## Assessing Factors that Influence Women's Participation in the Invention Ecosystem

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ASSA 2022
1/8/2022

## Background

- In 2019 women made up only $13 \%$ of all inventor-patentees in the United States (Toole et al. 2019).
- If women were to patent at the same rate as men, commercialized patents could rise by $24 \%$ and per-capita GDP could increase by $2.7 \%$. (Bell et. al 2019 and Hunt 2016)
- Gender diversity boosts the inventive process in essential ways:

1. unique female experiences and viewpoints help inform, and thus improve, the quantity and quality of innovation (Milli and Williams-Baron et al., 2016; OECD 2018; Xie et al., 2020)
2. gender diversity expands research into under examined topics thereby filling overlooked technology gaps (Koning et al., 2021)
3. women contribute social shrewdness that increases team cooperation and productivity (Xie et al., 2020)

## Questions

1. Where are the women inventors?
2. Does an environment with highly educated women help a county's chance of having its very first woman inventor-patentee?
3. How does team size affect the propensity for women to patent?

- Team size proxies capital investment in a technology development (Breitzman and Thomas, 2015)


## Past: Number of women inventors



## Present: Number of women inventors

Women Inventors by County, Average 2017-2019


411 new counties were added representing a growth of $32 \%$ in 30 years.

Midwest Region


## Differences in counties with and without women inventors that patent

|  | Counties with women inventors = 0 |  |  |  |  | Counties with women inventors > 0 |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max |
| Number of women inventors | - | - | - | - | - | 29,801 | 15 | 67 | 1 | 2,956 |
| Labor force | 34,145 | 16,481 | 16,508 | 261 | 416,540 | 29,801 | 120,298 | 250,215 | 460 | 5,121,584 |
| Per capita income (\$) | 34,145 | 27,615 | 10,474 | 7,096 | 175,998 | 29,801 | 33,672 | 13,570 | 9,798 | 230,141 |
| Number of women with... |  |  |  |  |  |  |  |  |  |  |
| Bachelor's degrees | 34,145 | 1,310 | 1,572 | 17 | 33,362 | 29,801 | 14,556 | 33,026 | 34 | 761,572 |
| Master's degrees | 34,145 | 521 | 664 | 0 | 22,797 | 29,801 | 6,252 | 14,227 | 3 | 287,419 |
| PhDs | 34,145 | 42 | 70 | 0 | 1,483 | 29,801 | 700 | 1,854 | 0 | 40,577 |

Controlling for population density, there are 38\% more highly educated women in counties with women inventors that patent than in counties without them.

Methods

## Zero-inflated negative binomial model (ZINB)?

- $Y$ is a count variable
- Used when our $Y$ variable (women inventor counts) is overdispersed; $\mu=5 \sigma=39$
- Used when there are a lot of zeros in the data



## ZINB

- The intuition behind the Zero Inflated Negative Binomial model is that there is a precursor process that determines whether a county is (structural-) zero or non-zero.
- Zero-counties= \{observational zeros, structural zeros\}
- Zero/non-zero process is determined by a logit model:
- In our model this process is characterized by the number of highly educated women (bachelors, masters and PhDs). Specifically, how it influences a county's probability of having its first female inventor.
- Once a county is determined to be non-zero, the Negative binomial process takes over to determine the number of women inventors.
- In our model the negative binomial process is a function county-level labor-force, per-capita income, team size, \# of all male teams and technology field concentrations and indicator variables.


## Empirical specification

## Logit:

$$
\lambda_{i t}=\exp \left(Z_{i t t} \Delta\right)=\exp \left(z_{i t j}^{\prime} \delta\right)
$$

$=\exp \left(\delta_{0}+\delta_{\text {fbachelors }}\right.$ fbachelors $_{\text {it }}+\delta_{\text {fmasters } \text { fmasters }_{\text {it }}}$
$+\delta_{f p h d} f p h d_{i t}+\sum_{c=2}^{8} \beta_{c} \% c p c_{c i t}+\sum_{c=1}^{8} \beta_{c} d c p c_{c i t}$ $+\delta_{t}$ YearFE $_{t}+\delta_{l}$ StateFE $\left._{l}\right)$

## Negative Binomial

$$
\begin{aligned}
& \mu_{i t}=\exp \left(\mathbf{X}_{i t} \mathbf{B}\right)=\exp \left(x_{i t j}^{\prime} \beta\right)=\beta_{0}+\beta_{L F} L F_{i t}+ \\
& \beta_{P C I} P C I_{i t}+\left(\beta_{T S} T S_{i t}+\beta_{T S^{2}} T S_{i t}^{2}\right)+\beta_{A M} A M_{i t}+ \\
& \sum_{c=2}^{9} \beta_{c} \% c p c_{c i t}+\sum_{c=1}^{9} \beta_{c} d c p c_{c i t}+\beta_{t} \text { Yearer }_{t}+ \\
& \beta_{\text {state } \left.^{\prime} \text { State }_{l}\right)}
\end{aligned}
$$

- where subscript $i$ refers to counties, $t$ refers to time (1991-2019), and $j=$ Labor force (LF), per capita income (PCI), Team size (TS), number of all male teams (AM), technology field concentration (\%cpc), technology field indicators (dcpc).


## Pooled, national summary statistics

Source: County-level data from BEA, BLS and PatentsView (1990-2019)


## Results:

| National Model |  |  |  |
| :---: | :---: | :---: | :---: |
| Variable | $\beta$ | $\exp (\beta)$ | p-value |
| Logit |  |  |  |
| Bachelors | -0.00046 | 0.999537 | 0.07 |
| Masters | -0.00077 | 0.999231 | 0.20 |
| PhD | -0.00482 | 0.995192 | 0.04 |
| Negative Binomal |  |  |  |
| Economic variables |  |  |  |
| Labor force | $1.64 \mathrm{E}-06$ | 1.000002 | 0.00 |
| Per capita income (USD) | 0.000019 | 1.000019 | 0.00 |
| Inventor team variables |  |  |  |
| Team size | 0.276013 | 1.317865 | 0.00 |
| Team size squared | -0.03085 | 0.96962 | 0.00 |
| Number of all male teams | 0.000681 | 1.000681 | 0.02 |
| \% of counties with Cooperative Patent Classification (CPC) concentrations |  |  |  |
| Performing operations; transporting | -0.9668 | 0.3803 | 0.00 |
| Chemistry; metallurgy | 0.669494 | 1.953248 | 0.00 |
| Textiles; paper | -1.47264 | 0.229321 | 0.00 |
| Fixed constructions | -2.06514 | 0.1268 | 0.00 |
| Mechanical engineering; lighting; heating; weapons; blasting engines or pumps | -1.68458 | 0.185522 | 0.00 |
| Physics | 0.321866 | 1.3797 | 0.09 |
| Electricity | -0.01247 | 0.987607 | 0.95 |

## Results summary

- Team size has non-linear relationship



## Results:

 Regional Model| Regional model |  |  |
| :---: | :---: | :---: |
|  | $\exp (\beta)$ | $p$-value |
| Negative Binomial |  |  |
| Labor force |  |  |
| East coast | 1.000002 | 0.00 |
| Midwest | 1.000002 | 0.42 |
| South | 1.000002 | 0.72 |
| Mountain | 1.000004 | 0.00 |
| West Coast | 1.000002 | 0.38 |
| Per Capita Income ( USD) |  |  |
| East Coast | 1.000015 | 0.00 |
| Midwest | 1.000015 | 0.49 |
| South | 1.000015 | 0.39 |
| Mountain | 1.0000023 | 0.00 |
| West Coast | 1.000015 | 0.63 |
| Team size |  |  |
| East Coast | 1.212372 | 0.00 |
| Midwest | 1.212372 | 0.45 |
| South | 1.097086213 | 0.00 |
| Mountain | 1.134009487 | 0.06 |
| West Coast | 1.364214319 | 0.07 |
| Number of all male teams |  |  |
| East Coast | 1.001505 | 0.00 |
| Midwest | 1.001505 | 0.35 |
| South | 1.001505 | 0.18 |
| Mountain | 1.001505 | 0.74 |
| West Coast | 1.000282663 | 0.00 |

## Results summary

- Doubling the number of female college graduates in a county that has never had a women inventor would increase the county's chance of hosting its first women inventor by $60 \%$.
- A county adding one female PhD has 10X the effect of increasing the county's chance of having its first female inventor than that of adding one female with a Bachelor's degree.
- Larger teams sizes up to 4.5 would increase the likelihood of women inventors. The average team size is currently 2.7.
- Increasing team size in the Silicone Valley region has the highest potential for increasing women's inventors.


## Additional slides

## Math (See appendix for detail)

- We substitute 3 into 1 and 2 and add them all together and take logs to get a log-likelihood function
- ZINB essentially nests the negative binomial distribution of $>0$ counties, $\Gamma($. $)$, inside the logistic distribution, $F($.$) .$ Several math steps later, we get the log-likelihood function...



## Negative binomial: Regional model

$$
\begin{aligned}
& \mu_{i t}=\exp \left(x_{i t j}^{\prime} \beta\right) \\
& =\exp \left(\beta_{0}+\left(\beta_{1} L F_{i t}+\beta_{2} L F_{i t} * R_{r-1}\right)\right. \\
& +\left(P C I_{i t} \beta_{3}+\beta_{4} P C I_{i t} * R_{r-1}\right)+\left(\beta_{5} T S_{i t}+\beta_{6} T S_{i t} * R_{r-1}\right) \\
& +\sum_{c=2}^{8} \beta_{(c+5)} \% c p c_{(c+5) i t}+\sum_{c=1}^{8} \beta_{(c+14)} d c p c_{(c+14) i t} \\
& +\beta_{t} \text { YearFE }+\beta_{l} \text { StateFE }
\end{aligned}
$$

where USPTO region subscript $r=$ Eastern, Midwest, South, Mountain, Western.;

Table 3. Regional model preliminary results


| \% of counties with Cooperative Patent Classification (CPC) concentrations |  |  |
| :---: | :---: | :---: |
| Performing operations; transporting | 0.3763327 | 0.00 |
| Chemistry; metallurgy | 2.218898 | 0.00 |
| Textiles; paper | 0.3363812 | 0.00 |
| Fixed constructions | 0.1533107 | 0.00 |
| Mechanical engineering; lighting; heating; weapons; blasting engines or pumps | 0.1946372 | 0.00 |
| Physics | 1.226501 | 0.14 |
| Electricity | 0.9786238 | 0.89 |
| Technology indicators by CPC |  |  |
| Human necessities | 1.610621 | 0.00 |
| Performing operations; transporting | 1.92963 | 0.00 |
| Chemistry; metallurgy | 1.533529 | 0.00 |
| Textiles; paper | 1.505251 | 0.00 |
| Fixed constructions | 1.722936 | 0.00 |
| Mechanical engineering; lighting; heating; weapons; blasting engines or pumps | 1.965105 | 0.00 |
| Physics | 1.357513 | 0.00 |
| Electricity | 1.482946 | 0.00 |
| Logit |  |  |
| Bachelors | 0.999495028 | 0.04 |
| Masters | 0.999589084 | 0.43 |
| PhD | 0.993760149 | 0.00 |

