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Abstract

In this paper, we make two novel contributions to the literature on trade and inequality. First, we show that the same mechanism that causes greater cross-sectional inequality, higher relative demand for skill, also facilitates intergenerational occupational mobility. In particular, we develop a stylized model that shows that the innovation induced by international trade causes an increase in the employment share of high-skill occupations. In turn, this allows an increasing number of sons to enter better occupations than their father. We then exploit spatial variation in exposure to trade liberalization in urban India to test our model's prediction. Our empirical results confirm that sons that live in urban districts with a greater exposure to trade liberalization have a higher probability of being in a better occupation than their father. Further, as predicted by our model, we find that this positive impact of trade liberalization on intergenerational mobility is stronger in relatively technologically advanced districts. In a second contribution, we show that increased investment in education alone need not facilitate intergenerational occupational mobility. Instead, it only does so in urban districts where there has been a sufficient increase in the employment share of high-skill occupations.

Keywords: Trade and Labor Markets, Intergenerational Mobility.
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1 Introduction

In this paper, we make two novel contributions to the literature on trade and inequality.[1] First, we show that the same mechanism that causes greater cross-sectional inequality, higher relative demand for skill, also facilitates intergenerational occupational mobility. In particular, we show that trade liberalization, by increasing the employment share of high-skill occupations, allows an increasing number of sons from underprivileged backgrounds to enter better occupations than their father. We also show that this effect is stronger in technologically advanced districts. Second, we show that greater investment in education alone need not facilitate intergenerational occupational mobility. Instead, it only does so in locations where there has been a sufficiently large increase in the employment share of high-skill occupations.

To study this relationship, we examine the patterns of intergenerational occupational mobility in post-reform India.[2] This setting provides us with three key advantages. First, India enacted dramatic trade reforms in 1991 at the urging of the International Monetary Fund (IMF). Given that the decision to lower tariffs was done under external pressure, this episode of trade liberalization provides exogenous variation in tariffs in the post-reform period that we exploit to causally examine the relationship between trade liberalization and intergenerational occupational mobility. Second, India's National Sample Survey Organisation (NSSO) collects detailed occupational data. These data are based on nationally representative household surveys and allows us to rank 335 three-digit occupations in our working sample. While rich occupational data are available for many developed countries, such data are relatively rare for developing countries.

Third, our data suggest that there is significant persistence in occupational choice in India. We find that, conditional on having a father who is at the bottom decile of the fathers' occupational distribution, there is a 57 percent chance that a son in 1999 is also in the bottom decile of the sons' occupational distribution. Similarly, we find that, conditional on having a father who is at the top

[1] See Goldberg and Pavcnik (2007) for a comprehensive review of this literature.

[2] Apart from being an important issue in its own right, a key advantage of focusing on intergenerational occupational mobility instead of intergenerational income mobility is that the former can be measured more reliably using the type of survey data that we use. This is especially true in a context where the vast majority of survey respondents work in the informal sector.

decile of the fathers' occupational distribution, there is a 39 percent chance that a son in 1999 is also in the top decile of the sons' occupational distribution. Thus, to the extent that greater trade leads to greater occupational mobility in India, it has the potential to significantly improve the lives of workers from underprivileged backgrounds.

To identify the impact of trade on occupational mobility, we exploit the geographic variation in exposure to trade liberalization in India. In particular, we examine whether, all else equal, a son residing in an urban district with greater exposure to trade liberalization is more likely to be in an occupation that is higher ranked than that of his father. We measure each district's exposure to trade liberalization using the difference in a district's tariffs between 1987 (pre-reform) and 1998 (post-reform).[3] Our results suggest that a 10 percentage point decrease in a district's tariffs increases the likelihood of upward intergenerational occupational mobility among its adult male residents by 1.85 percentage points. We find no evidence to suggest that an urban district's exposure to trade has an effect on downward occupational mobility. These results hold for sons who have fathers in below-median occupations and are robust to excluding sons who have migrated across districts in the post-reform period.

To understand this impact of trade on upward intergenerational occupational mobility, we build a model with worker and entrepreneur heterogeneity, occupation choice, and innovation. The production side of the model is similar to Aghion, Blundell, Griffith, Howitt, and Prantl (2009), where firms engage in step-by-step innovation. In our model trade liberalization leads to an increase in the threat of entry by foreign competitors into the domestic market.[4] As in Aghion et al. (2009), this threat of entry forces domestic firms that are relatively close to the world technology frontier (high-tech firms) to increase their innovation effort. This leads to an increase in the return to skill in such high-tech firms. On the other hand, domestic firms that are further away from the world technology frontier reduce their innovation effort and return to skill due to the discouragement effect of increased threat of entry.

[3] District tariffs are defined as the weighted average of industry tariffs for all industries located in a district, where the weights are each industry's share of a district's employment in 1987.

[4] Our modeling of trade liberalization is consistent with the Indian tariff reforms. India dramatically lowered its import tariffs in 1991 providing increased access to the domestic market for foreign firms. This was not accompanied by any significant direct expansion of export opportunities for domestic firms.

We then examine the impact of these changes in innovation on the distribution of occupations using insights from Yeaple (2005) and Munshi (2011). In particular, we assume that workers have heterogeneous ability, where a worker's ability affects the firm's probability of success in innovation. We also assume that workers can either be from privileged or underprivileged background. Privileged workers are those that have fathers who worked in high-tech firms. We assume that these workers inherit occupation-specific knowledge from their fathers, which lowers the fixed cost (e.g. training cost) of employing them in high-tech firms. On the other hand, underprivileged workers are those whose fathers worked in low-tech firms. They also inherit occupation-specific knowledge, but this only lowers the fixed cost of employing them in low-tech firms. Due to the specific nature of this inherited knowledge, the fixed cost of employing underprivileged workers in high-tech firms is relatively higher. In our model, a sufficiently large difference in fixed costs across the two types of firms and a higher marginal cost of innovation in low-tech firms ensures that the cutoff ability of entering high-skill firms is lower for workers from privileged backgrounds. This generates the type of intergenerational occupational persistence that we observe in our data.

Our model predicts that the increase in innovation by high-tech firms that is induced by trade raises the employment share in these types of firms. In other words, the employment share of high-skill occupations increases. In turn, this allows an increasing number of underprivileged workers to enter high-skill occupations and thereby experience upward intergenerational occupational mobility. An implication of our model is that urban Indian districts that have a greater initial concentration of high-tech firms, i.e. firms that are relatively close to to world technology frontier, will experience a relatively larger increase in upward intergenerational occupational mobility as a result of trade. We test this prediction by comparing the effect of trade on occupation mobility in urban districts with an above-median concentration of high-tech industries in the pre-reform period with the effect on all remaining urban districts. Our results strongly support the above prediction.

An alternate mechanism that could explain our results is that trade liberalization raises the returns to investment in education. This means that households that invest more in their son's education as a result of trade are the ones that experience greater upward intergenerational occupational mobility. However, our results suggest otherwise. First, we find that trade does not have a significant effect on the probability that a son has a higher educational attainment than his father. Second, we find that the impact of trade on occupational mobility remains robust when we restrict the sample to father-son pairs that have the same educational attainment, i.e. a sample where the educational mobility channel is shut down. This suggests that greater investment in the education of sons is not the key mechanism through which trade affects intergenerational occupational mobility in our overall sample.

Interestingly, our results suggest that investment in education can be important in some contexts. In particular, we find that in urban districts with a higher pre-reform concentration of high-tech industries, trade causes a relatively larger increase in upward occupational mobility among father-son pairs where the son has a higher educational attainment than his father. To the extent that these are also districts where there have been the largest changes in the employment share of high-skill occupations, these results suggests that when it comes to intergenerational occupational mobility, investment in education only pays off if there is also a significant increase in the share of high-skill occupations. Thus, our results suggest that, while trade does not necessarily lead to greater intergenerational educational mobility in India, it does lead to better occupational outcomes for higher-educated sons provided they live in a district that has had the necessary underlying changes in the distribution of occupations.

Our paper is related to a vast literature in economics on intergenerational income mobility. The initial literature, as surveyed by Solon (1999), focused on the precise measurement of intergenerational income mobility in developed countries (Solon, 1992; Mazumder, 2005). A more recent literature, as surveyed by Black and Devereux (2011), has instead focused on capturing the determinants of intergenerational income mobility in developed countries. In particular, this literature has attempted to determine whether the correlation between parents and children's earnings is driven by genetic factors or childhood environment. The issue of intergenerational income mobility has also been recently been brought to the forefront by an influential study by Chetty, Hendren, Kline, and Saez (2014).

Our paper is also related to an empirical literature on intergenerational occupational mobility, which has been pioneered by sociologists (Erikson and Goldthorpe, 2012). In the economics literature, a key early contribution was by Dunn and Holtz-Eakin (2000), who showed that children in their U.S. sample are more likely to become self-employed if a parent is self-employed. Similarly, Hellerstein and Morill (2008) showed that between 20-30 percent of children in their U.S. sample work in the same occupation as their father. More recently, a small but growing literature has examined trends in intergenerational occupational mobility in developing countries. For example, Emran and Shilpi (2010) and Hnatkovska, Lahiri and Paul (2013) have documented patterns of intergenerational occupational mobility in Nepal, Vietnam, and India respectively. While this literature provides us with a clearer sense of how mobility has changed in these developing countries, it does not clarify the factors that have driven this change.

The relationship between trade, innovation, and the skill premium has also been explored in the recent literature (Yeaple, 2005; Verhoogen, 2008; Bustos, 2011; and Burstein and Vogel, 2012). In contrast to this focus on cross-sectional inequality, we examine the effect of trade and innovation on intergenerational mobility. Lastly, our paper is related to a literature documenting the effect of trade on educational attainment in developing countries (Edmonds, Pavcnik, and Topalova, 2010 and Atkin, 2015).

The remainder of the paper is structured as follows. In section 2 we introduce a stylized model of trade, innovation, and occupation choice. In section 3 we describe the data used in our analysis as well as the method we use to rank occupations. In section 4 we describe our econometric strategy and results. In section 5 we describe the results of our robustness checks including our strategy for addressing potential threats to identification. Finally, in section 6 we provide a conclusion.

2 Model

2.1 Production

In this section, we develop a model of trade-induced entry, innovation, and intergenerational occupational mobility. The production side of the model follows Aghion et al. (2009). In each period t, a final good, henceforth the numeraire, is produced under perfect competition using a continuum of inputs according to the technology:

$$y_t = \left[\int_0^1 A_t(i)^{1-\alpha} x_t(i)^\alpha \mathrm{d}i \right] \tag{1}$$

where $x_t(i)$ is the quantity of intermediate input produced and $A_t(i)$ is the productivity/technology parameter associated with the latest version of that input. We assume that each district in India produces all intermediate inputs as well as the final good. The aggregate representative agent in each district consumes the final good. For simplicity, we assume that there is no inter-district trade or labor mobility.

Intermediate producers live for only one period and property rights over their technological capabilities are transmitted within dynasties. The final good is used as capital in the production of intermediate goods with a one-for-one technology. We assume that for each intermediate input, only the firm with the best technology ("incumbent") will actively produce the intermediate input. The equilibrium profits for each incumbent will be:

$$\pi_{t(i)} = \delta A_t(i) \tag{2}$$

where

$$\delta = (1-\alpha)\left(\alpha^{(1+\alpha)/(1-\alpha)}\right)$$

is a constant. The world's technology frontier for each input at the end of period t is given by

$$A_t = \gamma A_{t-1}$$

where $\gamma > 1$. At the beginning of period t firms can be one of two types: type-1 firms that operate at the current frontier with productivity A_{t-1} and type-2 firms that are one step behind the frontier with productivity A_{t-2}.

2.2 Worker Background and Cost of Innovation

There are two types of activities in a firm: production and innovation. Production only uses the final good one-for-one as described above. However, before they produce, firms can innovate to increase their productivity. Innovation only uses workers and allows a firm of type j, where $j \in \{1, 2\}$, to increase their productivity by the factor γ and thereby keep up with the frontier.[5]

In a departure from Aghion et al (2009), we assume that workers own the incumbent firm in which they work and that they are differentiated by their background. In particular, we assume that workers can come from two backgrounds: privileged (H) and underprivileged (L). Workers with privileged backgrounds are those whose fathers worked in type 1 firms. On the other hand, workers with underprivileged backgrounds are those whose fathers worked in type 2 firms. Workers are also differentiated by their inherent ability, λ, which affects their probability of successful innovation as defined below. We assume that λ is continuously distributed according to a probability function $g(\lambda)$ over a bounded space, $[0, \overline{\lambda}]$. This specification of heterogeneous workers choosing to work in a high or low-tech firm is similar to Yeaple (2005).[6]

Similar to Aghion et al. (2009), we assume that a firm's innovation will be successful with probability z within that period. On the other hand, with probability $1 - z$, the firm's innovation

[5] This is a stylized model where workers are only engaged in innovation while production only uses the final good. An alternate approach would allow production to use both the final good (and hence all intermediate inputs) and workers. In that case, demand for workers will arise from both production and innovation and will complicate the labor market clearing conditions further without providing any additional insight. The main result of the model, that the demand for skill rises after trade liberalization in districts with firms closer to the world technology frontier, is robust to this extension of the model.

[6] Workers owning the firm in which they work is a clear abstraction. A less stylized model would allow firms with heterogenous productivity to choose either an advanced technology (type 1) or a backward technology (type 2). Similarly, it would allow workers with heterogeneous productivity to chose either a high-skill occupation in a type-1 firm or a low skill occupation in a type-2 firm. Further, worker and firm productivity would complement each other in guaranteeing success in innovation. While such a model would have better captured the actual matching between firms and workers, it will not provide any additional empirical insight in terms of the effects of trade on intergenerational mobility.

will not be successful and it will lag behind the new frontier by one step. We assume that each firm's probability of success is a function of its worker's ability (λ) and its innovation effort (q), as follows:

$$z = \lambda q$$

where λ and q are such that $0 \leq z \leq 1$. This formulation of the probability of success in innovation captures the complementarity between worker ability and innovation effort, which is similar to complementarity between workers and managers as in Antras, Garicano, Rossi-Hansberg (2006).

A firm of type j, where $j \in \{1, 2\}$, must incur a cost of innovation, $w_{k,j}(q)$, that depends on the type of the firm, the background of its workers and its innovation effort in the following way:

$$w_{k,j}(q) = \alpha_{k,j} + \beta_j q^2$$

where $\alpha_{k,j}$ the fixed cost for a worker with background k ($k \in \{H, L\}$) of operating a firm of type j ($j \in \{1, 2\}$). Allowing for a fixed cost of innovation that differs by the background of workers is a crucial departure from Aghion et al. (2009) and allows us to incorporate the intergenerational occupational persistence we observe in our data. We make two assumptions about these fixed costs. First, we assume that, for a given k, the fixed cost of operating a type-1 firm is higher. That is,

$$\alpha_{k,1} > \alpha_{k,2} \tag{3}$$

Second, we assume that the fixed cost for a worker from a privileged background is lower in the high-tech, type-1 firm while the fixed cost for a worker from an underprivileged background is lower in the low-tech, type-2 firm. That is,

$$\alpha_{H,1} < \alpha_{L,1} \qquad \text{and} \qquad \alpha_{H,2} > \alpha_{L,2} \tag{4}$$

This assumption is consistent with the notion that sons inherit occupation-specific knowledge from their fathers, as in Munshi (2011). In other words, the occupation-specific knowledge that a son from a privileged (underprivileged) background receives from his father, lowers his fixed cost of operating a type-1 (type-2) firm. Our assumptions about relative fixed costs imply that

$$\alpha_{L,1} > \alpha_{H,1} > \alpha_{H,2} > \alpha_{L,2} \tag{5}$$

Thus, the fixed cost is highest for workers from underprivileged backgrounds in a type 1 firm and is the lowest for workers from underprivileged backgrounds in type 2 firms. We assume that the distribution of a workers' inherent ability, λ, is independent of background.

2.3 Optimal Innovation and Occupational Persistence

As in Aghion et al. (2009), in each period and for each intermediate input, there is one foreign firm that can pay for an opportunity to enter the market. We assume that if there is entry, it will be by a firm that has the frontier technology at the time of entry. We assume that the incumbent and the entrant engage in Bertrand competition. This means that an entrant will steal all of the market and become the new leading firm if its technology is superior to the incumbent's. On the other hand, if the incumbent innovates and has the frontier technology, then we assume that the incumbent retains the entire market.[7] Let us denote the probability of entry for an input produced by a type j firm as p_j, where $j \in \{1, 2\}$. For simplicity, we assume that $p_1 = p_2 = p$, although all of our comparative static results are independent of this assumption. Let $\nu_{k,j}(\lambda)$ denote the payoff from innovation for a worker with ability λ, background k and owning a firm of type j.

Let us first consider the optimal innovation problem for a type-2 firm. By definition, this firm has a technology equal to A_{t-2}. Suppose a foreign firm enters this market with probability p. Because the entrant has the frontier technology, it will capture the entire market and cause the incumbent firm to exit. Thus, the type-2 incumbent's payoff from innovation is a decreasing function of the probability of entry by a foreign firm. It follows that a type-2 firm's problem is to

[7] As in Aghion et al. (2009), a justification for this assumption is that an entrant must pay a fixed fee to enter. If it enters a market where the incumbent also has the frontier technology, then it will earn zero profits due to Bertrand competition. As a result, its net gains from entry will be negative and the firm will prefer not to enter.

pick the innovation effort (q_2) that maximizes the following objective function:

$$\delta((1-\lambda q_2)(1-p)A_{t-2}+\lambda q_2(1-p)A_{t-1})-(\alpha_{k,2}+\beta_2 q_2^2)A_{t-2}$$

This reflects the fact that a type-2 firm can only gain if there is no entry, regardless of whether or not it engages in innovation. Its incentive to innovate is due to profit being an increasing function of the level of technology it uses (see (2)). This innovation problem yields the following optimal effort for a type 2 firm as a function of its ability:

$$q_2(\lambda)=\frac{\delta\lambda(\gamma-1)(1-p)}{2\beta_2} \tag{6}$$

On the other hand, a type-1 firm with technology A_{t-1} can gain either if it successfully innovates (with probability $z=\lambda q$) or if it does not innovate but there is no entry. Therefore, its objective function is

$$\delta[\lambda q_1 A_t+(1-\lambda q_1)(1-p)A_{t-1}]-(\alpha_{k,1}+\beta_1 q_1^2)A_{t-1}$$

This innovation problem yields the following optimal effort for a type-1 firm as a function of its entrepreneurial abilities:

$$q_1(\lambda)=\frac{\delta\lambda(\gamma-1+p)}{2\beta_1} \tag{7}$$

Notice that the complementarity in innovation effort and entrepreneurial ability ensures that the success of an innovation yields a positively sloped optimal effort function in both sectors. That is, from (6) and (7), $q_2'(\lambda)>0$ and $q_1'(\lambda)>0$. Hence, more able entrepreneurs exert more effort in innovation activities. Also, in both sectors the value from innovation is increasing and convex in worker ability λ.

Using (6), we know that the payoff from innovation for a worker with ability λ, background

k and owning a type-2 firm is

$$\nu_{k,2}(\lambda) = A_{t-2}\left[\delta(1-p) - \alpha_{k,2} + \frac{\delta^2\lambda^2(\gamma-1)^2(1-p)^2}{4\beta_2}\right] \tag{8}$$

Similarly, using (7), we know that the payoff from innovation for a worker with ability λ, background k and owning a type-1 firm is

$$\nu_{k,1}(\lambda) = A_{t-1}\left[\delta(1-p) - \alpha_{k,1} + \frac{\delta^2\lambda^2(\gamma-1+p)^2}{4\beta_1}\right] \tag{9}$$

These payoff functions are illustrated in Figure 1. The horizontal axis represents the ability of a background k worker, λ. The vertical axis represents the worker's optimal return from operating either a type-1 and a type-2 firm, $\nu_{k,1}(\lambda)$ and $\nu_{k,2}(\lambda)$. At the cutoff ability, λ_k^*, the return from operating either type of firm is the same.[8] As a result, a worker with ability λ_k^* is indifferent between working in a type-1 or a type-2 firm. Workers with ability $\lambda > \lambda_k^*$ obtain a higher return from innovation in a type-1 firm, while workers with ability $\lambda < \lambda_k^*$ prefer working in a type-2 firm.

The existence of such a cutoff equilibrium requires two assumptions to hold. The first assumption is that the fixed cost of establishing a high-tech, type-1 firm is substantially larger than the fixed cost of establishing a type-2 firm, specifically $[(\alpha_{k,1} - \alpha_{k,2}) > \delta(\gamma-1)(1-p)]$. Note that we already assumed that fixed cost is higher for type 1 firms, as in (3). The additional restriction needed for the cutoff equilibrium to exist is that this difference in fixed cost is sufficiently large. This ensures that in equilibrium the lowest ability worker chooses to operate a low-tech, type-2 firm. That is, $\nu_{k,2}(0) > \nu_{k,1}(0)$.

The second assumption needed for a cutoff equilibrium to exist is that $\frac{\beta_2}{\beta_1} > \frac{(\gamma-1)^2)}{\gamma}$. Recall that β_j is the marginal cost of innovation for a type-j firm. Hence, this parameter restriction ensures that the relative marginal cost of innovation is sufficiently large for type-2 firms (relative to type-1). Thus, at the cutoff ability λ_k^*, the slope of the payoff function for a type-1 firm is greater than

[8] Since the fixed cost depends on the background of a worker, workers from a privileged background have a different cutoff ability for operating a type-1 firm than a worker from an underprivileged background. Hence, we denote the cutoff ability for owning a type-1 firm for a worker of background k as λ_k^*.

the slope of the payoff function for a type-2 firm. That is, $\frac{\partial v_{k,1}(\lambda_k^*)}{\partial \lambda} > \frac{\partial v_{k,2}(\lambda_k^*)}{\partial \lambda}$. This ensures that a worker with ability that is marginally higher than the cutoff will choose to operate a type-1 firm.[9]

Our assumption that the fixed cost for a privileged background worker to operate a type-1 firm is lower, as captured in (4), ensures that the cutoff to create type-1 firms is lower for workers with privileged backgrounds. Thus, $\lambda_H^* < \lambda_L^*$. Hence, a worker from a privileged background has a higher probability of being in a high-tech, type-1 firm. This equilibrium allocation is illustrated in Figure B.1 in the online appendix and is consistent with the high intergenerational occupation persistence we observe in the Indian data.[10] It is summarized by the following lemma.

Lemma

Assume $(\alpha_{k,1} - \alpha_{k,2}) > \delta(\gamma - 1)(1 - p)$ and $\frac{\beta_2}{\beta_1} > \frac{(\gamma-1)^2)}{\gamma}$. For any background k, there exists a cutoff ability λ_k^* such that all such workers with ability $\lambda > \lambda_k^*$ work in type-1 firms and those with ability $\lambda < \lambda_k^*$ work in type-2 firms.

The cutoff ability for establishing a type-1 firm is lower for workers from a privileged background. A higher fixed cost for a worker from an underprivileged background to operate a high-tech, type-1 firm (see (4)) implies that $\lambda_H^* < \lambda_L^*$.

Proof. See online appendix. ■

2.4 The Impact of Trade

We model trade liberalization as an increase in the probability of entry by technologically advanced foreign firms, p_j, where $j \in \{1, 2\}$. From (6), we know that a higher probability of entry will discourage innovation effort among type-2, incumbent firms. The intuition for this is as follows. We know that type-2 firms have a current technology, A_{t-2}, that is two-steps behind the technology that entrants will possess, A_t. As a result, if a foreign firm decides to enter, it will

[9] An isomorphic way of modelling the higher marginal impact of ability on innovation in type-1 firms is to allow probability of success (z) to be more sensitive to ability (λ) while keeping marginal costs same across types of firms ($\beta_1 = \beta_2$) .

[10] The online appendix can be downloaded from the following url: `https://sites.google.com/site/reshadahsan/research`.

capture the entire market and force the incumbent type 2 firm to exit. This is true regardless of whether the incumbent retains its current technology level or successfully innovates and achieves a technology of A_{t-1}. It follows that a higher probability of entry will lower the incentives for this incumbent to innovate.

On the other hand, from (7), we know that a higher probability of entry will encourage greater innovation effort among type-1, incumbent firms. Recall that such a firm has a current technology, A_{t-1}, that is only one-step behind the technology that entrants will possess. This means that if it successfully innovates, it can match the entrants technology level and prevent it from entering.

In addition to the effect of increased competition on incentives to innovate for incumbents, increased threat of entry lowers the cutoff probability of establishing a type-1 firm for workers from all backgrounds and leads to higher intergenerational occupational mobility. This comparative static effect of trade and associated increased threat of entry on occupation choice is illustrated in Figure 2. In this figure, $\nu_{L,j}(\lambda)$ denotes the optimal value of innovation for a worker with ability λ, background L and owning a firm of type j, and $\nu'_{L,j}(\lambda)$ denotes the optimal value of innovation for a worker with ability λ, background L and owning a firm of type j after probability of entry increases to $p' > p$.

A rise in threat of entry induced by trade liberalization shifts down the intercept for the the type-2 firm's payoff function and also flattens the slope. The latter is due to the reduced optimal innovation among type-2 firms. A rise in threat of entry induced by trade liberalization also shifts down the intercept for the type-1 firm's payoff function, but makes it steeper due to the increase in optimal innovation. Note that the marginal return to ability (in terms of value of optimal innovation) is increasing in threat of entry in type-1 firms.[11] Hence, a trade-induced rise in threat of entry increases the return to higher ability in type-1 firms. This results in a fall in λ_L^*, and expands the set of workers operating in type-1 firms. Hence, trade liberalization increases the fraction of workers from underprivileged backgrounds operating high-tech type-1 firms, leading to improvement in upward intergenerational occupational mobility. A similar comparative static result applies to the workers with background H. We summarize these comparative static properties of

[11] $\frac{\partial \nu_{k,1}}{\partial \lambda}$ is increasing in p, while $\frac{\partial \nu_{k,2}}{\partial \lambda}$ is decreasing in p.

the equilibrium allocation in the following proposition:

Proposition 1 (Trade and Intergenerational Occupation Mobility)

A rise in threat of entry (p) *increases optimal innovation effort in type-1 firms and decreases optimal innovation effort in type-2 firms. That is,* $\frac{\partial q_2(\lambda)}{\partial p} < 0$ *and* $\frac{\partial q_1(\lambda)}{\partial p} > 0$*. Further, the increased entry threat leads to an expansion of workers with an underprivileged background in type-1 firms. This follows from the result that* $\frac{\partial \lambda_H^*}{\partial p} < 0$ *and* $\frac{\partial \lambda_L^*}{\partial p} < 0$*. As a result, following trade-induced increased threat of foreign entry, more workers are employed in high-tech type-1 firms, irrespective of background, and this raises intergenerational occupational mobility.*

Proof. See online appendix. ■

To explore the implications of this proposition for our empirical analysis, consider the fact that urban Indian districts, due to differences in industrial composition, will have different exposure to trade liberalization. Proposition 1 suggests that, ceteris paribus, districts with greater exposure to trade liberalization (higher probability of foreign entry, p) will experience a larger improvement in upward intergenerational occupation mobility. This is the key theoretical prediction that we test using our data. In particular, we test whether districts with greater reduction in import tariffs experience a relatively larger improvement in intergenerational occupation mobility in Section (4).

We can also use our data to examine a second implication of our model. Suppose that urban Indian districts vary in their pre-liberalization concentration of high-tech firms (type 1 in our stylized model). Our model implies that, for a given increase in trade liberalization (higher p in our model), districts with a relatively higher concentration of high-tech firms will experience a larger increase in innovation activities as well as intergenerational occupation mobility. We test this key insight from our stylized model in Section (4.2).

3 Data

To examine the relationship between trade liberalization and intergenerational occupational mobility, we use the "employment-unemployment" household surveys conducted by India's National Sample Survey Organisation (NSSO). In particular, we use round 55 (1999–2000) of these nationally-representative surveys.[12,13]

Our working sample consists of all male sons. We follow Hnatkovska et al. (2013) and exclude female household members from our analysis because of the potential for changes in female labor force participation and lower co-residence rates of working-age females with biological parents (due to marriage-related migration) to confound our results. Focusing on only male household members allows us to minimize the effects of these confounding factors. Further, we restrict the sample to men that are currently in the labor force, are not currently enrolled in an educational institution, and those that report their principal occupation. We also restrict the sample to men in urban areas. Lastly, we restrict the sample to adult men between the ages of 16 and 35. Our choice of an upper age limit merits further discussion. Ideally we would prefer to include all adult males in our sample. However, the tradeoff we face is that the older an adult male is in our sample, the greater is the likelihood that his father is retired. In such cases, we cannot identify whether or not the son is in a better/worse occupation than his father. We choose an upper age limit of 35 to minimize the likelihood of observing retired fathers. As we discuss is section 5.1, our results are robust to using other upper age limits. Our final working sample consists of 7,739 men for whom we have complete data on all dependent and independent variables.

Apart from standard information regarding demographics, employment status, and wages, the 'employment-unemployment" household surveys also collect information on the occupation

[12]In the remainder of this paper, we refer to the survey year using the first year of the survey. In other words, we refer to the 1999–2000 round as 1999.

[13]The NSSO also collected another round of data after the trade liberalization episode of 1991. We excluded this 50th round (1993–1994) from our analysis because, as described below, we measure an individual's exposure to trade liberalization using the change in district tariffs where an individual resides. Unfortunately the NSSO did not record the district in which each household was located during the 50th round. As a result, this round of data is unsuitable for our analysis. In any case, given the short time difference between the collection of the 50th round of data and the trade liberalization episode of 1991, it is unlikely that we will capture any meaningful changes in intergenerational occupational mobility with these data.

of each respondent. This information is collected for two reference periods: (a) 365 days prior to the surveys (or "principal/usual status") and (b) one week prior to the surveys (or "current weekly status"). Given that a respondent's occupation during the past week may reflect temporary work, we use each respondent's principal occupation as our primary measure.[14] The NSSO assigns a three-digit code for each respondent's occupation. These codes are based on the 1968 version of the National Classification of Occupation (NCO). There are 335 such occupations in our working sample.

To measure intergenerational occupational mobility, we pair each adult son in our sample with his male household head (father). This allows us to determine whether the principal occupation of an adult son is higher or lower ranked than that of his father. The advantage of the NSSO data is that it provides a large sample of individuals with detailed occupational classification. Thus, we are able to construct a rich measure of intergenerational occupational mobility.

However, a key shortcoming of these data is the fact that not all adult sons co-reside with their fathers. This raises an important selection bias concern as co-resident households may be systematically different from non co-resident households. Fortunately, using NSSO data, Hnatkovska et al. (2013) show that co-resident households constitute approximately 62 percent of all households in the sample. They define co-resident households as ones in which multiple adult generations reside together. They also point out that these co-resident rates are stable across the various survey rounds. Such high co-resident rates are likely to attenuate any selection bias.

How different is our working sample of adult sons compared to the full, representative sample? Table 1 compares the observable characteristics of the two groups. Compared to the full sample, the adult sons in our working sample are younger, slightly more educated, less likely to be married, are in households that are larger, and are in slightly lower ranked occupations. In terms of intergenerational occupational mobility, the key difference between these samples is the average age. As is well known in the intergenerational income mobility literature, the correlation between a son and his father's earnings exhibits a clear life-cycle pattern (Haider and Solon,

[14]In our working sample, 6.41 percent of respondents report a current weekly occupation that is different from their principal occupation.

2006). In particular, there is a relatively low correlation between father-son earnings when the son is young and a relatively high correlation when the son is older. As a result, intergenerational income mobility is attenuated as the average age of the son increases. In the intergenerational occupational mobility case, the nature of the life-cycle pattern is likely to be the opposite. Younger sons are more likely to be working in an occupation that is not an accurate reflection of their permanent (or modal) occupation. This means that a sample with a lower average age will understate the extent of intergenerational occupational mobility.[15] Going back to the differences in Table 1, the fact that our working sample consists of sons with a lower average age means that the selection bias that exists should lead us to understate the effect of trade on such mobility. This is exactly what we find in section 5.1.

3.1 Ranking Occupations

A key challenge in quantifying intergenerational occupational mobility is to construct a ranking of occupations. In this section we discuss our preferred ranking of occupations. To construct our ranking, we define the educational intensity of an occupation o, EI_o, as:

$$EI_o = \sum_{f=1}^{n_o} \left(\frac{\omega_f}{\sum_f^{n_o} \omega_f} \right) \times e_f \tag{10}$$

where e_f is individual f's education level, ω_f is an individual's sampling weight, and n_o is the total number of individuals within an occupation.[16] We repeat this for every occupation in our sample. We construct this measure using pre-reform data from 1987 (round 43). We do this to ensure that our ranking of occupations is unrelated to India's trade liberalization of 1991.[17] For respondents in the 1999 surveys, we match each individual's occupation with the education-intensity of that occupation in 1987. Thus, individuals can change the education-intensity of their occupation by

[15]This is supported by the fact that the average occupational rank of the sons in our working sample is lower than the average in the full sample.

[16]The NSSO does not collect data on the years of schooling completed by each respondent. Instead, it categorizes a respondents' educational level into various categories. We place each respondent into one of the following five categories: (a) not literate, (b) below primary, (c) primary, (d) middle school, (e) secondary school, and (f) graduate and above.

[17]The correlation coefficient between a ranking based on 1987 data and one based on 1999 data in 0.82.

switching occupations. However, each occupation's education intensity is not allowed to change over time.[18,19]

Using this education-based ranking of occupations, we define an *upward* occupational switch as one where an adult son is in an occupation that has a higher ranking than that of his father. Similarly, we define a *downward* occupational switch as one where an adult son is in an occupation that has a lower ranking than that of his father. Our data suggests that there is tremendous persistence in occupations across generations. This is illustrated in Figure 3, which shows the occupational distribution of sons in 1999 who were born to bottom-decile fathers. That is, fathers whose occupations are in the bottom decile of the fathers' occupational distribution. This figure suggests that, conditional on having a bottom-decile father, there is a 57 percent chance that a son in our sample will also be in the bottom decile of the sons' occupational distribution. In Figure 4 we conduct a similar exercise where we illustrate the occupational distribution of sons in 1999 who were born to top-decile fathers. That is, fathers whose occupations are in the top decile of the fathers' occupational distribution. This figure suggests that, conditional on having a top-decile father, there is a 39 percent chance that a son in our sample will also be in the top decile of the sons' occupational distribution.

In addition, as Table B.1 in the online appendix documents, there is considerable geographic variation in occupational mobility in our data. Column (2) of this table lists the fraction of sons in each state in our sample that has a better occupation than their father. Similarly, column (3) lists the fraction of sons in each state in our sample that has a worse occupation than their father. On

[18] Education-based rankings have also been used by Hoffman (2010). He calculates the fraction of employees with a post-secondary education in each of the 338 occupations. He then categorizes the lowest third of occupations as "blue collar", the middle third of occupations as "pink collar", and the highest third of occupations as "white collar". A drawback of this ranking is that, due to the broad categories used, it is likely to miss a substantial number of occupational switches. For example, even if an individual switches from the lowest blue-collar job to the highest blue-collar job, his/her switch will not be categorized as an upward occupation switch.

[19] An alternate, widely used ranking has been pioneered by Autor, Levy, and Murnane (2003). This approach uses data from the U.S. Department of Labor's *Dictionary of Occupational Titles* (DOT) to examine the task content of occupation categories. Autor et al. (2003) use the DOT task descriptions to categorize occupations into four categories: nonroutine analytic, nonroutine interactive, routine cognitive, and routine manual. This task-based ranking has the advantage of providing a more direct measure of the nature of occupations, especially for measuring offshorability of a task. However, given the lack of appropriate data for India, this task-based ranking is not suitable for our application. Moreover, given the occupational prestige and implied social mobility associated with high-skill jobs in the Indian context, our education-based ranking is especially appropriate for measuring intergenerational mobility of occupations.

average, 26 percent of sons in a state have a better occupation than their father, while 30 percent have a worse occupation than their father. Among the major states, Kerala, Tamil Nadu, and Andhra Pradesh have the highest fraction of upwardly-mobile sons while states such as Tripura, Mizoram, and Bihar have the lowest fraction of upwardly-mobile sons.

Next, to get a better sense of the nature of intergenerational occupational mobility in our data, we report the five most common occupational transitions among upward and downward-mobility pairs in Table 2. Panel A of this table restricts the sample to upward-mobility pairs. These are father-son pairs where the son has a higher-ranked occupation than his father. Among this sub-sample, the difference in occupational rank between fathers and sons is relatively incremental. Nonetheless, these occupational transitions represent substantial improvements in wage income. For instance, among the five most common upward occupational transitions, the average weekly wage income of the son is 60 percent higher than the average weekly wage income of the father. On the other hand, Panel B of Table 2 restricts the sample to downward-mobility pairs. These are father-son pairs where the son has a lower-ranked occupation than his father. Once again, among this sub-sample, the difference in occupational rank between fathers and sons is relatively incremental although the implied change in wage income is not.

We also construct an alternate occupational ranking using wage data from 1987. However, there are several concerns with the wage-based ranking in our case. First, only 33.2 percent of male workers in our working sample in 1987 are engaged in wage employment. The remaining workers are self-employed. As a result of this, the wage-based occupational ranking is less representative of the distribution of occupations in India. In addition, because the wage-based occupational ranks are constructed using a smaller sample, they cover fewer occupations. For example, while our education-based ranking allows us to rank up to 496 occupations, the wage-based ranking allows us to rank up to 423 occupations. As a result, we only use the wage-based ranking to test the robustness of our results.

Lastly, the tariff data that we use are at the 3-digit National Industrial Classification (1987) level and are an extension of the series used by Hasan, Mitra, and Ramaswamy (2007). These tariff data cover only manufacturing industries and vary by industry and year. We convert these industry tariffs to district tariffs using the following:

$$\tau_d = \sum_{h=1}^{n_h} \left(\frac{L_{hd}}{\sum_h^{n_h} L_{hd}} \right) \times \tau_h \tag{11}$$

where h indexes industries and d indexes districts. n_h is the total number of industries in a district. τ_h is the one-year lagged output tariff at the 3-digit industry level, L_{hd} is the number of workers in industry h in district d, and τ_d is the district tariff. Note that τ_d varies by district and year and is lagged by one year. To construct τ_d above, we use weights $(L_{hd} / \sum_h^{n_h} L_{hd})$ from 1987 only. This ensures that our weights are not endogenous to trade liberalization. We use an equivalent procedure to calculate other district-level protection measures such as input tariffs and the effective rate of protection.

A strength of our analysis is that we exploit variation in district tariffs that are driven by an externally-influenced episode of trade liberalization. In particular, faced with an acute balance of payments crisis, the then Indian government approached the International Monetary Fund (IMF) for assistance in 1991. The IMF agreed to provide such assistance under the condition that significant reforms be undertaken. While these reforms included many elements, a key component was a reduction in import tariffs and a harmonization of these tariffs across industries. Ahsan, Ghosh, and Mitra (2014) shows that average tariffs in their data fell from 149 percent in 1988 to 45 percent in 1998. Given that these reforms represented a significant departure from India's post-independence trade policy, they were enacted in haste (Hasan, Mitra, and Ramaswamy, 2007). This was motivated by a desire to limit the political fallout from this rapid liberalization and prevent a consolidation of opposition to these policies (Goyal, 1996). In fact, such was the haste with which these reforms were enacted, that by late 1996, less than 20 percent of the population were even aware that such trade reform had been undertaken (Varshney, 1999). The sudden nature of these reforms provides an ideal natural experiment that can be exploited to identify the causal effect of these reforms on intergenerational occupational mobility.[20]

[20]A further advantage of such a dramatic trade reform is that it minimizes the chance that changes in tariffs during our sample period were driven by other industry characteristics. Topalova (2007) examines whether changes in tariffs in India during the 1990s were correlated with pre-reform industry characteristics such as the total number of employees, industrial concentration, share of skilled workers, consumption, wage and poverty. In all of these cases she does not

4 Estimation Strategy and Results

To examine the impact of a district's exposure to trade liberalization on the intergenerational occupational mobility of its residents, we estimate the following econometric specification:

$$m_{fd} = \alpha + \beta\Delta\tau_d + \gamma_1 X_{fd} + \gamma_2 V_d^{87} + \theta_s + \varepsilon_{fd} \tag{12}$$

where f indexes sons, d indexes districts, and s indexes states. The dependent variable (m_{fd}) is an indicator for upward intergenerational occupational mobility. This variable takes the value of one if a son's occupation has a higher rank than that of his father. It takes the value of zero otherwise. We also use two other measures: (a) mobility and (b) downward mobility. The former is an indicator variable that is one if a son's occupation is different than that of his father and zero otherwise. This variable is designed to capture the dynamism of a district's labor market. On the other hand, downward mobility is an indicator variable that is one if a son's occupation has a lower rank than that of his father and zero otherwise.

In our specification $\Delta\tau_d$ captures a district's exposure to trade liberalization. More precisely, it is the difference between a district's tariffs in 1987 and its tariffs in 1998. These tariffs are constructed using equation (11). X_{fd} is a series of individual control variables that are likely to be related to an individual's occupation choice. These controls include an individual's age, age squared, household size, and marital status indicator. In addition, we follow Hnatkovska et al. (2013) and examine whether the extent of mobility depends on whether a son belongs to a scheduled caste/tribe and whether he is Muslim. We also control for the father's age, age squared and educational attainment. The latter is a proxy for the genetic transmission of ability across generations. That is, a son's occupational choice will be a function of his ability that he inherits from his father. We include the father's educational attainment as a proxy for this unobserved inherited ability.

Despite the exogenous and sudden nature of the trade reforms, the fact that we are using

find any evidence to suggest that changes in tariff were correlated with these pre-reform characteristics. Further, Ahsan, Ghosh, and Mitra (2014) show that Indian tariffs in the 1993–2004 period were uncorrelated with the strength of unions in an industry as well as the union wage and union wage premium.

cross-sectional data raises the possibility that our results are being confounded by unobserved district characteristics. Of particular concern are unobserved district characteristics that are correlated with both an individual's occupation choice as well as a district's exposure to trade liberalization. Recall that the latter is constructed using a district's industrial composition in 1987 along with industry-level changes in tariffs. Thus, any unobservable district characteristic that is correlated with a district's pre-reform industrial composition as well an individual's occupation choice can cause endogeneity bias. To account for this, we include a series of district-level control variables from 1987 in V_d^{87}. This series includes each district's share of employment in agriculture, mining, manufacturing, and services in 1987. Further, we also include a district's share of literate individuals and individuals that belong to a scheduled caste or tribe in 1987. This will address concerns that the trade reforms were adjusted to protect industries concentrated in districts with lower educated and other disadvantaged individuals.

Lastly, θ_s are state fixed effects while ε_{fd} is a classical error term. Note that the state fixed effects will control for other secular factors that are unrelated to trade but are correlated with the extent of occupational mobility in a state. Because we are using cross-sectional data we cannot include both $\Delta\tau_d$ and district fixed effects. As a result, we include state fixed effects instead.[21]

As we discuss in greater detail in section 5.2 below, our results could also be explained by selective migration into districts with greater exposure to trade liberalization. For instance, suppose that particularly enterprising sons (i.e. sons that are more likely to be in higher ranked occupations than their fathers) disproportionately migrate into districts with greater exposure to trade liberalization. Such selective migration could also explain our primary results. Fortunately, cross-district migration in our sample, particularly for economic reasons, is quite small. Only 1 percent of individuals in our sample have moved since 1991 for employment reasons to another district. Thus, the kind of cross-district migration that is needed to pose measurement challenges for our analysis is fairly rare in our sample.[22] As a result, we believe that such migration is unlikely to be

[21] In our baseline econometric specification we do not include an individual's educational attainment or occupation fixed effects. Both of these are likely to be a function of trade liberalization. Thus, including them in our econometric specification will induce simultaneity bias.

[22] The relatively low migration rates in India has also been documented using census data. In particular, using decennial population census data, Dyson, Cassen, and Visaria (2004) show that most migration that occurs in India are

a first-order concern. We demonstrate that this is indeed the case in section 5.2.

4.1 Baseline Results

In Table 3 we report the results from estimating equation (12). Our aim here is to examine the impact of a district's exposure to trade liberalization on the intergenerational occupational mobility of its residents. We begin in columns (1) and (2) with a dependent variable that is one for sons who have an occupation that is different from their father and zero otherwise. In column (1) we estimate a version of equation (12) without the pre-reform district characteristics (V_d^{87}). The coefficient of the change in district tariffs variable is negative and significant. This suggests that districts that experienced a larger decrease in tariffs between 1987 and 1998 had adult sons that were much more likely to be in an occupation that is different from their father. In other words, there was greater mobility or dynamism in these districts due to trade. This result remains robust when we include the pre-reform district characteristics in column (2).

In columns (3) and (4) the dependent variable is an indicator that is one if a son's occupation has a higher rank than that of his father. This variable captures whether or not there has been upward intergenerational occupational mobility among father-son pairs. As before, we estimate a version of equation (12) without the pre-reform district characteristics in column (3). The coefficient of interest is negative and significant, which suggests that districts that experienced a larger decrease in tariffs between 1987 and 1998 had adult sons that were much more likely to be in a higher ranked occupation than their father. That is, these districts exhibited greater upward intergenerational occupational mobility. In column (4) we include the pre-reform district characteristics. Our coefficient of interest remains robust, although the magnitude decreases slightly. The coefficient suggests that a 10 percentage point decrease in a district's tariffs increases the likelihood of upward intergenerational occupational mobility among its adult male residents by 1.85 percentage points.

To better gauge the magnitude of this effect, consider the following two districts. Let the

among women on account of marriage. The lack of migration in India is also documented by Munshi and Rosenzweig (2009).

first district have a fraction of upward-mobility sons that places it at the 25th percentile among all districts. According to our data, approximately 13 percent of sons have an occupation that is higher ranked than their father in this district. This district has also experienced a change in tariffs between 1987 and 1998 equal to –75.6 percent. Next, let the second district have a fraction of upward-mobility sons that places it at the 75th percentile among all districts. This district is one where approximately 35 percent of sons have an occupation that is higher ranked than their father and has experienced a change in tariffs between 1987 and 1998 equal to –130 percent. According to our results, 46 percent of the difference in upward occupational mobility between these two districts can be explained by their differential exposure to trade liberalization.[23]

In columns (5) and (6) the dependent variable is an indicator that is one if a son's occupation has a lower rank than that of his father. This variable captures whether or not there has been downward intergenerational occupational mobility among father-son pairs. In both columns (5) and (6), the coefficient of the change in district tariffs variable is not significant. Thus, whether we include the pre-reform district characteristics or not, we cannot reject the hypothesis that greater exposure to trade liberalization does not affect the extent of downward intergenerational occupational mobility among father-son pairs in our sample.[24]

In all six columns of Table 3, a son's age and age squared do not have a significant effect on mobility. This is also the case for whether or not the son is married. On the other hand, these results suggest that sons that belong to a scheduled caste/tribe are much more likely to have an occupation that is different from their father. We also find that Muslim sons are less likely to be in an occupation that is higher ranked than their father and is more likely to be in an occupation that is lower ranked than their father. Finally, we find that sons belonging to larger households are less

[23]Using the coefficient estimate from column (4) of Table 3, we know that if the first district were to have the second district's exposure to trade liberalization, its upward mobility indicator would increase by 10.1 percentage points $(-0.185 \times (-1.30 + 0.756))$. This is approximately 46 percent of the difference in upward mobility between these two districts.

[24]As a robustness check, we've also used a multinomial logit estimator where the dependent variable takes the value of 1 for sons with a higher-ranked occupation that their father, 0 for sons with an occupation with the same rank as their father, and -1 for sons with a lower-ranked occupation than their father. The estimates from this regression support our baseline results. We find that a 10 percentage point decrease in a district's tariffs increases the likelihood of upward intergenerational occupational mobility among its adult male residents by 1.74 percentage points. We also find that lower district tariffs do not have a statistically significant effect on downward occupational mobility.

likely to be in an occupation that is higher ranked than their father.

Our estimates thus far are based on a sample that includes men in both manufacturing and non-manufacturing industries. The benefit of using this sample is that it allows us to fully capture the extent of mobility in the data. For instance, with this sample, we can capture cases where sons who have fathers in highly-ranked manufacturing jobs but are only able to find lower-ranked service jobs themselves. Further, we can capture the fact that a reduction in manufacturing tariffs will also affect other industries through backward and forward linkages. A sample that is restricted to manufacturing employment will not capture these aspects of mobility. Nonetheless, it is the case that the trade liberalization we exploit mainly led to a reduction in manufacturing tariffs. Thus, it is useful to examine whether the results are robust if we restrict our sample to only sons working in manufacturing industries. The results using this restricted sample are reported in columns (1)–(2) of Table 4. As these estimates clearly demonstrate, all of the conclusions from Table 3 remain unchanged. In fact, we now find that a 10 percentage point decrease in a district's tariffs increases the likelihood of upward intergenerational occupational mobility among sons working in the manufacturing sector by 4.14 percentage points.

In the remaining columns of Table 4 we examine whether greater exposure to trade liberalization raises the likelihood of upward intergenerational occupational mobility among sons from disadvantaged backgrounds. In particular, we are interested in the effect of trade on occupational mobility for sons with below-median occupation fathers. In column (3) we restrict the sample to sons whose father's are in the first quartile of the fathers' occupational distribution. We then estimate equation (12) using this restricted sample. The coefficient of interest remains negative and statistically significant and suggests that a 10 percentage point decrease in a district's tariffs increases the likelihood of upward intergenerational occupational mobility by 2.4 percentage points for sons with first-quartile fathers. In column (4) we estimate the effect of trade on downward occupational mobility for these sons. As was the case with the baseline sample, we do not find a statistically significant effect here.

In column (5) we restrict the sample to sons whose father's are in the second quartile of the fathers' occupational distribution and then re-estimate the effect of trade on upward occupational mobility. Once again, the coefficient of the change in district tariffs variable remains negative and significant. Next, in column (6) we estimate the effect of trade on downward occupational mobility for sons with second-quartile occupation fathers. As before, the coefficient of the change in district tariffs variable is statistically insignificant. To summarize, the results in columns (3)–(6) suggest that the improvements in occupational mobility due to trade that we have observed thus far are not restricted to sons from relatively privileged backgrounds.

4.2 Mechanism

Our results thus far suggest that sons in districts with greater exposure to trade liberalization are more likely to be in occupations that are higher ranked than that of their father. In section 2, we described a model that can explain this result. In our model, trade will lead to an increase in the threat of entry (and hence competition) by foreign firms in the domestic market. This will spur innovation activities in domestic, high-tech firms that are closer to the world technology frontier due to the pro-competitive effects of trade. It will also reduce innovation activities in low-tech firms that are relatively further away from the world technology frontier due to the discouragement effects of trade. We then showed that this increased threat of entry will increase the employment share of high-skill occupations. Since some of these high-skill occupations are taken by sons from underprivileged backgrounds (i.e. sons with fathers that are in low-skill occupations), then trade liberalization will increase intergenerational occupational mobility.

An implication of our model is that, for a given increase in the threat of foreign entry, districts with a higher pre-trade share of high-tech firms will experience greater innovation activity as well as a greater increase in upward intergenerational occupational mobility. We next test this implication. If our data support this implication, it will validate the view that our model provides an accurate description of the nature of the relationship between trade and occupational mobility that we observe in our data.

To implement this test, we first need to divide our sample into districts that have a high pre-reform concentration of high-tech firms and districts that have a low pre-reform concentration of such firms. Since we do not observe firm activity at the district level in our data, we use two proxies instead. The first proxy relies on the implication that districts that have a higher pre-reform concentration of high-tech firms should also have a larger pre-reform high-skilled workforce. To classify districts according to its workers' skill, we calculate the share of workers in a district that have at least a middle-school education in 1987.[25] We then define a district as having a high-skilled workforce if its share of workers with at least a middle-school education in 1987 is above the sample median. All other districts are classified as having a low-skilled workforce. Column (1) of Table 5 restricts our sample to high-skilled workforce districts while column (2) restricts the sample to low-skilled workforce districts. The results suggest that the effect of trade on intergenerational occupational mobility are indeed stronger in high-skilled workforce districts. This strongly supports the implication of our model described above.

Our second proxy for the pre-reform concentration of high-tech firms in a district uses industry-level data to calculate each district's distance to the world technology frontier (DTF). This proxy is based on the approach used in Aghion et al. (2009). Their approach defines the labor productivity in a U.S. industry as the technology frontier for that industry. With this definition of the frontier, we calculate each Indian industry's distance from this technological frontier (D_k) by using a three-year moving average over the period 1989–1991. In particular, we calculate the following

$$D_k = \frac{1}{3}\sum_{u=0}^{2}\left[\ln\left(\frac{Y_{ht-u}^{US}}{L_{ht-u}^{US}}\right) - \ln\left(\frac{Y_{ht-u}^{IND}}{L_{ht-u}^{IND}}\right)\right] \tag{13}$$

where Y_{ht-z}^{US} is the real value added in U.S. industry h in year $t-u$, L_{ht-u}^{US} is total employment in U.S. industry h in year $t-u$, Y_{ht-u}^{IND} is the real value added in Indian industry h in year $t-u$, and L_{ht-u}^{IND} is total employment in Indian industry h in year $t-u$. We follow Aghion et al. (2009) and use a three-year moving average to smooth out any idiosyncratic time variation. To further minimize any measurement error, we construct a binary variable that takes the value of one if the distance between an Indian and U.S. industry is above the median (low-technology industry) and zero otherwise (high-technology industry).[26]

[25]The average individual in our sample has a middle-school education. See Table 1.

[26]We used data from two sources to calculate the distance to the technology frontier. Data on U.S. real value added

To construct a district-level measure of the distance to the technology frontier, we calculate the fraction of high-technology industries in each district. We then define a low-DTF district as one which has an above median fraction of high-technology industries. All other districts are categorized as high-DTF districts.[27] In columns (3) and (4) of Table 5 we restrict the sample to low-DTF and high-DTF districts respectively. Given the mechanism highlighted in our model, we expect trade-induced innovation activities (and therefore upward occupational mobility) to be greater in the former sub-sample. This is exactly what we find. In both columns the coefficient of interest is negative and statistically significant, but the magnitude of the effect of trade liberalization on upward occupational mobility is greater in column (3). Thus, the results in Table 5 collectively support a key implication of our model that, for a given reduction in tariffs, sons in districts with a larger pre-reform concentration of high-tech firms are more likely to experience upward intergenerational occupational mobility. As mentioned above, this validates the view that our model provides an accurate description of the nature of the relationship between trade and occupational mobility that we observe in our data.

An alternate explanation for our results is that households are investing more in the education of sons in the post-reform period. This greater educational investment could be motivated by the rising skill premium in India after the trade reforms of 1991. All else equal, such educational investments will allow these sons to work in higher-ranked occupations than their father. If this were the case, we should observe that sons in districts with greater exposure to trade liberalization are also more likely to have higher educational attainment than their father. Further, if this education channel is dominant, we should also expect that the upward occupational mobility effects of trade to be stronger among father-son pairs that have experienced upward educational mobility.

and employment are drawn from the NBER-CES Productivity Database while data on Indian real value added and employment are drawn from the Annual Survey of Industries (ASI). The NBER-CES Database defines value added as: value of industry shipments – cost of materials – energy expenses + change in finished goods and work-in-process inventories during the year. To match this as closely as possible, we define value added in the ASI data as: output – cost of materials – fuel expenses + addition in stock of semi-finished and finished goods during the year. The average industry in the U.S. sample has a labor productivity of U.S. $95,316 while the average industry in the Indian sample has a labor productivity of U.S. $5,145. These monetary values are in constant 1997 U.S. dollars.

[27] As Figure B.2 in the online appendix demonstrates, there is significant variation in the fraction of high-technology industries in a district. As a result, our results below are unlikely to be driven by outlier districts with an unusually large/small concentration of high-technology industries.

We examine these issues in Table 6. In column (1) we examine whether there has been greater upward educational mobility in districts with greater exposure to trade liberalization. Here we estimate a version of equation (12) where the dependent variable is now an indicator that is one if a son has higher educational attainment than his father and zero otherwise. Further, in column (1) we restrict the sample to sons who were 18 or younger in 1991. In other words, we are restricting the sample to sons who are unlikely to have completed their education prior to the trade reforms. The coefficient of the change in district tariffs variable here is negative and statistically insignificant. Further, the magnitude of the effect of trade is also comparatively small. Thus, there is no evidence to suggest that sons in districts with greater exposure to trade liberalization are more likely to have an educational attainment that is greater than that of their father. This is also the case in column (2) where we restrict the sample to sons who were 15 or younger in 1991. Once again, the coefficient of interest is statistically insignificant.

In column (3) we shut down the educational mobility channel by restricting our sample to father-son pairs where both have the same educational attainment. The idea here is that, if we observe greater upward occupational mobility among these father-son pairs, it cannot be explained by upward educational mobility. The dependent variable here is our indicator for upward intergenerational occupational mobility. The coefficient of the change in district tariffs variable is negative and significant. In fact, the magnitude of this coefficient is very similar to our baseline estimate in column (4) of Table 3. This result suggests that educational mobility and greater investment in the education of sons are not driving our key result. This conclusion is reinforced by the results in column (4) where we restrict the sample to father-son pairs where the son has a higher educational attainment than his father. The coefficient of interest here is very similar to the estimate in column (3). This suggests that the magnitude of the effect of trade on occupational mobility is roughly the same for a son with a higher educational attainment than his father as it is for a son with the same educational attainment as his father. Together, the results in Table 6 suggest that the impact of trade liberalization on intergenerational occupational mobility that we've documented thus far are not due to trade-induced investment in education.

Thus far we have treated demand-side factors (prevalence of high-ranked occupations) and supply-side factors (education) as independent forces affecting occupational mobility. Next, we examine the complementarity between them. In particular, we ask whether education matters for occupational mobility in districts where there have been sufficient demand-side changes. We implement this by first restricting the sample to low-DTF districts (i.e. districts with an above median fraction of high-technology industries).[28] We then re-run the regression in columns (3) and (4). These new results are reported in columns (5)–(6) of Table 6. They suggest that in districts with relatively significant demand-side changes, education matters. In particular, we find that in these districts, trade has a larger effect on upward occupational mobility for sons who have higher educational attainment than their father. This suggests that educational attainment only matters for occupational mobility in districts where there have been sufficiently large increases in the relative demand for high-ranked occupations.

5 Robustness Checks

5.1 Selection Bias

As mentioned in section 3, we can only measure intergenerational occupational mobility for father-son pairs that co-reside in the same household. In this section we discuss the method we use to attenuate the resulting selection bias. First, it is important to note that our use of a selected sample is particularly problematic if a son's decision to not co-reside with his father (and therefore form his own household) is driven by a district's exposure to trade liberalization. In other words, if districts with greater exposure to trade liberalization have a greater/lower fraction of sons that co-reside with their father, then this heterogeneity can confound our results. We examine whether this is the case in column (1) of Table 7. Here we estimate a version of equation (12) where the dependent variable is one if a son does not co-reside with his father (and is therefore the head of his household) and zero otherwise.[29] The coefficient of the change in district tariffs is small and

[28]These results go through if we restrict the sample to high-skilled workforce districts instead.

[29]In principle, a household head can still co-reside with his father. However, the survey data we use places both the father of the household head and the father-in-law into the same category. As a result, we are unable to match a household head to his father even if they co-reside in the same home. This means that as long as a son is the household head, he is dropped from our sample.

statistically insignificant. This suggests that the fraction of sons that co-reside with their father in our data is not being driven by a district's exposure to trade liberalization.

Next, as mentioned in section 3, our working sample of co-resident sons are younger, on average, than the complete sample. To the extent that individuals are less likely to be in their permanent occupation at a younger age, this means that we are likely to be understating the extent of intergenerational occupational mobility. As a result, the selection bias that exists will likely cause us to understate the effect of trade on such mobility. To examine whether this is the case, we use the propensity score weighting (PSW) procedure recommended by Francesconi and Nicoletti (2006) to attenuate any selection bias in our analysis. They show that the PSW procedure performs the best in lowering the selection bias due to the co-residence requirement in their data.[30] The PSW procedure assumes that there exists only selection on observables and that the the selection equation is as follows:

$$r^*_{fd} = \Theta Z_{fd} + v_{fd} \tag{14}$$

where r^*_{fd} is a latent variable with an associated indicator function r_{fd} that takes the value of one for a son f in district d that co-resides with his father and zero otherwise. In other words, r_{fd} is an indicator variable for whether a son is in our sample. Z_{fd} is a set of explanatory variables that determine the probability of sons co-residing with their father and v_{fd} is a classical error term. The assumption here is that the set of variables included in Z_{fd} correctly predicts the probability that a son will co-reside with his father. We include in Z_{fd} cohort of birth fixed effects, an indicator for sons belonging to a scheduled caste, an indicator for sons that are Muslim, and state fixed effects. These control variables are chosen to match the variables included by Francesconi and Nicoletti (2006) as closely as possible.[31]

[30]They use the first 11 waves of the British Household Panel Survey (BHPS) that cover the period 1991–2001. This survey asks a representative sample of adults what their parents' occupation was when they (i.e. the respondents) were 14. As a result, they are able to measure intergenerational occupational mobility for all adult respondents in their survey. They then restrict the sample to only those adults that co-reside with their father. In other words, they impose a co-residence requirement to examine the extent and direction of the resulting selection bias and the ability of various methods to attenuate this bias.

[31]Francesconi and Nicoletti (2006) also examine a case where there is selection on unobservables. In this case, they use Heckman-style selection corrections. Their results suggest that such corrections do not significantly lower the selection

The PSW procedure works as follows. In the first step, the selection equation (14) is estimated using probit. The predicted values from this regression are the propensity scores. In the second step, equation (12) is estimated using weighted least squares where the weights are the inverse of the propensity scores from the first stage. Note that a low propensity score implies that a son, based on his observable characteristics, has a low probability of co-residing with his father. As a result, the weighting procedure above places a higher weight on sons who fall into this category. This means that the weighting creates a sample that is closer to a representative sample that includes all sons.

The results from using this method are reported in columns (2) and (3) of Table 7. In column (2) we estimate equation (12) using the PSW procedure described above with upward mobility as the dependent variable. The coefficient of the change in district tariffs is negative and statistically significant. Importantly, the magnitude of the effect is greater than our baseline. This supports the view that we are understating intergenerational occupational mobility in our baseline regressions due to the lower average age in our working sample. In column (3) we estimate equation (12) using the PSW procedure described above with downward mobility as the dependent variable. As before, the coefficient of the change in district tariffs is small and statistically insignificant. Lastly, in columns (4) and (5) we repeat the regressions from columns (2) and (3) respectively with the only difference being that we estimate equation (14) using logit rather than probit. The key results remain largely unaffected due to this change.

A second source of selection bias in our analysis may be due to our decision to omit men older than 35 years of age from our sample. This was done to minimize the probability that a son in our sample has a father that is retired and therefore does not have any information on their occupation. To examine the effect of this decision on our key results, we first illustrate how the raw number of upward and downward mobility pairs evolve with the cutoff age. Figure B.3 in the online appendix plots the fraction of sons in the sample with an occupation that is higher ranked than his father at various cutoff ages. As this figure illustrates, this fraction is fairly stable around

bias that results from the co-residence requirement. They show that this failure is due to the use of variables to estimate the selection equation that do not satisfy the exclusion restriction requirement.

the cutoff age of 35. This suggests that our results will not be too sensitive to our choice of cutoff age. This is confirmed by the results in columns (1)–(4) of Table B.2 in the online appendix, where we re-estimate equation (12) using various age cutoffs. In all four cases, the coefficient of the change in district tariffs is negative and statistically significant with a magnitude that is similar to our baseline. In Figure B.4 we examine how the fraction of sons with occupations that are lower ranked than their father changes with the cutoff age. As before, this fraction is fairly stable around the cutoff age of 35. We confirm that our choice of cutoff age does not affect the downward occupational mobility results in columns (5)–(8) of Table B.2. In all four cases, the coefficient of the change in district tariffs is small and statistically insignificant.

5.2 Additional Robustness Checks

A concern with our identification strategy is that our results could be picking up the effects of pre-existing trends. We address this concern by using a falsification test where we replace our default measure of trade exposure with the change in a district's tariffs between 1998 and 2004. If our baseline change in district tariffs variable is actually capturing pre-existing trends, then when we include the spurious 1998–2004 district tariff change variable we should still find a statistically significant effect. On the other hand, if our primary results are being driven by actual changes in district tariffs between 1987 and 1998, then this spurious change in district tariffs variable will not have an effect on intergenerational occupational mobility in 1999. We report the results from including the spurious change in district tariffs variable in column (1) of Table 8. The coefficient of the change in a district's tariffs between 1998 and 2004 is statistically insignificant. This suggests that the view that the greater intergenerational occupational mobility that we observe in districts with greater exposure to trade liberalization are not being driven by pre-existing trends.

Our results could also be confounded by migration of individuals in our sample, particularly if that migration is driven by changes in trade policy. However, as mentioned before, permanent migration across districts in India is uncommon. As a result, such migration is unlikely to confound our results. To verify this, we re-estimate our baseline specification in column (2) of Table 8 using a sample that excludes sons who report migrating into a district after 1991. Even with this restricted sample, our coefficient of interest is highly robust.

A further concern raised by migration is that it provides an alternate explanation for our results. In particular, consider our result that upward intergenerational occupational mobility is higher in districts with greater exposure to trade liberalization. This could be explained by the self-selection of individuals to liberalized districts. For instance, suppose that more liberalized districts also have more dynamic local economies and labor markets. Then, our key result can be explained by the migration of enterprising individuals (i.e. individuals that are more likely to exhibit upward intergenerational occupational mobility) to these highly liberalized districts. To examine whether this is a potential problem, we examine the relationship between in-migration patterns in a district and its exposure to trade liberalization in column (3) of Table 8. Here we estimate a version of equation (12) where the dependent variable is one if a son has migrated into a district after 1991 and zero otherwise. The coefficient of the change in district tariffs is small and statistically insignificant. Thus, the results in columns (2) and (3) suggest that (a) whatever migration we observe in our sample is not being driven by trade liberalization and (b) that our primary results are robust to excluding migrants from our sample. Thus, it is unlikely that selective migration can explain the primary results in this paper.

Next, we use a wage-based ranking of occupations to examine the robustness of our results. In particular, for each occupation, we calculate the weighted average wage for that occupation in 1987 as follows:

$$\overline{W}_o = \sum_{f=1}^{n_o} \left(\frac{\omega_f}{\sum_f^{n_o} \omega_f} \right) \times W_f \tag{15}$$

where W_f is individual f's weekly wage during the week prior to the survey period. All other variables in the expression above are as defined for the EI_o expression. As before, individuals can engage in upward/downward mobility by switching occupations. However, each occupation's wage-based ranking is not allowed to change over time. In column (4) of Table 8 we report the results from re-estimating equation (12) using this wage-based ranking. As these estimates demonstrate, our key result remains robust to the use of this alternate ranking.[32]

As described in greater detail in the online appendix, we vary the strictness with which we define mobility and re-estimate our key results. In particular, we define an upward occupational switch as one where a son is in an occupation with a rank that is 0.25, 0.5, 0.75, and 1 standard deviation higher than his father respectively. In all four cases, our key result remains robust. Finally, as also described in greater detail in the online appendix, we test the robustness of our results by controlling for other forms of liberalization that occurred in India during our sample period and also by using alternate measures of trade liberalization. In all of these cases, our key result remains robust.

6 Conclusion

In this paper, we exploit exogenous variation in tariffs due to an externally-imposed trade reform to causally examine the relationship between international trade and intergenerational occupational mobility in India. We first develop a stylized model that provides the following novel insight: the same forces that cause trade to exacerbate cross-sectional inequality also facilitates intergenerational occupational mobility. In particular, our model shows that trade-induced innovation in high-tech firms (i.e. firms that are closer to the world technology frontier) raises the employment share of high-skill occupations. While this may raise cross-sectional inequality, it also allows an increasing number of individuals to enter occupations that are better than their parents.

To empirically examine the relationship between trade and intergenerational occupational mobility, we use a rich dataset that allows us to categorize individuals in urban India into 335 occupations. We then exploit the geographic variation in exposure to trade liberalization in India. In particular, we compare the effect of trade on occupation mobility in urban districts with an above-median concentration of high-tech industries in the pre-reform period with the effect on all

[32]As mentioned earlier, the limitation of the wage-based ranking is that only a third of our sample are engaged in wage employment in 1987. The remaining workers are self-employed. As a result, the wage-based occupational ranking is less representative of the distribution of occupations in India and cover fewer occupations. For this reason, we only use the wage-based ranking to test the robustness of our results.

remaining districts. Our results strongly support the above prediction. Encouragingly, our results suggest that India's trade liberalization, by changing the distribution of occupations, has led to greater intergenerational occupational mobility. In particular, we find that a 10 percentage point decrease in a district's tariffs increases the likelihood of upward intergenerational occupational mobility among its adult male residents by 1.85 percentage points. This result holds when we restrict the sample to sons who have fathers that were in the bottom half of the fathers' occupational distribution.

We then explore the mechanism that is driving our baseline results. Our model suggests that the impact of trade on occupational mobility is being driven by trade-induced innovation and is effect on the share of high-skill occupations. This suggests that districts with a greater initial share of high-tech industries will experience greater intergenerational occupational mobility as a result of trade. To confirm whether this is the case, we restrict our sample to urban districts with an above-median share of high-tech industries in the pre-reform period. We find that trade raises occupational mobility disproportionately in these districts when compared to urban districts with a below-median share of high-tech industries. We also find that greater investment in the education of sons does not explain our baseline results. Instead, we find that increased investment in education only facilitates upward occupational mobility in urban districts where there has been the necessary changes in the distribution of occupations.

To summarize, in this paper, we highlight the role played by international trade in improving intergenerational occupational mobility in India. Our results suggest that trade liberalization, by allowing sons from low-income backgrounds to enter better occupations than their father, can lead to a more equitable distribution of income through occupational mobility even if it increases cross-sectional inequality. In our framework, trade raises occupational mobility by increasing the fraction of workers who are employed in high-tech firms. The fixed cost of entering an occupation depends on worker background as a proxy for access to background-specific informal networks. A richer model would allow the cost of switching occupations to be heterogeneous, where the cost will depend on a worker's age, education, experience, as well as their inherited skill and access to informal networks.[33] Thus, the overall impact of trade on the income distribution will depend on the magnitude of the cost of an upward occupation switch. Decomposing the upward intergenerational occupation mobility we observe in our data into worker characteristics and background-specific cost of switching occupations in a dynamic overlapping generations model will allow us to assess the overall redistributive effects of trade liberalization. This is an important avenue for future research.

References

[1] Aghion, P., Blundell, R., Griffith, R., Howitt, P., and Prantl, S., 2009. "The Effects of Entry on Incumbent Innovation and Productivity." *The Review of Economics and Statistics*, 91(1): 20–32.

[2] Ahsan, R.N., Ghosh, A., and Mitra, D., 2014. "International Trade and Unionization: Evidence from India." University of Melbourne, mimeograph.

[3] Antràs, P., Garicano, L., and Rossi-Hansberg, E., "Offshoring in a Knowledge Economy." *Quarterly Journal of Economics*, 121(1): 31–77.

[4] Atkin, D., 2015. "Endogenous Skill Acquisition and Export Manufacturing in Mexico." MIT, mimeograph.

[5] Autor, D.H., Levy, F., and Murnane, R.J., 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118(4): 1279–1334.

[6] Black, S., and Devereux, P., 2011. "Recent Developments in Intergenerational Mobility" in Ashenfelter, O., Card, D., eds., *Handbook of Labor Economics*, Vol. 4, part B: 1487–1541.

[7] Burstein, A., and Vogel, J., 2012. "International Trade, Technology, and the Skill Premium." Columbia University, mimeograph.

[8] Bustos, P., 2011. "The Impact of Trade Liberalization on Skill Upgrading. Evidence from Argentina." CREI, mimeograph.

[33] For example, Dix-Carneiro (2014) estimates a significant and heterogeneous cost of switching sectors in the Brazilian labor market.

[9] Chetty, R., Hendren, N., Kline, P., and Saez, E., 2014. "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics*, 129(4): 1553–1623.

[10] Dix-Carneiro, R., 2014. "Trade Liberalization and Labor Market Dynamics." *Econometrica*, 82(3): 825–885.

[11] Dunn, T., and Holtz-Eakin, D., 2000. "Financial Capital, Human Capital, and the Transition to Self-Employment: Intergenerational Links." *Journal of Labor Economics*, 18(2): 282–305.

[12] Dyson, T., Cassen, R., and Visaria, L., 2004. *Twenty-first Century India: Population, Economy, Human Development, and the Environment.* Delhi: Oxford University Press.

[13] Edmonds, E., Pavcnik, N., and Topalova, P., 2010. "Trade Adjustment and Human Capital Investment: Evidence from Indian Tariff Reform." *American Economic Journal: Applied Economics*, 2(4): 42–75.

[14] Emran, M.S., and Shilpi, F., 2010. "Intergenerational Occupational Mobility in Rural Economy: Evidence from Nepal and Vietnam." *Journal of Human Resources*, 46(2): 427–458.

[15] Erikson, R., and Goldthorpe, J.H., 2002. "Intergenerational Inequality: A Sociological Perspective." *Journal of Economic Perspectives*, 16(3): 31–44.

[16] Francesconi, M. and Nicoletti, C., 2006. "Intergenerational mobility and sample selection in short panels." *Journal of Applied Econometrics*, 21(8): 1265–1293.

[17] Goldberg, P., and Pavcnik, N., 2007. "Distributional Effects of Globalization in Developing Countries." *Journal of Economic Literature*, 45(1): 39–82.

[18] Goyal, S. K. 1996. "Political Economy of India's Economic Reforms." Institute for Studies in Industrial Development (ISID) Working Paper WP1996/04.

[19] Haider, S., and Solon, G., 2006. "Life-Cycle Variation in the Association between Current and Lifetime Earnings." *American Economic Review*, 96(4): 1308–1320.

[20] Hasan, R., Mitra, D., and Ramaswamy, K.V., 2007. "Trade Reforms, Labor Regulations and Labor Demand Elasticities: Empirical Evidence from India." *The Review of Economics and Statistics*, 89(3): 466–481.

[21] Hellerstein, J.K., and Morill, M.S., 2011. "Dads and Daughters. The Changing Impact of Fathers on Women's Occupational Choices." *Journal of Human Resources*, 46(2), 333–372.

[22] Hnatkovska, V., Lahiri, A., and Paul, S.B., 2013. "Breaking the Caste Barrier: Intergenerational Mobility in India." *Journal of Human Resources*, 48(2): 435–473.

[23] Hoffman, F., 2010. "An Empirical Model of Life-Cycle Earnings and Mobility Dynamics." University of British Columbia, mimeograph.

[24] Mazumder, B., 2005. "Fortunate Sons: New Estimates of Intergenerational Mobility in the U.S. Using Social Security Earnings Data." *The Review of Economics and Statistics*, 87(2): 235–255.

[25] Munshi, K., and Rosenzweig, M., 2009. "Why is Mobility in India So Low? Social Insurance, Inequality, and Growth." *NBER Working Paper 14850*.

[26] Solon, G., 1999. "Intergenerational Mobility in the Labor Market" in Ashenfelter, O., Card, D., eds., *Handbook of Labor Economics*, Vol. 3, Amsterdam, 1761–1800.

[27] Topalova, P., 2007. "Trade Liberalization, Poverty and Inequality: Evidence from Indian Districts." in Harrison, A., eds., *In Globalization and Poverty*, Chicago, 291–336.

[28] Varshney, A., 1999. "Mass Politics or Elite Politics? India's Economic Reforms in Comparative Perspective." in Sachs, J., Varshney, A., Bajpai, N., eds., in *India in the Era of Economic Reforms*, Delhi, 22260.

[29] Verhoogen, E., 2008. "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector." *Quarterly Journal of Economics*, 123(2): 489–530.

[30] Yeaple, S.R., 2005. "A Simple Model of Firm Heterogeneity, International Trade, and Wages." *Journal of International Economics*, 65(1): 1–20.

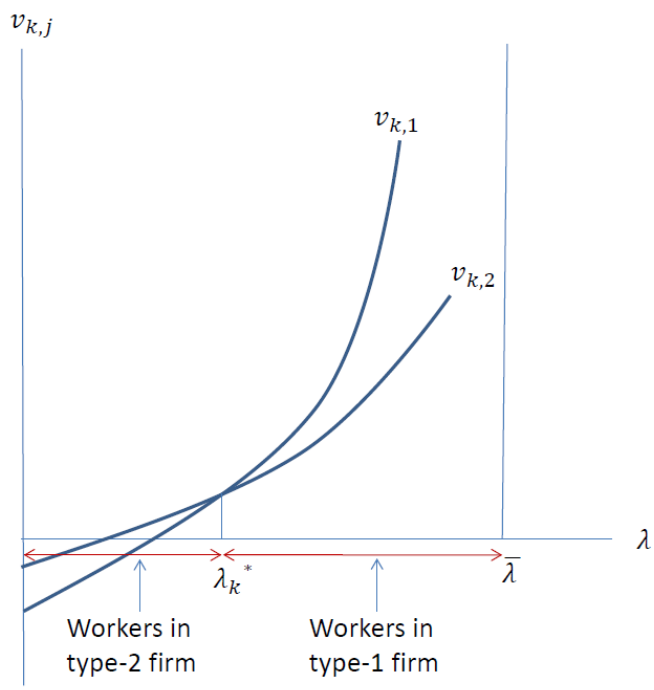

Figure 1: Cutoff Equilibrium: Sorting by Ability into Type-1 and Type-2 Firms

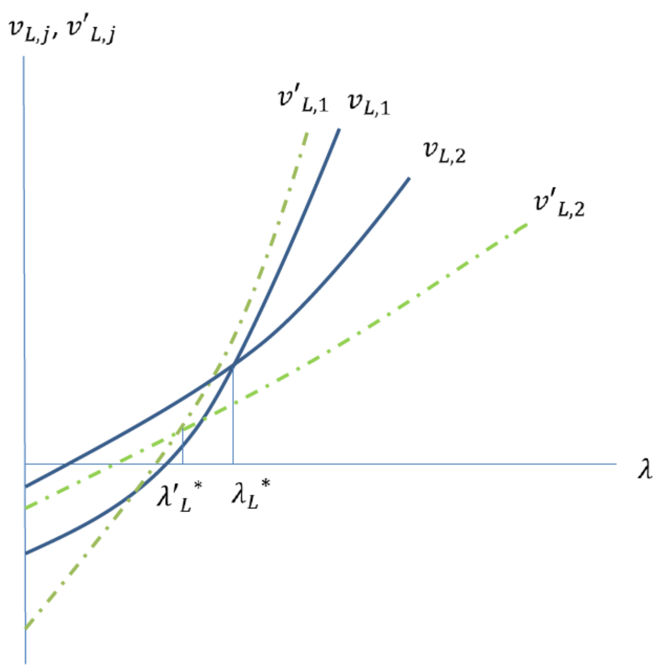

Figure 2: Effect of Trade on the Cutoff Equilibrium for Underprivileged Sons

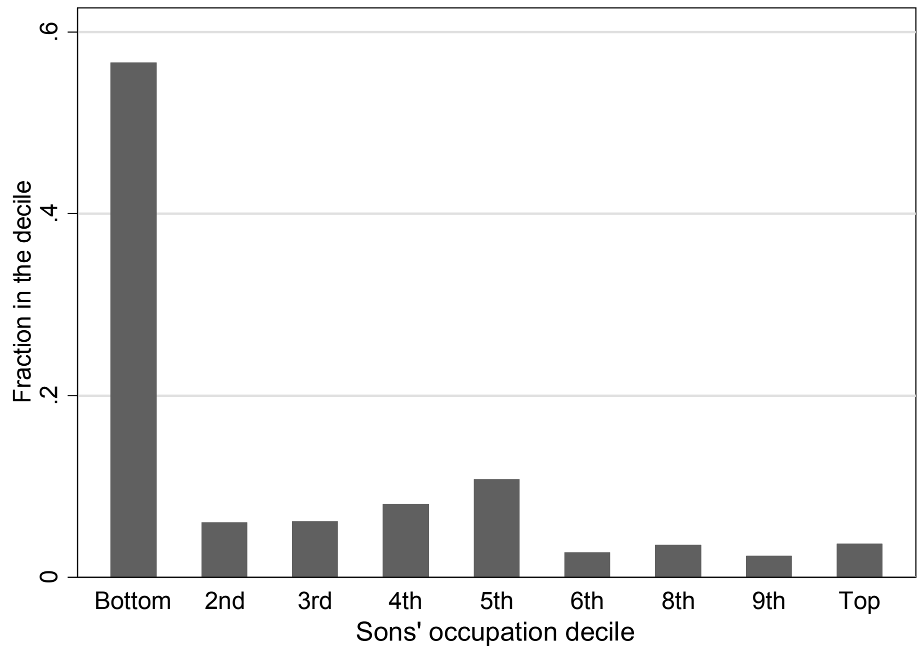

Figure 3: Occupational Deciles of Sons Born to Bottom-Decile Fathers

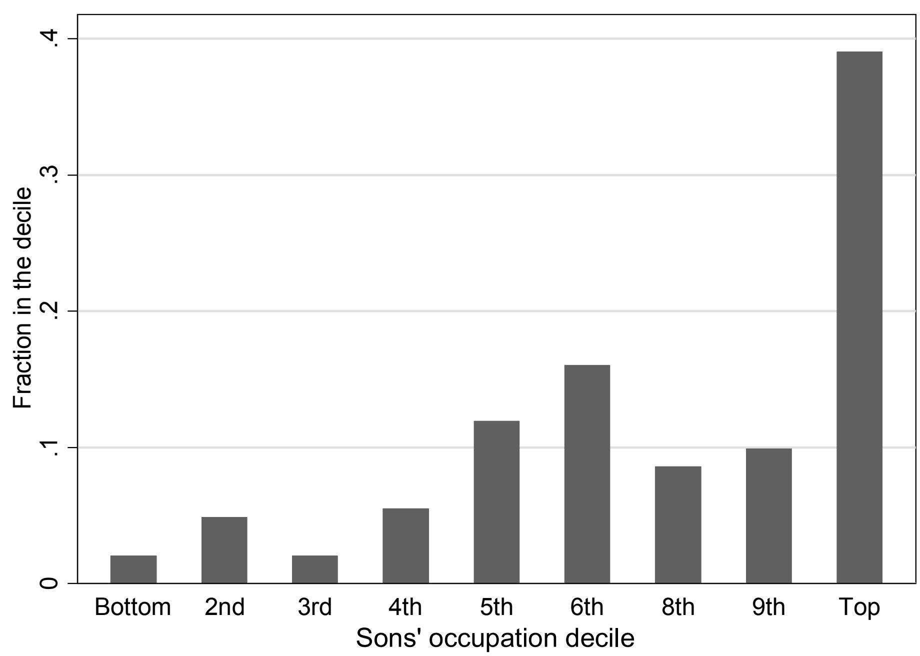

Figure 4: Occupational Deciles of Sons Born to Top-Decile Fathers

Table 1: Comparing the Working Sample to the Full Sample

	Working Sample	Full Sample
Age	24.02	27.44
	(4.94)	(5.44)
Education	3.05	2.90
	(1.49)	(1.60)
Married	0.38	0.66
	(0.49)	(0.48)
Scheduled Caste/Tribe	0.16	0.19
	(0.36)	(0.39)
Muslim	0.21	0.18
	(0.41)	(0.38)
Household Size	7.13	5.25
	(3.11)	(2.99)
Educational Intensity of Occupation	2.46	2.50
	(0.90)	(0.98)
Observations	7,791	18,460

Notes: The second column reports summary statistics for the working sample used in our regression analysis. These are the working-age sons in our sample that co-reside with their father. The third column includes all working-age males irrespective of whether they co-reside with their father. For each variable above, we report the mean and standard deviation (in parenthesis) for both samples. Education is a categorical variable that takes the following six values: (0) not literate, (1) below primary, (2) primary, (3) middle school, (4) secondary school, and (5) graduate and above. The educational intensity of an occupation is defined as the average educational attainment of individuals in an occupation in 1987.

Table 2: Common Mobility Transitions

Son's Occupation	Father's Occupation
Panel A: Upward-Mobility Pairs	
Retail Sales Assistant	Crop Cultivator
Auto Driver	Crop Cultivator
Court Examiner	Retail Shop Keeper
Retail Salesman	Auto Driver
Retail Merchant	Crop Cultivator
Panel B: Downward-Mobility Pairs	
Pipe Layer	Stone Mason
Retail Sales Assistant	Sales Manager
Agricultural Laborer	Crop Cultivator
Shop Attendant	Retail Merchant
Retail Sales Assistant	Retail Merchant

Notes: This table reports the five most common occupational transitions amount upward and downward-mobility pairs respectively. Panel A restricts the sample to father-son pairs where the son has a higher-ranked occupation than his father (upward-mobility pairs). Panel B restricts the sample to father-son pairs where the son has a lower-ranked occupation than his father (downward-mobility pairs).

Table 3: Trade Liberalization and Intergenerational Occupational Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Mobility		Upward Mobility		Downward Mobility	
Change in District Tariffs	-0.216***	-0.149***	-0.202***	-0.185***	-0.014	0.036
	(0.051)	(0.053)	(0.040)	(0.046)	(0.043)	(0.046)
Age	-0.009	-0.008	-0.009	-0.008	-0.000	-0.000
	(0.012)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)
Age Squared	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.011	-0.012	0.005	0.005	-0.017	-0.017
	(0.017)	(0.017)	(0.014)	(0.014)	(0.015)	(0.015)
Scheduled Caste/Tribe	0.086***	0.082***	0.043**	0.042**	0.042**	0.040**
	(0.019)	(0.019)	(0.017)	(0.017)	(0.019)	(0.018)
Muslim	0.019	0.019	-0.035*	-0.035*	0.054**	0.054**
	(0.023)	(0.023)	(0.018)	(0.018)	(0.021)	(0.021)
Household Size	-0.005*	-0.005	-0.005**	-0.005**	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.088	0.023	-0.031	0.006	-0.057	0.017
	(0.261)	(0.293)	(0.226)	(0.253)	(0.242)	(0.249)
Pre-Reform District Characteristics Included	No	Yes	No	Yes	No	Yes
Observations	7,739	7,739	7,739	7,739	7,739	7,739
R-squared	0.058	0.061	0.030	0.031	0.045	0.047

Notes: The dependent variable in columns (1)–(2) is an indicator that is one for sons that are in an occupation that is different from their father and zero otherwise. The dependent variable in columns (3)–(4) is an indicator that is one for sons that are in a higher ranked occupation than their father and zero otherwise. The dependent variable in columns (5)–(6) is an indicator that is one for sons that are in a lower ranked occupation than their father and zero otherwise. Change in district tariffs is the difference in a district's tariffs between 1998 and 1987. All regressions include controls for the father's age, age squared, and indicators for father's educational attainment. All regressions also include state fixed effects. The standard errors in parenthesis are robust and clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Results by Various Son's Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Upward Mobility	Downward Mobility	Upward Mobility	Downward Mobility	Upward Mobility	Downward Mobility
Sample	Manufacturing Sons		1st Quartile Father		2nd Quartile Father	
Change in District Tariffs	-0.414***	0.127	-0.241**	0.041	-0.189**	0.103
	(0.116)	(0.109)	(0.095)	(0.050)	(0.095)	(0.086)
Constant	-0.081	0.450	-0.003	-0.022	-0.534	1.088**
	(0.458)	(0.487)	(0.508)	(0.303)	(0.522)	(0.458)
Observations	1,695	1,695	2,105	2,105	1,787	1,787
R-squared	0.076	0.052	0.088	0.045	0.060	0.053

Notes: The dependent variable in columns (1), (3), and (5) is an indicator that is one for sons that are in a higher ranked occupation than their father and zero otherwise. The dependent variable in columns (2), (4), and (6) is an indicator that is one for sons that are in a lower ranked occupation than their father and zero otherwise. In columns (1)–(2) we restrict the sample to sons who work in the manufacturing sector while in columns (3)–(4) we restrict the sample to sons whose fathers are in the first quartile of the fathers' occupational distribution. Similarly, in columns (5)–(6) we restrict the sample to sons whose fathers are in the second quartile of the fathers' occupational distribution. Change in district tariffs is the difference in a district's tariffs between 1998 and 1987. All regressions include controls for age, age squared, marital status, indicator for scheduled caste, indicator for Muslim, household size, father's age, age squared, and indicators for father's educational attainment. All regressions also include pre-reform district characteristics and state fixed effects. The standard errors in parenthesis are robust and clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Mechanism - Demand Side Changes

	(1)	(2)	(3)	(4)
Dependent Variable	Upward Mobility			
Sample	High-Skilled Workforce	Low-Skilled Workforce	Low DTF	High DTF
Change in District Tariffs	-0.222***	-0.136***	-0.182***	-0.137**
	(0.079)	(0.050)	(0.059)	(0.063)
Constant	-0.230	0.184	-0.049	-0.071
	(0.386)	(0.311)	(0.381)	(0.359)
Observations	3,876	3,863	3,972	3,601
R-squared	0.036	0.037	0.038	0.033

Notes: The dependent variable in all columns is an indicator that is one for sons that are in a higher ranked occupation than their father and zero otherwise. Districts are categorized as having a high-skilled workforce if its share of workers with at least a middle-school education is above the sample median. Column (1) restricts the sample to these districts. The remaining districts are classified as having a low-skilled workforce. Column (2) restricts the sample to these districts. Column (3) restricts the sample to low DTF districts. These are districts with an above median fraction of industries with a low distance to the global technology frontier (DTF). All other districts are classified as high DTF districts. Column (4) restricts the sample to these districts. Change in district tariffs is the difference in a district's tariffs between 1998 and 1987. All regressions include controls for age, age squared, marital status, indicator for scheduled caste, indicator for Muslim, household size, father's age, age squared, and indicators for father's educational attainment. All regressions also include pre-reform district characteristics and state fixed effects. The standard errors in parenthesis are robust and clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Mechanism - Intergenerational Educational Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Upward Educational Mobility		Upward Occupational Mobility			
Sample	Age < 26	Age < 23	No Education Mobility	Upward Education Mobility	No Education Mobility	Upward Education Mobility
Districts Included	All		All		Low *DTF*	
Change in District Tariffs	-0.078	-0.087	-0.190***	-0.192***	-0.165*	-0.230***
	(0.063)	(0.081)	(0.059)	(0.055)	(0.087)	(0.068)
Constant	0.403	-0.391	0.289	0.166	0.248	-0.092
	(0.565)	(0.880)	(0.370)	(0.347)	(0.545)	(0.545)
Observations	4,986	3,349	2,605	4,149	1,293	2,185
R-squared	0.035	0.034	0.025	0.043	0.044	0.057

Notes: The dependent variable in columns (1)–(2) is an indicator that is one for sons that have a higher educational attainment than their father and zero otherwise. The dependent variable columns (3)–(6) is an indicator that is one for sons that are in a higher ranked occupation than their father and zero otherwise. In column (1) we restrict the sample to sons who were 18 or younger when the trade reforms of 1991 were enacted. In column (2) we restrict the sample to sons who were 15 or younger when the trade reforms of 1991 were enacted. In columns (3) and (5) we restrict the sample to father-son pairs that have identical educational attainment while in columns (4) and (6) we restrict the sample to father-son pairs where the son has a higher educational attainment than his father. In columns (5) and (6) we further restrict the sample to low–DTF districts. These terms are defined in the notes for the previous table. Change in district tariffs is the difference in a district's tariffs between 1998 and 1987. All regressions include controls for age, age squared, marital status, indicator for scheduled caste, indicator for Muslim, household size, father's age and age squared. All regressions also include pre-reform district characteristics and state fixed effects. The regressions in columns (3)–(6) also include indicators for father's educational attainment. The standard errors in parenthesis are robust and clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Selection Bias

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Household Head	Upward Mobility	Downward Mobility	Upward Mobility	Downward Mobility
First-Stage Estimator		Probit		Logit	
Change in District Tariffs	-0.002	-0.261***	0.087	-0.259***	0.083
	(0.006)	(0.063)	(0.061)	(0.062)	(0.060)
Constant	2.486***	-0.081	0.063	-0.082	0.060
	(0.066)	(0.311)	(0.277)	(0.311)	(0.275)
Observations	18,064	7,739	7,739	7,739	7,739
R-squared	0.958	0.032	0.047	0.032	0.047

Notes: The dependent variable in column (1) is an indicator that is one for sons that are household heads and zero otherwise. The dependent variable in columns (2) and (4) is an indicator that is one for sons that are in a higher ranked occupation than their father and zero otherwise. The dependent variable in columns (3) and (5) is an indicator that is one for sons that are in a lower ranked occupation than their father and zero otherwise. Change in district tariffs is the difference in a district's tariffs between 1998 and 1987. All regressions include controls for age, age squared, marital status, indicator for scheduled caste, indicator for Muslim, household size, father's age, age squared, and indicators for father's educational attainment. All regressions also include pre-reform district characteristics and state fixed effects. The standard errors in parenthesis are robust and clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness Checks

	(1)	(2)	(3)	(4)
Dependent Variable	Upward Mobility		Migrant	Upward Mobility
Mobility Measure Used	Education			Wage
Change in District Tariffs (1998-2004)	0.163			
	(0.108)			
Change in District Tariffs		-0.194***	-0.034	-0.156***
		(0.048)	(0.025)	(0.048)
Constant	0.189	0.164	0.153	-0.312
	(0.243)	(0.267)	(0.119)	(0.251)
Observations	7,739	7,350	7,739	7,170
R-squared	0.028	0.033	0.019	0.027

Notes: The dependent variable in columns (1), (2), and (4) is an indicator that is one for sons that are in a higher ranked occupation than their father and zero otherwise. The dependent variable in column (3) is an indicator that is one for sons in the sample that have migrated since 1991 and zero otherwise. In column (2) we omit individuals in the sample that have migrated since 1991. In column (4) we rank occupations using the average wage in that occupation in 1987. Here a son is classified as having a better occupation than his father if his occupation has a higher wage ranking than that of his father. All regressions include controls for age, age squared, marital status, indicator for scheduled caste, indicator for Muslim, household size, father's age, age squared, and indicators for father's educational attainment. All regressions also include pre-reform district characteristics and state fixed effects. The standard errors in parenthesis are robust and clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$