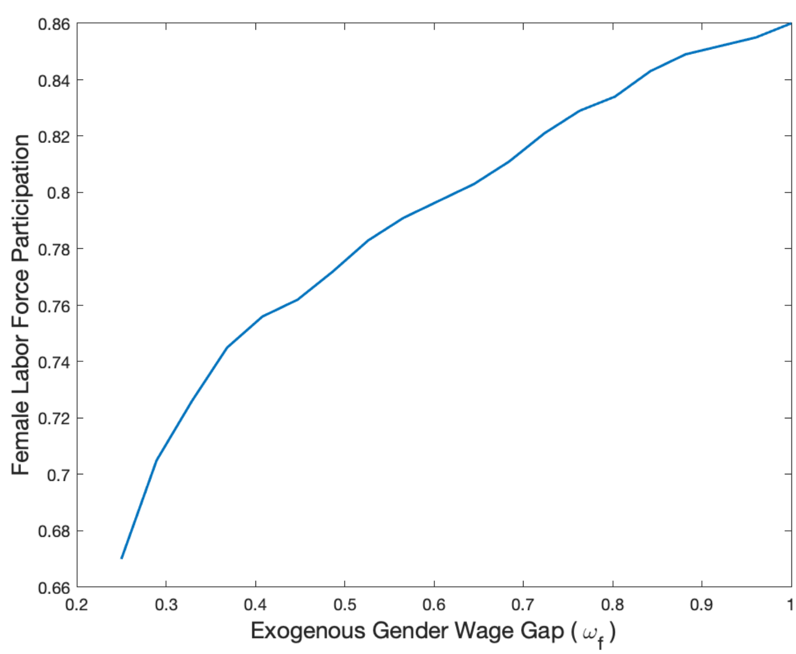
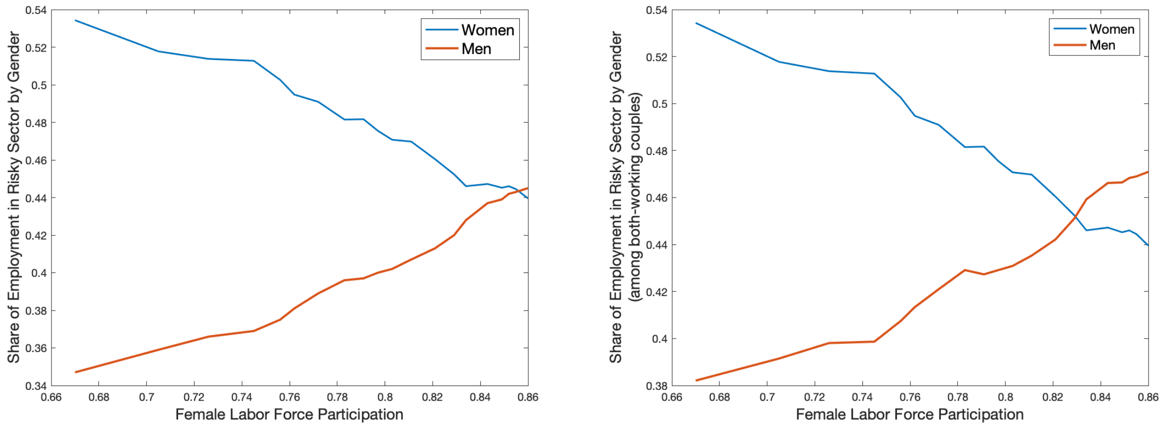


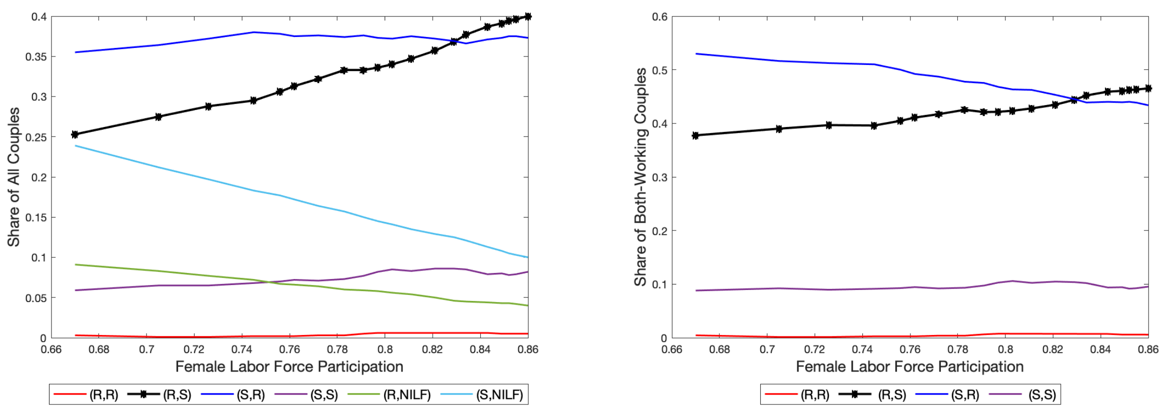
Figure 11: Share of Workers by Gender with SSHC



(a) All Couples

(b) Both Working

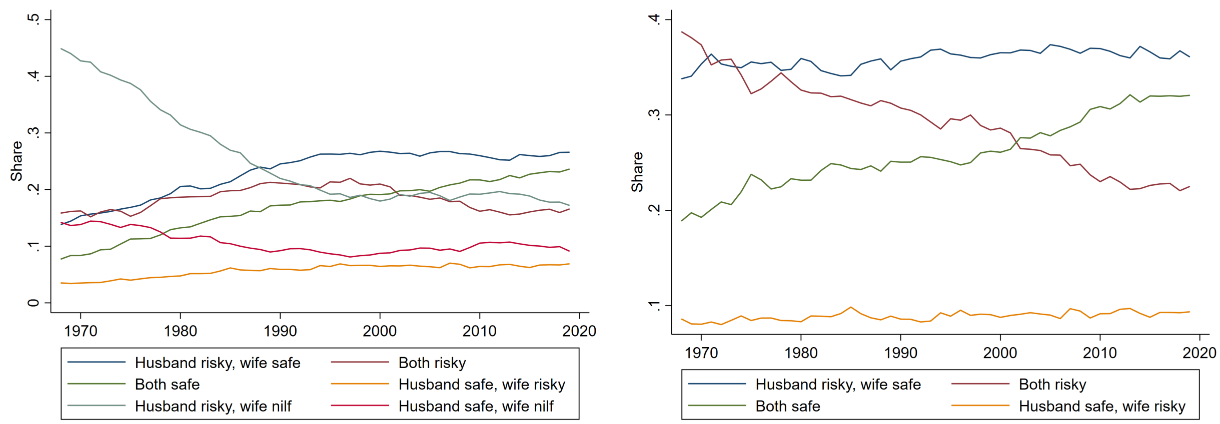
Figure 12: Share of Couples with SSHC: Model



(a) All Couples

(b) Both Working

Figure 13: Share of Couples: Data

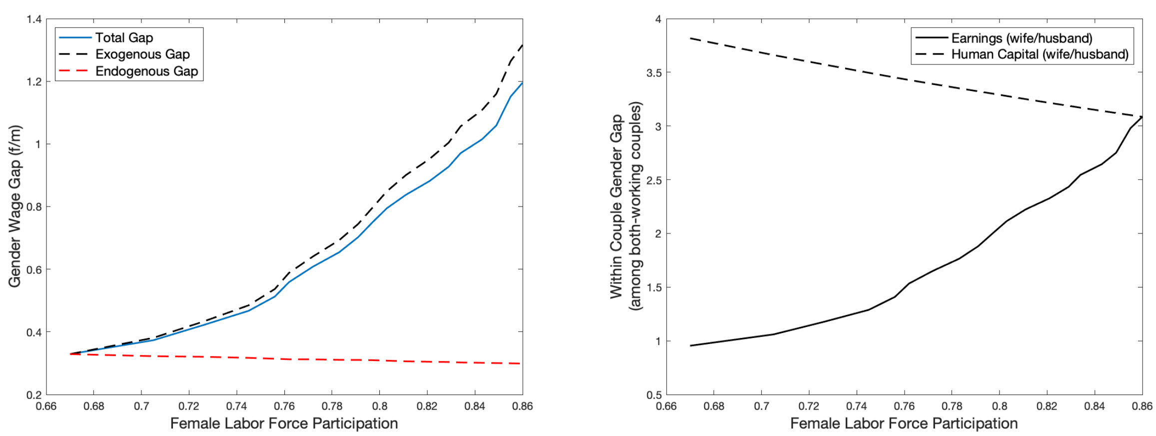


(a) All Families

(b) Both Working

Notes: Data source is CPS. Following the safe-risky industry definitions in Coskun and Dalgic (2023), we split couples based on industry of employment and compute the share of couples of each type.

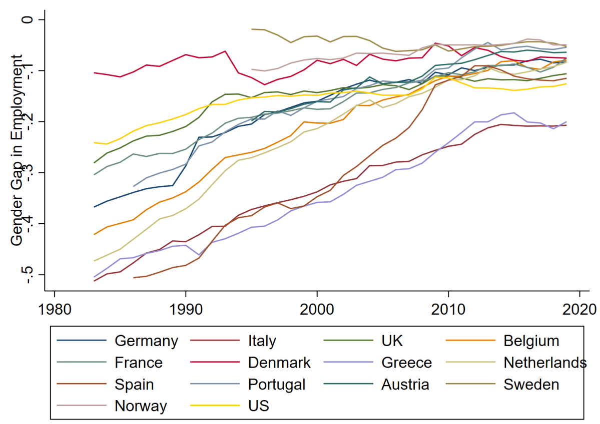
Figure 14: Gender Wage Gap with SSHC



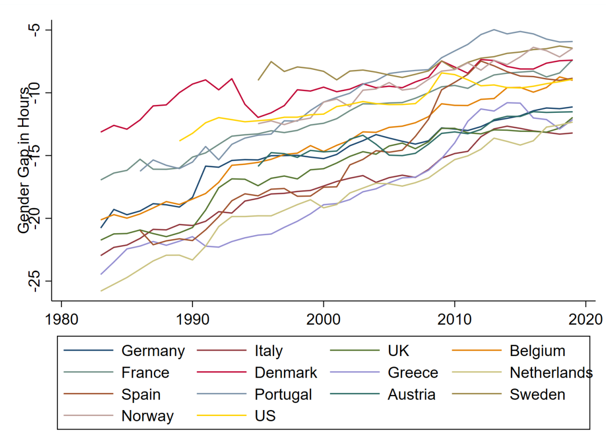
(a) All Couples

(b) Both Working

Figure 15: Gender Gap in Employment and Hours



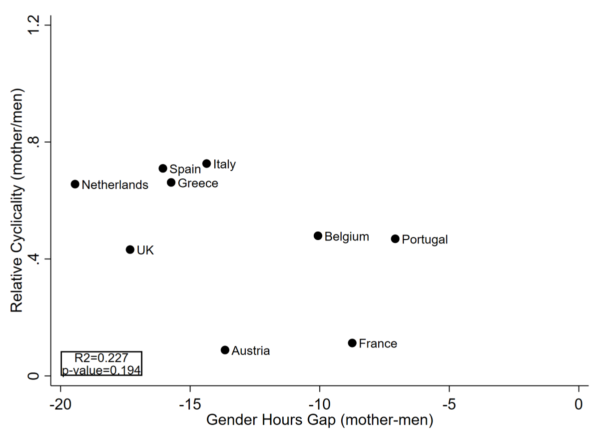
(a) Employment



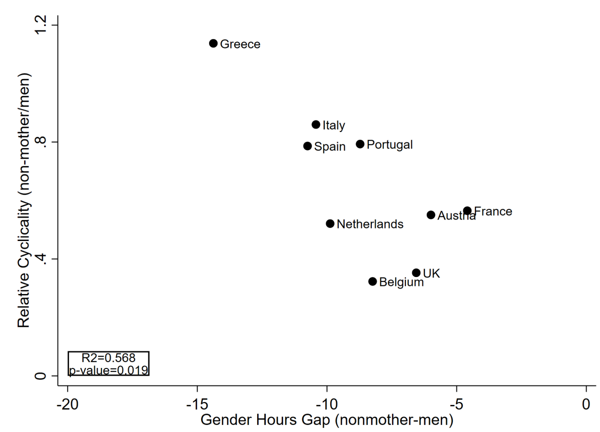
(b) Hours

Notes: Data source is EU-LFS, all individuals between age 25-54. Gender employment (hours) gap is defined as the difference between average female employment (hours) (per capita) and average male employment (hours) (per capita).

Figure 16: Relative Cyclical Volatility of Mothers and Nonmothers



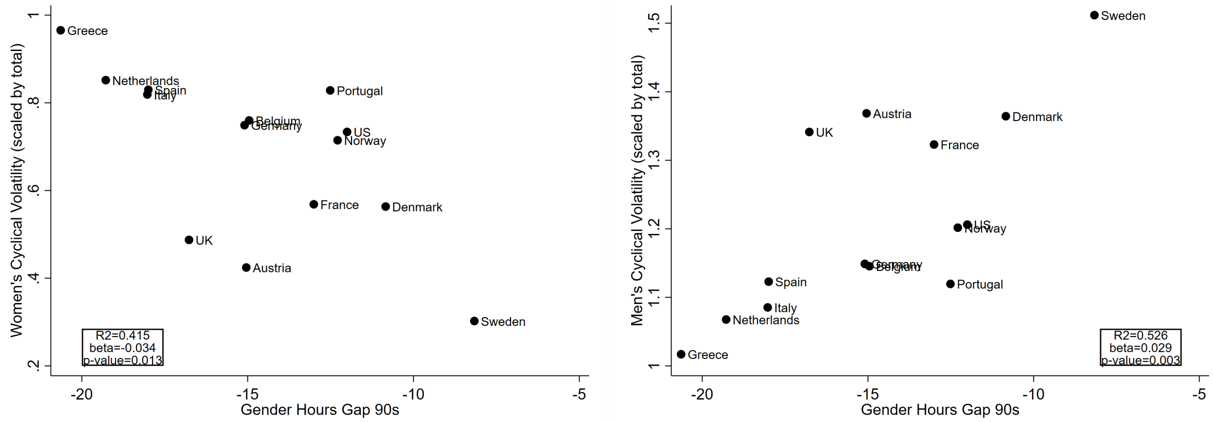
(a) Mothers



(b) Non Mothers

Notes: Data source is EU-LFS, all individuals between age 25-54. Gender hours gap is defined as the difference between average hours of mothers (and nonmothers) (per capita) and average male hours (per capita). Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual of men's and women's hours on the HP-residual of GDP over the period 1998-2019.

Figure 17: Cyclical Volatility of Men and Women

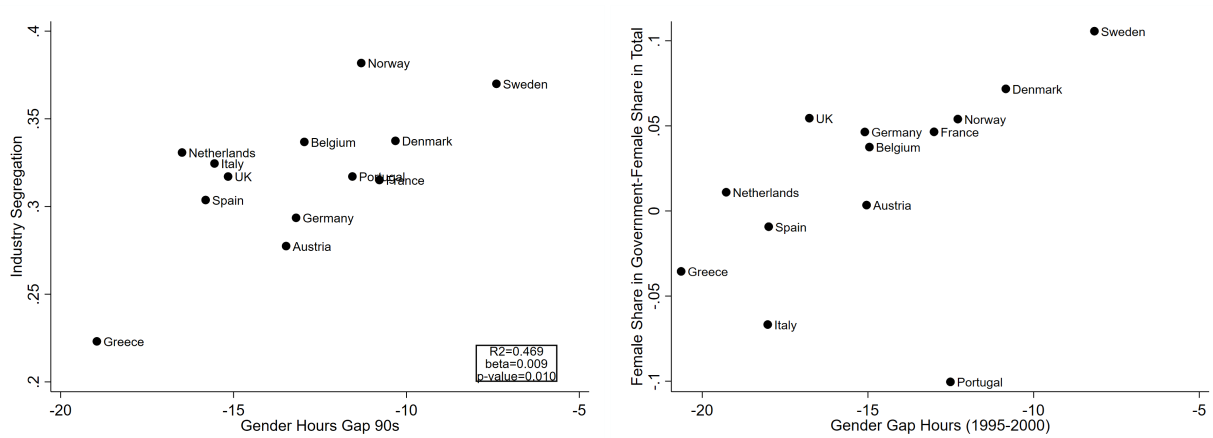


(a) Women

(b) Men

Notes: Data source is EU-LFS, all individuals between age 25-54. Gender hours gap is defined as the difference between average female hours (per capita) and average male hours (per capita). Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual of men's and women's hours on the HP-residual of GDP over the period 1995-2019.

Figure 18: Industry Segregation

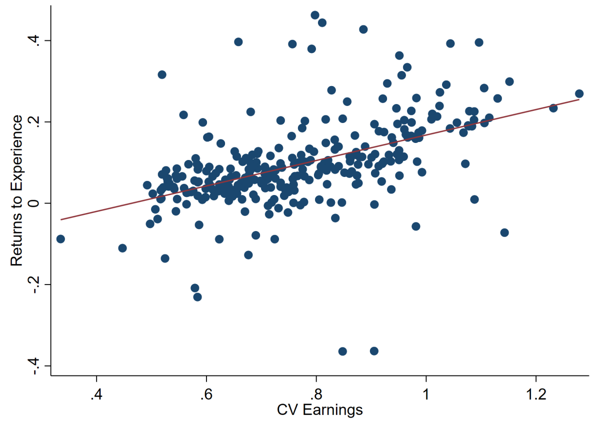


(a) Industry Distribution

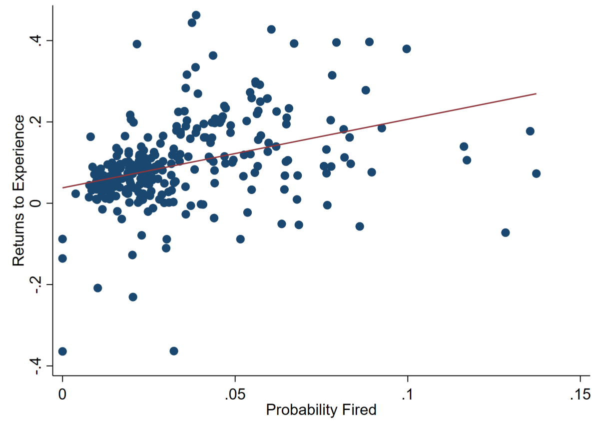
(b) Government

Notes: Data source is EU-LFS, all individuals between age 25-54. Gender hours gap is defined as the difference between average female hours (per capita) and average male hours (per capita). Left panel compares the industry distribution of female and male labor force. 0 means both genders are distributed across sectors in the same way, 1 means, sectors are completely gender segregated. Right panel provides an example safe sector "government" and show that in low gender gap countries women are over sorted into government, whereas in high gender gap countries they are under sorted.

Figure 19: Riskiness and Returns to Experience



(a) Coefficient of Variation of Earnings



(b) Probability of being Fired

Notes: Data source is CPS. Returns to experience is measured as the annual change in earnings conditional on keeping employment.