Online Appendix

Missing Women, Integration Costs, and Big Push Policies in the Saudi Labor Market

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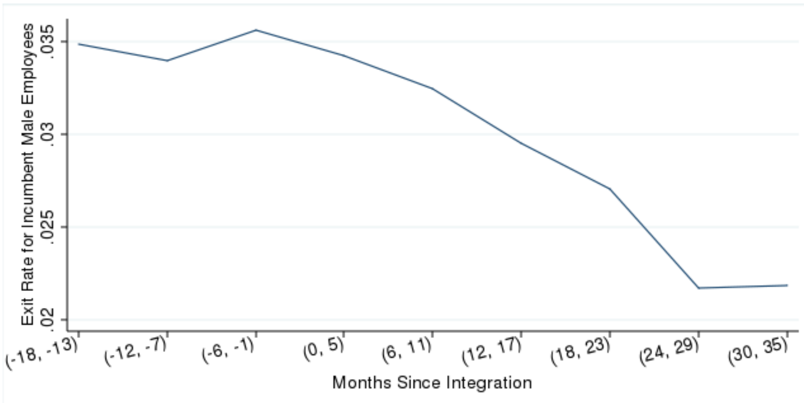
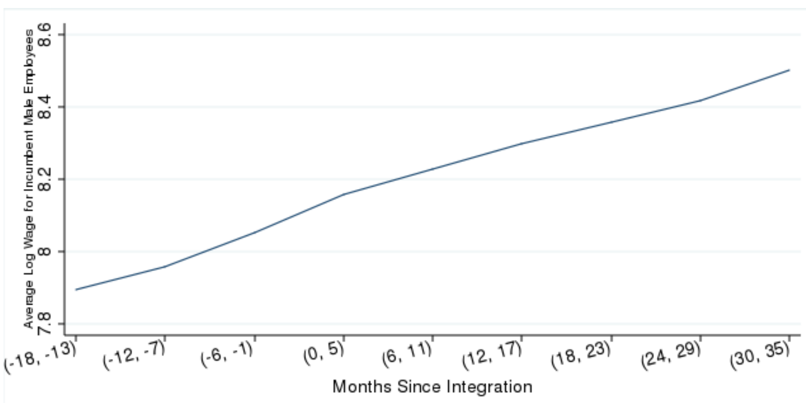
A Additional Tables and Figures

Figure A.1: Separation Rates and Wages for Incumbent Men at Newly Integrated Firms

(a) Separation Rates



(b) Log Wages



Note: This set of figures describes the separation rates and wages of incumbent male employees at newly integrated firms in the GOSI data. Incumbent male employees are defined as male employees that joined the firm more than 18 months prior to the firm's first female hire. Panel A plots the average monthly separation rate of incumbent male employees at integrating firms in six-month increments relative to a firm's first observed female hire, averaged across firms. Panel B plots the average log monthly wage of incumbent male employees at integrating firms in six-month increments relative to a firm's first observed female hire, averaged across firms. For both panels, we restrict to firms with at least five Saudi employees in the month prior to integration.

Table A.1: Observed and Simulated Distribution of Female Employment Across Firms

Panel A: θ Estimated Under Null

# of Female Employees	Observed	(1)	(2)	(3)	(4)	(5)	(6)
0	73.27	33.37	32.73	34.37	38.66	42.92	42.56
1	5.70	26.97	25.27	25.03	25.05	22.35	22.07
2	3.68	13.79	14.08	13.29	12.01	10.48	10.32
3	2.88	7.13	7.61	7.15	6.01	5.59	5.73
4	2.13	4.19	4.45	4.24	3.56	3.50	3.60
5	1.54	2.63	2.93	2.81	2.27	2.70	2.41
6-10	3.93	6.09	6.60	6.48	5.32	5.26	5.59
11-24	3.03	3.89	4.17	4.26	4.10	4.11	4.34
25+	3.83	1.94	2.17	2.37	3.01	3.53	3.37
Location			✓	✓	✓	✓	✓
1-Digit Occ.				✓			
2-Digit Occ.					✓	✓	
1-Digit Ind.						✓	
1-Digit Ind. × 1-Digit Occ.							✓

Panel B: θ Estimated Using Ex-Post Integrated

# of Female Employees	Observed	(7)	(8)	(9)	(10)	(11)	(12)
0	73.27	73.48	73.36	73.46	73.40	73.39	73.29
1	5.70	6.97	6.09	6.33	6.59	5.34	5.34
2	3.68	4.77	4.32	4.15	4.19	3.83	3.75
3	2.88	2.92	2.90	2.65	2.56	2.62	2.58
4	2.13	1.94	1.98	1.80	1.73	1.83	1.94
5	1.54	1.38	1.41	1.36	1.24	1.40	1.40
6-10	3.93	3.54	3.82	3.67	3.28	3.81	3.93
11-24	3.03	2.90	3.43	3.60	3.46	3.62	3.88
25+	3.83	2.10	2.70	2.98	3.54	4.15	3.90
Location			✓	✓	✓	✓	✓
1-Digit Occ.				✓			
2-Digit Occ.					✓	✓	
1-Digit Ind.						✓	
1-Digit Ind. × 1-Digit Occ.							✓

Source: This table compares the observed distribution of female employment across firms in January 2009 to various simulated distributions. Sample selection and simulation details are described in Sections 4.1.1 and 4.1.2. In Panel A, distributions are simulated under the null hypothesis that no firm faces binding integration costs. We use estimates of $\theta(X_i)$ for varying sets of observable job characteristics. In Panel B, we simulate the distribution of female employment while allow ex-ante integration rates to vary by $\bar{\theta}_j n_j$. The details of this simulation exercise are described in Section G.1.1.

Table A.2: Baseline-Segregated Firms in June 2011

	Below Quota	Above Quota
# of firms	2,224	1,559
Number of Saudi employees		
Mean	33.7	45.5
Median	12	16
SD	101	130
Female share of employees (%)		
Mean	2.2	1.7
Median	0	0
SD	8.6	7.0
Avg. monthly wage (Riyals)	3,680	4,898
Industry (%):		
Agriculture and fishing	1.4	0.8
Commerce	25.4	25.1
Community/social services	7.0	4.6
Construction	30.3	26.2
Electricity, gas, and water	1.2	1.6
FIRE	8.0	10.3
Manufacturing	20.1	22.4
Mining	1.7	3.7
Telecommunications	5.0	5.4

Notes: This table presents descriptive statistics as measured in June 2011 for firms with at least five Saudi employees in January 2009. The first column limits to Below Quota firms, those with Yellow and Red color statuses in June 2011. The second column limits to Above Quota firms, those with Green and Yellow color statuses in June 2011.

Table A.3: Manufacturing Firms with Zero Female Employees and Workforce Composition, by Region

	All-male share of firms (%), by size		Female share (%)	
	Medium (20–99)	Large (100+)	Surveyed firms	Labor force
Sub-Saharan Africa	10.7	2.3	27.0	47.5
East Asia and Pacific	1.8	0.5	41.2	42.8
Eastern and Central Europe	2.5	0.7	38.4	43.9
Latin America and Caribbean	3.0	0.8	32.8	41.1
Middle East and North Africa	48.1	22.7	16.9	21.1
South Asia	49.9	28.6	14.5	23.5

Source: World Bank Enterprise Survey, 2006–2018, Survey data cover manufacturing firms in 65 countries (The World Bank, 2019). Statistics are calculated using survey weights within each country and year, then averaged across years within a country, then averaged across countries within a region, weighting by 2018 population. Female share of labor force is derived from 2018 World Bank Development Indicators for the same countries, is also a population-weighted average, and is not restricted to manufacturing.

B Model Details

For each vacancy, the firm receives k applications from two types of candidates: type F and type M. Share δ of candidates are type F, and share $(1-\delta)$ are type M.

The expected value of the highest U_j in a sample of size $s \in \{\delta k, (1-\delta)k\}$ drawn from a single group, F or M, is

$$U_*^G = \mu^G + \beta \log(s),\ G \in (M, F),$$

where $\mu^G \equiv v^G + \beta\gamma$ is the expected net value of a single candidate from group G.

The expected value of the highest U_j drawn from a combined sample of all candidates is

$$U_*^I = \beta \log\left[\delta \exp\left(\frac{\mu^F}{\beta}\right) + (1-\delta)\exp\left(\frac{\mu^M}{\beta}\right)\right] + \beta \log k.$$

The firm's problem of choosing what pools to hire from is equivalent to choosing the maximum of nU_*^F (only type F), nU_*^M (only type M), and $nU_*^I - c$ (both types).

We first consider the choice between hiring only type M candidates and hiring from both types. The firm will pay the fixed integration cost and hire from both types if

$$U_*^I - U_*^M > \frac{c}{n}. \tag{B.1}$$

The left-hand side of this expression can be expressed as

$$U_*^I - U_*^M = \beta \log\left[\frac{\delta}{1-\delta}\exp\left(\frac{v^F - v^M}{\beta}\right) + 1\right]. \tag{B.2}$$

Let θ denote the probability that the firm's preferred candidate from the combined pool is type F, where

$$\theta = \frac{\delta \exp\left(\frac{v^F}{\beta}\right)}{\delta \exp\left(\frac{v^F}{\beta}\right) + (1-\delta)\exp\left(\frac{v^M}{\beta}\right)}.$$

Rearranging, we get

$$\frac{1}{1-\theta} = \frac{\delta}{1-\delta}\exp\left(\frac{v^F - v^M}{\beta}\right) + 1. \tag{B.3}$$

Combining (B.2) and (B.3), we have

$$\begin{aligned} U_*^I - U_*^M &= \beta \log\left[\frac{\delta}{1-\delta}\exp\left(\frac{v^F - v^M}{\beta}\right) + 1\right] \\ &= -\beta \log[1-\theta] \\ &\approx \beta\theta. \end{aligned}$$

Combining the expression above with (B.1), an *approximate* condition for the firm to pay the fixed integration cost and hire from the combined pool is

$$n\theta > \frac{c}{\beta}. \tag{B.4}$$

C Saudi Female Employment Policies

In addition to Nitaqat, the Saudi government also pursued a slate of practical measures designed to increase women's employment over the study period, including the Retail Employment Decree, the Hafiz program, and updates to the guardianship system. The King issued a royal decree in 2011 mandating that shops selling lingerie and cosmetics employ only Saudi women as salesclerks beginning in August 2012. The decree was expanded to also cover stores selling women's clothing and accessories beginning in January 2014. There were recently plans to further expand the decree to cover all stores selling goods of primary interest to women, such as pharmacies with cosmetics sections and fabric stores (Evidence for Policy Design, 2015).

Though not gender-specific, the Hafiz unemployment assistance program has also drawn women into the workforce and supported their private sector job search. Hafiz provides a monthly financial stipend to unemployed Saudis who make weekly check-ins to a government-sponsored online job search portal (Taqat Online). More than 90% of Hafiz beneficiaries have been women (Evidence for Policy Design, 2017). The MLSD removed regulations requiring women to obtain permission from a male guardian to apply for private sector jobs.[1] Many firms still require a guardian's approval, though the Ministry recently forbade this practice among government employers.[2]

D Data Details

D.1 Matching GOSI and Nitaqat Firms

Administrative data from the Nitaqat program is used to identify the Nitaqat compliance status of firms. As described by Peck (2017), the Nitaqat database is used to track compliance with national quotas on Saudi employment in the private sector. The database collects information on whether a given firm was subject to quotas during a given week, and, if so, whether it met the quotas for that particular week. These data provide weekly quota compliance information from June, 2011 (the start of the Nitaqat program) until December, 2013.

Firms are defined differently between the Nitaqat and GOSI data sets. In the latter, firms are defined by their legal status as a commercial organization operating in potentially multiple industries. In the Nitaqat data, however, the operations of such firms are further classified into entities, which are subject to different quotas depending on the industry category each entity operates in and, as described in the main text, the size group based on the total number of employees. For example, a firm operating a bakery and a jewelry store would be considered two separate entities facing different quotas (and would therefore contain two entries in the data for each time period)[3]. In the GOSI data, however, such a firm would be considered a single firm. Firms with multiple entities can also list as a single entity (in the "Multiple Economic Activities" industry) but would be subject to the most stringent quota they face based on the entities under their umbrella. To harmonize the definition of the firm between the two data sets, firms with multiple entities in the Nitaqat data were aggregated together by summing their employee counts, and assigning the color and size status by the most binding entity quota (as measured by the number of Saudis required to fulfill it) the firm faces. The number of Saudis the firm needs to hire, however, was summed across all entities to create a single metric for the distance of the firm to the quota. This transformation

[1] Jafar AlShayeb, *Arab News* June 15, 2010 "Women's rights gain focus in the Kingdom"

[2] Lulwa Shalhoub, *Arab News* May 5, 2017 "Saudi women no longer need guardians' consent to receive services" `http://www.arabnews.com/node/1094681/saudi-arabia`

[3] An entity consisting of multiple branches (e.g., a national franchise) are counted as a single entity for each branch of the MLSD labor office they are linked to.

only affects 58,000 of the approximately 1.07 million firms in the Nitaqat data.

In addition to the distinction between entities and firms, it should be noted that the firm identifiers used by both GOSI and the Nitaqat data define firms with a national or multicity presence as separate commercial organizations depending on the geographic MLSD office they register with. For example, a firm with branches in Riyadh and Dammam would count as two firms, both of which are subject to separate quota calculations. The geographic scope of the MLSD offices is quite broad, and are typically at the provincial level. The definition of the firm we use in this paper therefore can be thought of as a legal commercial organization within a particular province.

D.2 Other Data Notes

We classify each occupation to the two-digit ISCO-08 group, reducing the number of occupations from 2,151 to 40. This significant drop in occupations is primarily due to inconsistent naming, misspellings, and changes to the GOSI classification scheme over time. Table D.1 lists the top ten most common ISCO-08 coded occupations in June 2011.

Table D.1: Employees by ISCO-08 occupation, June, 2011

ISCO Code	ISCO Category	Frequency	Percent
96	Refuse workers and other elementary workers	104,744	14.4
41	General and keyboard clerks	84,406	11.6
54	Protective services workers	65,032	9.0
42	Customer services clerks	64,265	8.9
99	Unclassified	48,382	6.7
33	Business and administration associate professionals	36,547	5.0
52	Sales workers	32,943	4.5
74	Electrical and electronic trades workers	26,754	3.7
83	Drivers and mobile plant operators	25,296	3.5
21	Science and engineering professionals	23,465	3.2
	Total	511,834	70.5

Note: This table presents the number of Saudi employees in the ten most common ISCO-08 2-digit occupation group in the GOSI data (General Organization for Social Insurance, Kingdom of Saudi Arabia, 2015). The large number of unclassified occupations is due to the significantly large number of cases where the GOSI occupation verification process was still processing or was incomplete.

There are 37 work locations provided in the data. We limit our analysis to locations with at least 50 firms with five or more Saudi employees in January 2009. This leaves us with 17 locations that account for 95% of firms and 98% of workers. In January 2009, 83% of workers are located in four cities: Riyadh, Jeddah, Dammam, and Khobar.

To clean up potentially erroneous observations, we drop individuals with ages below 10 or above 100 in the GOSI data. We also drop entries for part-time work, which only affects about 47,000 of the 2.8 million employees in the data. If an individual has more than one full-time job in a given month, we keep only the observation for the job with the highest wage.

E Ghost Employment

The main text mentions the concern that firms may falsify their employee records with GOSI to meet their quotas after Nitaqat, so reported employment numbers may not reflect real employment, particularly for women. Private sector firms are required to register their employees with GOSI and to pay a fraction of the reported wage into the employee's social security account. Nationals may not be registered as full-time employees for more than one firm at the same time. Workers have some incentive to make sure these records are filed accurately so that their eventual retirement payments are accurate. The Nitaqat enforcement system draws directly on these GOSI records to monitor the number of Saudi workers registered as employees at each firm. "Ghost employment" is used to refer to a variety of situations in which the worker is not doing the job as reported to GOSI. This can range from cases of outright fraud (e.g., where a worker's National ID Number is used without the worker's knowledge or permission) to cases where the worker draws the reported salary but does not perform meaningful work at the firm.[4] This ghost employment would cause our analysis to overstate the degree to which firms hire Saudi women in response to employment quotas. In this analysis we investigate whether this phenomenon becomes more common after the start of Nitaqat and whether it appears to be more common for women than for men.

To do this, we examine the share of workers hired in each month who appear to have "active" career trajectories. We define a worker as being active if their job history shows that they switch firms, receive wage increases, change occupations, or make above minimum wage. We can be reasonably confident that workers that experience these events are "real" employees: firms have no incentive to report paying fake workers above minimum wage (as this simply increases their GOSI payments without providing Nitaqat benefits), and there is similarly no reason to promote them, give them raises, or move their IDs to other firms. We construct an indicator equal to 1 if the worker experiences any of these actions (change wage or occupation, switch firms, or make above minimum wage) within 24 months of their first appearance in the GOSI system.[5]

In addition to capturing ghost employment, GOSI records may be inaccurate for several other reasons. First, firms may register artificially low wages in order to minimize their social security payments on behalf of their employees. This can in principle be checked by the worker, but there are some accounts of workers being surprised by their wage records upon retirement. Firms may also neglect to record promotions in the GOSI system, so recorded wages may lag actual wages. Movements across firms seem likely to be accurate, as a prior employer will not want to make payments for people who are no longer employees, and new firms will want to have the worker's national ID number released so they can register a new hire. These will bias the measure toward under-counting active employees, so the count of "inactive" workers should be assumed to include not only ghost employees, but also employees whose records are not updated promptly as well as workers who simply do not experience job status changes over the period.[6]

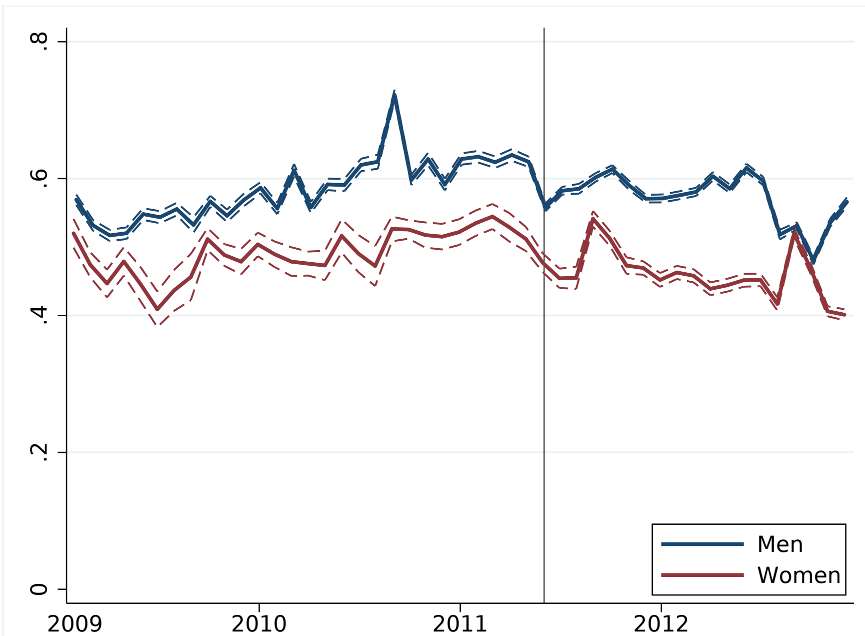
[4] There may also be cases in between, for example where workers collect a one-time payment or ongoing small payment from the firm to use their ID numbers.

[5] One potential issue is the de facto increase in the minimum wage in 2013. GOSI had previously required firms to enter a minimum wage of 1500SAR per month. In January 2013 firms were only given pro-rated Nitaqat credit for Saudi employees paid less than 3000SAR a month (e.g., a worker being paid the previous minimum of 1500SAR would count as 0.5 Saudis for Nitaqat purposes). Because of this, we do not consider increases from 1500 to 3000SAR that occur after January 2013 to be wage increases.

[6] Firms may also retain previous workers who have exited the labor market on their GOSI employment rolls. These workers will mistakenly appear to be active. Because we focus on workers hired between 2009 and 2013 we expect that this will comprise a only a very small part of the workforce, as these workers would need to enter the labor force after 2009, experience a change in wage, occupation, or firm, and then leave the private sector workforce without retiring and drawing their GOSI pension.

Figure E.1 shows a plot of the share of workers hired in each month that experience at least one of these events within 24 months of being hired. The share of workers who change job status is relatively steady for both genders at about 58% for men and 47% for women. As discussed before, there are a variety of reasons (aside from ghost employment) why this might only apply to half of workers. First, workers may simply not be promoted within 24 months of their first entry into the private sector. Second, they may be promoted but not have the promotions recorded in GOSI. Although only about half of workers experience official status changes within two years of hire, the patterns are similar across genders and relatively stable over time. There is a slight decrease in the share of workers promoted for those hired after Nitaqat.

Figure E.1: Share Hired in Month Who Change Status

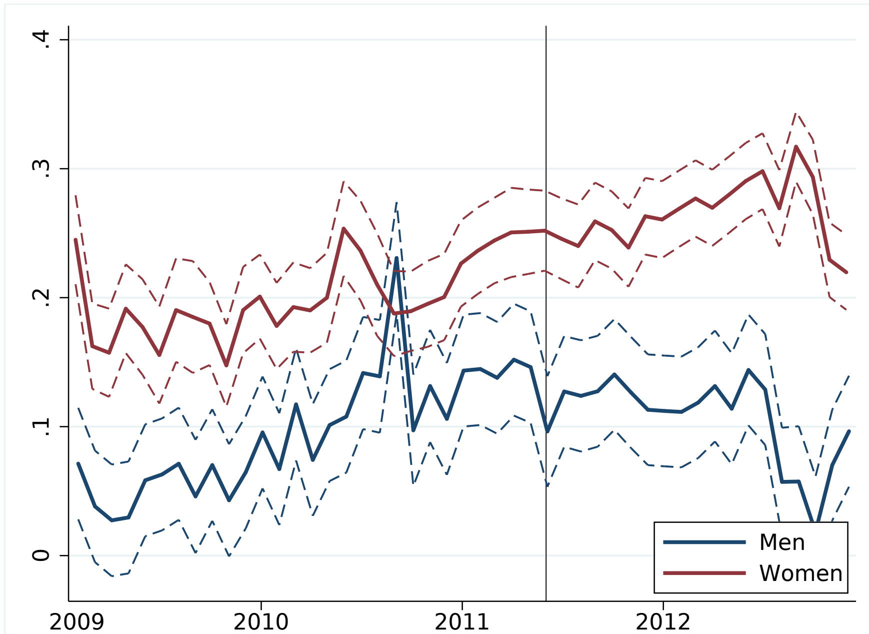


Note: This figure plots the share of Saudi employees in the GOSI matched employee-employer data who are first hired in each month who change wage or occupation, switch firms, or earn above minimum wage within two years of hire. Dashed lines show the 95% confidence interval for month indicator variables.

Within these series we may be concerned also about compositional changes in the types of workers that are being hired before and after Nitaqat as well as the types of firms that hire Saudis before and after the policy change. There is ample evidence that Saudis hired after Nitaqat are different from those hired before: more are women, more are hired with lower skill levels, and married women are more likely to join the labor force. Red and Yellow firms, which were most incentivized to increase Saudi hiring, were also potentially less desirable places for Saudis to work and may be less likely to keep their GOSI records up to date and to promote their employees over time. Figure E.2 shows the plot of these shares controlling for some worker characteristics: age, education, and marital status of the new hires.

Women are more likely to be active workers when controlling for observable worker characteristics, and the likelihood of promotion appears to be steadily increasing over time for women. We therefore conclude that even if ghost employment is captured by the GOSI data it does not appear to worsen after Nitaqat, and does not worsen for women in particular.

Figure E.2: Share Hired in Month Who Change Status (with worker-level controls)



Note: This figure plots the share of Saudi employees in the GOSI matched employee-employer data who are first hired in each month who change wage or occupation, switch firms, or earn above minimum wage within two years of hire when controlling for employee characteristics. Indicator variables are used to flexibly control for age, education, and marital status of new hires. Dashed lines show the 95% confidence interval for month indicator variables.

F Testing and Estimation Details

F.1 Simulating Bunching at Zero When Integration Costs Bind

In this section we demonstrate the rationale for our test of the null hypothesis that no firms face binding integration costs, developed in Section 4.1. In this test, we simulate the distribution of female hires across firms under the null hypothesis, and compare this to the distribution we observe in practice. We show here that if some firms are in fact ex-ante segregated, the distribution we simulate will generally *underpredict* the number of firms with zero female hires. We demonstrate this point using simulation.

Our simulation exercise builds on the model above by positing that some exogeneously determined γ share of firms are integrated and that, under the null hypothesis, θ_0 is the probability that each hire is female. Under both hypotheses, θ_0 is the expected female share of employees pooled across all firms. Firms are characterized by their number of hires, n.

Under the null hypothesis (H_0), all firms are integrated ($\gamma = 1$). In this case, firms which do not hire any women do so by chance alone. Alternatively (H_a), if $\gamma < 1$, then some firms do not hire women because they are ex-ante segregated. We show via simulation that under H_a there are generally a greater share of firms with zero female employees.

We consider two scenarios: one where the probability of integration is constant across firms and a second where integration rates are increasing in firm size.

F.1.1 Constant Integration Probability

First, we assume that the probability of integration is constant across firms, and given by γ. In this case, under H_a, the probability that a hire is female at an ex-ante integrated firm is $\theta_a = \theta_0/\gamma$. Our simulation is structured as follows. We first set a value of γ, the share of integrated firms, and θ_a, the probability a hire is female in an ex-ante integrated firm under H_a. Then, for each run of the simulation, we:

1. sample firm sizes (ie. the total number of employees) from a log-normal distribution with mean 50 and standard deviation 500, approximately matching the distribution of firm sizes we observe in our Saudi employment data (see Table 3);

2. determine whether a firm in our sample is integrated with probability $\gamma < 1$ for H_a; all firms are considered integrated under H_0 ($\gamma = 1$);

3. for H_a determine the gender of each hire via a binomial draw with probability θ_a that each hire is female. Sum these hires to determine the count of female employees for each firm under H_a;

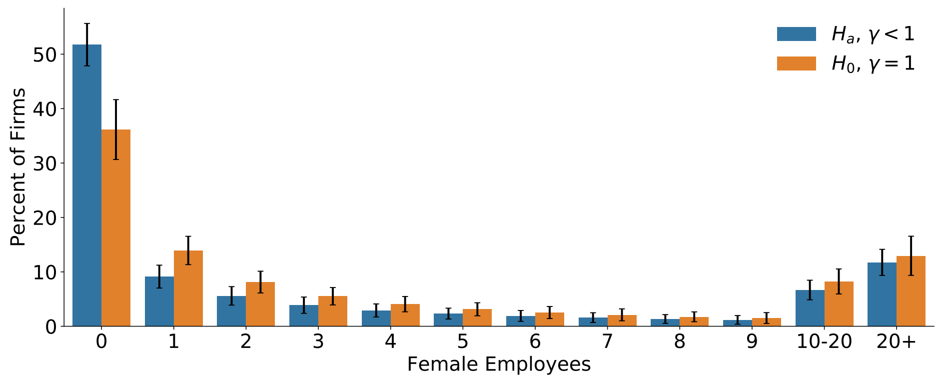
4. set θ_0, the probability of a hire being female under H_0 using the overall female share of employment simulated in the prior step[7], then similarly determine the gender of each hire and count the number of female employees for each firm under H_0

After running the above simulation 1,000 times, we calculate the share of simulations where the number of firms with zero female employees under H_a (Z_a) exceeds the same value under H_0 (Z_0). We show in Figure F.1 what the distribution of female employee counts look like under

[7] This allows us to have approximately equal numbers of female employees under both hypotheses.

both hypotheses for $\gamma = 0.7$ and $\theta_a = 0.5$.[8] Each column represents the mean across simulations, whereas the error bars represent the 5th and 95th percentiles.

Figure F.1: Simulated Distribution of Female Employment for $\gamma = 0.7$ and $\theta_a = 0.5$

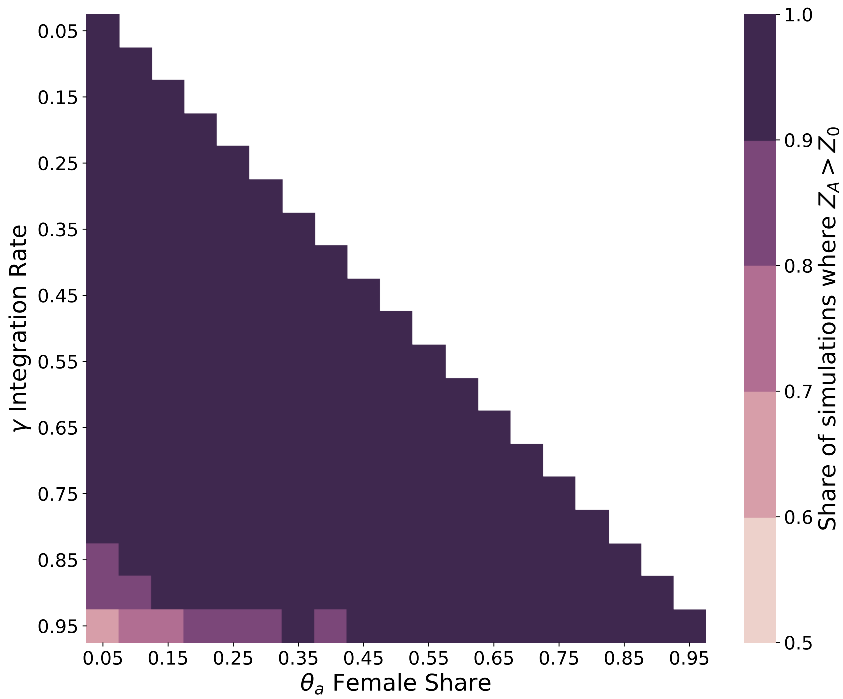


Note: This figure plots the distribution of the count of female employees across firms based on 1,000 simulations of firm sizes, integration probabilities (γ) and the share of female labor in the workforce (θ_a). The H_0 category supposes that all firms are integrated ($\gamma = 1$), and the H_a category supposes that some firms are ex-ante segregated ($\gamma < 1$). Sample selection and simulation details are described in Sections 4.1.1 and 4.1.2.

We then repeat this exercise by iterating over values of $\gamma \in (0, 1)$ and $\theta_a \in (0, 1)$. We plot the share of simulations where $Z_a > Z_0$ for each γ and θ_a value in Figure F.2 below.

[8] These values are chosen primarily for testing purposes. Repeating the exercise for different values results in similar patterns as shown below.

Figure F.2: Share of Simulations with $Z_a > Z_0$ by θ_a and γ



Note: This heatmap plots the share of simulations with $Z_a > Z_0$, or the share of simulations where there are more firms with no female employees under H_0 vs. H_a while varying values of θ and γ. Sample selection and simulation details are described in Sections 4.1.1 and 4.1.2.

Except the largest values of γ ($\gamma \geq 0.9$), $Z_a > Z_0$ for virtually all simulation draws. When γ is large, $Z_a > Z_0$ for the majority of simulation draws, but this share gets as low as the $0.6 - 0.7$ range (when $\gamma = 0.95$ and $\theta_a < 0.075$).

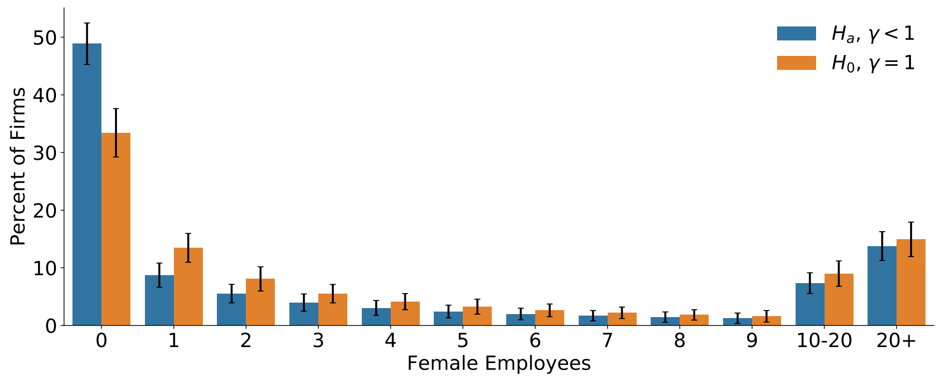
F.1.2 Integration Rates Increasing in n

If integrated costs are largely fixed, firms which have to hire more employees may be more likely to integrate. In this case, integration rates are increasing in n. To account for this, we again draw n from log-normal distribution, and also generate firm specific integration likelihoods $\gamma_i \sim Beta(\beta\frac{\gamma}{1-\gamma}, \beta)$ where $\gamma = \bar{\gamma}_i$.[9] To introduce the correlation between these two marginal distributions, we conduct a Cholesky decomposition to create a joint distribution of n_i and γ_i across such that the correlation between n and γ is positive.

We then continue the simulations as above, but iterate over values of $\bar{\gamma}_i$ and θ_a, and determine whether a firm is integrated according to its specific γ_i integration probability. We show in Figure F.3 the distribution of female employment for $\gamma = 0.7$ and $\theta_a = 0.5$ as above. We similarly plot the share of simulations where $Z_a > Z_0$ for each γ and θ_a value in Figure F.4.

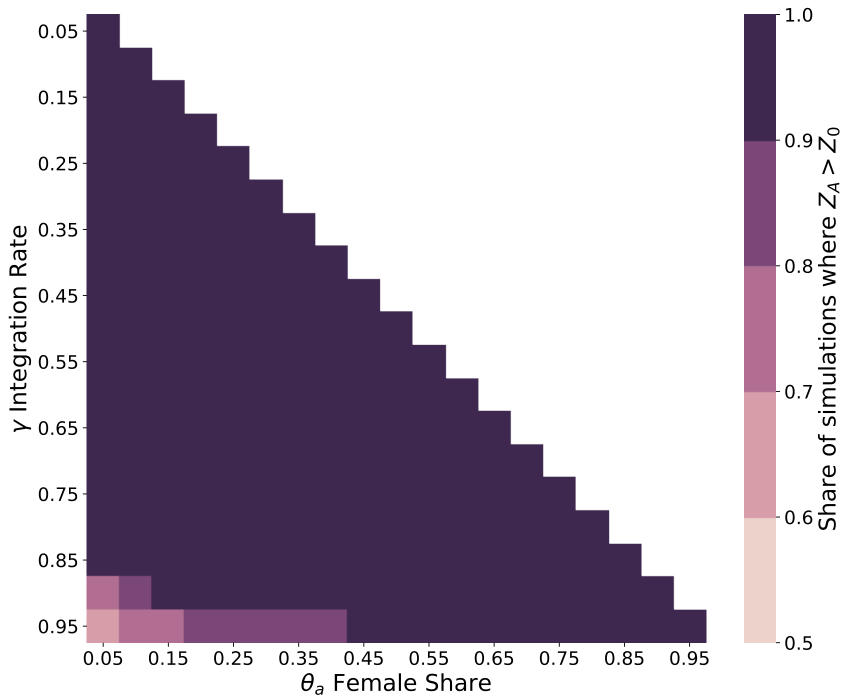
[9] We pick this particular form of the *Beta* distribution as its mean is γ. In other words, for a given share of firms integrated, we can generate a distribution of integration likelihoods for each firm such that the mean is equal to the overall share of firms integrated. In this case β acts as a scaling parameter but does not affect the mean.

Figure F.3: Simulated Distribution of Female Employment for $\bar{\gamma}_i = 0.7$ and $\theta_a = 0.5$ – Integration Rates Increasing in n



Note: This figure plots the distribution of the count of female employees across firms based on 1,000 simulations of firm sizes, integration probabilities (γ) and the share of female labor in the workforce (θ_a) when firm integration probabilities correlate positively with firm size. The H_0 category supposes that all firms are integrated ($\gamma = 1$), and the H_a category supposes that some firms may still be segregated ($\gamma < 1$). Sample selection and simulation details are described in Sections 4.1.1 and 4.1.2.

Figure F.4: Share of Simulations with $Z_a > Z_0$ by θ_a and γ – Integration Rates Increasing in n



Note: This heatmap plots the share of simulations with $Z_a > Z_0$, or the share of simulations where there are more firms with no female employees under H_0 vs. H_a while varying values of θ and γ and when firm integration probabilities correlate positively with firm size. Sample selection and simulation details are described in Sections 4.1.1 and 4.1.2.

As above, except the largest values of γ ($\gamma \geq 0.9$), $Z_a > Z_0$ for virtually all simulation draws.

F.2 Structural Estimation of θ using Expectation-Maximization

In Section G.1 we modeled the distinction between ex-ante and ex-post integrated firms to structurally estimate $\theta(X_i)$. We use an expectation-maximization algorithm to estimate these parameters. Continuing from Section G.1, the likelihood function for firm j is

$$P(Y_j = Y) = \begin{cases} \pi_j + (1-\pi_j)\prod_{i=1}^{N_j}(1-\theta_{ij}) & \text{if } K_j = 0 \\ (1-\pi_j)\prod_{i=1}^{K_j}\theta_{ij}\prod_{K_j+1}^{N_j}(1-\theta_{ij}) & \text{if } 0 < K_j < N_j \\ (1-\pi_j)\prod_{i=1}^{N_j}\theta_{ij} & \text{if } K_j = N_j. \end{cases}$$

We model both θ_{ij} and π_j in logistic regression models with explanatory variables X_{ij} and Z_j, respectively:

$$\theta_{ij} = \Lambda(X_{ij}\beta)$$
$$\pi_j = \Lambda(Z_j\gamma)$$

where Λ is the logistic function.

The log-likelihood for firm j is

$$\log(f_j) = \log(P(Y_j = Y)) = \begin{cases} -\log\left(1+e^{Z_j\gamma}\right) + \log\left(e^{Z_j\gamma} + \prod_{i=1}^{N_j}\left(1+e^{X_{ij}\beta}\right)^{-1}\right) & \text{if } K_j = 0 \\ -\log\left(1+e^{Z_j\gamma}\right) - \sum_{i=1}^{N_j}\left(1+e^{X_{ij}\beta}\right) + \sum_{i=1}^{K_j} X_{ij}\beta & \text{if } 0 < K_j < N_j \\ -\log\left(1+e^{Z_j\gamma}\right) + \sum_{i=1}^{N_j}\left[X_{ij}\beta - \log\left(1+e^{X_{ij}\beta}\right)\right] & \text{if } K_j = N_j. \end{cases}$$

Combining each firm's log likelihood, we write our log-likelihood function as:

$$l(\beta, \gamma; Y_j, X_{ij}, Z_j) = \sum_{j=1}^{J} \log(f_j)$$

We obtain maximum likelihood estimates of γ and β using the expectation-maximization (EM) algorithm. The EM algorithm is an iterative method to find maximum likelihood estimates, where the model depends on unobserved latent variables. The EM algorithm alternates between an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated at the current estimate for the parameters, and a maximization (M) step, which computes parameters maximizing the expected log-likelihood found in the E step.

For each firm j, let the unobserved random variable I_j indicate whether a firm has ex-ante integrated. When $I_j = 0$, firm j is ex-ante segregated and Y_j is necessarily zero. When $I_j = 1$, firm j is ex-ante integrated. If we could observe I_j for every firm, then the log-likelihood for firm j given complete data (Y_j, I_j) would be

$$\log(f_j|I_j, X_{ij}, Z_j) = (1-I_j)\underbrace{\left(Z_j\gamma - \log\left(1+e^{Z_j\gamma}\right)\right)}_{\log_\gamma(f_j|I_j,X_{ij},Z_j)} + \underbrace{I_j\left[-\sum_{i=1}^{N_j}\log\left(1+e^{X_{ij}\beta}\right) + \mathbf{1}_{0<K_j\leq N_j}\sum_{i=1}^{K_j} X_{ij}\beta\right]}_{\log_\beta(f_j|I_j,X_{ij},Z_j)}.$$

Therefore the complete data log-likelihood function is

$$
\begin{aligned}
l_c(\beta,\gamma|Y_j,I_j,X_{ij},Z_j) &= \sum_{j=1}^{J}\log(f_j|I_j,X_{ij},Z_j) \\
&= \sum_{j=1}^{J}[\log_\gamma(f_j|I_j,X_{ij},Z_j)+\log_\beta(f_j|I_j,X_{ij},Z_j)] \\
&= l_c(\gamma|Y_j,I_j,X_{ij},Z_j)+l_c(\beta|Y_j,I_j,X_{ij},Z_j).
\end{aligned}
$$

The EM algorithm begins with starting values $\omega^{(0)} = \left(\gamma^{(0)},\beta^{(0)}\right)$. Our starting value for $\beta^{(0)}$ is derived from estimating the linear regression $Y_j = X_{ij}\beta$ and setting $\beta^{(0)} = \hat{\beta}$. For $\gamma^(0)$, we estimate the regression $\mathbf{1}_{K_j>0} = Z_j\gamma$ and similarly set $\gamma^(0) = \hat{\gamma}$.

From these initial values, we proceed iteratively, with (r) indexing the iteration:

- **E Step**: estimate I_j by its conditional mean $I_j^{(r)}$ given $\omega^{(r)} = \left(\gamma^{(r)},\beta^{(r)}\right)$:

$$
\begin{aligned}
\hat{I}_j^{(r)} &= E[I_j|Y_j,X_{ij},Z_j,\gamma^{(r)},\beta^{(r)}] \\
&= \frac{P(Y_j|I_j=0)P(I_j=0)}{P(Y_j|I_j=0)P(I_j=0)+P(Y_j|I_j=1)P(I_j=1)} \\
&= \begin{cases} \left[1+e^{-G_j\gamma}\prod_{i=1}^{N_j}\left(1+e^{X_{ij}\beta}\right)^{-1}\right]^{-1} & \text{if } K_j=0 \\ 0 & \text{if } K_j\neq 0 \end{cases}
\end{aligned}
$$

- **M Step for** γ: we find $\gamma^{(r+1)}$ by maximizing $l_c(\gamma|Y_j,I_j,X_{ij},Z_j)$. This can be accomplished by logistic regression of $I_j^{(r)}$ on Z_j. It is equivalent to solving the FOC of $l_c(\gamma|Y_j,I_j,X_{ij},Z_j)$:

$$\sum_{j=1}^{J}\left(I_j^{(r)}-\frac{e^{Z_j\gamma}}{1+e^{Z_j\gamma}}\right)Z_j = 0.$$

- **M Step for** γ: we find $\gamma^{(r+1)}$ by maximizing $l_c(\gamma|Y_j,I_j,X_{ij},Z_j)$. This can be accomplished by logistic regression of $I_j^{(r)}$ on Z_j. It is equivalent to solving the FOC of $l_c(\gamma|Y_j,I_j,X_{ij},Z_j)$:

$$\sum_{j=1}^{J}\left(I_j^{(r)}-\frac{e^{Z_j\gamma}}{1+e^{Z_j\gamma}}\right)Z_j = 0.$$

From the above, we obtain estimates for β and γ for iteration (r) and repeat the exercise until $\left\|\beta^{(r+1)}-\beta^{(r)}\right\|+\left\|\gamma^{(r+1)}-\gamma^{(r)}\right\| < 0.0001$.

G Additional Analyses

G.1 Modeling Firm Integration States

The second approach we take is to directly model the distinction between ex-ante and ex-post integrated firms and to structurally estimate $\theta(X_i)$.

Let j index firms, and let N_j denote the number of positions at firm j. Let y_{ij} be an indicator that equals one if position i in firm j is filled by a female employee. Denote $K_j = \sum_i^{N_j} y_{ij}$ as the number of female employees at firm j.

Let π_j denote the probability that firm j has *not* paid its integration cost and so is not able to employ women. Hence, with probability $1 - \pi_j$, the firm is ex-ante integrated. We will model π_j as a function of observable firm characteristics. Finally, among ex-ante integrated firms, denote the probability that position i is filled by a female employee as θ_{ij}. As above, we model θ_{ij} as a function of observable job characteristics, X_{ij}.[10]

With these terms defined, we can define the likelihood function for each firm. Without loss of generality, we order each firm's workers such that the first K_j workers are female and the remaining $N_j - K_j$ are male. Denote $Y_j = (Y_{1j}, ..., Y_{N_j j})$ as the firm-specific vector of outcomes. The likelihood function for firm j is

$$P(Y_j = Y) = \begin{cases} \pi_j + (1 - \pi_j) \prod_{i=1}^{N_j} (1 - \theta_{ij}) & \text{if } K_j = 0 \\ (1 - \pi_j) \prod_{i=1}^{K_j} \theta_{ij} \prod_{K_j+1}^{N_j} (1 - \theta_{ij}) & \text{if } 0 < K_j < N_j \\ (1 - \pi_j) \prod_{i=1}^{N_j} \theta_{ij} & \text{if } K_j = N_j. \end{cases}$$

We model both θ_{ij} and π_j in logistic regression models with explanatory variables X_{ij} and Z_j, respectively:

$$\theta_{ij} = \Lambda(X_{ij}\beta)$$
$$\pi_j = \Lambda(Z_j\gamma)$$

where Λ is the logistic function. In the vector of firm characteristics, Z_j, we include fixed effects for location and industry and a cubic in log firm size.[11] For the vector of hire characteristics, X_{ij}, we include fixed effects for two-digit occupation codes, location, and one-digit industry. We estimate the model using an expectation-maximization (EM) algorithm. Estimation details are provided in Appendix F. We label these structural estimates for $\theta(X_i)$ as $\hat{\theta}^S(X_i)$.

Column (3) of Table 4 summarizes the estimates and how they vary across jobs. The average value of $\hat{\theta}^S(X_i)$ is 0.123. These estimates are similar to those from Section 4.2 using only ex-post integrated firms; the correlation between $\hat{\theta}^S(X_i)$ and $\hat{\theta}^{EP}(X_i)$ is 0.82. The average value of π_j is 0.65, indicating 65% of firms are ex-ante segregated.

[10] For ease of notation, in this section we index positions separately by firm.

[11] We measure firm size here using the firm's number of Saudi employees.

G.1.1 Can $\theta(X_i)$ Match the Distribution of Female Employment?

As an additional test for whether $\theta(X_i)$ is well specified, we evaluate whether a simulation of the distribution of female employment across firms that allows for integration rates to vary by $\bar{\theta}_j n_j$ fits the observed distribution. For each firm, we take a uniform random draw and label the firm as integrated if the draw is below the corresponding values in Panel B of Figure 2 given the firm's value of $\bar{\theta}_j^{EP} n_j$. If the firm is not labeled as integrated, we assign it a value of zero for its female employment. For firms labeled as integrated, we simulate a value of female employment as above, this time using $\hat{\theta}^{EP}(X_i)$ to assign the gender for the employee in each position.

Panel B of Appendix Table A.1 compares the simulated distribution of female employment to the observed distribution for various specifications of $\theta(X_i)$. While, by construction, we will match the share of firms with zero female employees, the simulation is not guaranteed to match other parts of the distribution. Yet, our baseline specification, where X_i includes job location, two-digit occupation, and one-digit industry fixed effects, matches the observed distribution. Across all simulations, we fail to reject equality of the simulated and observed distributions in a Kolmogorov-Smirnov test at the 1% significance level. The average p-value is 0.75. This suggests that we have included the most relevant job characteristics in X_i (or that other relevant characteristics are not concentrated within firms) and have mapped them appropriately to hiring probabilities, at least among ex-ante integrated firms.

G.1.2 Checking Predictions for Counterfactual Female Employment

First, we test whether our estimate of $\theta(X_i)$ provides unbiased predictions for the female share of hires at newly integrated firms. This is a powerful out-of-sample test for whether our estimate of $\theta(X_i)$ predicts counterfactual female employment at segregated firms because we do not use this set of firms to estimate $\theta(X_i)$. We also examine the transition dynamics of these newly integrated firms.

We first examine hiring at newly integrated firms in an event study. We plot the female share of new hires at integrating firms in the months following a firm's first observed female hire.[12] We limit to firms with at least five Saudi employees in the month prior to integration. We observe 8,307 transitioning firms meeting this size threshold. Prior to integrating, we observe transitioning firms in the GOSI data for an average of 39 months. At each firm, we calculate the female share of all new hires made in six-month increments before and after a firm's first female hire.[13] We then take the average across all firms meeting the sample restrictions and exclude firms that do not make a hire in a given six-month increment from the calculation for that period.

The event study is shown in Panel A of Figure G.1. By construction, among hires made prior to integration, there are no women. Among firms that we observe integrating, we observe an average of 33 male hires made prior to a firm's first female hire. We see that the female share of hires changes abruptly at newly integrated firms, consistent with an extensive margin response.[14] Among hires made in the six months following integration, including the first female hire, 55% are female. This drops to about 26% in the following six-month period and remains relatively steady thereafter. By contrast, if the excess mass of firms with zero female workers we observed in Figure 1 was driven by unobserved heterogeneity in job characteristics, we would expect a gradual and potentially short-lived increase in female hiring rather than the discrete and sustained increase we observe.

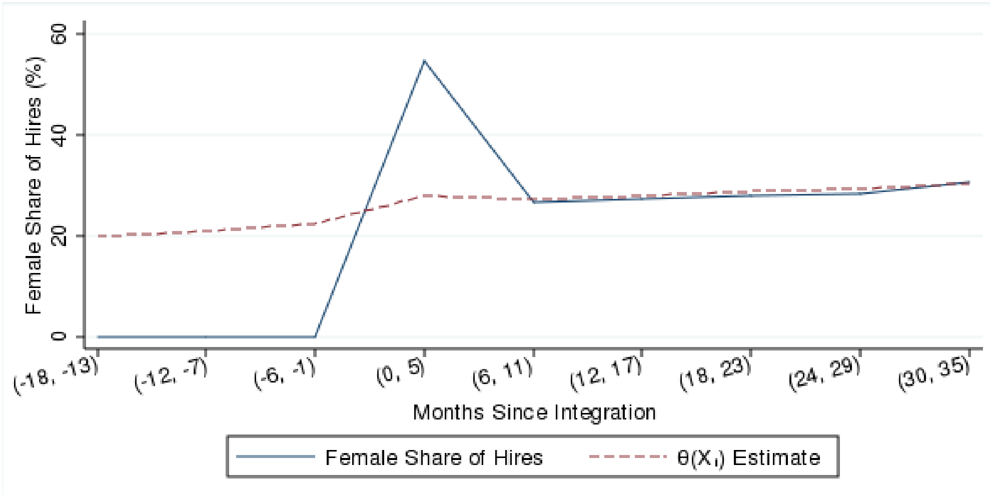
[12] In this exercise, we exclude firms that have female employees when they are first observed in the GOSI data.

[13] Hires include any employee that begins a new job spell at the firm in a given period.

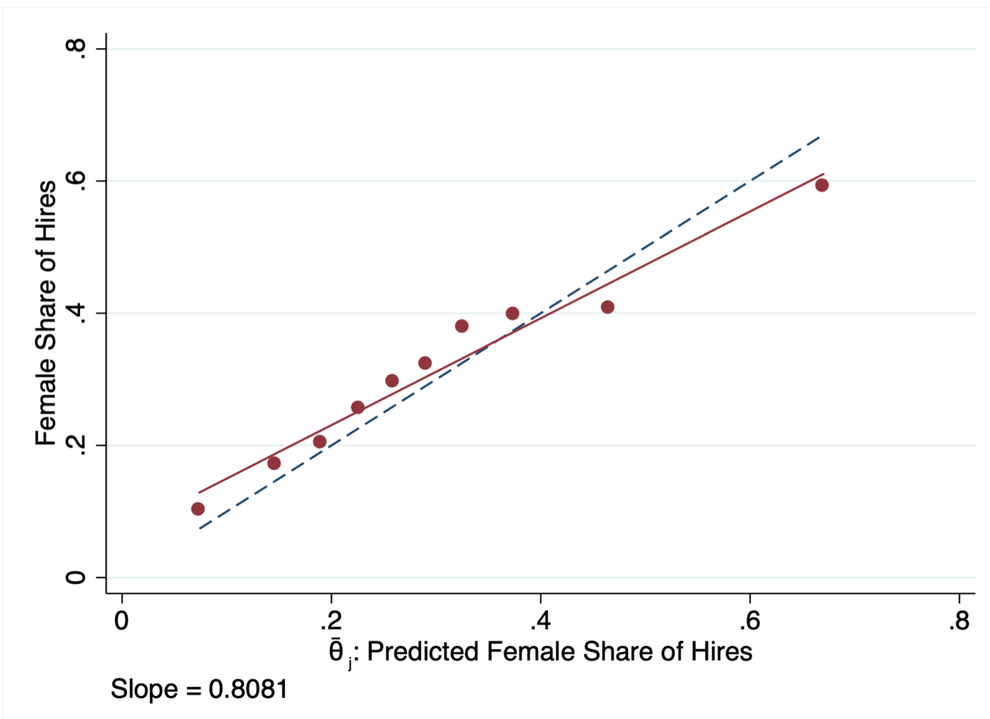
[14] Note that the period labeled as "0 to 5" months includes the first female hire herself.

Figure G.1: Female Share of Hires at Newly Integrated Firms

(a) Female Share of Hires



(b) Observed Versus Predicted Female Share of Hires



Note: This set of figures describes the gender composition of hires at newly integrated firms. Panel A plots the female share of hires made at integrating firms in six-month increments relative to a firm's first observed female hire, averaged across firms. Using the GOSI data, we restrict to firms with at least five Saudi employees in the month prior to integration. Panel B compares the female share of hires at newly integrated firms to their $\theta(X_i)$-based predicted values, where $\theta(X_i)$ is estimated using firms that are ex-post integrated in January 2009. $\theta(X_i)$ estimation details are provided in Section G.1.2. The vertical axis depicts the female share of hires that are made 12 or more months following a firm's first female hire. The horizontal axis depicts the $\theta(X_i)$-based prediction for this value.

We compare the observed increase to what we would predict using an estimate of $\theta(X_i)$ derived from hires at incumbent integrated firms. As in Section 4.2, we construct our predictions by estimating a logistic regression of the form:

$$P(\text{Worker } i \text{ is female}) = \Lambda(X_i\beta),$$

where i indexes the position for each hire. As above, X_i includes fixed effects for job location, two-digit occupation, and one-digit industry. In addition, we allow predictions to vary over time by including in X_i fixed effects for each half-year and interactions between the location, occupation, and industry controls with an indicator for hires made after June 2011, the month Nitaqat is implemented. We limit estimation to all firms that are ex-post integrated in January 2009, regardless of whether any of their subsequent hires are female. These firms should provide a valid estimate for $\theta(X_i)$ if integrated firms remain ex-ante integrated moving forward, an assumption we verify in the next section. We label this estimate $\hat{\theta}(X_i)$.

We include the $\hat{\theta}(X_i)$-based prediction for the female share of hires in Panel A of Figure G.1. We find that the magnitude of this change matches what we would predict using $\hat{\theta}(X_i)$, at least on average. Next, we check how well firm-specific predictions for the female share of hires of newly integrated firms matches the realized female share of hires. In Panel B of Figure G.1, we group newly integrated firms into deciles based on the predicted female share of hires and plot bin averages against their observed female share of hires 12 or more months following their first female hire. If the predictions are *unbiased*, the binned averages will fall on the 45-degree line. This is similar to the pattern we observe, though the observed female share of hires is slightly below the 45-degree line, with the gap increasing in the predicted female share of hires.

G.2 State Dependence

An immediate implication of the model is state dependence: the hiring behavior of firms that have already paid their integration costs will differ from the behavior of firms that have not. In particular, we should *not* observe bunching for the former set of firms. While we cannot observe each firm's current state, we proxy for their current state using their baseline ex-post segregation status. This proxy should closely correlate with a firm's current state if integration costs are sunk or if the conditions that led the firm to integrate are highly persistent over time. We test the null hypothesis of no binding integration costs but conduct separate tests for firms that are ex-post integrated and ex-post segregated as of January 2009.

We conduct a similar test to that described in Section 4.1, except we pool *hires* between February 2009 and June 2015. We limit to firms that have at least five Saudi hires over this period. To classify firms as ex-post integrated or segregated in January 2009, we also limit to firms that had Saudi employees in January 2009. We estimate $\theta(X_i)$ separately by baseline integration status and include the same job characteristics we use in Section G.1.2: fixed effects for each half-year and fixed effects for job location, two-digit occupation, and one-digit industry, all interacted with an indicator for hires made after June 2011.

Table G.1 compares the two sets of firms. There are 2,796 firms meeting the sample criteria that were ex-post integrated in January 2009 ("baseline integrated") and 12,617 firms that were ex-post segregated ("baseline all male"). Baseline integrated firms are larger, pay higher wages, and concentrated in community and Social services. For baseline all-male and integrated firms, the female share of recent hires is 19.2% and 48.4%. Figure G.2 plots the simulated and observed distribution of female employment for baseline all-male (Panels A and B) and integrated firms (Panels C and D).

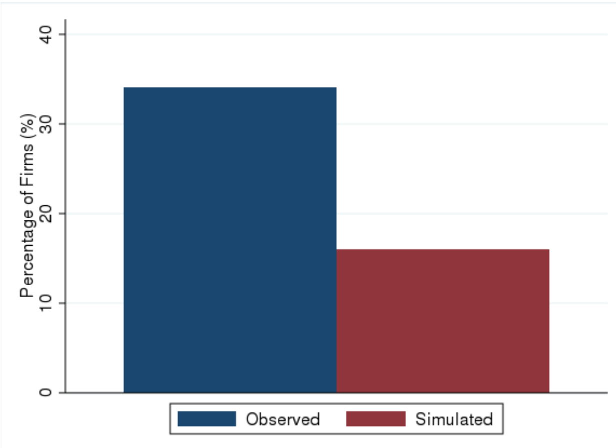
Table G.1: Firm Descriptive Statistics, by Baseline Integration Status

	Baseline all male	Baseline integrated
# of firms	12,617	2,796
Number of Saudi hires		
Mean	61.9	219.7
Median	18	47
SD	194.6	930.9
Female share of hires (%)		
Mean	19.2	48.4
Median	10.0	46.3
SD	23.4	33.4
Avg. monthly wage (Riyals)	3,238	3,709
Industry (%):		
Agriculture and fishing	1.0	0.3
Commerce	29.7	20.6
Community/social services	6.9	41.6
Construction	30.0	11.4
Electricity, gas, and water	0.8	0.9
FIRE	9.9	12.5
Manufacturing	16.3	10.4
Mining	1.4	0.6
Telecommunications	3.9	1.7

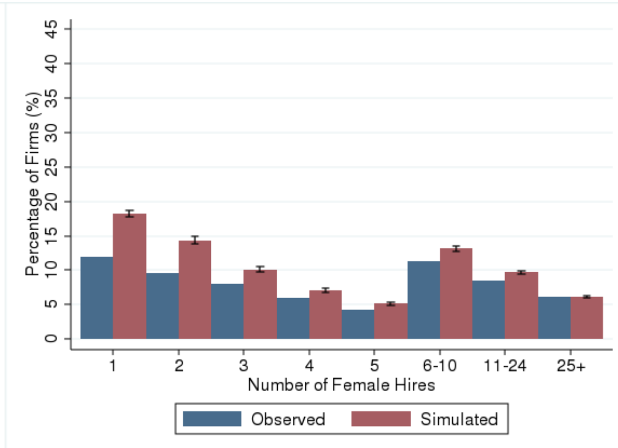
Notes: This table presents descriptive statistics for firms with any Saudi employee in January 2009 that hire at least five Saudis between February 2009 and June 2015 in the GOSI data (General Organization for Social Insurance, Kingdom of Saudi Arabia, 2015). The first column includes firms that are all-male in January 2009. The second column includes firms that are ex-post integrated in January 2009. The average wage at a firm is measured in nominal Saudi Riyals at the time of hiring.

Figure G.2: Distribution of Female Hiring, Baseline All-Male and Integrated Firms

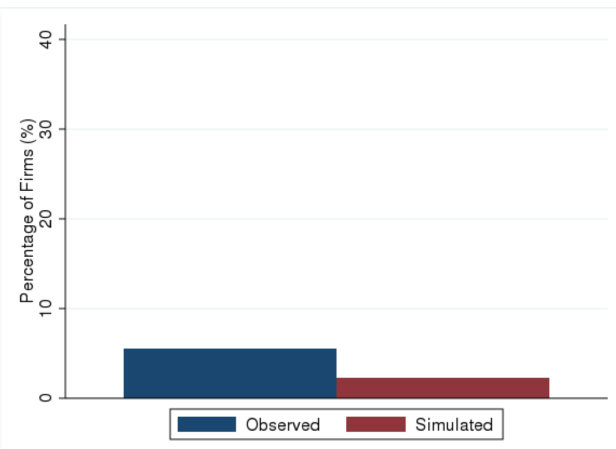
(a) % of Baseline All-Male Firms with Zero Female Hires



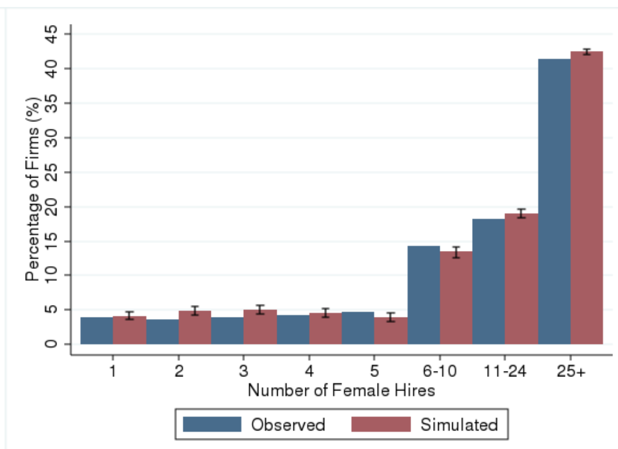
(b) % of Baseline All-Male Firms with > 0 Female Hires



(c) % of Baseline Integrated Firms with Zero Female Employees



(d) % of Baseline Integrated Firms with > 0 Female Hires



Note: This set of figures compares the observed and simulated distributions of female hires across firms that are (1) ex-post segregated in January 2009 and (2) ex-post integrated in January 2009 for hires made between February 2009 and June 2015. The simulated distributions are simulated under the null hypothesis that no firm faces binding integration costs over the hiring period. Sample selection and simulation details are described in Sections G.2. Panels A and B plot simulation results for firms that are ex-post segregated in January 2009. Panels C and D plot simulation results for firms that are ex-post integrated in 2009. Panels A and C plots the share of firms with zero female hires in both the observed and simulation distributions. Panel B plots the share of firms with various nonzero totals of female hires in both the observed and simulated distributions. For all simulations for firms that are ex-post segregated in January 2009, a Kolmogorov-Smirnov test rejects equality of the observed and simulated distributions at the 1% significance level. For firms that are ex-post integrated in January 2009, across simulations we fail to reject equality of distributions with an average p-value of 0.10. Sample selection and simulation details are described in Sections 4.1.1 and 4.1.2.

For baseline all-male firms, the pattern is similar to that observed in Figure 1. The simulations underpredict the number of firms that employ zero female workers (16.1% versus 34.2%) and overpredict the number of firms that employ fewer than ten (68.1% versus 51.2%). For all simulations, a Kolmogorov-Smirnov test rejects equality of the observed and simulated distributions at the 1% significance level.

By contrast, the simulated distribution for baseline integrated firms matches the observed distribution relatively well. Across all simulations, a Kolmogorov-Smirnov test fails to reject equality of the observed and simulated distributions at the 1% significance level. The average p-value is 0.10.

Consistent with our interpretation of bunching as evidence for the presence of ex-ante segregated firms, there is little evidence of bunching at firms that are likely ex-ante integrated.

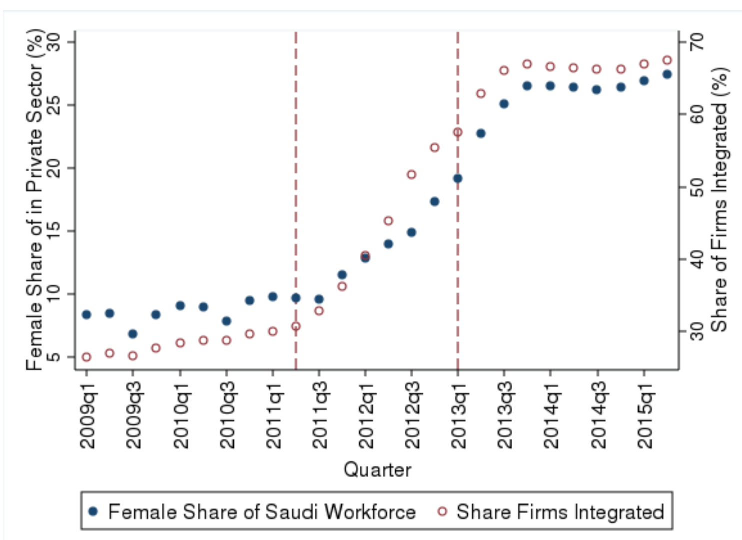
H Aggregate Effects of Nitaqat

It is unclear what would happen in the aggregate if integration costs were eliminated across the labor market. Would aggregate demand for female labor increase or the female share of the workforce and gender differences in wages change? As in Becker (1957), integrated firms may be sufficiently numerous or large to absorb female labor so that the existence of constrained male-only firms has no bearing on female wages and employment. On the other hand, in the presence of search frictions or insufficient entry or growth of integrated firms, integration costs will reduce aggregate demand for female labor.

To assess the aggregate consequences of integration costs, exogenous variation in integration costs across labor markets is needed. Lacking such variation, we take a different approach. We examine the labor market response to a policy that reduces the share of firms that face binding integration costs and assess the effects of the policy on female employment and the gender wage gap. If the policy increases female employment or relative wages, this would suggest that the presence of integration costs depresses those outcomes. The logic of our approach is to essentially use the policy as an instrument for (binding) integration costs. The exclusion restriction implicit in our argument is that the policy only affects our outcomes of interest by reducing the set of firms with binding integration costs. We discuss this exclusion restriction below.

In particular, we investigate the aggregate effects of Nitaqat. As discussed in Section 4.4, Nitaqat induced many firms to integrate and hire women. We show this in Figure H.1, which plots over time the share of firms with at least five Saudi employees that employ both Saudi men and women. There is a clear trend break that begins just as Nitaqat is implemented, followed by a flattening which occurs soon after a doubling of the effective minimum wage for Saudis in the private sector. We discuss the effects of this minimum wage increase in more detail below.

Figure H.1: Integration Rates and Female Share of Workforce Over Time



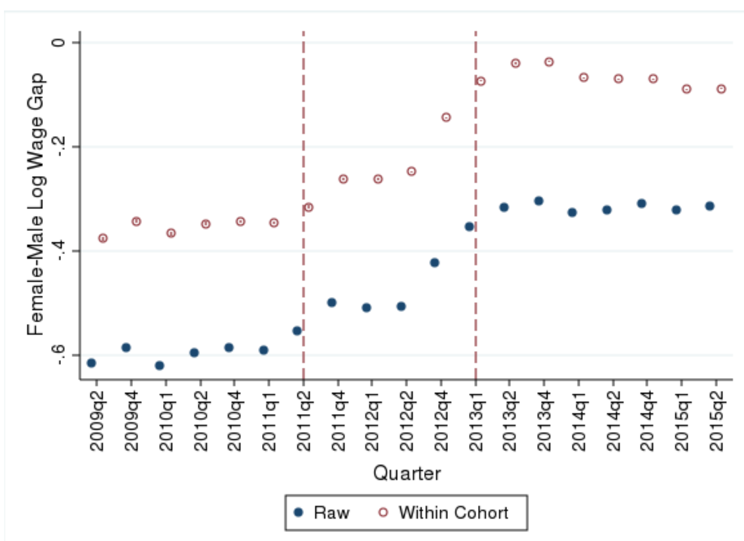
Note: This figure plots the female share of full-time Saudi workers and the share of firms that employ both men and women, both on a quarterly basis from the GOSI matched employee-employer data. For the latter outcome, firms are restricted to those with at least five Saudi employees. The vertical lines correspond to the implementation of Nitaqat (in Q2 of 2011) and the increase in the de facto minimum wage (in Q1 of 2013). This figure does not include employees in the security and military sectors. Source: Ministry of Civil Service.

Next, we explore how the female share of the workforce evolves in response to Nitaqat. In Section 4.4 we document that among firms that are all male in January 2009, Below Quota firms increase their female share of hires relative to Above Quota firms. Figure H.1 plots the female share of Saudis in the private sector over time, pooling employment at all firms. The overall pattern matches that of integration rates. Nitaqat led to a dramatic increase in the female share of Saudis in the private sector, from 10% in 2011 to 27% in 2015. This increase occurs primarily within sectors, as measured by industry and occupation. This increase in the female share of Saudis in the private sector is not offset by a decrease in the public sector; in fact, the female share of Saudis working in the public sector also increases over this period, from 33% in 2011 to 40% in 2015.

While this increase is striking, it does not necessarily indicate an important role for integration costs. Nitaqat may also increase the female share of employment through a *price effect*. Suppose aggregate male labor supply is inelastic relative to aggregate female labor supply, perhaps due to the relative scarcity of available and qualified male workers. Then Nitaqat may bid up men's relative wages, increasing relative demand for female labor. This would be a violation of our exclusion restriction: a path through which Nitaqat increases the female share of employment that is unrelated to integration costs per se.

However, the evidence suggests that changing prices are not the driving force behind the dramatic increase in the female share of the workforce. In fact, the gender wage gap *decreases* following Nitaqat. Moreover, after the effective minimum wage reduces the wage gap even further, the female share of the workforce remains elevated. This is illustrated in Figure H.2, which plots the female-male wage gap over time. The figure includes two measures of the gender wage gap: (1) the raw difference in average log wages for women and men and (2) the gap within labor market entry cohorts.

Figure H.2: Gender Wage Gap Over Time



Note: This figure plots the female-male log wage gap on a quarterly basis. It includes both the raw log wage gap and the log wage gap controlling for cohort fixed effects, where cohorts refer to the year of the earliest start date for a worker as recorded in the GOSI data (General Organization for Social Insurance, Kingdom of Saudi Arabia, 2015). The veritcal lines correspond to the implementation of Nitaqat (in Q2 of 2011) and the increase in the de facto minimum wage (in Q1 of 2013).

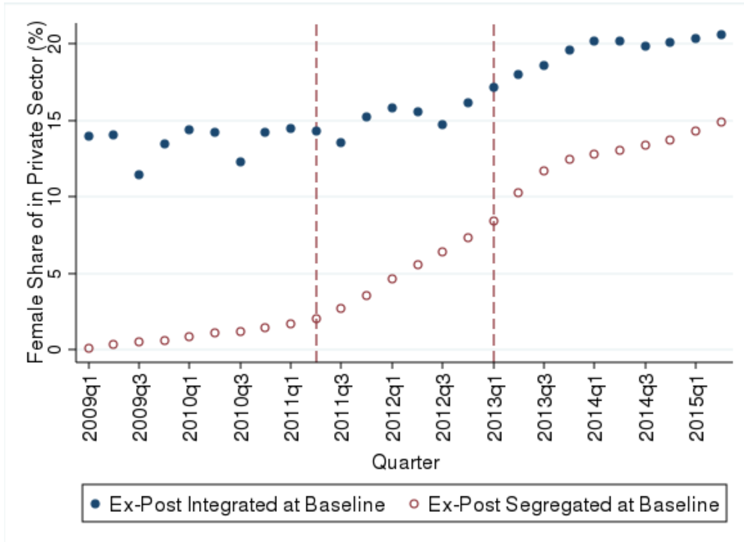
Prior to Nitaqat, the wage gap is relatively flat. The raw wage gap is 60 log points; within cohorts, the gap is about 35 log points. Following Nitaqat, but prior to the minimum wage increase, the wage gap decreases by about 10 log points. The 2013 minimum wage increase leads to a substantial reduction in the gender wage gap. Following its introduction, about 65% of women and 40% of men earn the new minimum wage. The raw wage gap drops to about 30 log points. Within cohorts, the wage gap drops to 4–9 log points. Yet, from Figure H.1, we can see that the female share of the private sector workforce is *increasing* over this period. This share stagnates beginning in 2013 but remains elevated thereafter. The fact that both female relative wages and employment increase is difficult to reconcile with a price-based explanation. Instead, the evidence is consistent with Nitaqat increasing relative demand for female labor by increasing the set of firms that integrate.

Finally, we explore the possibility that Nitaqat led to a shift in women's labor *supply*. Female labor force participation in Saudi Arabia is among the lowest in the world, at 17.8% in 2011 (GaStat, 2011). While this low rate is likely driven by multiple factors, one may be that households perceive that few firms are willing to hire women in the first place. Nitaqat may cause an outward shift in women's labor supply by increasing the set of firms that are ex-ante integrated. In fact, integration costs as a barrier to women's employment may generate feedback effects: women may only enter the labor market if enough firms have integrated, while firms only integrate if they can anticipate employing enough women to justify the costs of integration.

Unfortunately, we do not have data on labor supply decisions; in particular, we do not have data on anyone that is not employed in the private sector. Instead, we look at the response to Nitaqat for firms that had integrated prior to the policy's implementation. While Figure H.1 shows that the female share of the workforce is increasing, we expect this increase to be concentrated at firms induced to integrate by the policy. Firms that integrated prior to Nitaqat are already employing a mix of men and women and face an increase in the relative price of women. In the absence of a supply response, we would expect to see the female share of employment at these firms weakly decreasing.

Figure H.3 plots the female share of employment over time in firms that employed Saudis in January 2009, split by the firm's ex-post integration status in that month. For *both* sets of firms, there is a marked increase in the female share of employment beginning with Nitaqat's integration. As expected, the increase is larger for baseline-segregated firms. But for baseline integrated firms, the increase is also substantial: from 14.5% in Q1 of 2011 to 20.6% of Q1 2015.

Figure H.3: Female Share of Workforce by Baseline Integration Status



Note: This figure plots the female share of Saudi employment in the GOSI matched employee-employer data over time in firms that employed Saudis in January 2009, split by the firm's ex-post integration status in that month. These shares are measured on a quarterly basis. The vertical lines correspond to the implementation of Nitaqat (in Q2 of 2011) and the increase in the de facto minimum wage (in Q1 of 2013).

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