Trade Liberalization and Intergenerational Occupational Mobility in Urban India*

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Abstract

We exploit highly disaggregated occupation data to examine the impact of trade liberalization on intergenerational occupational mobility in urban India. We find that sons that live in urban Indian districts with a greater exposure to trade liberalization have a higher probability of being in a better occupation than their father. Taken together, our results allow us to make two new 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. Second, 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.

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1 Introduction

In this paper, we make two new 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 in 1999, 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

[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 such as ours where the vast majority of survey respondents work in the informal sector.

at the top decile of the fathers' occupational distribution in 1999, 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.

It is worth asking why we are interested in intergenerational changes instead of changes in the employment share of high-skill occupations. After all, an increasing share of high-skill occupations will ensure a net increase in intergenerational occupational mobility. The answer to this is that a net increase in intergenerational occupational mobility does not tell us whether the increase in mobility is concentrated among privileged workers or is more evenly shared. This distinction is important because the extent of upward intergenerational mobility among underprivileged workers informs us about the inequality of opportunity in a society (Roemer, 2012).[4] Thus, to the extent that we are interested in this dimension of inequality, it is insufficient to only examine post-reform changes in the employment share of high-skill occupations.

Having identified the effect of trade on intergenerational occupational mobility, we then ex-

[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]Brunori, Ferreira, and Peragine (2013) use cross-country data to document a negative correlation between inequality of opportunity and intergenerational mobility.

amine two mechanisms that can explain this result. The first mechanism is an an increase in the relative demand for skill. Here we build on the insight provided by Aghion, Blundell, Griffith, Howitt, and Prantl (2009) that an increased threat of entry causes incumbent firms that are close to the technology frontier to engage in greater innovation while it causes incumbents that are far away from the frontier to engage in less innovation. To the extent that the Indian trade reforms of 1991 made it easier for foreign firms to enter the domestic market, it will also encourage greater innovation activity among local firms that are close to the technology frontier.[5] It follows that this trade-induced innovation will raise the employment share in frontier firms, which is equivalent to increasing the employment share of high-skill occupations. In theory, this will allow a growing number of workers to enter high-skill occupations and thereby experience upward intergenerational occupational mobility.

To examine whether this is a credible explanation of our results, we exploit a second implication of such trade-induced innovation. Since the innovation activity is only likely to occur in frontier firms, urban Indian districts that have a greater pre-reform concentration of such firms will experience a relatively larger increase in upward intergenerational occupational mobility as a result of trade. We examine this insight by comparing the effect of trade on occupation mobility in urban districts with an above-median concentration of frontier industries in the pre-reform period with the effect on all remaining urban districts. Our results suggest that the effect of trade on occupational mobility is greater in the former sub-sample. This suggests that trade-induced innovation is a plausible explanation for our main result.

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

[5]The trade reforms undertaken by India in 1991 dramatically lowered import tariffs and was not accompanied by any significant direct expansion of export opportunities for domestic firms. Thus, it is reasonable to think of the reforms as mainly providing easier access to the local market to foreign firms.

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 frontier firms, 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, 2016).

We structure the remainder of the paper as follows. In section 2 we describe the data used in our analysis as well as the method we use to rank occupations. In section 3 we describe our econometric strategy and results. In section 4 we describe the results of our robustness checks including our strategy for addressing potential threats to identification. Finally, in section 5 we provide a conclusion.

2 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.[6,7]

[6] 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.

[7] 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

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 4.1, 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 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.[8] 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.

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.

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

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.

The use of a co-resident sample in our context is particularly problematic if an individual son's decision to not co-reside with his father (and therefore form his own household) is driven by his district's exposure to trade liberalization. As we discuss in greater detail in section (4.1), we do not find that this is the case. More precisely, we find that a district's exposure to trade liberalization does not have a statistically significant effect on a son's decision to form his own household.

Despite the above, it is worth examining the difference between our working sample of adult sons compared to the full, representative sample. In Table 1 we compare 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, 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.[9] 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 4.1.

2.1 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:

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

where e_f is individual f's education category, ω_f is an individual's sampling weight, and n_o is the total number of individuals within an occupation.[10] 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.[11] For respondents in the 1999 surveys, we match each individual's occupation in 1999 with the education-intensity of that occupation in 1987. Thus, individuals can change the education-intensity of their occupation by switching occupations. However, each occupation's education intensity is not al-

[9]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.

[10]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.

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

lowed to change over time.[12,13]

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 1, 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 in 1999. 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 1999. In Figure 2 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 in 1999. 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 1999.

In addition, as Table B.1 in the online appendix documents, there is considerable geographic variation in occupational mobility in our data.[14] 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

[12] 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.

[13] 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.

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

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. 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:

$$\tau_d = \sum_{h=1}^{n_h} \left(\frac{L_{hd}}{\sum_h^{n_h} L_{hd}} \right) \times \tau_h \tag{2}$$

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.[15] 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.[16]

[15] This method of converting industry tariffs to district tariffs is a common approach in the literature with Topalova (2010) being a prominent example.

[16] 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

3 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:

$$m_{fd} = \alpha + \beta\Delta\tau_d + \gamma_1 X_{fd} + \gamma_2 V_d^{87} + \theta_s + \varepsilon_{fd} \quad (3)$$

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 (2). 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.

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 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 to 2004 period were uncorrelated with the strength of unions in an industry as well as the union wage and union wage premium.

Despite the exogenous and sudden nature of the trade reforms, the fact that we are using 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.[17]

As we discuss in greater detail in section 4.2 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

[17] 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.

analysis is fairly rare in our sample.[18] As a result, we believe that such migration is unlikely to be a first-order concern. We demonstrate that this is indeed the case in section 4.2.

3.1 Baseline Results

In Table 3 we report the results from estimating equation (3). 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 (3) 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 (3) 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

[18] 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 among women on account of marriage. The lack of migration in India has also been documented by Munshi and Rosenzweig (2009).

percentage points.

To better gauge the magnitude of this effect, consider the following two districts. Let the 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.[19]

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.[20]

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

[19]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.

[20]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.

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 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) to (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 in 1999. We then estimate equation (3) 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 in 1999 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) to (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.

3.2 Mechanisms

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 this section we explore two mechanisms that can explain this finding. First, we examine whether our main result can be explained by changes in the relative demand for skilled workers. Second, we explore whether differential investment in education can explain our main finding. To examine the former channel, we use the insights from the competition and innovation model in Aghion et al. (2009).[21] Their model suggests that a higher threat of entry will force incumbents that are close to the technology frontier (high-tech firms from hereon) to engage in greater innovation activity while it will force lagging incumbents to engage in less innovation activity.

In our context, we know that the Indian government implemented a unilateral reduction in import tariffs in 1991. Thus, this reform can be thought of as an exogenous increase in the probability of entry by foreign firms in the Indian market. Using the insights from Aghion et al. (2009), we can conclude that this greater threat of entry will provide high-tech, local firms with an incentive to engage in greater innovation and therefore demand more workers. In contrast, lagging local firms will lower their innovation activity and demand fewer workers when entry by foreign firms is more likely. This suggests that trade liberalization will increase the share of employment in high-tech firms in an Indian district. That is, it will increase the share of high-skill

[21] We develop the results described in this section more formally in the online appendix.

occupations in a district. To the extent that some of these new jobs in high-tech firms are taken by underprivileged sons, trade liberalization will lead to upward intergenerational occupational mobility.

To tie this back to our main empirical result, consider the fact that urban Indian districts will have different exposure to trade liberalization due to differences in pre-reform industrial composition. The discussion above suggests that, *ceteris paribus*, districts with greater exposure to trade liberalization (higher probability of foreign entry) will experience greater innovation activity and a larger increase in upward intergenerational occupation mobility.

To what extent is this a credible explanation for our main result? One way to answer this question is to examine a second implication of our framework. Suppose that urban Indian districts vary in their pre-liberalization concentration of high-tech firms. We know that these are the only firms that will engage in innovation activity after liberalization. Thus, our framework implies that, for a given trade liberalization, districts with a relatively higher initial concentration of high-tech firms will experience a larger increase in innovation activities as well as intergenerational occupation mobility. This is an insight that we can directly test using our data. If our data support this implication, it will validate the view that higher relative demand for skill is an explanation for the relationship between trade and occupational mobility that we observe in our analysis.

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 innovation 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.[22] 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

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

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.

To construct our second proxy for the pre-reform concentration of high-tech firms in a district, we use industry-level data to calculate each district's distance to the world technology frontier (DTF). This proxy is based on 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 to 1991. In particular, we calculate the following

$$D_k = \frac{1}{3}\sum_{u=0}^{2}\left[\ln\left(\frac{Y^{US}_{ht-u}}{L^{US}_{ht-u}}\right) - \ln\left(\frac{Y^{IND}_{ht-u}}{L^{IND}_{ht-u}}\right)\right] \tag{4}$$

where Y^{US}_{ht-z} is the real value added in U.S. industry h in year $t-u$, L^{US}_{ht-u} is total employment in U.S. industry h in year $t-u$, Y^{IND}_{ht-u} is the real value added in Indian industry h in year $t-u$, and L^{IND}_{ht-u} 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).[23]

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.[24] In columns (3) and (4) of Table 5 we restrict the sample to low-DTF

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

[24] As Figure B.4 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

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.

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 (3) 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

large/small concentration of high-technology industries.

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 statistically 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).[25] We then re-run the regression in columns (3) and (4). These new results are reported in columns (5) to (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

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

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.

4 Robustness Checks

4.1 Selection Bias

As mentioned in section 2, 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 (3) 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.[26] The coefficient of the change in district tariffs is small and 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 also mentioned in section 2, 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

[26] 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.

(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.[27] The PSW procedure assumes that there exists only selection on observables and that the the selection equation is as follows:

$$r^*_{fd} = \Theta Z_{fd} + v_{fd} \tag{5}$$

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.[28]

The PSW procedure works as follows. In the first step, the selection equation (5) is estimated using probit. The predicted values from this regression are the propensity scores. In the second step, equation (3) 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.

[27]They use the first 11 waves of the British Household Panel Survey (BHPS) that cover the period 1991 to 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.

[28]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 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 results from using this method are reported in columns (2) and (3) of Table 7. In column (2) we estimate equation (3) 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 (3) 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 (5) 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.5 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 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) to (4) of Table B.2 in the online appendix, where we re-estimate equation (3) using alternate age cutoffs of 25, 45, 55, and 65 respectively. 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.6 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) to (8) of Table B.2. In all four cases, the coefficient of the change in district tariffs is small and statistically insignificant.

4.2 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 to 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 (3) 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:

$$\overline{W}_o = \sum_{f=1}^{n_o} \left(\frac{\omega_f}{\sum_f^{n_o} \omega_f} \right) \times W_f \tag{6}$$

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 (3) using this wage-based ranking. As these estimates demonstrate, our key result remains robust to the use of this alternate ranking.[29]

A key advantage of our data is that it provides us a rich classification of occupations. This allows us to observe intergenerational occupational mobility at a very disaggregated level. While there are clear advantages to having a more disaggregated classification of occupations, there is also a potential downside. If occupational categories are too disaggregated then a movement between closely-ranked occupations may not truly reflect mobility. In this regard, having broader categories where the distinction between occupations is relatively larger may yield a more accurate measure of mobility. This is particulary important in our case as we have shown in Table 2 that

[29] 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.

the most common intergenerational occupational transitions in our data are relatively incremental in nature.

To examine the importance of this for our results, we vary the strictness with which we define mobility and re-estimate our key results. These are reported in Table 9. In column (1) we define an upward occupational switch as one where a son is in an occupation with a rank that is 0.25 standard deviations higher than his father. We then re-estimate equation (3) with this new indicator for upward mobility. The coefficient of the change in district tariffs remains negative and statistically significant. In columns (2) to (4) we define an upward occupational switch as one where a son is in an occupation with a rank that is 0.5, 0.75, and 1 standard deviation higher than his father respectively. In all three case, our coefficient of interest remains negative and statistically significant. Naturally, as we use stricter definitions of upward mobility, the magnitude of the impact of trade liberalization on upward occupational mobility diminishes.

Lastly, in Table 10 we control for other forms of liberalization that occurred in India during our sample period. We also use alternate measures of trade liberalization. In column (1) we add the change in a district's fraction of delicensed industries to our baseline specification. The delicensing measure is an indicator variable that is one for 3-digit manufacturing industries that have been delicensed and zero otherwise. This is constructed using data from Aghion, Burgess, Redding, and Zilibotti (2008). Our intention here is to capture the fact that the economic reforms initiated in 1991 included more than trade liberalization. Thus, it is possible that these alternate reforms are the primary cause of the subsequent changes in intergenerational occupational mobility. As with tariffs, we aggregate the industry-level delicensing indicator to the district level using each districts' employment share in a given manufacturing industry in 1987.[30] The results in column (1) suggest that even after controlling for delicensing, our coefficient of interest remains negative and statistically significant. In column (2) we conduct a similar exercise where we control for the change in a district's share of manufacturing industries where foreign direct investment requirements were liberalized in 1991. As in column (1), our coefficient of interest remains robust.

[30]More precisely, we construct a district-level delicensing measure using a version of equation (2) where in place of industry tariffs (τ_h) we use an indicator for whether an industry is delicensed in any given year.

In column (3) of Table 10, we use the change in a district's effective rate of protection between 1987 and 1999 instead of our default measure of trade liberalization. In other words, we replace industry output tariffs (τ_k) in equation (3) with an industry's effective rate of protection. The coefficient of the change in a district's effective rate of protection is negative and statistically significant. This supports the result from using our default measure of trade liberalization in a district. Lastly, in column (4) we add the change in a district's input tariffs to our baseline specification. To construct this measure, we replace industry output tariffs (τ_k) in equation (3) with an industry's input tariffs instead. We then add this new variable to our baseline specification that already includes the change in a district's output tariffs. As before, our coefficient of interest remains robust.

5 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. To do so, 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 to examine the extent to which increased trade raised upward occupation mobility in urban Indian districts. Encouragingly, our results suggest that India's trade liberalization 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. We first examine whether the impact of trade on occupational mobility is being driven by trade-induced innovation. To do so, 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 upward intergenerational 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. 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.[31] 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.

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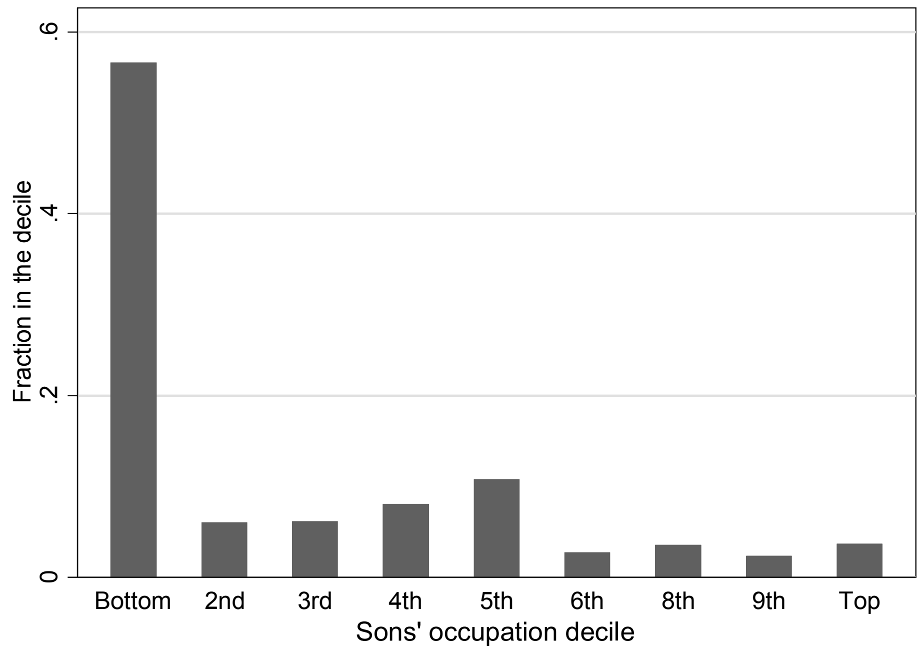

Figure 1: Occupational Deciles of Sons Born to Bottom-Decile Fathers

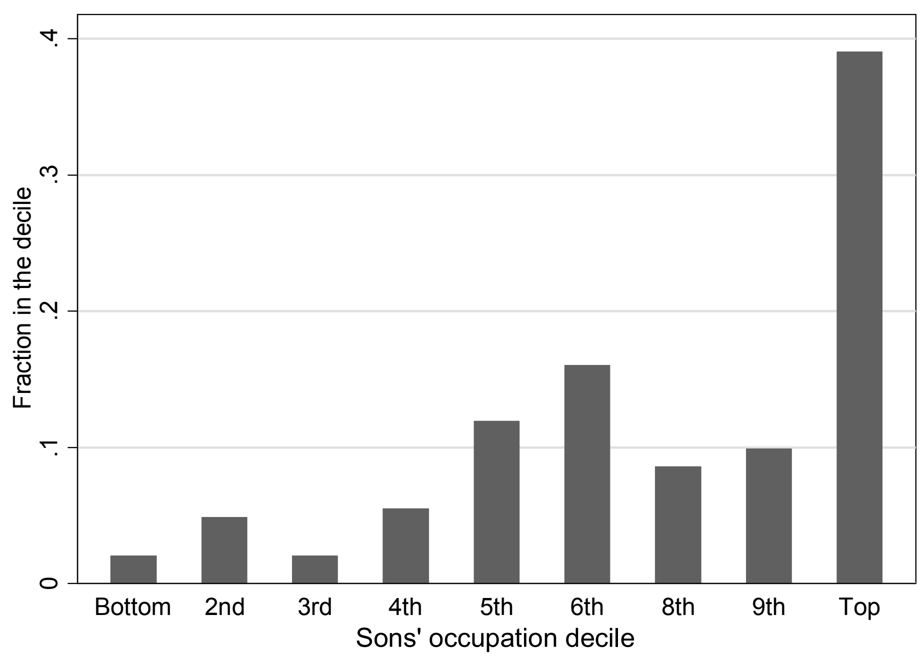

Figure 2: Occupational Deciles of Sons Born to Top-Decile Fathers

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 that 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) to (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) to (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) to (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) to (2) we restrict the sample to sons who work in the manufacturing sector while in columns (3) to (4) we restrict the sample to sons whose fathers are in the first quartile of the fathers' occupational distribution. Similarly, in columns (5) to (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) to (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) to (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) to (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	N/A	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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Alternate Definitions of Mobility

	(1)	(2)	(3)	(4)
Dependent Variable	Upward Mobility			
Mobility Measure Used	0.25 sd	0.5 sd	0.75 sd	1.0 sd
Change in District Tariffs	-0.128***	-0.111***	-0.108***	-0.093**
	(0.044)	(0.041)	(0.036)	(0.036)
Constant	0.193	0.151	0.161	0.085
	(0.235)	(0.209)	(0.191)	(0.166)
Observations	7,739	7,739	7,739	7,739
R-squared	0.030	0.028	0.027	0.020

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. In columns (1) to (4), we use increasingly conservative definitions of upward mobility. For example, in column (1) a son is classified as having a better occupation than his father if the educational intensity of his occupation is 0.25 standard deviations (sd) above the educational intensity of his father's occupation. In columns (2), (3), and (4), we use a cutoff of 0.5, 0.75, and 1.0 standard deviation respectively. 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 10: Alternate Reforms and Measures of Protection

	(1)	(2)	(3)	(4)
Dependent Variable		Upward Mobility		
Change in District Tariffs	-0.195***	-0.190***		-0.151***
	(0.048)	(0.047)		(0.045)
Change in District Delicensing	0.018			
	(0.027)			
District FDI Liberalization		-0.019		
		(0.049)		
Change in District Effective			-0.063***	
Rate of Protection (ERP)			(0.018)	
Change in District Input Tariffs				-0.255**
				(0.118)
Constant	-0.008	0.002	0.129	-0.236
	(0.256)	(0.254)	(0.248)	(0.281)
Observations	7,739	7,739	7,739	7,739
R-squared	0.031	0.031	0.030	0.031

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. For all measures of protection, the change in district protection is the difference in a district's protection 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