# Gender Segregation in Occupations: The Role of Tipping and Social Interactions*

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**Abstract**

This paper explores how the labor market responded to the entry of women into occupations and documents that the dynamics of occupational segregation are highly nonlinear and exhibit "tipping"-like patterns. Occupations experience discontinuous declines in male employment growth at candidate tipping points ranging from 30 to 60 (12 to 25) percent female in white (blue)-collar occupations from 1940 to 1980. These patterns are consistent with a simple framework based on Schelling's (1971) social interaction model where tipping results from male preferences toward the fraction female in their occupation. Supporting the model, tipping points are lower in regions where males hold more sexist attitudes. Alternative explanations such as omitted variables, changes in production technology and learning fall short in explaining the full set of empirical observations.

## 1 Introduction

The large-scale movement of women into formal employment marks one of the most significant labor market changes of the last century. Despite this increase in female representation in the labor force, occupations continue to be segregated along gender lines (Blau, Simpson and Anderson, 1998). A large body of research documents the rise in female labor force participation and the resulting impact on female labor market outcomes. However, little is known about the dynamics of the process through which occupations and firms responded to the entry of women into the labor force. This paper explores the dynamics of occupational segregation by gender over the last century. More specifically, I assess whether the observed patterns of occupational change are consistent with predictions from a Schelling-type social interaction model. Learning about how

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occupational segregation evolved historically may allow us to better understand why occupational segregation persists today, an observation which has been shown to be important for explaining wage differentials between men and women (Groshen, 1991, Hirsch and Macpherson, 1995, Bayard et al, 2003).

With the rise in female labor force participation, the majority gender share in a relatively large number of occupations have changed sex over time. A number of studies have suggested that once an all-male occupation receives a large influx of women, the occupation often becomes virtually all-female, and this process rarely reverses (Strober and Arnold, 1987). Common examples of occupations which switch from being predominantly male to predominantly female include bank tellers, secretaries, teachers and sales positions. However, it is less well known how occupational segregation as a process operates.

As suggestive evidence that the dynamics of occupational segregation has potentially interesting patterns, consider Figure 1 which graphs the evolution of male share over time for bank tellers and five other occupations which experienced a 50-percentage point or more increase in female share from 1910-2000.[1] In each of these figures, there is striking evidence of an inverse-S pattern in male shares over time. To show that these time-series patterns of occupational change hold true for a broad set of occupations in the Census, Figure 2 displays pooled versions of Figure 1 for groups of occupations that experience a 50, 40, 30 and 20 percentage point decline in male share from 1910-2000.[2] These figures show that, in the aggregate, occupational change is characterized by similar inverse S-shape patterns in the evolution of male share for a broad set of occupations that experienced varying declines in male share over time.

Admittedly, the limited number of occupations and time-periods make it difficult to generalize the aggregate time-series evidence and to distinguish general patterns from occupation-specific shocks. Figure 3 further illustrates that sudden changes in male employment in occupations appear to be related to an occupation's initial female share. Here, I plot the mean change in net male employment growth (defined as male employment growth net of female employment growth) from 1950 to 1960 against the female share in 1950 for white-collar and blue-collar occupations. These figures show striking evidence of nonlinearities in net male employment growth as a function of initial female share. This is suggestive of a "tipping phenomenon" where occupations rapidly feminize as the share of females in an occupation exceeds a critical threshold or range. The threshold at which this rapid change occurs is commonly referred to as a "tipping-point".

What theoretical model can account for these nonlinear patterns of occupational change? I argue that the basic empirical observations are consistent with predictions from a classic social

[1] There are a total of 14 occupations that experienced a 50-percentage point or more increase in female share from 1910-2000 and although graphs of the remaining eight occupations are not shown, they too exhibit similar inverse-S shape patterns.

[2] In order to pool the occupations into a single figure, I first identify the year in which an occupation begins to experience the largest decline in male share. This "critical point" provides a rough proxy for when an occupation begins to experience a steep change in male employment. The evolution of male share for each occupation is then centered on this point. Each panel is constructed by aggregating the male share of occupations in each decade, relative to the decade of the "critical-point" for occupations that experience varying declines in male share.

interaction model as posited by Schelling (1971). In this model, Schelling demonstrates how substantial segregation can result from weak prejudice against one group. Even if both groups prefer integration, the desire to avoid minority status can lead to segregated outcomes. A rich literature on the relationship between occupations and identity has shown that the existence of society-wide gender-job associations can lead to the reluctance of men and women to take on gender atypical roles both at home and at the workplace (Akerlof and Kranton, 2000, England, 2003). As a result, the gender composition of an occupation can convey a signal of occupational prestige. Males' aversion to associating with females in the workplace need not be entirely taste-based. In the presence of uncertainty about changes in technology, female entrants into an occupation may convey apparent information that the job has undergone a negative productivity shock, even when it has not.[3] Thus, in order to protect their status as members of an occupational group, men are reluctant to associate with females in the workplace (Goldin, 2002).

In line with this view, I outline a simple model of occupational choice in which males care about the share of females in their occupation or firm. As long as the female share in an occupation remains below a critical threshold, shocks to the relative female supply to an occupation produces small changes in the location of the integrated equilibrium. Beyond this threshold, all the males will leave the occupation, resulting in a fully segregated equilibrium. The model also suggests that the location of the tipping point decreases with the strength of males' distaste for working in the same occupations as females.

To assess whether occupations exhibit "tipping-like" behavior, the main empirical strategy used in this paper draws on the empirical framework developed by Card, Mas and Rothstein (2008a) in their analysis of neighborhood tipping. As illustrated in Figure 3, this procedure makes use of the cross-sectional variation in initial female shares across occupation-state cells to test whether occupations exhibit tipping-like behavior as the female share in an occupation exceeds a critical threshold. The location of the candidate tipping points is identified by a search procedure which looks for the largest structural break in the data (CMR, 2008a, Chay, McEwan and Urquiola, 2005). I show that there is relatively strong evidence of discontinuities in net male employment growth across various classifications of occupational groups from 1940-1980 at candidate tipping points ranging from 30 to 60 percent female in white-collar occupations and 12 to 25 percent female in blue-collar occupations. Depending on the decade, occupations experience an 18 to 50 percentage point decline in net male employment growth at the candidate tipping points. Interestingly, there is little evidence that wages and other occupational characteristics change discontinuously at the tipping points, suggesting that the effects of tipping are observed mostly in the *quantity* domain.

To test whether the location of tipping points are related to male preferences for working in the same occupations as females, I use data from the General Social Survey on males' prejudicial attitudes toward the role of women in society as a proxy for their gender-work preferences. One

[3] In this "pollution" model of discrimination (Goldin, 2002), society has imperfect information about technology shocks and infers the change from observables, such as the gender composition of an occupation. Occupational prestige is reduced when females enter an occupation even if they meet the qualification for entry because society can only infer the quality of the new entrants from the group's average.

can think of these attitudes as reflecting males' views regarding the identity of women in society and, by extension, the degree to which female entrants are seen as "polluting" (Goldin, 2002) the prestige of their occupation. Consistent with my model, I find suggestive evidence that the location of tipping points are lower in regions where males hold more sexist attitudes toward women.This is also consistent with evidence presented in Charles, Guryan and Pan (2009), which reports a strong relationship between male sexism and cross-state differences in female-male employment and wage gaps.

While the empirical findings appear to support a model based on identity and social interactions, it is nonetheless useful to consider whether these findings are consistent with alternative explanations. A candidate explanation is that occupational tipping is driven by omitted variables which happen to be discontinuously related to an occupation's initial female share. For example, males may be leaving an occupation due to low or declining wages. To the extent that these wage patterns are correlated with initial female share, this may generate the observed tipping patterns. One possible test of these omitted variable concerns is to look at the behavior of occupational characteristics such as average male wages, schooling and age in a period prior to the change, around the candidate tipping point. I find little evidence that differences in these baseline occupational characteristics around the tipping point drive the observed tipping patterns.

A number of alternative models predict S-shape dynamics in female employment growth as a function of the initial female share. For example, changes in production technologies might generate nonlinear employment changes across genders. Suppose there are two ways of organizing production - a male-intensive and a female-intensive production technology. At low female shares, occupations are organized around male-intensive production technologies; however, as the female share in an occupation rises, it becomes more cost effective for employers to utilize the female-intensive production technology. At some critical threshold where firms decide to switch to the female-intensive mode of production, this can result in a sharp increase in female employment growth. Male employment growth may also fall sharply generating a tipping-like phenomenon. Alternatively, learning dynamics can also generate S-shape patterns of female employment growth. Suppose there is uncertainty about a woman's ability to perform in a particular occupation - at low female shares, information diffuses slowly and females are reluctant to enter the occupation. As the initial female share in an occupation rises, information accumulates and learning accelerates, leading to a rapid increase in female employment growth. As more women are hired in these occupations, male employment growth may slow-down, resulting in tipping-like patterns.

The empirical findings do not appear fully consistent with these alternative models for two reasons. First, both explanations predict a sharp increase in female employment growth at the candidate tipping points. However, in the earlier time-periods of my sample (1940-1950 and 1950-1960), I find that occupational tipping is driven by a sharp decline in male employment growth and is accompanied by only a small increase in female employment growth. This suggests that, over this period, occupational tipping is unlikely to be driven by changes in production technology or learning dynamics. In the later two time periods (1960-1970 and 1970-1980), occupational tipping is driven by a combination of a sharp decline in male employment growth and a sharp increase in female employment growth. Hence, it is not possible to reject that the alternative models may be responsible for the tipping patterns in the later two time periods. Secondly, both alternative models do not have strong predictions that the location of tipping points should be lower in regions with higher male sexism.[4] The finding that the tipping point locations are related to male prejudice in a way that is consistent with the social interaction model further suggests that social preferences matter for occupational tipping and the dynamics of occupational segregation.

Most of the literature on occupational segregation has focused on factors that explain cross-sectional differences in gender segregation at a single point in time and how this relates to wage gaps.[5] To my knowledge, the nonlinear dynamics of occupational segregation have not been systematically explored in the literature on occupational segregation.[6] This paper suggests that in order to fully understand current gender distinctions in the labor market, one has to look at historical processes. Understanding the potential role of tipping and social interactions in the process of occupational segregation provides some answers to three puzzles in the literature on occupational segregation. First, why has occupational segregation persisted for so long in spite of rapid changes in labor force composition. Second, why is it that some occupations feminize while others do not, and third, why do seemingly similar occupations feminize at different points in time. The striking patterns of tipping observed from 1940-1970 can account, at least in part, for the persisting levels of segregation observed in the labor market today and may be an important explanation for why the historical path to gender equality has been relatively slow. Moreover, this paper shows how small initial differences in gender composition across occupations can result in large differences in outcomes over time. While I find some evidence that tipping is probably less important today than in the 1970s and earlier, future work should assess the salience of the tipping phenomenon today and also in other workplace environments such as firms.

The rest of the paper proceeds as follows. The next section outlines the basic Schelling tipping model that will guide the empirical work. Section 3 presents evidence of tipping behavior in various occupations. Section 4 explores the relationship between the location of tipping points and measures of male sexism. In Section 5, I consider various alternative theories that could account for the observed tipping patterns. Section 6 explores the dynamic evolution of occupations close to the tipping points. Section 7 concludes.

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[4] In fact, as will be explained in greater detail later, I argue that the learning model suggests that tipping should occur at a *higher* female share in regions where males are more sexist.

[5] For example, see, Polachek (1981), England et al. (1988), Hirsch and Macpherson (1995) and Bayard et al. (2003). Blau et al. (2009) provide a comprehensive summary of the literature looking at occupational segregation and female-male wage gaps as well as trends in occupational segregation over time.

[6] A notable exception is England et al. (2006) who examine gender segregation and the tipping phenomenon in academic fields from 1971-2002 and find evidence that men are deterred from entering academic fields that feminize above a certain percentage of women. They suggest that this observation is consistent with Schelling's tipping model and the devaluation of these fields. There is also a literature, mostly in sociology, that looks at the tipping phenomenon in occupations, but these are mostly case studies that focus on particular occupations such as bank tellers (Strober and Arnold, 1987), court reporters (Jacobson, 2007) and computer work (Wright and Jacobs, 1994). Case studies of occupational change in eleven different occupations can be found in Reskin and Roos, 1990.

# 2 Theoretical Framework

The time-series patterns provide relatively striking evidence that the dynamic process of occupational segregation is highly nonlinear. As described at the outset, the aim of this paper is to investigate what theoretical model accounts for these nonlinear patterns of occupational change. The main analysis in this paper will assess whether the empirical evidence is consistent with the predictions of social interaction models, as originally outlined by Schelling (1971). A key implication of this model that I test empirically is whether there is evidence of discontinuous changes in male employment growth at candidate tipping points. While the tipping model structures the main empirical approach adopted in this paper, I will carefully consider alternative interpretations and suggest some empirical tests to differentiate between the competing hypotheses.

## 2.1 A Model of Occupational Tipping

I present a simple model of occupational choice in which males' labor supply to an occupation depends on the female share in an occupation. This model is a modified version of the neighborhood segregation model developed by Card, Mas and Rothstein (2008a).

To focus attention on the supply side of labor, I assume that the demand for each occupation is fixed and that employers are non-discriminating. Under these assumptions, the market-clearing wage for men and women ($w^*$) is identical. Let $n^f$ and $n^m$ be the number of females and males in an occupation, respectively. The labor supply of men and women to an occupation depend on the wage rate and $f$, the female share in an occupation, where $f = \frac{n^f}{n^f + n^m}$. Define $w^m(n^m, f)$ and $w^f(n^f, f)$ to be the inverse labor supply functions of males and females, respectively. This function implies that $n^m$ males are willing to work in an occupation with female share $f$ and wage, $w^m$. It is assumed that there is some degree of job specificity - to increase the supply of men or women to an occupation, higher wages need to be offered.[7] That is, $\frac{\partial w^m}{\partial n^m}$ and $\frac{\partial w^f}{\partial n^f}$ are weakly positive.

The social interaction effects work through the cross derivatives of the inverse labor supply function. Due to identity concerns, males require a premium to work in occupations with a higher female share: $\frac{\partial w^m(n^m,f)}{\partial f} > 0$. Moreover, it is assumed that this distaste for working in the same occupations as females increases convexly in the female share: $\frac{\partial^2 w^m(n^m,f)}{\partial f^2} > 0$.[8]

Given the assumption of fixed occupational demand and non-discriminating employers, the total

[7]Note that instead of assuming job-specificity, if males regard a small share of women in their occupations as an amenity, this is sufficient to generate declining male reservation wages as the female share increases below the threshold $f^*$.

[8]There are alternative ways of modeling the social interaction effect that would similarly generate tipping behavior. Earlier tipping models such as Schelling (1971) and Card, Mas and Rothstein (2008a and 2008b) generally assume that individual preferences are discontinuous - in this context, this assumes that males only require a premium to work in occupations when the female share in an occupation exceeds a critical female share ($\frac{\partial w^m(n^m,f)}{\partial f} > 0$ for some $f > \bar{f}$). Perhaps not surprisingly, such models will also generate a tipping point (although $f^*$ does not necessarily have to equal $\bar{f}$). One advantage of modeling the social interaction effect the way I have done here is that it does not assume the presence of discontinuous individual preferences. Other tipping models such as Brock and Durlauf (2001) also have features where tipping results from smooth preferences.

number of workers in an occupation can be normalized to $\bar{L} = 1$. This implies that in an integrated occupation,

$$w^* = w^f(f, f) = w^m(1 - f, f) \tag{1}$$

where $m = 1 - f$. In an all-female occupation, $w^* = w^f(1, 1) < w^m(0, 1)$ and in an all-male occupation, $w^f(0, 0) > w^m(1, 0) = w^*$.

Next, we can analyze what happens as the female share in an occupation increases. With no gender distaste, there would be a stable point of intersection where the male and female inverse labor supply functions cross. The equilibrium gender share would be the point at which the marginal male and female were willing to accept the same wage. With gender distaste, the male inverse labor supply function is initially downward sloping in the female share since we are moving down the labor supply curve. As the female share rises further, male distaste increases such that beyond a certain point ($f^*$), males start demanding a higher wage to enter the occupation, even though fewer of them are entering.[9] The male and female inverse labor supply functions are depicted in Figure 4. For this occupation, there are three equilibria, two-mixed and one all-female. Points A and C are stable, but point B is unstable since a small deviation from B would result in a movement towards point C since male wages are higher than female wages to the right of B.

An increase in the supply of women over time pushes down the inverse supply function of women as shown in the figure. As $w^f$ shifts down, wages fall and some females displace more expensive male workers, resulting in a new integrated equilibrium at A1. Further increases in the supply of women will cause the female share to increase until $w^f$ is just tangent to $w^m$. The female share at this tangency point is a "tipping point". Once $f = f^*$, any further increases in female supply causes the integrated equilibrium to disappear, leading to a fully segregated equilibrium. Once this process has started, even an increase in female supply may not reverse this process; $f$ will continue converging to $f = 1$ if it lies to the right of the unstable equilibrium. The location of the tipping point ($f^*$) depends on the strength of males' distaste for working in the same occupations as females. That is, a larger $\frac{\partial w^m}{\partial f}$ would tend to lead to a lower tipping point. Notice that this model delivers a tipping point even though male distaste does not exhibit a discontinuity. Tipping here arises from two, simultaneous monotone effects where at low female shares, one is dominant (upward sloping male labor supply) and at higher female shares, the second one is dominant (social interactions).

In this model, wages evolve smoothly through the tipping point, even though employment changes discontinuously. The reason for this is that the upward sloping supply of women takes over smoothly from the supply of men at the discontinuity. The long-run wages in an all-female occupation could be lower or higher than wages at the tipping point depending on the shape (elasticity) and eventual position of the female labor supply function.

[9] For the critical point $f^*$ to arise, it needs to be true that $\frac{\partial^2 w^m(n^m,f)}{\partial f^2} > \frac{\partial^2 w^m(n^m,f)}{\partial {n^m}^2}$. That is, the second derivative of the social interaction function is steeper than the second derivative of the own labor supply curve.

## 2.2 Empirical Implications

Since the early 1900s, there has been a steady increase in relative female labor supply in the US labor market. At any point in time, different occupations are likely to experience occupation-specific shifts in relative female labor supply. The framework presented above has several implications for how occupations with different levels of initial female share $f_{t-10}$ will react to these shocks in relative female labor supply:

1. For occupations with initial female share below $f^*$, small shocks in relative female supply will produce very small changes in the location of the integrated equilibrium as long as the new equilibrium remains below $f^*$. More formally, these are the set of occupations with initial female shares in the range $f_{t-10} \in [0, f^* - r)$ where $r$ denotes the maximum relative female supply shock that an occupation can face.

2. Occupations with initial female share above $f^*$ have already begun tipping - therefore, the expected change in female share, $E(\triangle f_t | f_{t-10})$ for these occupations is positive and large.

3. Occupations in the intermediate range, $[f^* - r, f^*]$ will only tip if they experience large enough shocks.

Based on these observations, the test for "tipping"-behavior will look for a (near)-discontinuity in $E(\triangle f_t | f_{t-10})$ at the threshold, $f^*$. Assuming that $r$ is small, the expected change in female share changes abruptly for occupations just below and above $f^*$ - leading to a "jump" at $f^*$. Strictly speaking, depending on the smoothness of the process of occupational change, the time-horizon considered or (some) heterogeneity in the location of tipping points, the model may not predict a strict discontinuity at $f^*$. Hence, the empirical strategy will look for a steep negative slope in a small range surrounding $f^*$ as evidence of tipping.

## 2.3 Data and Unit of Analysis

To explore whether occupations exhibit "tipping-like" patterns, I use data from the 1940-1980 US Censuses available from IPUMS.[10] There is a question of what the appropriate unit of analysis should be. The model based on gender identity and social interactions in the previous section suggests that tipping should occur at the occupation-level. For the empirical work, I make use of occupation-states to incorporate possible sub-national spatial boundaries that might arise due to geographical boundaries on the knowledge of workers in occupations in other states as well as the relevant social group that determines one prestige. It is worth pointing out that the mechanism based on social interactions and gender identity that could result in occupation-level tipping is distinct from a model based on co-worker interaction that might generate firm-level tipping. Theoretically, in the presence of co-worker distaste, firms will try to segregate their workforce across

[10] The time period is chosen to ensure the representability of *OCC1950*, the consistent 1950 occupation code across census years. Due to changes in occupation codes over time, the *OCC1950* code in the 1990 and 2000 Census is a lot less reliable.

firms or at least across occupations within firms. If firms are able to segregate their workforces, this would limit the role of tipping within firms. However, tipping might occur at the firm-level if it is costly to segregate. Ideally, one would use data at both the firm and occupation-level to test separately for tipping at each unit of analysis. Unfortunately, firm-level datasets in the US are not publicly available and do not go that far back in time. Future work should test for tipping at the firm-level.

To facilitate the computation of female shares and comparison of employment changes, the analysis is restricted to occupation-state cells with at least 30 observations in the two adjacent Census years.[11] Since occupations differ on many dimensions, potential tipping points are allowed to vary by decade and by white-collar and blue-collar occupations. Additional details on the construction of the occupation-state dataset can be found in the data appendix.

### 2.4 Empirical Strategy

Let $M_{isj,t}$, $F_{isj,t}$ and $P_{isj,t} = M_{isj,t} + F_{isj,t}$ denote the male, female and total employment in occupation $i$, state $s$ and the group of white or blue collar occupations $j$ in year $t$. The main dependent variable used in the analysis is the net change in male employment growth, defined as the difference between the growth in male employment and the growth in female employment: $Dm_{isj,t} = (M_{isj,t} - M_{isj,t-10}/P_{isj,t-10}) - (F_{isj,t} - F_{isj,t-10}/P_{isj,t-10})$. This formulation uses female employment growth as a proxy for occupational demand, hence changes in the dependent variable will be net of occupational demand shocks that affect both male and female employment. This is a potentially salient issue when analyzing the labor market since it is possible that changes in occupational demand are somehow correlated with the initial female share in occupations. The key explanatory variable is the base-year female employment share in an occupation, $f_{isj,t-10} = F_{isj,t-10}/P_{isj,t-10}$.

If tipping behavior exists, one would expect to see a greater than average net growth in male employment for occupations below the tipping point and, conversely, lower than average net growth in male employment for occupations above the tipping point. Let $f^*$ be the potential tipping point for an occupation and define $\delta_{isj,t-10} = f_{isj,t-10} - f^*_{j,t-10}$ to be an occupation's deviation in female share from the tipping point. The basic econometric specification is:

$$Dm_{isj,t} = p(\delta_{isj,t-10}) + d1[\delta_{isj,t-10} > 0] + \tau_j + \gamma_s + X_{isj,t-10}\beta + \epsilon_{isj,t} \tag{2}$$

where $p(\delta_{ij,t-10})$ is a smooth control function, modeled as a fourth-order polynomial, $\tau_j$ is a dummy for white-collar occupations, $\gamma_s$ is a vector of state fixed effects and $X_{ij,t-10}$ is a vector of occupation-level controls. These occupation-level controls include the average age, education and log male wages in the initial period.

[11]While this choice of the number of observations in each occupation-state cell appears somewhat arbitrary, the empirical analysis has been repeated weighting all occupation-state cells with more than 30 observations by the number of observations in each cell and the results remain similar.

Since the location of the tipping point, $f^*$ is unknown, in order to estimate equation (2), I make use of a two-step procedure. The first step locates the female share at which tipping is most likely to occur, assuming that a tipping point exists, using an econometric procedure similar to that used in the literature to identify structural breaks in the data. In particular, I regress decadal changes in $Dm_{isj,t}$ on a constant and a dummy for an initial female share above $f^*$ where $f^* \in (5, 95)$. I restrict the range of initial female share to ensure that occupations that are almost exclusively all-male or all-female are not driving the results. This structural break procedure is estimated separately for white collar and blue collar occupations in each decade using all occupation-states with initial female share between 5 and 95 percent. The candidate tipping point is the value of $f^*$ that maximizes the $R^2$ of the regression. In the second step, to estimate the magnitude of tipping, equation (2) is estimated using the full data and allowing the tipping points $f^*_{j,t}$ to differ for white and blue collar occupations.

It is worth noting that by allowing tipping points in each time-period to vary only by white and blue-collar occupations, I am making the implicit assumption that there are no regional differences in the location of the candidate tipping point. In Section 4, I relax this assumption by allowing tipping points to vary by Census region. While there is suggestive evidence that tipping points do indeed vary across regions, several issues arise in hypothesis testing.[12] As such, the main results are based on the assumption of a national tipping point. Assuming a national tipping point in the presence of heterogeneity in the location of tipping points across regions will tend to smooth away true discontinuities and lead to an *underestimate* of the tipping magnitude. Similarly, while the classification of occupations into white and blue collar may appear somewhat arbitrary, any improper classifications or heterogeneity in the location of tipping points within these occupation groups would also tend to lead to a downward bias in tipping magnitude.[13]

It is important to distinguish this empirical procedure from conventional regression discontinuity methods. The most important difference is that in the tipping point application, the location of the tipping point is unknown and there is a possibility that it does not exist. In the presence of an unknown discontinuity, it is not clear that the regression discontinuity assumptions are satisfied, thus the estimation of equation (2) should *not* be regarded strictly as an RD approach.[14] Since tipping is empirically defined as a steep change in male employment growth at some initial female

[12] In particular, for quite a few regions, there are no occupations to the right of the tipping point for some range of initial female share (see Appendix Figure 2 for an example of this). In the presence of strong tipping behavior, this observation is actually a feature of the model. To the extent that the mixed equilibrium is unstable, one would not expect to see many occupations with intermediate female shares. This lack of support over the entire range of initial female share makes it particularly difficult to perform hypothesis testing using the Monte Carlo simulation procedure as the data necessarily has a break in that region.

[13] In Appendix Table 1, I re-run all the main results but this time assuming separate tipping points for white and blue-collar occupations in each of the nine Census regions. The estimates are qualitatively similar and generally very close to or larger than those reported in Table 3.

[14] In the conventional RD approach, identification comes from a discontinuity of the forcing variable $X$ at some known cut-off $c$. Assuming that agents do not have precise control over the forcing variable and that all other covariates evolve smoothly through the threshold, the jump in outcome $Y$ at the cut-off $c$ can be interpreted as the treatment effect at $c$ (Lee and Lemieux, 2009).

share, the empirical specification proposed in (2) first uses a structural break procedure to locate the female share at which this change is most likely to occur, assuming that a tipping point exists. The second step then ascertains whether the pre-identified point is consistent with tipping. The test for this looks at whether there is greater than average growth in net male employment for occupations just below the tipping point, compared to occupations just above the tipping point, relative to a smooth control function, which is modeled as a fourth order polynomial in initial female share.

### 2.5 Hypothesis Testing

To estimate the size of the discontinuity ($d$), equation (2) is estimated by OLS using the candidate tipping point located using the structural break procedure as outlined above. However, there are potential problems with conventional standard errors if the same sample is used to identify the tipping point and to estimate the magnitude of the discontinuity. In particular, conventional test statistics will tend to reject the null hypothesis that $d = 0$ too often. To get around this issue, CMR propose a split-sample technique that uses a randomly selected two-third subsample of the data to estimate the tipping point and the remaining one-third subsample for further analysis. Since these two subsamples are independent, such a procedure permits conventional hypothesis tests on the holdout sample.

The main drawback of this approach for this paper is that it is very data-intensive. Given the relatively small number of observations in the data, such a procedure is not feasible. This is especially true in this paper since the second (regression discontinuity inspired) step involves comparing the dynamic behavior of occupations close to the threshold. By definition, these are occupations that are in unstable mixed equilibria, and not surprisingly, there are relatively few of them from 1940 to 1960. Hence, it seems far from ideal to perform hypotheses tests based on a considerably smaller subsample of the original data.

Instead, I address this issue by using a Monte Carlo estimation procedure to simulate the distribution of the test statistic under the null hypothesis that there is no break in the functional relation (Hansen, 2000, MacKinnon, 2007, CMR, 2008a). In principle, this procedure takes into account the specification search bias induced by the two-step estimation procedure as outlined in the section above by simulating the distribution of test statistics under the null hypothesis. Using this simulated distribution, one can obtain the appropriate set of critical values for hypothesis testing.

To simulate the distribution of $\hat{d}$ under the null, I estimate the model using simulated data that assumes a smooth data generating process (DGP) that retains the key properties of the data, except that it does not assume the presence of a structural break. Specifically, I first estimate the following model using the true data and obtain the fitted values:

$$Dm_{isj,t} = \beta_1 \delta_{isj,t-10} + \beta_2 \delta^2_{isj,t-10} + \beta_3 \delta^3_{isj,t-10} + \beta_4 \delta^4_{isj,t-10} + \tau_j + \gamma_s + \epsilon_{isj,t} \tag{3}$$

Note that the crucial difference between equation (3) and equation (2) is that it does not include a discontinuity ($d$) at the candidate tipping point. For simplicity, I omitted the covariates although in some specifications they will also be included.

Next, for each observation in the data (an occupation-state), I draw a new error term ($\epsilon_t$) from a normal distribution with variance equal to the observed residual variance from the model above and add it to the fitted values from the estimation of equation (3). I then apply the estimation procedure to this simulated sample, first identifying the location of the structural break, separately for white and blue collar occupations, and then estimating equation (2), using the same simulated sample in both steps. For each simulated sample, I obtain the coefficient of $\hat{d}$ and the associated standard error to compute the Wald statistic $(\frac{\hat{d}}{s(\hat{d})})$. I repeat this procedure for 5000 simulations to get the empirical distribution of the Wald statistic. Using this distribution, one can obtain the critical value (using a 5% one-sided test in most cases) for the hypothesis that $d = 0$ under the null that the true DGP is a continuous 4th-order polynomial as specified in equation (3). Most of the formal hypothesis tests presented in the results section will involve comparing estimates from the full sample to the critical values obtained from similar Monte Carlo exercises.

# 3 Do Occupations Exhibit 'Tipping-like' Patterns?

## 3.1 Descriptive Statistics

Table 1 presents some descriptive statistics. The variation in the number of observations across the years stem mainly from differences in the sample size available in IPUMS (1% for 1940-1970 and 5% for 1980) and the number of consistently defined occupation codes available over time.[15] I drop occupation codes that indicate that occupations are in a "not elsewhere classified" category. As these categories tend to combine a large number of occupations with potentially different female shares, including them in the analysis would tend to bias the results toward not detecting a tipping effect.

The first panel in Table 1 considers the overall sample and the unit of observation is an occupation (including the "not elsewhere classified" categories). The average female share in occupations has risen steadily over time, from 24 percent in 1940 to 38 percent in 1970. On average, occupations experience larger relative growth in female employment, consistent with the idea that the relative supply of female labor has increased over time. The bottom half of Table 1 considers how the growth in male employment is affected by initial female share. Here, the unit of observation is an occupation-state with at least 30 observations and the "not elsewhere classified" categories are dropped. For male occupations that were 0 to 20 percent female in 1940 and 1950, the growth in total employment across the ten-year period was almost exclusively driven by the growth in male employment. In contrast, occupations that were more than 20 percent female saw a much lower

[15] The analysis from 1940-1980 makes use of occ1950, the consistent 1950 occupation codes available from IPUMS. Note that for 1940-1960, the quality of the cross-Census coding is very high since the occupation codes in 1940 and 1960 were very similar to 1950. Due to changes in occupational classification, the codes in 1970 and 1980 do not overlap so well with the 1950 occupational classifications.

growth in male employment, and in some cases, even negative male employment growth. While these patterns were less stark in 1960 and 1970, it remained the case that male employment growth as a percentage of total employment growth was considerably lower in occupations with higher female shares in the initial period. For example, while male employment growth accounted for 60 percent of total employment growth from 1960-1970 in occupations with 20-50 percent female in 1960, for occupations with 50-80 percent female, this dropped to 17 percent. Similarly, from 1970-1980, male employment growth accounted for 44 percent of total employment for occupations with 20-50 percent female in 1970, and only 22 percent for occupations with 50-80 percent female. Interestingly, over time, the growth in male employment appears to be steadily increasing in majority female occupations over time, suggesting that males are increasingly willing to enter majority female occupations.

The average female share masks considerable variation in the distribution of female shares across occupations. Figure 5 displays the distribution of female shares in each occupation relative to the fraction female in the labor force in each year. In the 1940s, the distribution was very skewed toward all-male occupations, but this changed considerably in the 1960s. Within a narrow span of 20 years, the proportion of majority female occupations rose considerably, suggesting that a possible tipping mechanism might be at work. The distribution in the 1960s to 1970s remained highly bimodal, with a large proportion of majority male and majority female occupations and relatively few integrated occupations. By the 1990s, the distribution flattened considerably.

### 3.2 Graphical Evidence of Tipping from 1940 to 1980

Similar to Figure 3, in Figure 6, I plot the decadal change in net male employment growth (defined as male employment growth minus female employment growth) on the initial female share for white-collar and blue-collar occupations for each time period from 1940-1950, 1960-1970 and 1970-1980.[16] In each panel, the vertical lines represent the estimated tipping points using the structural break procedure and the full sample. The horizontal line is the average change in net male employment growth in each occupation group, $E(Dm_{isj,t}|j)$. Each dot is the mean of $Dm_{isj,t}$ among all occupations with $f_{isj,t-10}$ in each two-percentage-point bin. The solid lines are local linear regressions fit to the underlying data, allowing for a break at the estimated $f^*$.

The upper left panel shows white-collar occupations in 1940-1950. The estimated tipping point using the search procedure identifies a potential tipping point at a female share of about 33 percent in 1940. On average, occupations with female share less than 33 percent in 1940 experienced greater than average net male employment growth while occupations with female share greater than 33 percent in 1940 experienced lower than average growth in net male employment. Moving along the initial female share in 1940 (x-axis), as female share increased just past 33 percent in 1940, occupations experienced a decline of approximately 40 percentage points in net male employment growth. Most of the figures from 1960-1980 show similar patterns of occupational tipping. In a couple of cases, tipping behavior is less evident; for example, for blue collar occupations in 1970-

[16] Graphs for 1950-1960 are shown in Figure 3.

1980, although there appears to be a decline in net male employment growth as a function of the initial female share, it seems to evolve relatively smoothly through the candidate tipping point.

Table 2 presents the candidate tipping points obtained using the structural break method for the full-sample. For comparison, the last two columns of Table 2 also report estimates of the candidate tipping point identified using the fixed point procedure as discussed in Card, Mas and Rothstein (2008a).[17] Reassuringly, both methods yield similar tipping point estimates. The analysis in this paper will focus on candidate tipping points obtained from the simpler structural break procedure.

In most cases, the candidate tipping points for white-collar occupations are generally higher than that for blue-collar occupations. This is generally consistent with evidence from the General Social Survey that indicates that males in blue-collar occupations tend to be more gender prejudiced as compared to those in white-collar occupations. These differences, along with differences in the location of the tipping points by region, will be considered more systematically in Section 4.

### 3.3 Pooled Analysis of Changes in Net Male Employment Growth

To facilitate formal econometric estimation of the magnitude of tipping, it is useful to consider specifications that pool white and blue-collar occupations. These pooled specifications allow the introduction of flexible polynomials when testing whether there is indeed a "discontinuity" at the candidate tipping points. Before turning to the regression models, Figure 7 provides a graphical overview of the combined data that pools white and blue collar occupations to visually depict the tipping magnitude by decade.

Each panel plots the net male employment growth deviated from the mean of this for each occupation group against the initial female share deviated from the occupation-group specific tipping point. The dots in each figure represent mean changes for two-percentage-point bins of $\delta_{isj,t-10} = f_{isj,t-10} - f^*_{j,t-10}$, while the solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The dashed lines are fitted values for a fourth-order polynomial in $\delta_{ij,t-10}$, allowing for an intercept shift at $\delta_{isj,t-10} = 0$. In the figures, the range is restricted to $\delta_{isj,t-10} \in [-0.5, 0.5]$. These figures suggest that the tipping phenomenon is quite pervasive over the past few decades. There is a clear separation of points at the candidate tipping points in each decade - similar to Figure 6, on average, occupations below the threshold experience above average net male employment growth, while occupations above the threshold experience a smaller than average growth in net male employment. As an occupation's initial female share increases just past the tipping point (at a value of 0 on the x-axis), there is a decline in mean net male employment growth of approximately 40 percentage points in 1940-1950, 1950-1960 and 1960-1970. The tipping phenomenon appears to be considerably less pronounced in 1970-1980, as a few occupations near the tipping point smooth away some of the differences between the trends on either side of the tipping point. Nevertheless, there appears to be about a 10 percentage point decline in net male

[17] The fixed point procedure identifies the female share at which net male employment in an occupation grows at the average rate for all white or blue collar occupations. To identify this fixed point, the data is smoothed to obtain a continuous approximation, $R(f_{t-10})$, to $E(Dm_{isj,t}|j, m_{isj,t-10}) - E(Dm_{isj,t}|j)$. The root of this function is then obtained.

employment growth at the candidate tipping points from 1970-1980. These figures provide relatively strong evidence that occupational tipping was a feature of the labor market, at least from the 1940s to 1970s.

### 3.4 Formal Econometric Evidence on the Magnitude of Tipping

While visually striking, these figures have two potential issues. The first is that these figures do not control for any covariates, making it hard to distinguish whether the observed tipping behavior is due to differences in characteristics of occupations close to the tipping point. Secondly, the figures were constructed based on tipping points that were estimated using the full data, hence, they may overestimate the importance of tipping. In this section, I will estimate equation (2) to provide formal econometric evidence on the magnitude of tipping. To address the specification search bias induced by the two-step procedure that first identifies the candidate tipping point using the full data and then estimates the magnitude of tipping using the same data, I will perform a series of Monte Carlo simulations as described in Section 2.5.

Table 3 presents estimates of $\hat{d}$ from equation (2) for each ten-year period from 1940 to 1980. The regressions assess the magnitude of tipping for occupations with initial female share just above the candidate tipping points, compared to occupations just below the tipping points, controlling for a flexible fourth order polynomial in initial female share. The dependent variable in each regression is the net growth in male employment over a ten-year period. Each panel displays separate regressions for each ten-year period considered. Within each panel, the first row reports the coefficient estimate of $\hat{d}$, while the second row reports the associated robust standard error. The third row indicates the adjusted p-value of the estimate based on the simulated distribution of the t-statistic under the null hypothesis of no break in the functional relation. The adjusted p-value is computed as the fraction of simulations with t-statistics at least as great as the estimated t-statistic.

Column (1) shows the estimated magnitude of tipping ($\hat{d}$) in the baseline specification that uses the pooled data. The regression includes a fourth order polynomial in the initial female share deviated from the tipping point and a dummy variable for white-collar occupations.[18] Note that the adjusted critical values based on the Monte Carlo simulations are all larger than 1.96; hence, failure to account for specification search bias will tend to lead to an over-rejection of the null hypothesis. The estimated magnitude of tipping at the candidate tipping points are economically large and statistically significant - net male employment growth declines by about 49, 46, 41 and 18 percentage points from 1940-1950, 1950-1960, 1960-1970 and 1970-1980, respectively.

A potential concern with the estimates in column (1) is that the initial female share may be proxying for some omitted variables that happen to be correlated discontinuously with initial female share. To test this, column (2) controls for pre-period ($t - 10$) occupational characteristics that include average age, number of years of schooling and log male wages. These specifications also

[18] I have also estimated models with alternative specifications for $p()$, such as including quadratics allowing for separate coefficients on both sides of the candidate tipping points and the results are very similar.

include a vector of state fixed effects. The addition of these controls has a very small impact on the estimates, suggesting that the tipping patterns are not driven by discontinuous changes in occupational characteristics at the candidate tipping points.[19] To control further for potential unobserved differences across occupations, in an additional specification (not shown), I also include fixed effects for 1-digit occupation categories.[20] The magnitude of the estimates remain largely unchanged.

To test whether the results are sensitive to constraining the polynomial $p(\delta)$ to be the same for white and blue-collar occupations in a given decade, column (3) reports estimates of $\hat{d}$ from the same regression model that allows the fourth-order polynomial to differ for white and blue-collar occupations. While the estimated magnitude of $\hat{d}$ tends to be smaller than that in column (2), the results are qualitatively similar and continue to be statistically significant. To further relax this specification, columns (4) and (5) report results from models that were estimated separately for white and blue-collar occupations, respectively. With the exception of the 1950-1960 time period, the magnitude of the estimates are similar to those reported in columns (1) to (3), although the significance of the estimates are reduced. Overall, the graphical plots and results from the regression models provide relatively strong evidence that occupational tipping is a feature of the labor market.

### 3.5 Effect on Wages and Occupational Composition

The empirical analysis thus far has looked at changes in quantities - specifically, focusing on changes in gender composition due to male or female employment growth. Apart from quantities, there are a number of other outcomes worth exploring. These include whether prices are affected by tipping and whether the tipping behavior is driven by particular subgroups of the population. For example, if younger workers tend to avoid occupations that have tipped, occupations to the right of the tipping point will tend to have older male workers as compared to occupations that have yet to tip. This section looks at how other occupational characteristics such as average log male wage, log female wage, male age and male schooling in an occupation change at the candidate tipping points.

Table 4 reports results from regressions where the usual dependent variable, net growth in male employment, is replaced by changes in average log male wage, log female wage, male age and male schooling from time $t-10$ to $t$. Perhaps surprisingly, there is little evidence of significant changes in these occupational characteristics at the tipping points. Unlike the results on employment, wages do not exhibit a sharp discontinuity at the candidate tipping points.[21] The tipping model presented in Section 2.1 predicts that both male and female wages will evolve relatively smoothly as an occupation exceeds the tipping point. This is because at the tipping point, the female inverse labor supply curve takes over smoothly from the male inverse labor supply curve at the discontinuity.

[19] In additional robustness checks, I also include quartic polynomials in all the pre-period covariates and the results remain largely unaffected.

[20] The 1-digit occupational categories include: Professional and Technical, Managers, Officials and Proprietors, Clerical and Kindred, Sales workers, Craftsmen, Operatives, Service workers and Laborers.

[21] Plots of log changes in male wages around the tipping points in each decade are shown in Appendix Figure 1.

This is not a strong prediction since the model does not factor in expectations and anticipatory behavior - if males in an occupation close to the tipping point believed that the occupation was about to tip, this might smooth out wage changes. Nevertheless, this finding is in contrast with several hypotheses that predict that the feminization of occupations will result in lower pay.

Although it appears surprising that there is little change in the average male age and schooling of occupations close to the tipping point, there are two possible reasons why one might see a large change in male employment growth, but little or no change in the composition of males at the tipping point. One possibility is that the ten-year horizon considered is long enough to enable older workers or workers of different educational levels to switch occupations. Worker mobility would tend to smooth away discontinuities at the tipping points as moving costs tend to decrease with a longer time horizon and different types of workers are able to switch into occupations with gender ratios that are closer to their desired levels. Secondly, in the presence of worker heterogeneity, it is not clear which groups are most affected by tipping - for example, while older workers may have higher moving costs, they may also be more affected by the female share in their occupation. This may induce older workers to incur higher moving costs to switch occupations.

# 4 Male Sexism and Tipping Points

The social interaction model outlined in Section 2.1 predicts that the location of the tipping point should be related to the degree of males' distaste for working in the same occupations as females. In the absence of data on actual male preferences toward working in female-intensive occupations, I use an index of male attitudes toward the appropriate role of women as a proxy for the degree to which males would have to be compensated for working in the same occupations as females. These attitudes reflect males' views regarding the identity of women in society, and by extension, the degree to which female entrants are viewed as "polluting" (Goldin, 2002) the prestige of an occupation. Hence, areas where males have more sexist attitudes toward women are likely to tip at a lower initial female share. To test this prediction, I allow candidate tipping points to vary across Census regions. Next, I relate the location of these tipping points to measures of male sexism constructed using the General Social Survey (GSS).

The male sexism index is constructed by combining responses to the eight gender-related questions available in the GSS. These questions touch on various aspects of sexism such as the appropriate role of women in society and whether working mothers are able to juggle their dual roles effectively. I combine male responses to these questions into a one-dimensional sexism index based on the same procedure used in Charles, Guryan and Pan (2009). By aggregating the individual-level male sexism indices, I create aggregate community measures of male sexism separately for men working in white or blue-collar occupations. Throughout, responses are recoded so that higher values correspond to more gender-prejudiced answers.[22]

One potential issue with the attitude data is that the time period covered (1977 to 1998) is much later than the time period for which tipping points were identified (1940 to 1980). Unfortunately,

[22]Additional details on the construction of the sexism index can be found in the data appendix.

prior to the GSS there were few large-scale attitude surveys of comparable quality.[23] Nevertheless, for the purpose of this paper, since the interest is mostly in differences in attitudes across regions, the sexism index constructed using the GSS is still a reasonable proxy for cross-regional differences in gender prejudice. Examining the GSS data from 1977 to 1998, while male sexism has declined considerably over time, the cross-region relative rankings of sexism are relatively stable over time. Therefore, the sexism index is likely to capture stable cross-regional attitudinal differences over time.

The average tipping points across regions and occupation groups from 1950 to 1970 are reported in the first three columns of Table 5. To ensure that these differences in tipping points across regions are not driven by differences in the set of occupations that are present in each region, I use an identical set of occupations in each region to identify the potential tipping points.[24] The estimates indicate a great deal of variation in the location of tipping points across Census regions and across white and blue-collar occupations. Tipping points are highest in New England and Middle Atlantic and lowest in West South Central and East South Central. Moreover, mirroring patterns found in Table 2, for all regions, tipping points for white-collar occupations are higher than those for blue-collar occupations. In a series of figures in the appendix, I plot the patterns of occupational change for pooled white and blue-collar occupations by region in 1950-1960 (Appendix Figure 2) and a combined plot for each time period from 1950-1980 that allows one to assess the tipping magnitude by decade allowing tipping points to vary by region and occupational group (Appendix Figure 3).

To explore the link between male sexism and tipping point locations, the next three columns of Table 5 report the average male prejudice across regions and also separately for white and blue-collar occupations. The values in column (4) are identical to those reported in Table 2 in Charles, Guryan and Pan (2009). Columns (5) and (6) compute the average sexism separately for men working in white and blue-collar occupations, respectively. Not surprisingly, men in blue-collar occupations are generally more sexist than men in white-collar occupations.[25] More interestingly, the two most sexist regions, East South Central and West South Central, have the smallest tipping points, while the least sexist region, New England, has the largest tipping point.

While the summary statistics in Table 5 are suggestive of a link between male sexism and the location of tipping points across regions, I address this issue more formally using a regression model that pools together observations from the eight regions, two occupation groups and three time periods.[26] The dependent variable is the location of the tipping point, while the main independent

[23] A potential source of historical attitude data is the IPOLL databank, maintained by the Roper Center for Public Opinion Research. However, they only asked one gender-related question in 1936, 1938, 1945 and 1970, and the phrasing of the question differs slightly over time.

[24] The set of occupations in each region is limited to occupations that are present in every Census region. The Mountain region is dropped due to the small sample size; since the set of occupations are constrained to be the same across all regions, including the Mountain region would entail a much smaller sample of occupations for every region used in the analysis. The results are similar when the full set of occupations in each region are used.

[25] the only exception is the Mountain region, but the difference is not statistically significant.

[26] The 1940-1950 time period is excluded from this analysis due to the relatively small number of observations by

variable is the average male prejudice across regions and white and blue-collar occupations. The econometric specification is:

$$f^*_{jrt} = \alpha + \beta Sexism_{jr} + \tau_j + \theta_t + \gamma X_{jrt} + \epsilon_{jrt}$$

where $j$ is an occupation-group, $r$ denotes the Census region and $t$ is the time-period. $\tau_j$ is a dummy for white-collar occupations, $\theta_t$ is a vector of year fixed-effects and $X_{jrt}$ is a vector of covariates. The regression estimates are shown in Table 6. The standard errors are clustered by region*occupation-group. The first column reports estimates from the baseline specification which includes only year fixed effects and a dummy for white-collar occupations. The coefficient is negative, large and economically significant and implies that a one-standard deviation increase in average male prejudice is associated with a 14 percentage point lower tipping point. Put differently, consider the difference between East South Central and New England. The difference in the overall average male sexism index between these regions is 0.275. A coefficient of -0.67 implies that tipping points are 18 percentage points lower in East South Central than New England. Compared to an average tipping point of 0.37 across the three time periods, this is a relatively large effect.

While the results in column (1) support the prediction coming from Schelling's model, a natural concern is whether this relationship is driven by male sexism or other factors that are correlated with male sexism and affect the location of tipping points. One might also be concerned that there is a mechanical relationship between the fraction female working in a region or occupation group and the location of the tipping point. To address these possibilities, column (2) includes controls for the fraction female and the fraction of males and females with a high-school degree and column (3) adds in controls for the occupational structure in each region. While the fraction female is likely to be endogenous since it is an outcome of male prejudice, the fact that the coefficient on male prejudice does not change substantively when the fraction female and other controls are added is reassuring.

Another concern with these specifications is that male attitudes may merely be a reflection of some community sentiment that is related to the location of tipping points. Column (4) confirms that the index of female prejudice is also negatively related to the location of tipping points although the coefficient is smaller in magnitude and significance than male prejudice. In column (5), I present results from a regression that includes both the male and female prejudice indices. The magnitude of the coefficient on male attitudes remains largely unchanged, although it is less significant. Interestingly, the coefficient on female attitudes is very small and close to zero, suggesting that it is largely male prejudicial attitudes toward women that matters. The final column includes the full set of controls to the model in column (5) - although the coefficient magnitudes change slightly, the interpretation remains qualitatively similar. This finding also suggests that the results are not driven by omitted community characteristics that affect both men and women

region and occupation-group. The results, however, do not change substantively when the estimated tipping points from 1940-1950 are added. As discussed in the previous footnote, the Mountain region is also excluded due to the small sample size.

- such omitted variables should also load onto the female prejudice measure, implying that both, and not just male prejudice, should be related to the location of the candidate tipping points.

# 5 Alternative Explanations

The previous sections have documented that the dynamics of occupational segregation exhibit "tipping-like" patterns. I also show that tipping points are lower in regions where males hold more sexist attitudes toward the appropriate role of women. These patterns are consistent with predictions from a simple Schelling-type social interaction model where occupational tipping results from male preferences over the fraction female in their occupation. In this section, I will consider alternative explanations that might generate similar empirical patterns.

## 5.1 Omitted Variables

A potential concern with the models presented in Table 3 is whether the observed tipping pattern is a result of differences in initial female share or omitted variables that happen to be correlated in a discontinuous way with initial female share. For example, males may be leaving (or not entering) occupations that experience low or declining wages. If these wage patterns are correlated with the initial female share in an occupation, this may result in tipping-like patterns. The results in Section 3.5 suggest that occupational tipping is not accompanied by significant changes in wages and occupational characteristics. Nevertheless, it is useful to ask whether occupations that tip differ systematically in terms of their *levels* of pre-period characteristics such as average male and female wages, schooling and age around the candidate tipping points.

Figure 8 plots the levels of average log male wage, average age and average schooling of occupations in the pre-period ($t-10$) against the female share in an occupation deviated from the tipping point. This is identical in structure to the pooled figures shown earlier except that the dependent variable is replaced by the levels of various occupational characteristics in the initial period. There is little evidence of significant discontinuities in baseline occupational characteristics at the candidate tipping points, suggesting that occupations with initial female shares just above and below the candidate tipping points are comparable on pre-period characteristics. Appendix Table 2 presents the regression version of Figure 8, where I estimate equation (2) replacing the dependent variable with each of the pre-period occupational characteristics. Similar to the figure, with a few exceptions, the regression estimates are generally small, positive or statistically insignificant, suggesting that pre-period occupational differences are not driving the tipping patterns.

These results suggest that any alternative hypothesis based on some form of omitted variables, such as technological change that leads to declining wages in some occupations (the implications of this model will be addressed more thoroughly in the next section), would have to be able to account for why a large change in male employment occurs among occupations that differ only slightly in initial female share and among occupations that have similar log wages, age and educational composition. In other words, for an omitted variable to account for these findings, it would have to be the case that it is not strongly correlated with average male and female wages, age and educational composition and yet is discontinuously related to the initial female share.

## 5.2 Changes in Production Technology

The production technology argument suggests that the increase in female labor supply into the labor market might lead firms to switch to a female-intensive production technology, resulting in a sharp increase in female employment growth over some range of initial female share. Recent literature has shown that technological change tends to increase the relative demand for women as computer use and automation have tended to de-emphasize physical tasks (Weinberg, 2000). Moreover, since women tend to be particularly well endowed in people skills, the increase in demand for these skills in non-routine interactive and analytical tasks may have favored women (Borghans, Ter Weel and Weinberg, 2008, Black and Spitz-Oener, 2010). To the extent that occupations may be undergoing these forms of technical change over time, such a process may appear in the data as a steep S-curve in female employment growth, mirroring the tipping patterns observed in the data.

A number of observations suggest that production technology alone does not seem to be able to fully account for the observed tipping patterns. First, it is worth noting that most computer-related technological change that resulted in male jobs becoming more substitutable than female jobs were largely a post-1960s phenomenon. Thus, it is unlikely that large-scale technological changes due to computers or automation can account for the tipping patterns observed in the earlier time period from 1940-1960.

Another useful way to try to distinguish the production technology model from the social interaction model is to consider whether occupational tipping is driven by a decrease in male employment growth or an increase in female employment growth. The production technology model predicts that female employment growth should increase sharply at the candidate tipping points. By contrast, the Schelling mechanism suggests that occupational tipping should be driven primarily by a sharp decline in male employment growth. It is possible, of course, that female employment growth may rise in response to male flight even in the Schelling model. In this case, it would not be possible to differentiate between the various models on the basis of this test. However, if we observe a sharp decline in male employment growth that is *not* accompanied by a sharp increase in female employment growth, this would suggest that tipping is not driven entirely by production technology changes or learning dynamics.

To explore this issue, Figure 9 plots the growth in male employment and the growth in female employment for white and blue-collar occupations against the initial female share deviated from the tipping point for each of the four time-periods. These graphs are identical in structure to Figure 7.[27] Focusing on the earlier period (top panel), it is apparent that occupational tipping is driven by a sharp decline in male employment growth at the candidate tipping points. However, there is little evidence of a discontinuous increase in female employment growth - in fact, female employment

[27]Note also that they "add-up" to Figure 7 since the net growth in male employment is by definition equal to the growth in male employment net of the growth in female employment.

growth appears to evolve relatively smoothly through the tipping point over the range of initial female share. This is not consistent with the implications of the production technology model.

In the later time periods (lower panel), however, occupational tipping is driven by a combination of a sharp decline in male employment growth and a sharp increase in female employment growth. Hence, based on this test, it is not possible to reject that changes in production technology may be responsible for tipping patterns in these time periods. Appendix Table 3 presents the regression version of these figures. The dependent variable, net male employment growth, is replaced by its individual components, male employment growth in columns (1) and (2) and female employment growth in column (3) and (4). The results confirm what was depicted in the figures. In all four time periods, occupational tipping is, at least in part, a result of sharp declines in male employment growth. At the candidate tipping points, male employment growth declines by approximately 41, 49, 13 and 13 percentage points from 1940-1950, 1950-1960, 1960-1970 and 1970-1980, respectively. Female employment growth in the early periods from 1940-1960 is small and statistically insignificant. However, from 1960-1980, the magnitude of female employment growth at the tipping points is approximately similar to the decline in male employment growth. In columns (5) and (6), I use the traditional variable of interest in tipping models (Easterly, 2009), the change in male share, as the dependent variable. The estimates in the last two columns imply that the net effect of these changes in male and female employment growth results in an overall decline in male share of between 5 to 13 percentage points.

One concern that arises with these models is that by focusing on net male employment growth as the dependent variable, these specifications impose the constraint that tipping points are identical for male and female employment growth. To relax this assumption, I search for tipping points separately for male employment growth and female employment growth in each ten-year period. Appendix Figure 4 plots the growth in male employment and the growth in female employment as a function of an occupation's initial female share separately for white-collar occupations for each ten-year time period from 1940 to 1980.[28] Interestingly, while there is some evidence of a sudden increase in female employment growth at some initial female share (for example, at about 60% female for white-collar occupations in 1950-1960), the estimated tipping points for female employment growth are always at a female share larger than that for male employment growth. This suggests that even if there may be nonlinear increases in female employment growth at some initial female share, this occurs only *after* male employment growth has fallen sharply at a smaller initial female share.

Finally, another testable implication of the production technology model is that the reduced demand for male workers as a result of technological change should be accompanied by declines in male wages as long as male labor supply is not perfectly elastic. I estimate additional models that include controls for a 4th order polynomial in the average male wage in the base period ($t-10$) as

[28]In each figure, the dashed grey line indicates the location of the tipping point estimated using the net growth in male employment. The solid blue line indicates the location of tipping point estimated using the growth in male employment, while the solid red line indicates the location of the tipping point estimated using the growth in female employment.

well as a 4th order polynomial in the *growth* in average male log wage in the previous decade (from $t-20$ to $t-10$). These specifications are shown in Appendix Table 4. There is little indication that the results are sensitive to the inclusion of flexible controls for either the levels or growth of average male wages, suggesting that declining male wages due to technology changes are not driving the observed tipping patterns. Interestingly, this finding is also consistent with earlier results showing that, unlike employment, male and female wages do not change discontinuously at the tipping points.

## 5.3 Learning Dynamics

A learning process whereby there is initial uncertainty about a woman's ability to perform an occupation may also generate discontinuities in net male employment growth. According to this model, at low female shares, there is little information about the job, hence female employment growth is slow. As the female share rises, information accumulates and learning accelerates, leading to a rapid increase in female employment growth (Fernandez, 2007 and Fogli and Veldkamp, 2009).

One of the main implications of this model is that tipping should be driven primarily by a discontinuous increase in female employment growth. This implication is similar to that of a production technology model and as shown in Table 7, female employment growth does not appear to increase discontinuously at the tipping points in the earlier periods from 1940-1960.

The finding in Section 4 that tipping points are lower in regions where males are more sexist is also incompatible with the learning model. Uncertainty about females' own abilities or statistical discrimination by male employers may lead to tipping points that vary across regions and correlate with male or female gender prejudice. However, one would expect that in more sexist regions, there would be greater uncertainty about women's abilities. Hence, the learning model predicts that more information would have to be accumulated before an occupation experiences an acceleration in female employment growth. This suggests that tipping points should be *higher* in regions with more sexist male or female attitudes. This is in direct opposition to the predictions of the social interaction model and the empirical evidence in Section 4.

## 5.4 Combining Multiple Explanations

On their own, each of the alternative explanations appears to fall short in explaining the full set of empirical observations. However, I cannot rule out that multiple explanations may be responsible for the overall patterns observed in the data. While both the production technology and learning models would have trouble fitting the 1940-1960 patterns, I cannot reject a possible role for these explanations in the later periods (1960-1980). The social interaction model provides a simple framework that is able to generate the tipping patterns observed that is consistent with the trends observed over the entire time period from 1940 to 1980. That said, it is possible and even likely that more than one process is operating here. Understanding how social interactions interact with production technology changes or learning dynamics will provide a far richer picture of the dynamics of occupational segregation. The aim of this paper is to document the striking tipping patterns and to show that at least some of these patterns are related to male preferences or attitudes toward women, and are broadly consistent with predictions from a simple Schelling-type social interaction model.

# 6 Which occupations tip? Evolution of occupations close to the tipping points

The finding that dynamic changes in occupational segregation are characterized by tipping suggests that occupations at intermediate female shares are inherently unstable. However, there are two potentially puzzling issues with this interpretation. Firstly, it appears hard to reconcile this view with the general observation that occupations are becoming substantially more, not less gender integrated over time. Secondly, how is it possible for female employment shares to rise steadily without all occupations tipping? In this section, I explore these issues by looking at how the distribution of female shares changes over time for a subset of occupations close to the tipping points. This exercise will provide a descriptive sense of how occupational change in the longer-run is influenced by tipping behavior.

I show that the observed tipping pattern is, in fact, consistent with both increasing gender integration over time, and persistently high levels of segregation. This occurs because occupations with female shares below the tipping point are largely stable and continue to attract both males and females. This group of occupations are likely to become more gender integrated over time. Moreover, related to the second "puzzle", the secular rise in female employment over time implies that most occupations will experience a relative rise in female labor supply. Rising tipping points over time ensures that not all occupations tip even though their female shares may be increasing over time. For example, consider an occupation close to the tipping point. If the female share in that occupation rises faster than the tipping point, this occupation will probably tip. However, if it stays below the moving threshold, it may not tip. The combination of these two forces is consistent with a pattern of increasing gender integration in the presence of tipping and persistent occupational segregation.

Figure 10 plots the change in female share in occupations over time relative to the 1940 tipping point for white and blue-collar occupations separately. To construct Figure 10, white-collar occupations are first grouped into two separate groups depending on whether they have 1940 female shares 15 percentage points above or below the 1940 tipping point.[29] To investigate the evolution of occupational change over time, I compare the distributions of female shares deviated from the candidate tipping point, $f^*_{40}$ for both these groups between 1940-1980. The vertical line at 0 in each figure indicates the location of the 1940 tipping point. In each figure from 1950-1970, the second vertical line indicates the location of the current year tipping point.

Figure 10 displays the CDFs of $f_t - f^*_{40}$ ($t = 40, 50, 60, 70, 80$) for white and blue-collar occupations, respectively. The occupations below the 1940 tipping point are denoted by a solid line, while

[29] A list of occupations close to the tipping points in each year is shown in Appendix Table 5.

those above are denoted by a dashed line. By construction, the CDFs in the top left-hand panel for the 1940s are compressed and spaced 15 percentage points from one another. More meaningful patterns emerge as one looks across the figures from 1950 to 1980. For white-collar occupations, in 1950, 50 percent of occupations with initial female share above the 1940 tipping point saw an increase in female share in excess of 20 percentage points. The gap between occupations above and below the 1940 tipping point increases steadily over time - by 1980, the CDF of occupations above the 1940 tipping point had shifted further to the right, with 50 percent of occupations with female shares above the 1940 tipping point experiencing more than 35 percentage points increase in female share. These patterns are especially pronounced for occupations in the top part of the distribution where the rightward spread of the CDF generally coincides with when the CDF crosses the current tipping point. Occupations in the lower part of the distribution are relatively more stable since the rise in female share for this group is often slower than the rise in the tipping points.

Interestingly, the CDF of occupations below the tipping point also see a rightward shift over time. In 1950, about 20 percent had crossed the 1940 tipping point. By 1980, this number had risen to 70 percent. This suggests that while a large number of occupations above the 1940 tipping point transition toward an all-female equilibrium, occupations below the 1940 tipping point are generally stable, attracting both female and male employees. Overall, the increasing gap that emerges between occupations 15 percentage points above and below the 1940 tipping point over time is consistent with the tipping hypothesis, while the finding that occupations below the tipping point tend to increase their female shares over time, albeit at a slower rate than occupations to the right, is consistent with the observation of increasing gender integration in the presence of tipping points. Notice that a majority of occupations below the 1940 tipping point are relatively stable since the increase in female share is generally slower than the rise in the tipping points over time.

While the general patterns are similar for blue-collar occupations (Figure 10, bottom panel), there are a few key differences. The tipping points for blue-collar occupations have remained relatively stable over time (or even decreased) - as a result, there is a rather pronounced right-shift of the CDFs for occupations on *both* sides of the 1940 tipping points. The increasing gap between occupations above and below the 1940 threshold indicates that occupations above the threshold generally tipped faster. However, some occupations with female shares initially below the 1940 tipping point also tipped as their female shares increased past the tipping points in the current period.

## 7 Conclusion

This paper examines the dynamics of occupational segregation and finds strong evidence that tipping is an important, but generally overlooked, feature of the process of occupational change. This has implications for understanding the persistence of occupational segregation and evaluating various policy measures aimed at increasing female representation in various occupations.

Using Census data from 1940-1980, I demonstrate the importance of tipping in two ways. First, historical time-series evidence shows that occupations with large declines in male share tend to exhibit striking inverse-S patterns - suggesting the presence of nonlinearities in the decline in male share. Due to the limited time-series variation, the main empirical strategy makes use of a similar econometric technique as Card, Mas and Rothstein (2008a) in their study of neighborhood tipping. This approach makes use of the cross-sectional variation in initial female shares across occupation-states to test whether occupations exhibit tipping-like behavior in response to occupation-specific shocks in female employment that occur as a result of the secular increase in female labor supply over separate ten-year periods. Candidate tipping points located using a structural break procedure range from 30 to 60 percent female in white-collar occupations and 12 to 25 percent female in blue-collar occupations. Occupations experience a 18 to 50 percentage point decline in net male employment growth at the candidate tipping points, depending on the decade considered.

I present some evidence suggesting that the observed tipping pattern appears most consistent with a Schelling (1971) social interaction model. A direct implication of the Schelling model that I test and empirically confirm is that the location of tipping should be lower in regions where males hold more gender-prejudiced attitudes. Allowing tipping points to vary across regions and using data from the GSS to construct regional measures of male sexism, I find that a one standard deviation increase in average male prejudice is associated with a 14 percentage-point lower tipping point. Interestingly, conditional on male sexism, neither female attitudes nor the fraction female are significantly related to the location of tipping points. This finding suggests a link between male gender-attitudes and occupational segregation.

I consider a number of alternative explanations for tipping: omitted variables, changes in production technology and learning dynamics. First, I show that the results do not appear to be driven by other covariates that are discontinuously related to the initial female share in an occupation. Occupations with initial female share just above and below the tipping points are largely comparable on pre-period characteristics such as average male wage, female wage, age and schooling. Secondly, the production technology and learning models predict that female employment growth should increase sharply at the candidate tipping points. When I decompose the decline in net male employment growth into its separate components, male employment growth and female employment growth, I find that in the earlier two periods of my sample (1940-1950 and 1950-1960), occupational tipping is driven by a sharp decline in net male employment growth that is accompanied by only a small increase in female employment growth. This finding is inconsistent with the predictions of the production technology and learning models. In the later time period (1960-1970 and 1970-1980), however, occupational tipping is due to the combination of a sharp decline in male employment growth and a sharp increase in female employment growth; hence, on the basis of this test it is not possible to distinguish whether the tipping patterns are due to social interactions, production technology or learning dynamics. The learning model also has the additional prediction that tipping points should be higher in regions where males are more prejudiced toward women since more information would need to be accumulated before an occupation experiences a rise in female employment. This is opposite to what is predicted by the social interaction model and observed empirically. Overall, these results suggest that the alternative explanations are not able to account for the full set of empirical results.

Looking at the dynamic evolution of a subset of occupations close to the 1940 tipping points, I find that occupations with initial female share exceeding the 1940 tipping point tipped rapidly, experiencing a relatively large increase in female share from 1950-1980. More interestingly, occupations with initial female share below the 1940 tipping point were largely stable and continued to attract both males and females. Some occupations initially below the 1940 tipping points eventually tipped and this usually occurred if the female share in these occupations increased faster than the rise in tipping points over time. Occupations whose female shares remained below the tipping points in each year remained stable and integrated. These dynamics suggest that the tipping patterns are, in fact, consistent with increasing gender integration over time, and persistent levels of segregation. Moreover, the rise in tipping points over time insure that not all occupations experiencing relative increases in female employment necessarily tip - occupations that remain below the (rising) tipping points in each decade are stable and remain integrated.

Taken together, the analysis in this paper provides some of the first evidence that the dynamics of occupational segregation are highly nonlinear and exhibit patterns that are largely consistent with social interaction models inspired by Schelling's (1971) seminal paper.[30] The findings in this paper are also notable when compared with the results in Card, Mas and Rothstein (2008a and 2008b), the papers to which it is closest in spirit. Although this paper draws on a similar empirical methodology, the context and types of social interaction studied (labor market versus housing market) are markedly different. That the findings of both papers are so similar highlights the applicability of social interaction models in various disparate settings and the potential importance of preferences of the dominant group in determining segregation in both the labor and housing markets.

Finally, while the empirical evidence suggests that social interactions are important for understanding the process of occupational segregation from 1940 to 1960, the results do not rule out a possible role of changes in production technology and learning dynamics, especially in the later periods (1960-1980). Furthermore, it is possible and even likely that more than one process is operating here - social interactions that prompt an initial outflow of men may increase the likelihood that occupations adopt new technologies, causing more men to leave. Conversely, the effects of technological shocks or learning dynamics may be magnified by social interactions. Understanding the relative importance of social interactions and technological change and the interaction between tastes, social interaction and production technology in generating occupational segregation is an important area for future work.

[30] While Schelling's seminal paper (1971) focused mainly on neighborhood tipping as a result of social interactions between blacks and whites, he suggested in the same article that "the same or a similar phenomenon has occasionally been observed for ethnic groups other than blacks, also for clubs, schools, occupations, and apartment buildings, sometimes with males and females rather than ethnic groups, and sometimes with age groups".

# Data Appendix

## Construction of occupation-state level dataset using the Census

The occupation by state data are constructed from the 1940, 1950, 1960, 1970 and 1980 public-use US Censuses available from IPUMS. The sample for each decade is restricted to individuals aged 16 and above who are in the labor force. Occupation by state tabulations are computed using the consistent *OCC1950* coding[31] and weighted using person-level weights (*PERWT*) available from IPUMS.

The occupation by state level tabulations exclude cells that meet any of the following criteria:

- Cells containing fewer than 30 observations.
- The ten-year growth in male or female employment exceeds 200% of the base-year total employment.

The following occupations were also excluded from the analysis:

- Occupations that are labeled as "not elsewhere classified".
- Farming-related occupations (OCC1950 codes: 100, 123, 810, 820, 830, 840).
- Apprentices (OCC1950 codes: 600 to 615).

## Construction of sexism index using the General Social Survey (GSS)

The data used to construct measures of gender-based prejudice is from the 1977 to 1998 waves of the GSS. The sexism index is based on the full set of eight gender-related questions asked consistently across the survey years. Responses for all races aged 18 and older are used and are recoded such that higher values correspond to more gender-prejudiced answers. The full list of questions include:

1. Do you approve of disapprove of a married woman earning money in business or industry if she has a husband capable of supporting her? [FEWORK]
2. Do you agree or disagree with this statement? Women should take care of running their home and leave running the country up to men. [FEHOME]
3. If your party nominated a woman for president, would you vote for her if she were qualified for the job? [FEPRES]
4. Tell me if you agree or disagree with this statement: Most men are better suited emotionally for politics than are most women. [FEPOL]

[31] To maintain consistency across the decades, a number of adjustments were made to the OCC1950 codes. The following occupation codes were combined into a single category: Professors and instructors (12 to 29), engineers, metallurgical and mining (47 and 48), nurses (58 and 59), technicians (94, 95 and 96), motormen (660 and 661).

5. A working mother can establish just as warm and secure a relationship with her children as a mother who does not work. [FECHILD]

6. A preschool child is likely to suffer if his or her mother works. [FEPRESCH]

7. It is more important for a wife to help her husband's career than to have one herself. [FE-HELP]

8. It is much better for everyone involved if the man is the achiever outside the house and the women takes care of the home and family. [FEFAM]

The responses to the GSS questions are combined into a unidimensional sexism index based on a procedure similar to Charles and Guryan (2008). To create an individual-level index for each GSS respondent, I create a normalized measure that subtracts off from the individual responses to each question the mean of the response of the full population in 1977 and divides by the standard deviation in the first year the question was asked. This index is then normalized by the mean and standard deviation of both male and female responses to the gender-prejudice questions. The one-dimensional aggregate individual-level sexism index is computed by taking the average of the normalized responses in each survey year for each individual.

To obtain an aggregate census region level index, the individual-level sexism index is regressed on a full set of year dummies, separately for males and females. Next, I use the residuals from this regression to create a measure of "average" male (female) sexism, which is simply the mean across all years of the residual individual-level sexism index for males (females) in a census region. Similarly, to construct the aggregate sexism index by region and white/blue collar occupations ($Sexism_{jr}$), the residuals from this regression are used to compute the mean for males (females) in white or blue-collar occupations in a census region.

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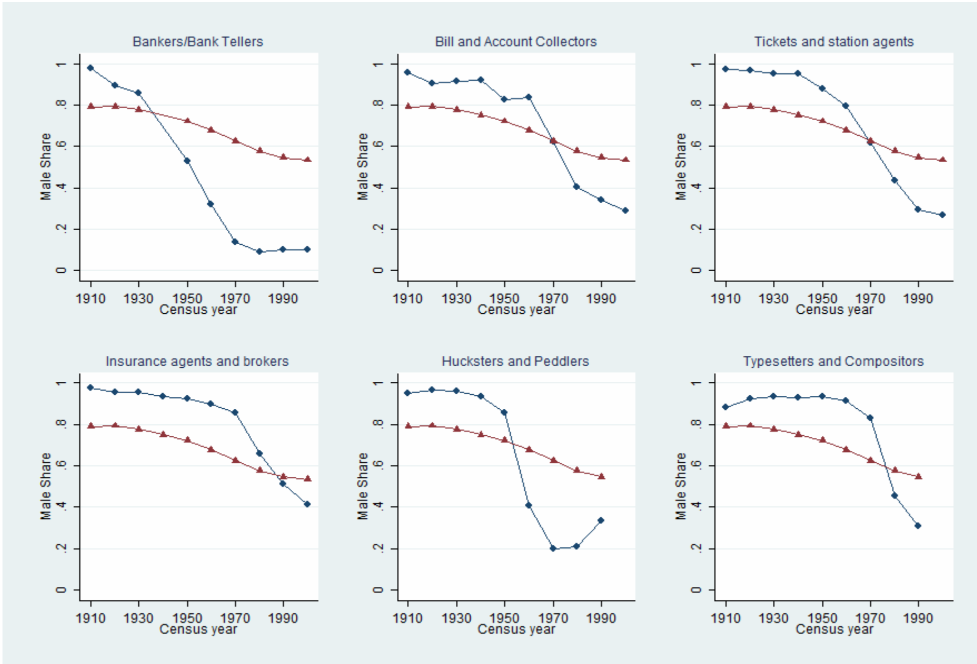
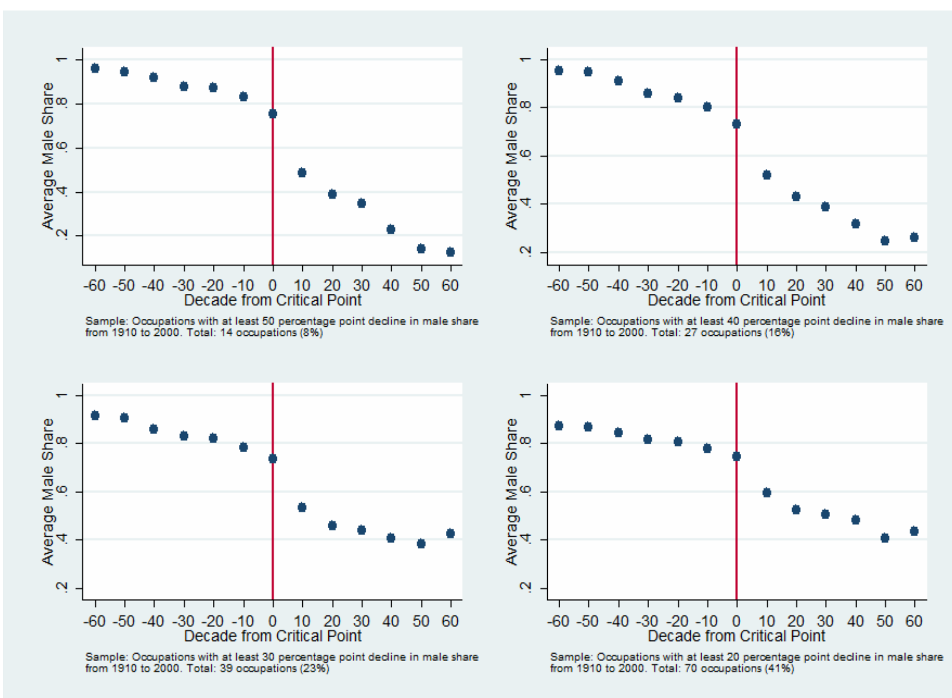
Figure 1: Changes in gender composition over time for selected occupations



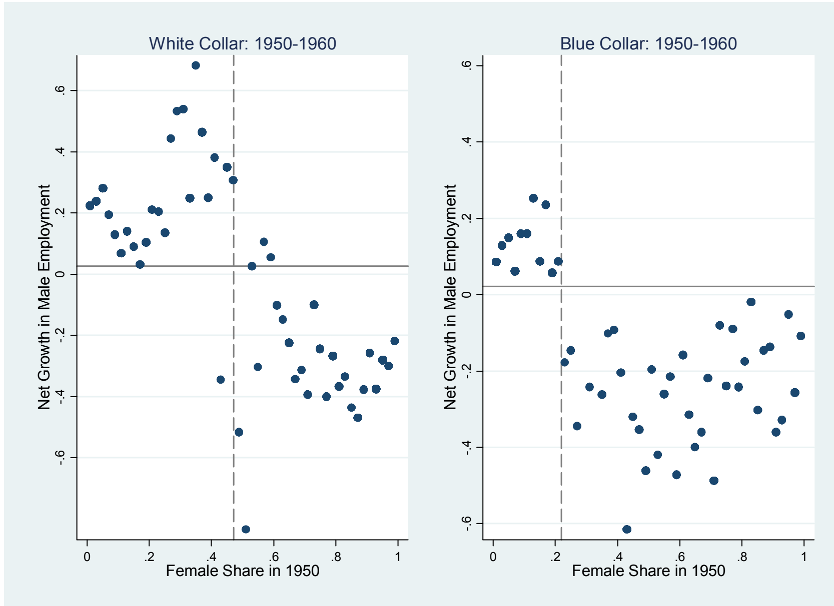

Notes: The lines with a circle indicate the fraction male in each occupation at each time period. The lines with a triangle indicate the overall fraction male across all occupations in each year (identical for all occupations). The figures include six of the fourteen occupations that experienced at least a 50 percentage point increase in female share from 1910 to 2000.

Figure 2: Pooled graphs of changes in gender composition over time for selected groups of occupations (1910-2000)




Notes: The top-left hand panel is the pooled version of Figure 1. Each dot is the average male share for a group of occupations in the relevant decade deviated from the decade of the occupation-specific "critical-point". For each occupation, the "critical-point" is assigned to be the year preceding the largest decline in male share that the occupation experienced from 1910-2000). The decade of the "critical-point" is assigned a value of zero and is indicated by the vertical line. The figures correspond to groups of occupations experiencing a 50 percentage point (top-left), 40 percentage point (top-right), 30 percentage-point (bottom-left) and 20 percentage-point (bottom-right) decline in male share from 1910-2000. These figures include 88% of all occupations in the Census with consistent codes from 1910-2000.

Figure 3: Change in occupational composition and potential tipping points from 1950-1960




Notes: Each dot is the mean of the net change in male employment (defined as the difference between male employment growth and female employment growth between time t-10 and t) among all occupation-states with initial female share in each two-percentage-point bin. The dashed vertical lines in each panel represent the estimated break-points using the structural break procedure and the full sample. The horizontal line is the average change in net male employment growth in each occupation group.

Figure 4: Occupational change: Different equilibria as the labor supply of females increase over time

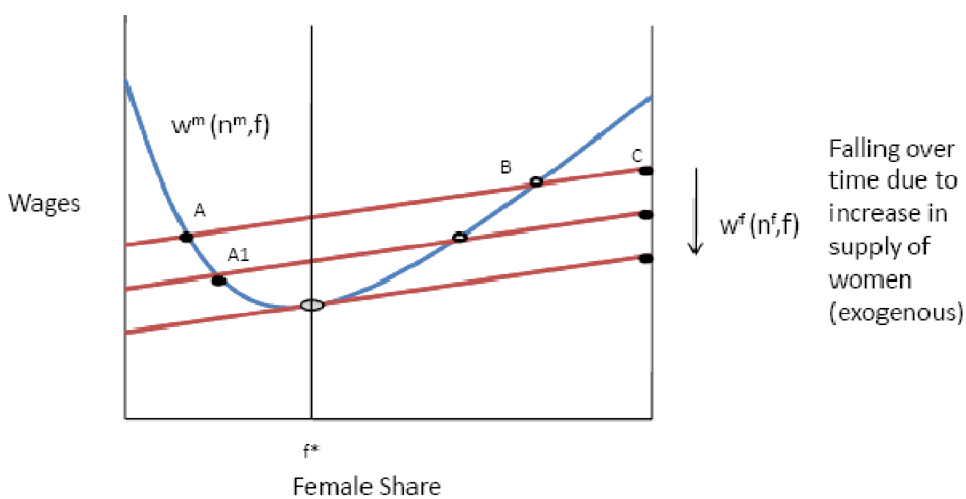
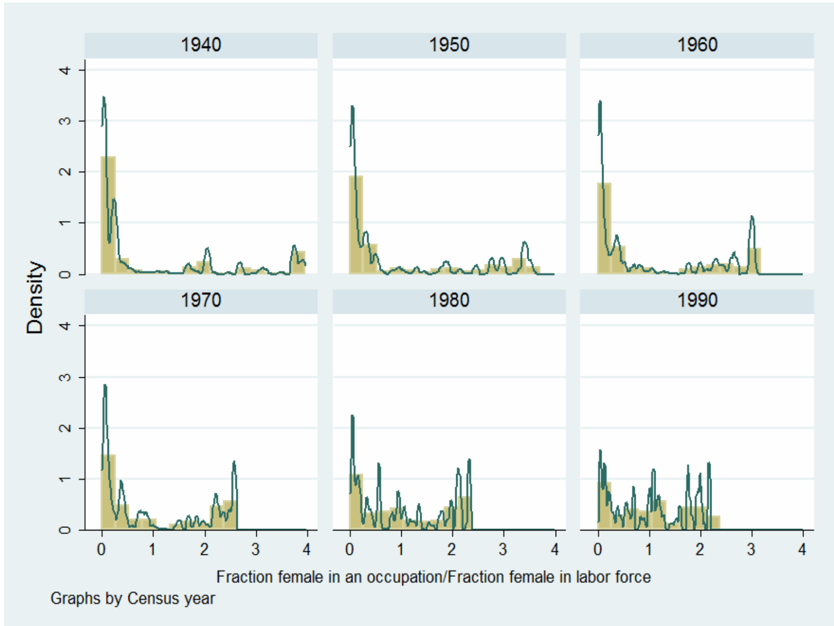
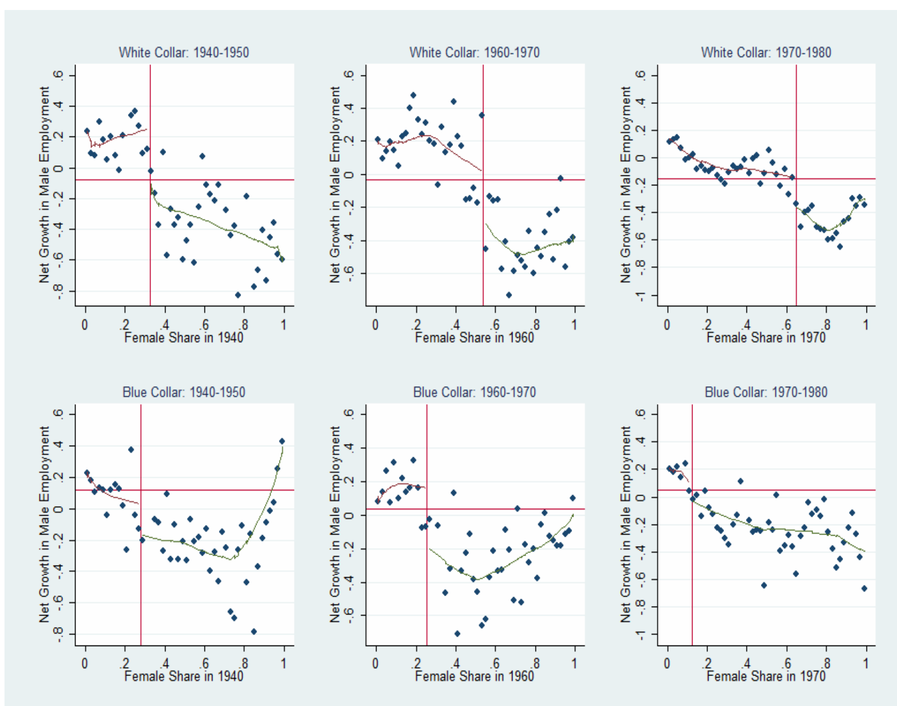


Figure 5: Distribution of fraction female relative to the fraction female in the labor force across occupations from 1940-1990



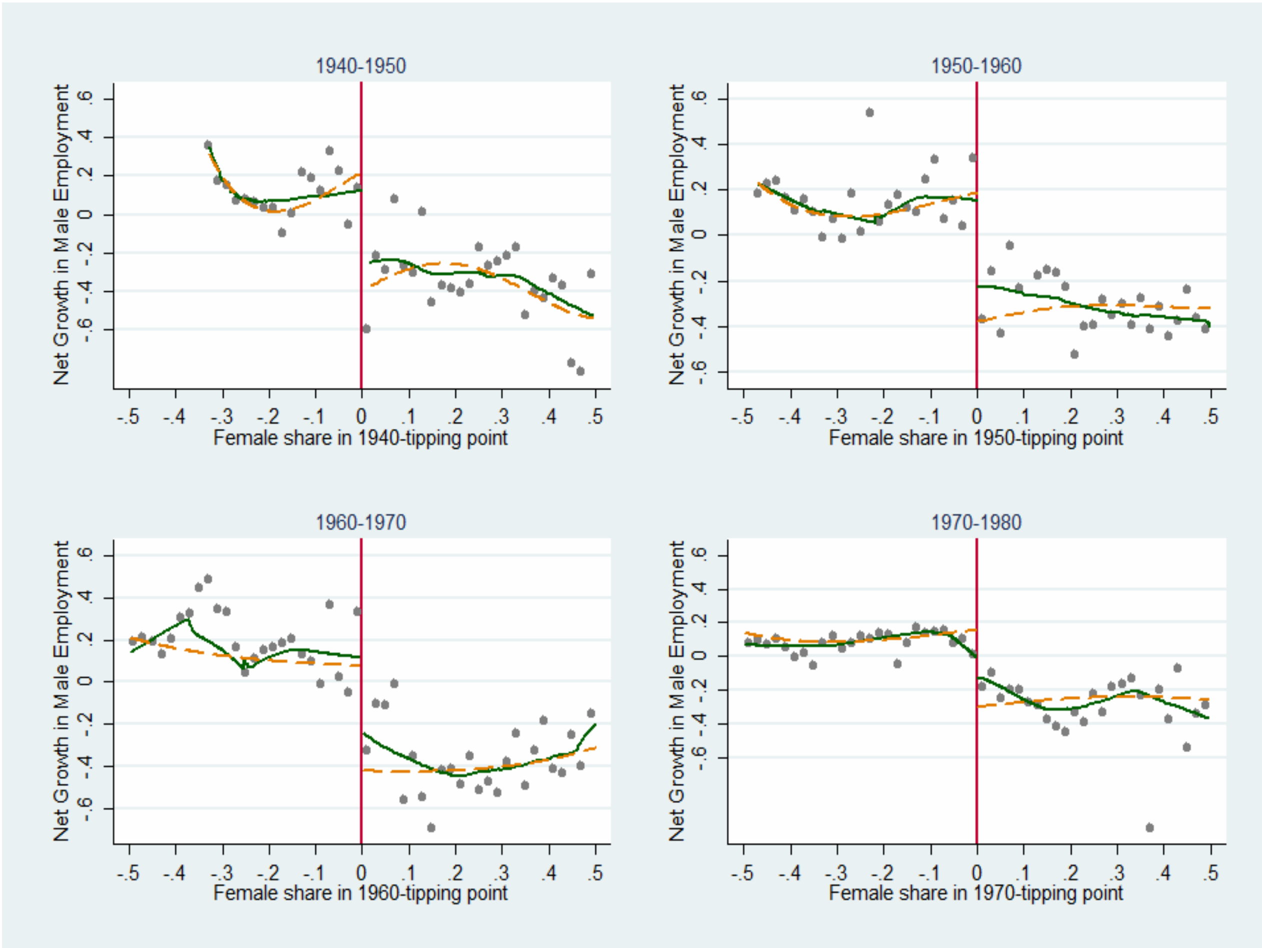

Notes: The unit of analysis is an occupation (based on the 3-digit occ1950 occupational coding available in the census). This figure plots the distribution of female shares in each occupation relative to the fraction female in the labor force in each year. "Not-elsewhere classified" occupations are dropped from the figure. Each occupation is weighted by employment size.

Figure 6: Occupational change in white and blue-collar occupations from 1940-1980




Notes: Each dot is the mean of the net change in male employment (defined as the difference between male employment growth and female employment growth between time t-10 to t) among all occupations with initial female share in each two-percentage-point bin. The vertical lines in each panel represent the estimated tipping points using the structural break procedure and the full sample. The horizontal line is the average change in net male employment growth in each occupation-group. The solid lines are local linear regressions fit to the underlying data, allowing for a break at the estimated tipping point, f*. Graphs for 1950-1960 are shown in Fig 3.

Figure 7: Occupational change in a pooled sample of occupations from 1940-1980, by relationship to white/blue collar-specific tipping point

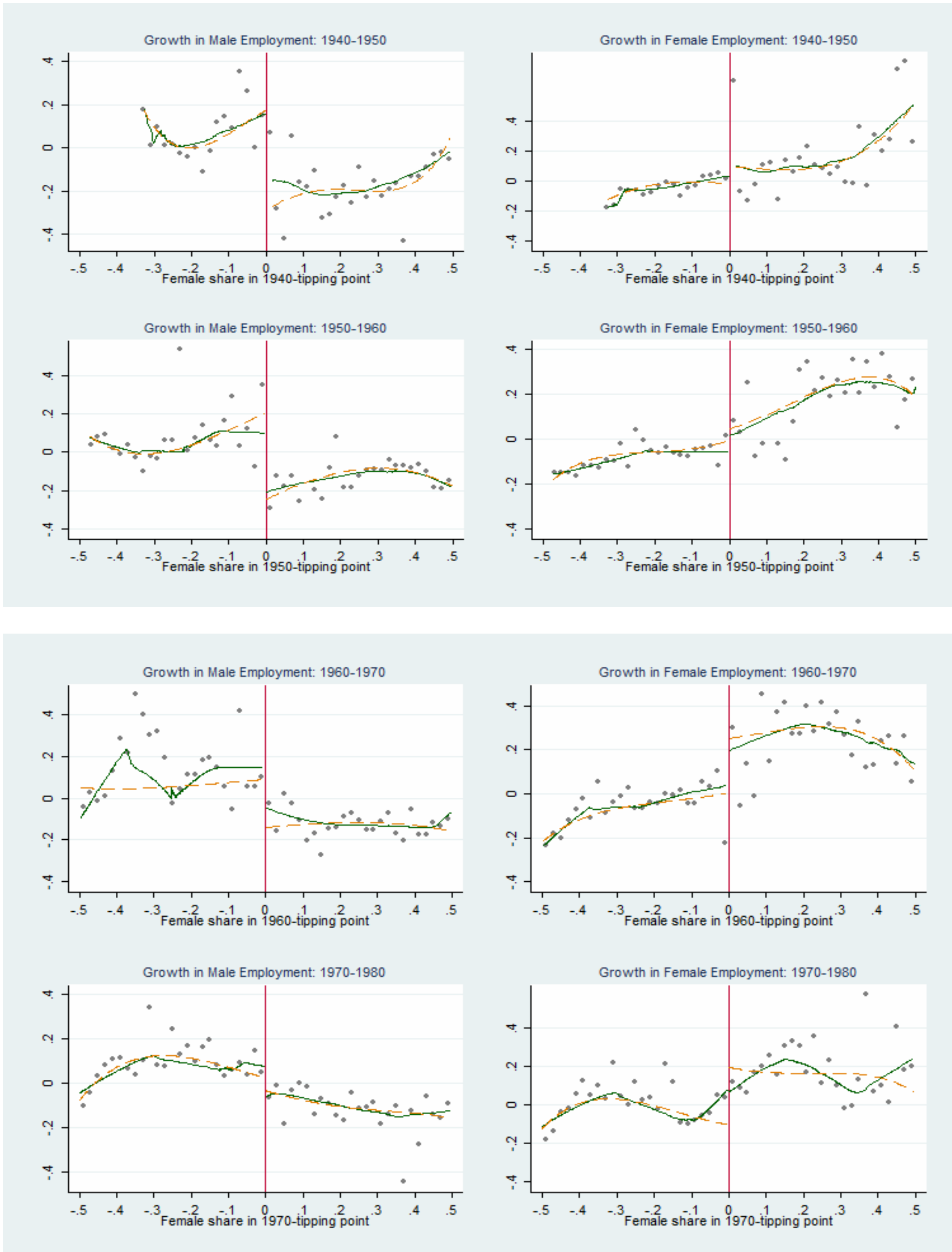



Notes: Each figure plots the net male employment growth deviated from the average net male employment growth for each occupation group against the initial female share deviated from the occupation-group specific tipping point (δij=fij -f*) The dots in each figure represent mean changes for two-percentage-point bins of δij. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The dashed lines are fitted values for a fourth-order polynomial in δij, allowing for an intercept shift at δij =0. The range is restricted to δij =[-0.5, 0.5].

Figure 8: Robustness – Behavior of pre-period covariates (average log male wage, age and schooling) at the candidate tipping points

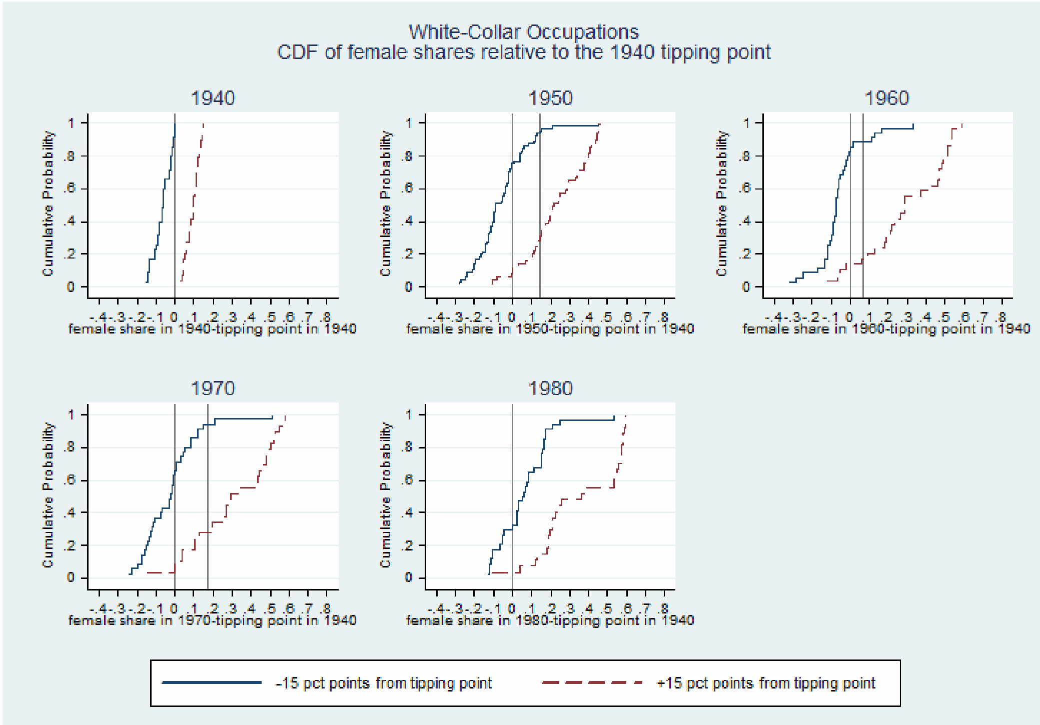

Notes: Each figure plots the levels of pre-period covariates that include average log male wages, average age and average schooling deviated from the mean of this for each occupation group against the initial female share deviated from the occupation-group specific tipping point ($\delta_{ij}=f_{ij}-f^*$) The dots in each figure represent mean changes for two-percentage-point bins of $\delta_{ij}$. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The range is restricted to $\delta_{ij}=[-0.5, 0.5]$.

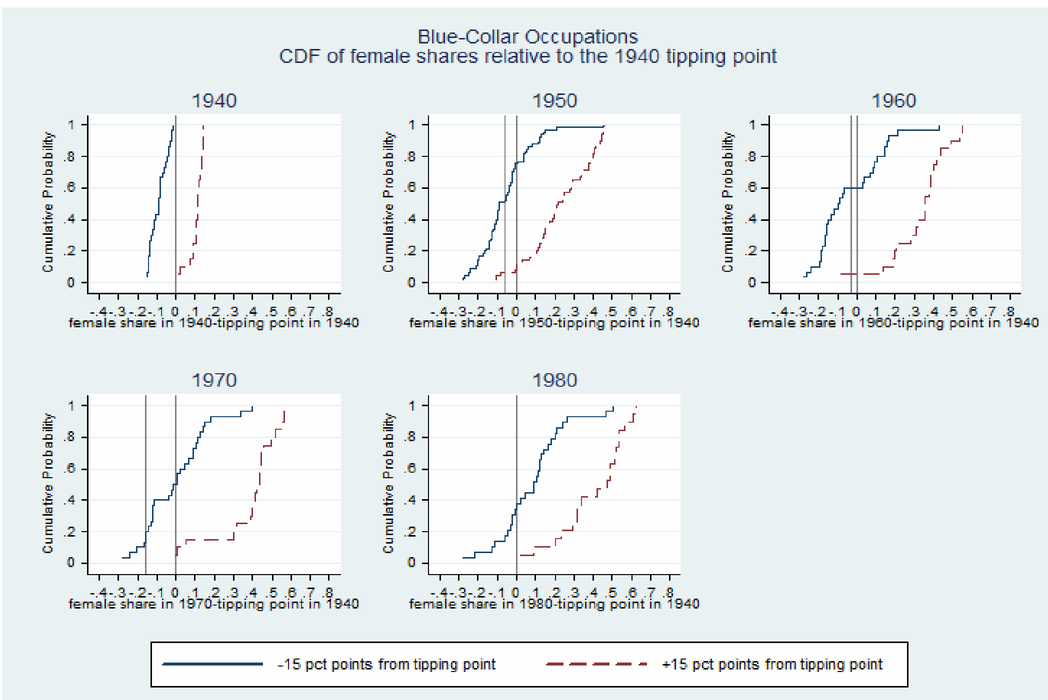
Figure 9: Male flight or females entering? Occupational change in a pooled sample of occupations from 1940-1980, by relationship to white/blue collar-specific tipping point




Notes: Each figure plots the male employment growth (left panel) or female employment growth (right panel) deviated from the average for each occupation group against the initial female share deviated from the occupation-group specific tipping point (δij=fij -f*) The dots in each figure represent mean changes for two-percentage-point bins of δij. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The dashed lines are fitted values for a fourth-order polynomial in δij, allowing for an intercept shift at δij =0. The range is restricted to δij =[-0.5, 0.5].

Figure 10: Evolution of female share for white-collar occupations close to the 1940 tipping point at different points in time from 1940-1980




Notes: Each panel plots the CDF of female shares for white (top figure) or blue-collar (bottom figure) occupations relative to the 1940 tipping point in (from left to right) 1940, 1950, 1960, 1970 and 1980, respectively. The vertical line centered at 0 on the x-axis in all the figures indicates the location of the 1940 tipping point. The second vertical line indicates the current year tipping point. The CDF indicated by the solid lines correspond to occupation-states with female shares 15 percentage points below the 1940 tipping point while the CDF indicated by the dashed lines correspond to occupation-state with female share 15 percentage points above the 1940 tipping point. Tipping points are identified using the full-sample using the structural break procedure allowing for a separate break point for white and blue-collar occupations in each year. The list of occupations included can be found in Appendix Table 5.

Table 1: Descriptive statistics from the 1940-1980 IPUMS

| | Base year (t-10) | | | | |
|---|---|---|---|---|---|
| | **1940** | **1950** | **1960** | **1970** | **1980** |
| *Overall* | | | | | |
| # of occupations | 211 | 250 | 242 | 205 | 204 |
| Mean % female | 0.24 | 0.27 | 0.32 | 0.38 | 0.42 |
| Growth in male employment, t-10 to t | 7.1% | 1.3% | 9.8% | 13.3% | 6.8% |
| Growth in female employment, t-10 to t | 7.2% | 7.1% | 14.4% | 17.4% | 11.2% |
| Growth in total employment, t-10 to t | 14.3% | 8.4% | 24.2% | 30.7% | 18.0% |
| *Restricting to specific occupation-states with at least 30 observations* | | | | | |
| # of occupation-state groups (with >30 obs) | 1354 | 1747 | 1947 | 2476 | |
| *0 to 5% female in base year:* | | | | | |
| #of total number of occ-state groups | 751 | 907 | 908 | 885 | |
| as % of total number of occ-state groups | 55.5% | 51.9% | 46.6% | 35.7% | |
| Growth in total employment | 15.3% | 4.7% | 8.8% | 26.6% | |
| Growth in male employment | 14.4% | 4.1% | 6.7% | 23.2% | |
| *5 to 20% female in base year:* | | | | | |
| # of occupation-state groups | 189 | 272 | 339 | 535 | |
| as % of total number of occ-state groups | 14.0% | 15.6% | 17.4% | 21.6% | |
| Growth in total employment | 15.7% | 11.4% | 43.8% | 39.3% | |
| Growth in male employment | 11.9% | 10.0% | 32.8% | 22.8% | |
| *20 to 50% female in base year:* | | | | | |
| # of occupation-state groups | 120 | 151 | 169 | 344 | |
| as % of total number of occ-state groups | 8.9% | 8.6% | 8.7% | 13.9% | |
| Growth in total employment | 15.1% | 37.4% | 55.7% | 70.2% | |
| Growth in male employment | -2.0% | 19.5% | 33.2% | 31.0% | |
| *50 to 80% female in base year:* | | | | | |
| # of occupation-state groups | 123 | 186 | 215 | 282 | |
| as % of total number of occ-state groups | 9.1% | 10.6% | 11.0% | 11.4% | |
| Growth in total employment | 11.1% | 23.4% | 45.6% | 49.1% | |
| Growth in male employment | -9.2% | -0.6% | 8.0% | 11.4% | |
| *80-100% female in base year:* | | | | | |
| # of occupation-state groups | 171 | 231 | 316 | 430 | |
| as % of total number of occ-state groups | 12.6% | 13.2% | 16.2% | 17.4% | |
| Growth in total employment | 28.4% | 29.7% | 52.4% | 40.5% | |
| Growth in male employment | 1.9% | 1.1% | 5.7% | 3.2% | |

Table 2: Candidate tipping points

| | Structural Break Method | | Fixed Point Method | |
|---|---|---|---|---|
| | White Collar | Blue Collar | White Collar | Blue Collar |
| 1940-1950 | 0.327 | 0.281 | 0.327 | 0.281 |
| 1950-1960 | 0.471 | 0.219 | 0.475 | 0.244 |
| 1960-1970 | 0.537 | 0.255 | 0.442 | 0.273 |
| 1970-1980 | 0.646 | 0.125 | 0.607 | 0.165 |

Table 3: Basic regression models for net male employment changes around the tipping point

| | Dependent variable: Net growth in male employment | | | | |
|---|---|---|---|---|---|
| | Pooled Sample | | | White-collar | Blue-collar |
| | (1) | (2) | (3) | (4) | (5) |
| | *Time period: 1940-1950* | | | | |
| Beyond candidate tipping point | -0.58 | -0.545 | -0.49 | -0.422 | -0.52 |
| | [0.119] | [0.127] | [0.126] | [0.174] | [0.178] |
| Adjusted P-value | 0.007 | 0.024 | 0.026 | 0.078 | 0.075 |
| Observations | 1329 | 1329 | 1329 | 383 | 946 |
| R-squared | 0.27 | 0.31 | 0.33 | 0.52 | 0.27 |
| | *Time period: 1950-1960* | | | | |
| Beyond candidate tipping point | -0.565 | -0.542 | -0.464 | -0.684 | -0.254 |
| | [0.084] | [0.087] | [0.105] | [0.169] | [0.120] |
| Adjusted P-value | 0.000 | 0.000 | 0.005 | 0.002 | 0.208 |
| Observations | 1667 | 1667 | 1667 | 552 | 1115 |
| R-squared | 0.22 | 0.29 | 0.3 | 0.41 | 0.27 |
| | *Time period: 1960-1970* | | | | |
| Beyond candidate tipping point | -0.593 | -0.575 | -0.407 | -0.395 | -0.456 |
| | [0.097] | [0.096] | [0.110] | [0.131] | [0.186] |
| Adjusted P-value | 0.009 | 0.009 | 0.029 | 0.025 | 0.121 |
| Observations | 1908 | 1908 | 1908 | 730 | 1178 |
| R-squared | 0.26 | 0.28 | 0.29 | 0.48 | 0.18 |
| | *Time period: 1970-1980* | | | | |
| Beyond candidate tipping point | -0.351 | -0.359 | -0.183 | -0.184 | -0.188 |
| | [0.044] | [0.045] | [0.058] | [0.101] | [0.068] |
| Adjusted P-value | 0.000 | 0.000 | 0.065 | 0.249 | 0.051 |
| Observations | 2461 | 2461 | 2461 | 1073 | 1388 |
| R-squared | 0.29 | 0.33 | 0.34 | 0.38 | 0.3 |
| Controls: | | | | | |
| White-collar fixed effect | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share | Yes | Yes | Yes | Yes | Yes |
| State fixed effects | No | Yes | Yes | Yes | Yes |
| Pre-period occ. characteristics | No | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share*white-collar | No | No | Yes | No | No |

Notes: The unit of observation is an occupation-state. Each panel corresponds to a separate regression for the stated time period. Columns (1) to (3) report OLS estimates of d* from the full data using the candidate tipping points estimated using the full sample. Columns (4) and (5) restrict the sample to white and blue-collar occupations separately. Robust standard errors are reported in parantheses. The adjusted P-value is computed based on a monte carlo simulation of the distribution of the t-statistic under the null hypothesis using 5000 simulations. The p-value is the fraction of simulations that have a t-statistic at least as large as the t-statistic of the estimate.

Table 4: Changes in wages and occupational composition around the candidate tipping point

| Dependent variable: | Change in average log male wage | | Change in average log female wage | | Change in average male age | | Change in average male schooling | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 1940-1950 | | | | | | | | |
| Beyond candidate tipping point | -0.066 | 0.013 | -0.087 | -0.061 | -1.064 | -0.372 | 0.755 | 0.691 |
| | [0.176] | [0.180] | [0.277] | [0.289] | [1.384] | [1.417] | [0.468] | [0.477] |
| Observations | 1278 | 1278 | 655 | 630 | 1312 | 1312 | 1287 | 1287 |
| R-squared | 0.16 | 0.17 | 0.09 | 0.09 | 0.07 | 0.08 | 0.07 | 0.08 |
| 1950-1960 | | | | | | | | |
| Beyond candidate tipping point | -0.197 | -0.154 | -0.212 | -0.329 | 0.421 | 0.549 | 0.06 | -0.119 |
| | [0.116] | [0.147] | [0.177] | [0.176] | [0.983] | [1.247] | [0.277] | [0.327] |
| Observations | 1659 | 1659 | 877 | 797 | 1661 | 1661 | 1661 | 1661 |
| R-squared | 0.06 | 0.07 | 0.05 | 0.07 | 0.08 | 0.08 | 0.05 | 0.05 |
| 1960-1970 | | | | | | | | |
| Beyond candidate tipping point | -0.152 | -0.064 | 0.043 | -0.022 | 2.046 | -0.467 | -0.469 | -0.101 |
| | [0.078] | [0.101] | [0.118] | [0.125] | [1.113] | [1.463] | [0.227]* | [0.317] |
| Observations | 1903 | 1903 | 1376 | 1337 | 1904 | 1904 | 1904 | 1904 |
| R-squared | 0.06 | 0.07 | 0.05 | 0.05 | 0.09 | 0.11 | 0.15 | 0.17 |
| 1970-1980 | -0.001 | -0.002 | -0.062 | -0.058 | 0.192 | 1.694 | 0.181 | -0.042 |
| Beyond candidate tipping point | [0.028] | [0.034] | [0.043] | [0.057] | [0.466] | [0.588]** | [0.074]* | [0.092] |
| Observations | 2461 | 2461 | 2161 | 2146 | 2461 | 2461 | 2461 | 2461 |
| R-squared | 0.09 | 0.1 | 0.05 | 0.05 | 0.11 | 0.12 | 0.22 | 0.23 |
| Controls: | | | | | | | | |
| White-collar fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share*white-collar | No | Yes | No | Yes | No | Yes | No | Yes |

Notes: The dependent variables are the change in average log male wage (1), change in average log female wage (2), change in average male age (3) and change in average male schooling (4) from t-10 to t. Results from the pooled specification including both white and blue-collar occupations are reported.

Table 5: Regional variation in tipping points and male sexism in the GSS

| | Average tipping point | | | Average male sexism index | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | p-value for difference |
| Census region | Overall | White-collar | Blue-collar | Overall | White-collar | Blue-collar | (6)-(5) |
| New England | 0.516 | 0.627 | 0.406 | -0.131 | -0.241 | -0.001 | 0.00 |
| Middle Atlantic | 0.403 | 0.463 | 0.343 | 0.036 | -0.083 | 0.143 | 0.00 |
| E. North Central | 0.385 | 0.442 | 0.327 | -0.035 | -0.162 | 0.052 | 0.00 |
| W. North Central | 0.378 | 0.520 | 0.236 | -0.053 | -0.125 | 0.020 | 0.002 |
| South Atlantic | 0.336 | 0.453 | 0.220 | 0.050 | -0.027 | 0.117 | 0.00 |
| E. South Central | 0.318 | 0.485 | 0.150 | 0.144 | -0.019 | 0.210 | 0.00 |
| W. South Central | 0.280 | 0.423 | 0.138 | 0.065 | -0.032 | 0.149 | 0.00 |
| Mountain | 0.375 | 0.436 | 0.335 | -0.085 | -0.060 | -0.105 | 0.371 |
| Pacific | 0.361 | 0.461 | 0.262 | -0.058 | -0.117 | 0.007 | 0.00 |

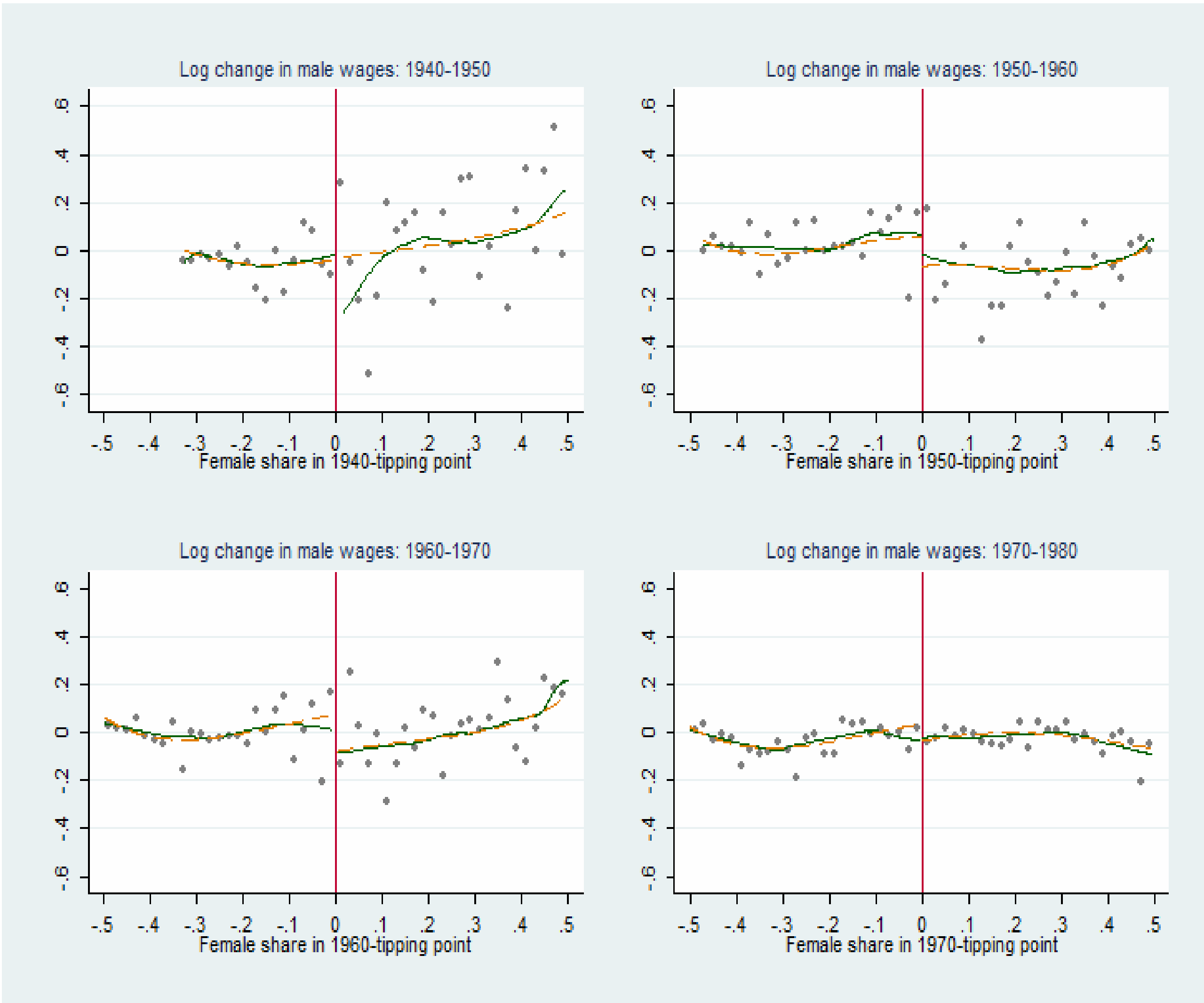
Notes: The average tipping points reported are the simple means of the candidate tipping points across the three time period (1950-1960, 1960-1970 and 1970-1980) for each region. The average male sexism index is constructed based on male answers to eight gender-related questions in the General Social Survey. The overall index is the aggregate male sexism index at the regional level while the white-collar and blue-collar index restricts the index to males whose reported occupation in the GSS is white-collar or blue-collar, respectively. Tipping points are estimated based on an identical set of occupations in each census region. Tipping points were not estimated for the Mountain region due to small samples sizes.

Table 6: Relationship between location of tipping points and male sexism index

| | | Dependent variable: Candidate tipping point (mean: 0.37, sd: 0.21) | | | | | |
|---|---|---|---|---|---|---|---|
| | Mean (sd) | (1) | (2) | (3) | (4) | (5) | (6) |
| Average male prejudice | -0.01 | -0.666 | -0.676 | -0.777 | | -0.672 | -0.728 |
| | [0.12] | [0.214]** | [0.216]** | [0.275]* | | [0.435] | [0.298]* |
| Average female prejudice | 0.00 | | | | -0.485 | 0.009 | -0.143 |
| | [0.12] | | | | [0.256] | [0.411] | [0.798] |
| Fraction female | 0.34 | | 1.859 | -2.064 | | | -2.015 |
| | [0.11] | | [0.714]* | [1.831] | | | [1.723] |
| Fraction high-school (male) | 0.43 | | -0.475 | -0.626 | | | -0.638 |
| | [0.26] | | [1.146] | [1.155] | | | [1.171] |
| Fraction high-school (female) | 0.44 | | 0.531 | -0.109 | | | -0.104 |
| | [0.26] | | [1.252] | [1.354] | | | [1.372] |
| 1960 | | -0.101 | -0.17 | 0.075 | -0.101 | -0.101 | 0.092 |
| | | [0.049] | [0.144] | [0.218] | [0.049] | [0.049] | [0.293] |
| 1970 | | 0.125 | -0.007 | 0.292 | 0.125 | 0.125 | 0.327 |
| | | [0.067] | [0.232] | [0.350] | [0.067] | [0.068] | [0.514] |
| White-collar | | 0.099 | -0.333 | 6.703 | 0.13 | 0.099 | 7.418 |
| | | [0.047] | [0.266] | [3.645] | [0.066] | [0.052] | [3.895] |
| Occupational structure | | No | No | Yes | No | No | Yes |
| Observations | | 48 | 48 | 48 | 48 | 48 | 48 |
| R-squared | | 0.55 | 0.58 | 0.65 | 0.53 | 0.55 | 0.65 |

Notes: The unit of observation is a region*year*occupation-group. The total number of observations corresponds to 8 regions (Mountain region omitted), 3 years (1950, 1960 and 1970) and 2 occupation groups (white-collar and blue-collar occupations). For comparability, the tipping points were estimated based on an identical set of occupations in each region. The prejudice indices are constructed using the 1977 to 1998 waves of the GSS and vary by region and occupation-group. The fraction female in a region*occupation-group is constructed using the census. All regressions are clustered by region*occupation-group.
**Significant at 1% *at 5%.

Appendix Figure 1: Log change in male wages around the candidate tipping points, 1940-1980

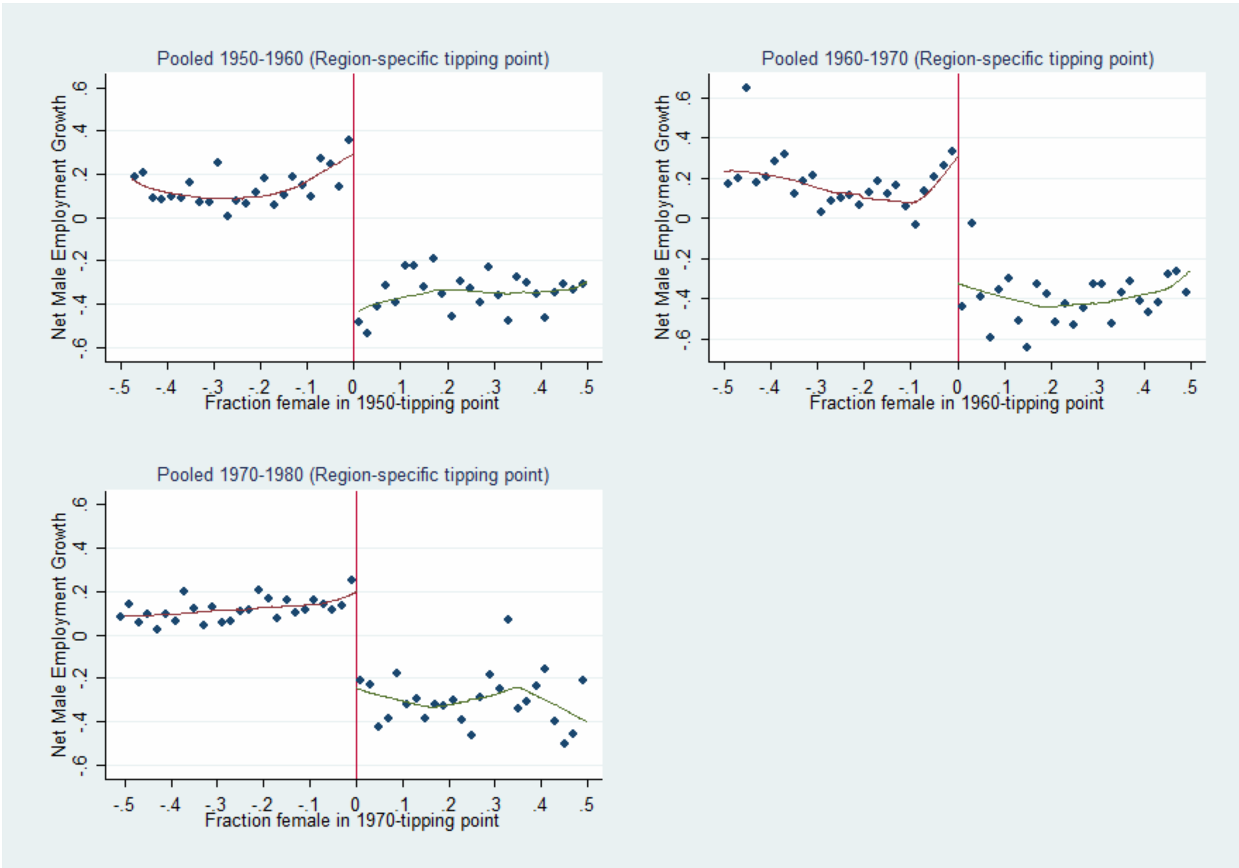



Notes: Each figure plots the log change in male wages deviated from the average of this for each occupation group against the initial female share deviated from the occupation-group specific tipping point ($\delta ij$=fij -f*). The dots in each figure represent mean changes for two-percentage-point bins of $\delta ij$. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The dashed lines are fitted values for a fourth-order polynomial in $\delta ij$, allowing for an intercept shift at $\delta ij$ =0. The range is restricted to $\delta ij$ =[-0.5, 0.5].

Appendix Figure 2: Occupational change in a pooled sample of occupations by region from 1950-1960, by relationship to white/blue collar-specific tipping point

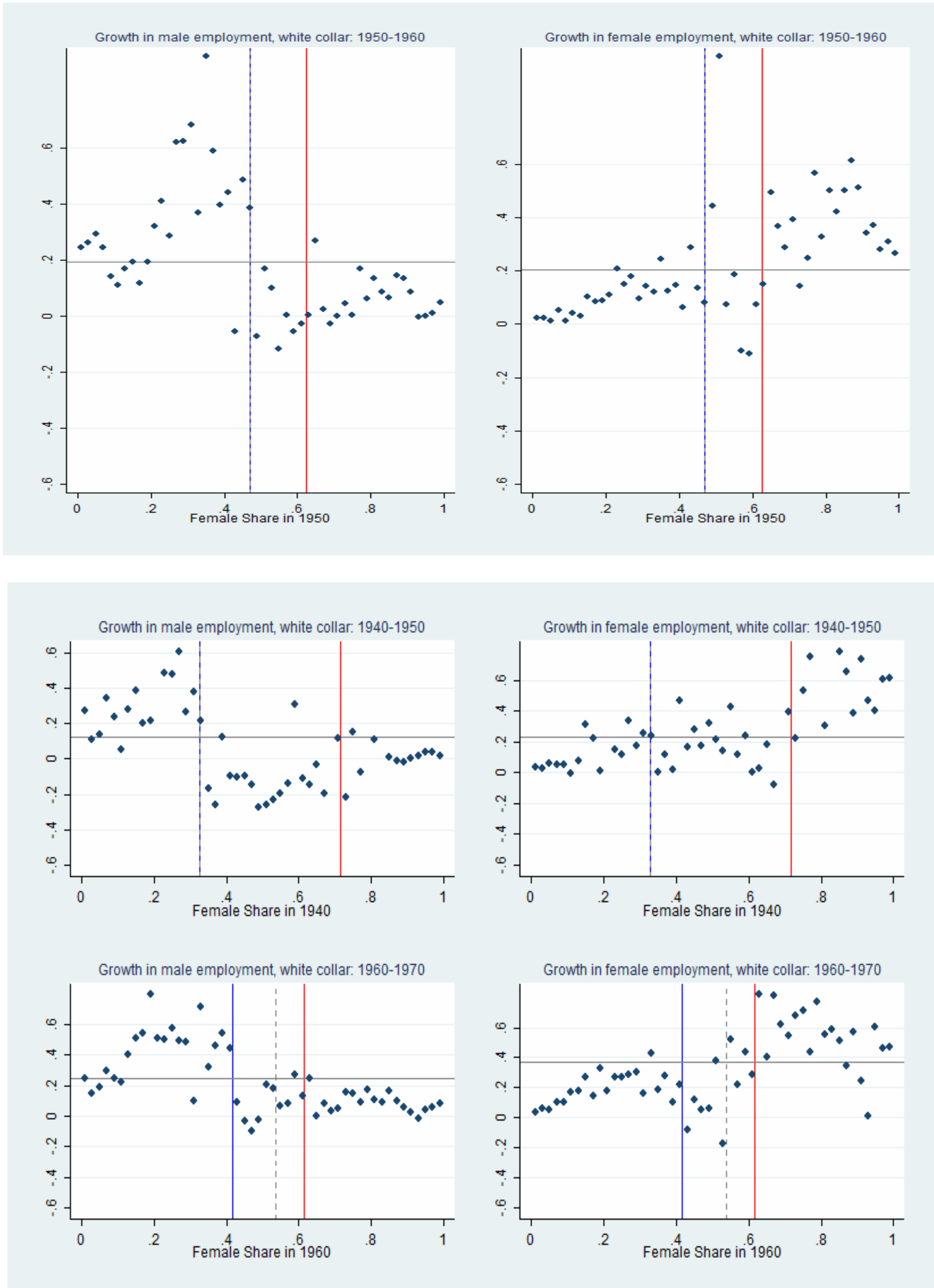

Notes: Each figure plots the net male employment growth deviated from the average net male employment growth for each occupation group against the initial female share deviated from the occupation-group specific tipping point ($\delta_{ij}=f_{ij} - f^*$) in each region. The dots in each figure represent mean changes for two-percentage-point bins of $\delta_{ij}$. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The range is restricted to $\delta_{ij}$ =[-0.5, 0.8]. The tipping points depicted in the figures are estimated from a restricted sample that keeps the set of occupations constant across regions. The figures also plot data from this restricted sample.

Appendix Figure 3: Occupational change in a pooled sample of occupations from 1950-1980, by relationship to region*occupation-group specific tipping point




Notes: Each figure plots the net male employment growth deviated from the average net male employment growth for each occupation group against the initial female share deviated from the occupation-group specific tipping point ($\delta_{ij}=f_{ij}-f^*$) The dots in each figure represent mean changes for two-percentage-point bins of $\delta_{ij}$. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The range is restricted to $\delta_{ij}=[-0.5, 0.5]$. The tipping points are estimated using the full data (not just the set of consistent occupations across regions as in Appendix Figure 2). This is done for comparability with the regression results from Appendix Table 1. The figure that restricts the data to the set of consistent occupations across regions (not shown) is similar.

Appendix Figure 4: Male employment growth, female employment growth and associated tipping points for white-collar occupations from 1940-1980




Notes: Each dot is the average male employment growth (left panels) or the average female employment growth (right panels) among all white-collar occupations with initial female share in each two-percentage point bin. The horizontal line is the average male employment growth or female employment growth for each time-period. The vertical grey dotted line is the candidate tipping point estimated using the net growth in male employment as the variable of interest. The blue line is the tipping point estimated using the growth in male employment as and the red line is the tipping point estimated using the growth in female employment as the variable of interest.

Appendix Table 1: Basic RD models for net male employment changes around the tipping point allowing for region*occupation-group specific tipping points

| | Dependent variable: Net growth in male employment | | | | |
|---|---|---|---|---|---|
| | Pooled Sample | | | White-collar | Blue-collar |
| | (1) | (2) | (3) | (4) | (5) |
| | *Time period: 1950-1960* | | | | |
| Beyond candidate tipping point | -0.731 | -0.725 | -0.722 | -0.869 | -0.607 |
| | [0.088]** | [0.087]** | [0.092]** | [0.100]** | [0.126]** |
| Observations | 1657 | 1657 | 1657 | 542 | 1115 |
| R-squared | 0.27 | 0.31 | 0.32 | 0.41 | 0.28 |
| | *Time period: 1960-1970* | | | | |
| Beyond candidate tipping point | -0.559 | -0.546 | -0.537 | -0.668 | -0.365 |
| | [0.160]** | [0.152]** | [0.125]** | [0.082]** | [0.188] |
| Observations | 1908 | 1908 | 1908 | 730 | 1178 |
| R-squared | 0.27 | 0.28 | 0.29 | 0.49 | 0.17 |
| | *Time period: 1970-1980* | | | | |
| Beyond candidate tipping point | -0.411 | -0.418 | -0.395 | -0.369 | -0.402 |
| | [0.045]** | [0.039]** | [0.055]** | [0.074]** | [0.068]** |
| Observations | 2461 | 2461 | 2461 | 1073 | 1388 |
| R-squared | 0.33 | 0.36 | 0.37 | 0.37 | 0.32 |
| Controls: | | | | | |
| White-collar fixed effect | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share | Yes | Yes | Yes | Yes | Yes |
| State fixed effects | No | Yes | Yes | Yes | Yes |
| Pre-period occ. characteristics | No | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share*white-collar | No | No | Yes | No | No |

Notes: The unit of observation is an occupation-state. Each panel corresponds to a separate regression for the stated time period. Columns (1) to (3) report OLS estimates of d* from the full data using the candidate tipping points estimated using the full sample and allowing tipping points to vary by region and occupational group. Columns (4) and (5) restrict the sample to white and blue-collar occupations separately. Standard errors are clustered by region*occupation-group and are reported in parentheses. The time-period from 1950-1960 has fewer observations than Table 3 because no tipping point was found for white-collar occupations in the mountain region.

Appendix Table 2: Behavior of pre-period covariates around the candidate tipping point

| Dependent variable: | Average log male wage (t-10) | | Average log female wage (t-10) | | Average age (t-10) | | Average schooling (t-10) | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 1940-1950 | | | | | | | | |
| Beyond candidate tipping point | 0.22 | -0.154 | 0.284 | 0.101 | -2.123 | 0.306 | -0.952 | -0.453 |
| | [0.164] | [0.133] | [0.222] | [0.226] | [1.224] | [1.239] | [0.439]* | [0.452] |
| Observations | 1329 | 1329 | 869 | 869 | 1329 | 1329 | 1329 | 1329 |
| R-squared | 0.36 | 0.46 | 0.3 | 0.32 | 0.25 | 0.28 | 0.69 | 0.7 |
| | | | | | | | | |
| 1950-1960 | | | | | | | | |
| Beyond candidate tipping point | -0.036 | 0.085 | -0.055 | 0.106 | 2.336 | 0.588 | 0.186 | 0.4 |
| | [0.111] | [0.133] | [0.177] | [0.177] | [1.317] | [1.442] | [0.360] | [0.385] |
| Observations | 1667 | 1667 | 871 | 871 | 1667 | 1667 | 1667 | 1667 |
| R-squared | 0.19 | 0.22 | 0.19 | 0.21 | 0.19 | 0.22 | 0.63 | 0.63 |
| | | | | | | | | |
| 1960-1970 | | | | | | | | |
| Beyond candidate tipping point | -0.149 | -0.098 | -0.116 | -0.002 | -2.069 | -2.442 | -0.284 | 0.073 |
| | [0.089] | [0.119] | [0.104] | [0.113] | [1.173] | [1.541] | [0.317] | [0.367] |
| Observations | 1908 | 1908 | 1384 | 1384 | 1908 | 1908 | 1908 | 1908 |
| R-squared | 0.31 | 0.34 | 0.21 | 0.22 | 0.15 | 0.18 | 0.7 | 0.71 |
| | | | | | | | | |
| 1970-1980 | | | | | | | | |
| Beyond candidate tipping point | -0.05 | 0.141 | 0.057 | 0.128 | 1.081 | -0.915 | -0.367 | 0.061 |
| Observations | [0.033] | [0.041]** | [0.046] | [0.058]* | [0.491]* | [0.599] | [0.131]** | [0.159] |
| R-squared | 2461 | 2461 | 2153 | 2153 | 2461 | 2461 | 2461 | 2461 |
| | 0.36 | 0.37 | 0.18 | 0.19 | 0.14 | 0.16 | 0.69 | 0.71 |
| Controls: | | | | | | | | |
| White-collar fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share*white-collar | No | Yes | No | Yes | No | Yes | No | Yes |

Notes: Each cell is a separate estimate of equation (2) replacing the dependent variable with the relevant pre-period covariate (t-10 value). Robust standard errors are reported. *significant at 5% level, **significant at 1% level.

Appendix Table 3: Male flight or females entering? Behavior of male employment growth and female employment growth around the tipping points

| Dependent variable: | Male employment growth | | Female employment growth | | Male share | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 1940-1950 | | | | | | |
| Beyond candidate tipping point | -0.457 | -0.412 | 0.088 | 0.078 | -0.108 | -0.098 |
| | [0.118] | [0.120] | [0.094] | [0.096] | [0.039] | [0.040] |
| Observations | 1329 | 1329 | 1329 | 1329 | 1329 | 1329 |
| R-squared | 0.18 | 0.19 | 0.44 | 0.48 | 0.25 | 0.26 |
| 1950-1960 | | | | | | |
| Beyond candidate tipping point | -0.406 | -0.486 | 0.136 | -0.023 | -0.16 | -0.134 |
| | [0.074] | [0.083] | [0.065] | [0.087] | [0.026] | [0.034] |
| Observations | 1667 | 1667 | 1667 | 1667 | 1667 | 1667 |
| R-squared | 0.21 | 0.22 | 0.36 | 0.37 | 0.18 | 0.21 |
| 1960-1970 | | | | | | |
| Beyond candidate tipping point | -0.276 | -0.127 | 0.298 | 0.28 | -0.12 | -0.122 |
| | [0.090] | [0.093] | [0.063] | [0.087] | [0.023] | [0.029] |
| Observations | 1908 | 1908 | 1908 | 1908 | 1908 | 1908 |
| R-squared | 0.13 | 0.17 | 0.43 | 0.44 | 0.11 | 0.21 |
| 1970-1980 | | | | | | |
| Beyond candidate tipping point | -0.144 | -0.132 | 0.216 | 0.051 | -0.138 | -0.052 |
| | [0.042] | [0.053] | [0.032] | [0.037] | [0.014] | [0.017] |
| Observations | 2461 | 2461 | 2461 | 2461 | 2461 | 2461 |
| R-squared | 0.2 | 0.21 | 0.36 | 0.4 | 0.22 | 0.29 |
| Controls: | | | | | | |
| White-collar fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| State fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-period occupational characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share | Yes | Yes | Yes | Yes | Yes | Yes |
| 4th order polynomial in initial female share*white-collar | No | Yes | No | Yes | No | Yes |

Notes: The unit of observation is an occupation-state. Each panel corresponds to separate regressions for the stated time period. The sample here includes both white and blue-collar occupations and the model includes a fixed effect for white-collar occupations. The standard errors are reported in parenthesis.

Appendix Table 4: Sensitivity of estimates to flexible controls for wages

| | Dependent variable: Net growth in male employment | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| 1940-1950 | -0.545 | -0.49 | | -0.61 | |
| | [0.127] | [0.127] | | [0.131] | |
| 1950-1960 | -0.542 | -0.542 | -0.528 | -0.523 | -0.481 |
| | [0.087] | [0.087] | [0.083] | [0.089] | [0.081] |
| 1960-1970 | -0.575 | -0.564 | -0.544 | -0.524 | -0.504 |
| | [0.096] | [0.096] | [0.097] | [0.094] | [0.095] |
| 1970-1980 | -0.359 | -0.363 | -0.362 | -0.356 | -0.354 |
| | [0.045] | [0.045] | [0.045] | [0.046] | [0.045] |
| *Including 4th order polynomial in:* | | | | | |
| Average male log wage in base period (t-10) | No | Yes | No | Yes | No |
| Growth in average male log wage (t-20 to t-10) | No | No | Yes | No | Yes |
| Average age in t-10 | No | No | No | Yes | Yes |
| Average schooling in t-10 | No | No | No | Yes | Yes |

Notes: Column (1) is that from column (2) of Table 3. The baseline specification includes controls for white-collar occupations, a 4th order polynomial in initial female share, state fixed effects and linear controls for average male log wages, average age and average schooling. Remaining specifications add 4th order polynomials in the listed control variables. Robust standard errors are reported in parentheses. Values are missing for column (3) and (5) for the 1940-1950 time period as wages were not reported in the 1930 Census.

Appendix Table 5: List of occupations close to the candidate tipping points in each year

| Occupation | Number of states | Occupation | Number of states |
|---|---|---|---|
| 10 percentage points to the left of tipping point | | 10 percentage points to the right of tipping point | |
| 1940: White-Collar Workers | | | |
| Artists and art teachers | 4 | Actors and actresses | 2 |
| Authors | 2 | Professors and instructors | 1 |
| Professors and instructors | 4 | Musicians and music teachers | 5 |
| Editors and reporters | 4 | Social and welfare workers | 1 |
| Musicians and music teachers | 2 | Buyers and dept heads, store | 1 |
| Medical and dental-technicians | 3 | Bookkeepers | 6 |
| Buyers and dept heads, store | 6 | | |
| Bookkeepers | 1 | | |
| Shipping and receiving clerks | 1 | | |
| 1940: Blue-Collar and Service Workers | | | |
| Decorators and window dressers | 1 | Hospital attendents | 1 |
| Tailors and tailoresses | 1 | Barbers, beauticians, and manicurists | 1 |
| Attendants, auto service and parking | 1 | Cooks, except private household | 2 |
| Attendants, recreation and amusement | 2 | Elevator operators | 1 |
| Charwomen and cleaners | 2 | | |
| Cooks, except private household | 6 | | |
| Elevator operators | 2 | | |
| Janitors and sextons | 2 | | |
| 1950: White-Collar Workers | | | |
| Accountants and auditors | 1 | Musicians and music teachers | 7 |
| Actors and actresses | 1 | Social and welfare workers | 1 |
| Artists and art teachers | 2 | Statisticians and actuaries | 1 |
| Authors | 1 | Bank tellers | 2 |
| Professors and instructors | 2 | | |
| Musicians and music teachers | 4 | | |
| Personnel and labor relations workers | 1 | | |
| Sports instructors and officials | 1 | | |
| Medical and dental-technicians | 6 | | |
| Bank tellers | 3 | | |
| 1950: Blue-Collar and Service Workers | | | |
| Bakers | 1 | Tailors and tailoresses | 2 |
| Compositors and typesetters | 1 | Charwomen and cleaners | 2 |
| Cranemen, derrickmen, and hoistmen | 1 | Cooks, except private household | 4 |
| Decorators and window dressers | 2 | Counter and fountain workers | 1 |
| Radio and TV-mechanics and repairmen | 1 | Elevator operators | 2 |
| Tailors and tailoresses | 1 | Guards, watchmen and doorkeepers | 1 |
| Dyers | 1 | Janitors and sextons | 1 |
| Painters | 10 | | |
| Photographic process workers | 1 | | |
| Bartenders | 2 | | |
| Janitors and sextons | 16 | | |
| Porters | 1 | | |
| Gardeners | 1 | | |

Appendix Table 5 [continued]

| Occupation | Number of states | Occupation | Number of states |
|---|---|---|---|
| 10 percentage points to the left of tipping point | | 10 percentage points to the right of tipping point | |
| 1960: White-Collar Workers | | | |
| Actors and actresses | 1 | Musicians and music teachers | 9 |
| Artists and art teachers | 1 | Social and welfare workers | 4 |
| Editors and reporters | 1 | Building managers | 1 |
| Musicians and music teachers | 5 | Bank tellers | 2 |
| Statisticians and actuaries | 1 | Cashiers | 1 |
| Bank tellers | 1 | Office machine operators | 1 |
| | | Hucksters and peddlers | 1 |
| 1960: Blue-Collar and Service Workers | | | |
| Bakers | 4 | Bakers | 2 |
| Compositors and typesetters | 2 | Bookbinders | 1 |
| Decorators and window dressers | 1 | Bus drivers | 1 |
| Pressmen and plate printers, printing | 1 | Barbers, beauticians and manicurists | 1 |
| Tailors and tailoresses | 1 | Cooks, except private household | 2 |
| Tinsmiths, coppersmiths | 1 | Janitors and sextons | 1 |
| Bus drivers | 1 | | |
| Painters | 1 | | |
| Photographic process workers | 1 | | |
| Attendants, recreation and amusement | 2 | | |
| Bartenders | 3 | | |
| Janitors and sextons | 11 | | |
| 1970: White-Collar Workers | | | |
| Musicians and music teachers | 13 | Librarians | 2 |
| Social and welfare workers | 6 | Musicians and music teachers | 4 |
| Statisticians and actuaries | 1 | Social and welfare workers | 12 |
| Office machine operators | 2 | Library attendants and assistants | 2 |
| Hucksters and peddlers | 1 | Bank tellers | 2 |
| | | Bookkeepers | 1 |
| | | Cashiers | 2 |
| | | Office machine operators | 12 |
| | | Hucksters and peddlers | 1 |

Appendix Table 5 [continued]

| Occupation | Number of states | Occupation | Number of states |
|---|---|---|---|
| 1970: Blue-Collar and Service Workers | | | |
| 5 percentage points to the left of tipping point | | 5 percentage points to the right of tipping point | |
| Bakers | 2 | Cabinetmakers | 1 |
| Cabinetmakers | 1 | Compositors and typesetters | 7 |
| Compositors and typesetters | 3 | Radio and TV-mechanics and repairme | 1 |
| Electricians | 1 | Metal molders | 3 |
| Linemen and servicemen | 1 | Painters, construction and maintenanc | 1 |
| Machinists | 3 | Photoengravers and lithographers | 1 |
| Airplane-mechanics and repairmen | 1 | Shoemakers and repairers | 1 |
| Automobile-mechanics and repairmen | 1 | Tailors and tailoresses | 1 |
| Radio and TV-mechanics and repairmen | 1 | Bus drivers | 1 |
| Metal molders | 3 | Filers, grinders, and polishers | 5 |
| Painters, construction and maintenance | 6 | Painters | 5 |
| Photoengravers and lithographers | 2 | Sawyers | 2 |
| Pressmen and plate printers | 7 | Taxicab drivers and chauffers | 1 |
| Shoemakers and repairers | 3 | Welders and flame cutters | 1 |
| Upholsterers | 1 | Bartenders | 1 |
| Deliverymen and routemen | 1 | Janitors and sextons | 16 |
| Filers, grinders, and polishers | 9 | Policement and detectives | 1 |
| Meat cutters | 5 | Sheriffs and bailiffs | 1 |
| Mine operatives and laborers | 2 | | |
| Painters | 2 | | |
| Sawyers | 3 | | |
| Taxicab drivers and chauffers | 1 | | |
| Welders and flame cutters | 6 | | |
| Bartenders | 4 | | |
| Guards, watchmen and doorkeepers | 2 | | |
| Janitors and sextons | 29 | | |
| Policement and detectives | 2 | | |
| Fishermen and oystermen | 2 | | |
| Gardeners | 1 | | |
| Lumbermen | 1 | | |