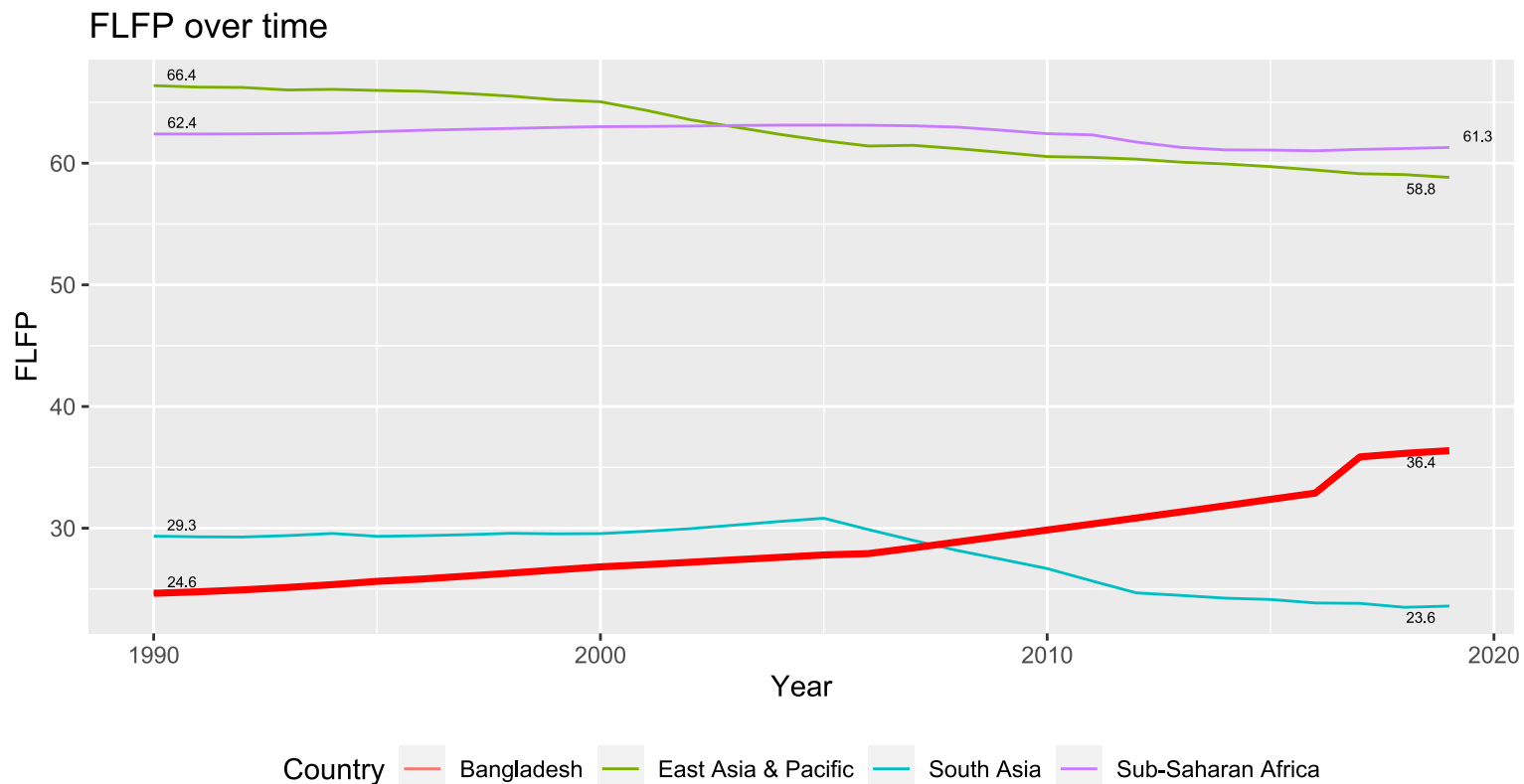# Ready Made Garments, FLFP, Fertility and Human Capital in Bangladesh

SM Shihab Siddiqui

13 May, 2022

Introduction

Against the grain: Bangladeshi FLFP

FLFP over time

World Bank (2021)

- **Female labor force participation (FLFP)** among 20-24 year olds stood at about 49% in 2015 (ADB 2016).

Expansion of the garments industry

- Bangladeshi **Ready Made Garments (RMG)** grew at about 11% a year since 1991.
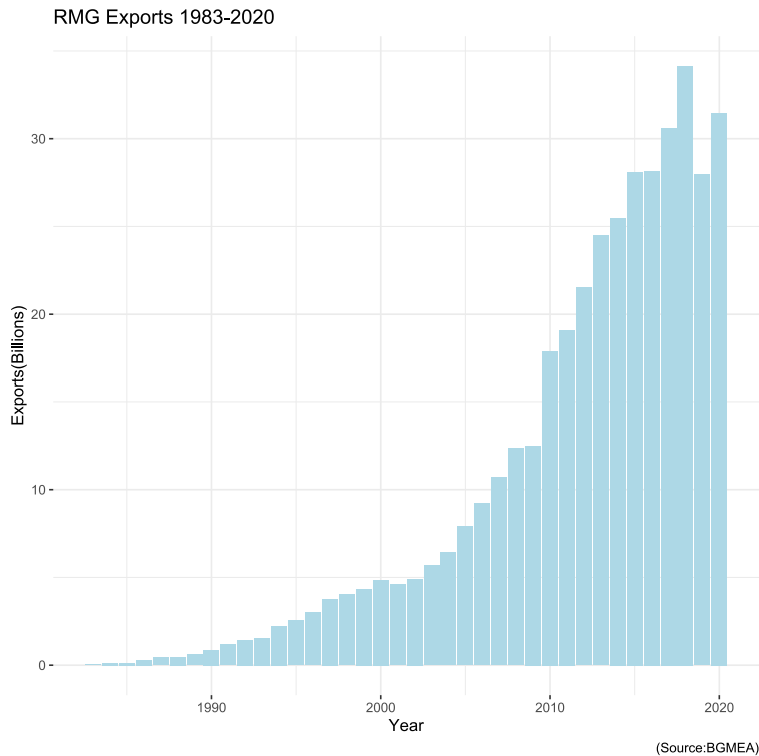
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(Source:BGMEA)
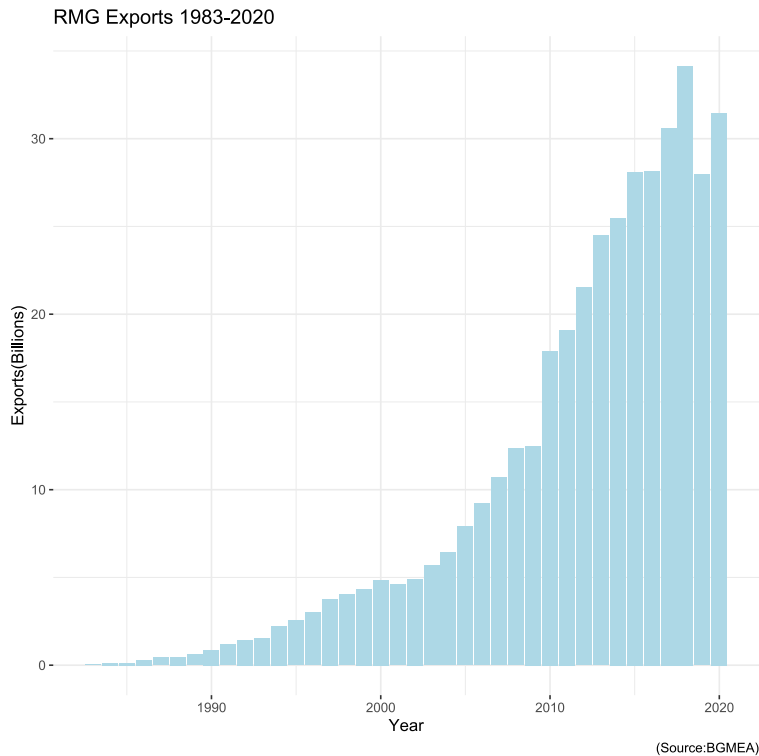
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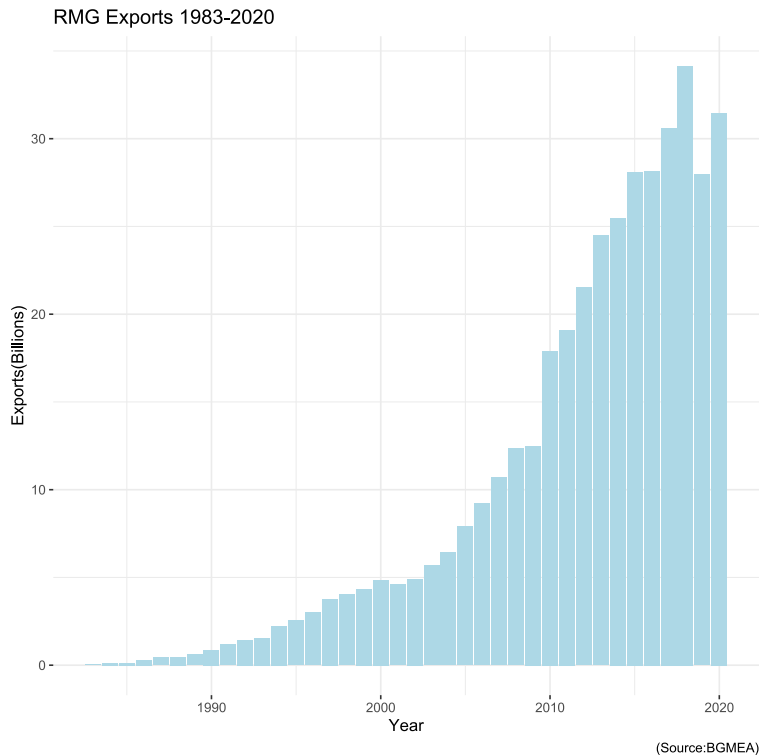
- Accounts for 75-85% of Bangladesh's exports in recent decades.

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- **About 60% of workers in export oriented RMG industry are women.**

Research questions

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2. What is the effect of the RMG industry on fertility and human capital accumulation of Bangladeshi women.

This paper

- Estimates the long run impact of female labor demand shock on FLFP, fertility and human capital accumulation by:

    - Bartik shift-share method to identify labor demand shocks following a methodology similar to **Li (2018) and Autor et al (2019).**

    - Specifically, it exploits product specialization in the RMG industry along the knit versus woven line across sub-districts (Bangladesh administrative level-3) for identification.

Preview of results

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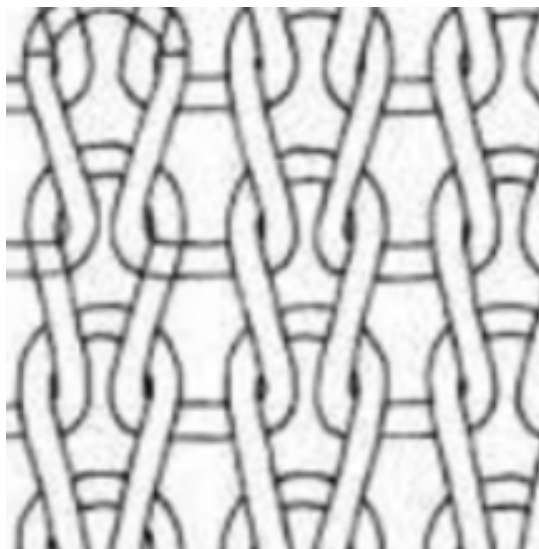
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- No impact on school enrollment of younger girls.

RMG industry in Bangladesh

Knit versus Woven prodcuts

Knit

- Single yarn looped repeatedly.
- HS code 61.
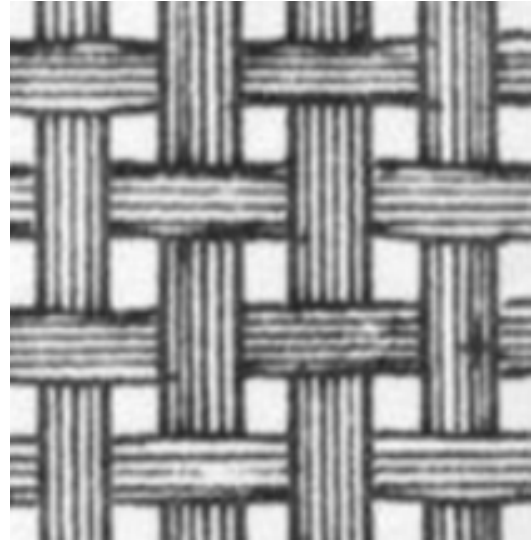- Product examples: Most sweaters, cotton T-shirts.
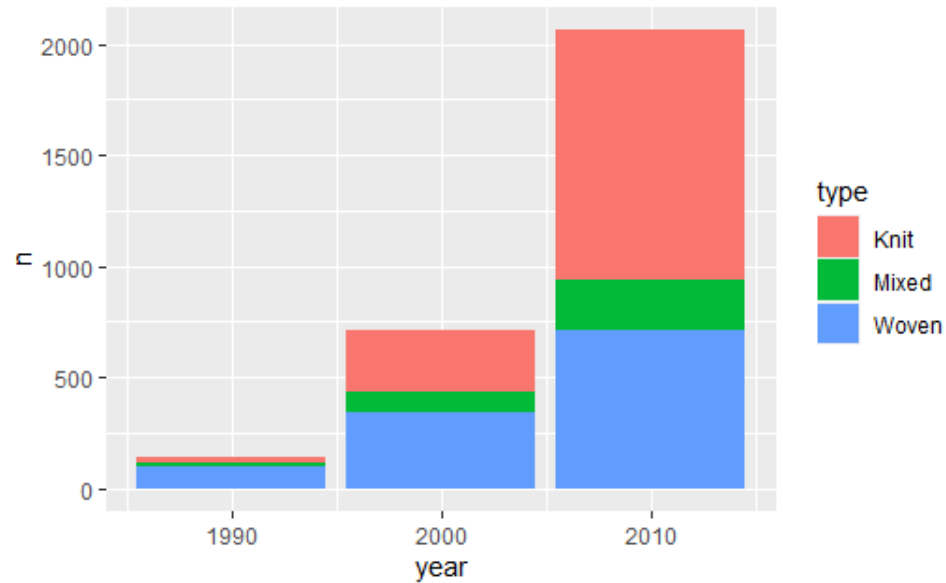
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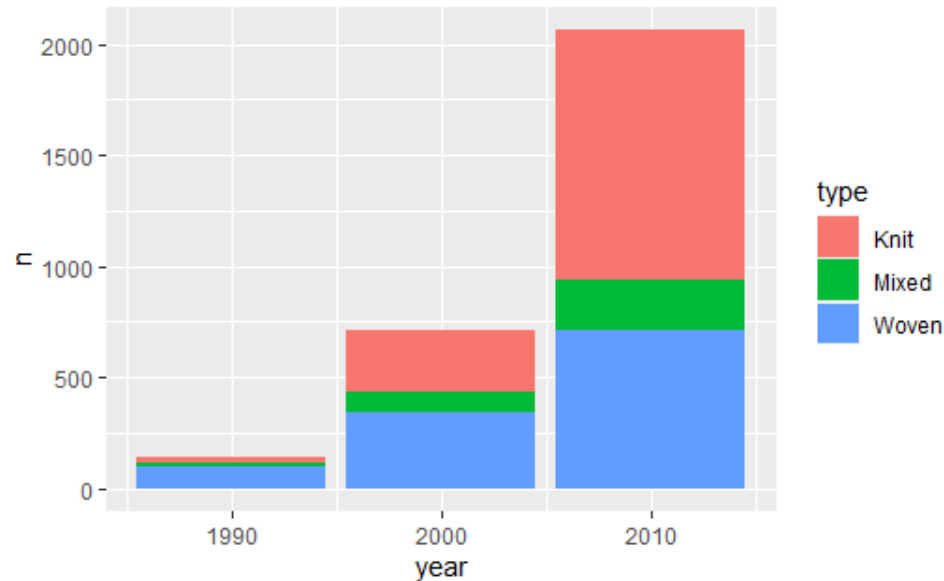
Woven

- Multiple yarn criss-crossed over and under each other.
- HS code 62.
- Product examples: Shirts, jackets, pants.

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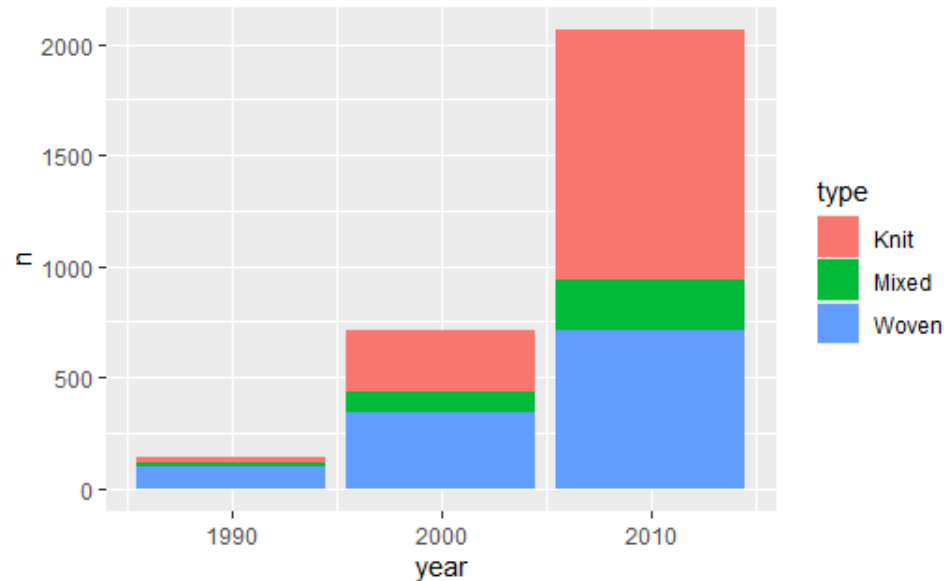- Woven factories are larger, and employs more women.

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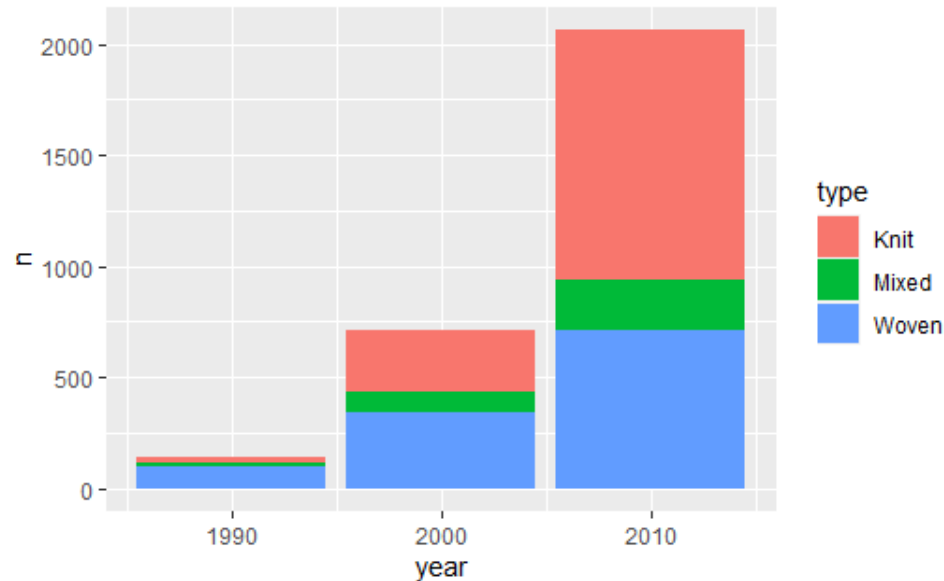

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- About 90% labor tasks overlap.

Location of RMG factories
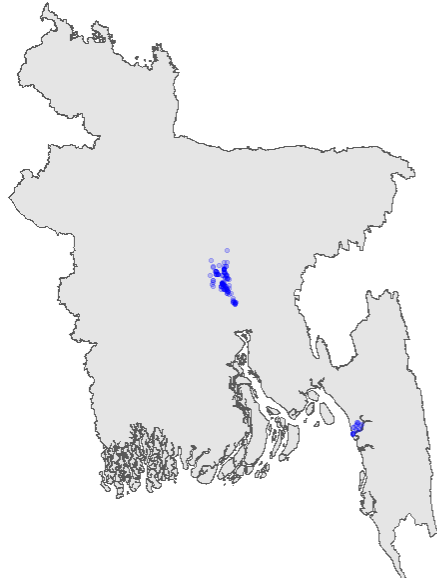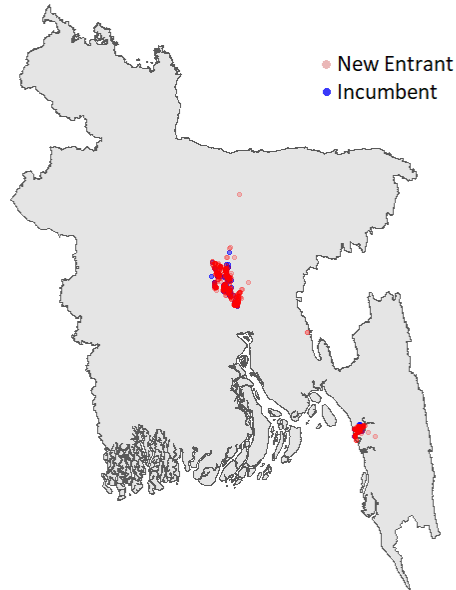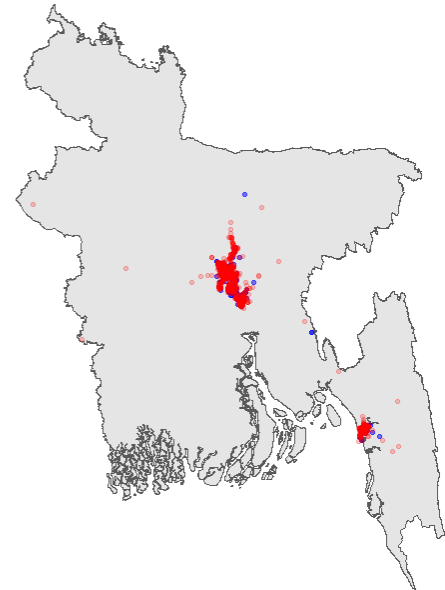
- RMG factory location choice is mostly dependent on infrastructure quality (kagy, 2014).

Identification strategy and data

Overview of the identification strategy

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- Export exposure in sub-district s in at time period t depends on:

  - Intensity of knit versus woven specialization.
  - Variation in changes in demand for knit versus woven products products from Bangladesh.

Regression Model

$$\Delta Y_{s,t} = \beta \; \Delta\text{Export Exposure}_{s,t} + Z\beta_z + \delta_t + \epsilon_{s,t}, \;\; \text{where,}$$

- $\Delta Y_{s,t}$ is the decadal change in outcome variables in sub-district s over decade ending at year t.

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- $\text{Export Exposure}_{s,t}$ measures export exposure in sub-district over decade ending at year t.

- δ_t are census-year fixed-effects and $Z_{s,t}$ is a vector of sub-district specific controls including start of period electrification, urbanization, density, share of 15-64 year old in population, adult women's and men's education levels, measures of male labor force participation. Fertility regression also controls for starting period fertility, and schooling regression controls for male schooling.

Export shock

Follows Autor et al (2019):

$$\Delta Export\ Exposure_{s,t} = \alpha_{s,t-10}^{knit} * \Delta Knit\ Export_{t-10} +$$
$$\alpha_{s,t-10}^{Woven} * \Delta Woven\ Export_{t-10}$$
$$and\ \alpha_{s,t-10}^{knit} = \frac{Workers_{s,knit,t-10}}{Workers_{BD-Knit,t-10}},$$
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- Estimates are not very sensitive to 1-5 year lag used.

Identifying assumption

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- **Identifying assumption 2:** FLFP responds similarly to woven and knit based shocks.

- **Identifying assumption 3:** Usual Bartik assumptions.

Data Sources

- **Outcome data** is obtained by aggregating individual-level data from the Bangladesh Census 1991 (10% sub-sample), 2001 (10% sub-sample) and 2011 (5% sub-sample).

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- **Factory data** are primarily from **Mapped in Bangladesh Project.**

  - Between 2017 and 2021, the project gathered information on all potentially existing factories from government and trade groups.

  - Processed the list and physically verified locations of 3805 factories in outside of export processing zones (EPZs).

  - I obtained EPZ factory data by scraping Bangladesh Garments Manufacturers and Exporters Association (BGMEA) website.

Threats to identification

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- Factory data does not account for exits.

  - For example, my dataset identifies about 1914 firms in 2009. Astarloay (2015) identified 3548 firms.

  - Key concern is if exits are geographically correlated.

Results

FLFP

	Δ F-LFP		Δ Ind F-LFP		Δ M-LFP
	15-64	15-39	15-64	15-39	15-64
β	0.0071***	0.0081***	0.0097***	0.0113***	0.0012*
Std. Error	0.0008	0.0009	0.0009	0.0010	0.0007

- Modest impact on FLFP that is stronger on industrial FLFP and among younger women.

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- At mean export exposure for a sub-district over two decades (203 million USD):

  - FLFP increases by 1.44 percentage point.

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  - Possibly since FLFP varies substantially by proximity to factories and I use a larger definition of labor markets.

  - Perhaps suggestive of limited diffusion?

Education and Fertility

	Δ Fertility (15-39)	Δ Enrollment (<15)
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- Weak evidence of declining school enrollment.

Conclusions

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Thank you. Suggestions and comments are very appreciated!