Government as Marketer: The Labor Market Effects of Product Promotion and Cluster Formation Initiative by the Government*

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Abstract

Traditionally, product promotion has fallen under the purview of marketers. Rarely do governments act as conventional marketers. In this paper, we assess the labor market effects of a government-led product promotion in an Indian state. The policy promotes one specific product in each district in the state. The breadth of the program offers a rare opportunity to evaluate how product promotion affects those who work for the promoted products on a wider scale. Using a nationally representative household survey, we employ a difference-in-differences strategy by exploiting plausible exogenous district and product level variance due to program implementation. We find evidence of a short-term decline in the earnings of associated workers. Mechanism analysis indicates that product-promotion policy draws an influx of intra-industry inter-district migrants, resulting in labor market congestion. This causes a decline in income for the affected workers. However, over time and as the program evolves, the negative impact on the job market begins to diminish, and the workers begin to realize the benefits of the program. Perforce, despite the fact that government product promotion may adopt a more holistic approach and have broader social goals, it is imperative to account for the short-term negative effects caused by migration shocks.

Keywords: product promotion, government policy, labor market congestion, migration, emerging markets, India

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1 Introduction

Product promotion is one of the core techniques used by marketers to obtain effective results (Nakanishi, 1973; Liu, Liu and Chintagunta, 2017; Shapiro, Hitsch and Tuchman, 2021). Marketers bear the primary responsibility for this task. Governments occasionally provide support for specific products, but their objectives differ significantly. The notable contrast lies in the fact that governments focus on products that serve the public interest. Governments frequently engage in local economic development, which may include the promotion of products. It has broader social purposes. Consequently, it may have potentially greater macro effects. We lack a rigorous understanding of the effects of government product promotion on those who work for the promoted products.

Promoting equitable and sustainable economic growth and ensuring productive employment are vital to achieving sustainable development goals (SDG 8).[1] Micro, Small, and Medium-Sized Enterprises (MSMEs) play a crucial role in attaining these objectives, yet their typical products are not sufficiently competitive to have a broad market presence. In theory, the government can address this issue by promoting these products and supporting the development of superior products (Shohibul et al., 2019). Occasionally they do. One noteworthy example is the Japanese government's one village one product effort. But it is uncommon for governments to assume the traditional role of the marketer. Government serves as a marketer and promotes a product is in contrast to the conventional role of government, which is to provide favorable conditions for small enterprises by, for example, expanding their access to capital and markets. Traditional place-based policies are mostly supply-side measures, whereas product promotion is more likely to be considered as a demand-side intervention.

In this study, we analyze the labor market impact of a product promotion program intended to form clusters, One District One Product (hereinafter ODOP), implemented by the government of Uttar Pradesh, the largest state in India. The program was started

[1] https://sdgs.un.org/goals/goal8

in 2018 by the government of Uttar Pradesh in an effort to promote one selected product in each of the state's 75 districts. Our primary purpose is to investigate the policy's short- and long-term effects on the labor market. The policy permits us to comprehend the effects of product promotion and cluster formation initiative on a macro level. This approach is constrained by the microfocus of the conventional promotion strategy employed by marketers. The scope of the program provides a unique opportunity to assess how product promotion affects those who work for the promoted products on a larger scale.

Economic theory predicts that workers of promoted products will likely benefit from market access (Donaldson and Hornbeck, 2016). However, product promotion is anticipated to boost employment prospects for relevant skilled workers, which could result in an influx of immigrants. If the demand cannot catch up with the supply of workers in the short term, the promotion of the product may have negative effects on people whose work is associated with the promoted products. As a result, the net short-term benefits of the cluster formation initiative could go either way. On the other hand, demand may eventually catch up and be able to absorb further supply pressure. Thus, the promotion strategy may, in the long term, be advantageous to the workers.

We exploit district and product level variation arising from the ODOP program. It differs from other promotion initiatives, such as the one village one product program of the Japanese Government, which was a community-led economic revitalization program in which the majority of the initiative was taken care of by the locals, and the local government provided mostly encouragement and technical support, but little financial assistance (Igusa, 2006). In contrast, the One District One Product (ODOP) initiative has allocated Rs. 2.5 billion and raised Rs. 4.68 trillion to transform each district of the state into an export hub for a specific product. The goal is to increase the scale and visibility of these products through marketing assistance and targeting all aspects of the 4Ps of marketing.

Under the program, the government has devised a micro plan for each ODOP product aimed at improving the quality of products. Extensive research is conducted to explore production, development, and marketing possibilities. Based on the research findings, both general and technical training are provided to eligible workers to improve the product. To ensure quality certification, the government has signed a memorandum of understanding (MOU) with 'Quality Control of India' (QCI), which will bolster consumer confidence. Furthermore, local businesses will receive technical assistance from General Electric, making them more competitive in the global market. The ODOP project also focuses on ensuring that eligible workers receive a fair price for their products, as financial assistance is granted to participants, enabling them to showcase and sell their ODOP products at national and international fairs/exhibitions. In terms of placements, the state government has made significant investments to establish a distribution network and value chain for the ODOP-selected products. Collaborating with Amazon through an MOU, the government provides a platform for local businesses to sell their products online. Additionally, an MOU with Wipro enables local businesses to leverage IT solutions, thereby expanding their global reach. Promotion is a crucial aspect of the initiative. The state government facilitates advertising, publicity, and marketing opportunities at various levels, including district, state, national, and international platforms. The program focuses on brand development and enhances products through effective packaging and branding. Additionally, the initiative seeks to connect production with tourism by featuring live demonstrations and establishing retail outlets.

We utilize high-frequency household panel data containing around 0.1 million observations. We employ a difference-in-differences strategy to assess the effects on individuals (eligible workers) involved in the production of the identified ODOP product in the respective selected district. The difference-in-differences identification strategy takes advantage of cohort eligibility variance based on the selection of ODOP products and their district, as well as time variation based on the administrative rollout of the ODOP program. To provide a fair and balanced comparison in the empirical framework, we do industry-specific analysis to compare individuals from the same industry. Furthermore, based on the data, we confirm that there was a negligible movement of workers between industries due to the implementation of the policy, a factor that could have introduced potential contamination. To identify the eligible workers, we map government-identified products with broadly defined industries available in our data. After addressing any endogeneity concerns, this empirical framework allows us to obtain an aggregate causal estimate of the ODOP program's effect on the income of qualified workers. In our empirical model, we also account for a variety of household and individual controls, as well as region-specific impacts, in order to account for adequate heterogeneity in worker productivity.

Our findings indicate that after the implementation of the ODOP program, the average income of eligible workers declined in the short term by around 20% of the sample mean. Additionally, to see if the average negative impact persists across industries, we evaluate the impact of the program separately on each industry. We observe a comparable negative effect in all industries, ranging from a decline of 14% in the income of Handicraft workers to a decline of 35% in the income of Food Processing workers. This gives us the confidence to generalize our observation of the negative short-term effects of product marketing, given both the aggregate and industry-specific results are significant, robust, and consistent.

We do exhaustive checks to address potential endogeneity issues. We perform a pre-policy analysis to establish that the difference-in-differences methodology's identification assumption holds true. In the pre-policy period, we demonstrate the parallel trends preceding the enactment of the program, and additionally provide empirical evidence supporting the absence of a statistically significant disparity between eligible and ineligible workers over time in the absence of the aforementioned program. The major findings remain unchanged even though we winsorize our outcome variable to account for outliers. In addition, we conduct placebo studies utilizing randomly assigned district-based treatment status and conduct falsification exercises on potentially unaffected individuals, but we discover no impact. All of these robustness checks indicate that the primary conclusion is not erroneous, bolstering the identification assumptions and our confidence in the results.

To learn about the potential mechanism, we conjecture that intra-industry inter-district migration serves as a potential mechanism causing this negative effect on incomes. In accordance with the existing literature (Pernia and Pernia, 1986; Imbert et al., 2022), and using an event study of the ODOP program, we also find that the drop in incomes of eligible workers was only observed immediately after the delivery of the program benefits; and slowly, with the evolution of the program, the congestion in the labor market begins to subside, and workers begin to realize the benefits of the program. Our data imply that an influx of around 34 percentage points of eligible workers in their respective promoted districts is attributable to exogenous government intervention, which can be explained by the "labor pull" concept, in which migrants are drawn to the destination by enhanced work prospects (Imbert et al., 2022). A separate heterogeneity check reveals that post policy implementation, the indigenous population faces more pronounced adverse effects in the short term compared to the migrants, attributable to the relocation of workers from the identified industries to their designated districts in anticipation of enhanced opportunities.

Next, we investigate the long-term effects of the program. Our analysis is limited to the pre-covid period. We employ a dynamic difference-in-differences framework. Despite the fact that the workers initially experience negative impacts, we find that these effects tend to diminish over time.

Taken together, we provide novel evidence that when the government acts as a traditional marketer by promoting a product, associated workers experience income losses due to the supply pressure caused by intra-industry inter-district migration. However, the negative impact on the labor market begins to diminish over time, and workers begin to recognize the advantages of the program.

We view our study contributing most to the product promotion literature (Nakanishi, 1973; Raju, 1992; Blattberg, Briesch and Fox, 1995; Horváth and Fok, 2013; Liu, Liu and Chintagunta, 2017; Shapiro, Hitsch and Tuchman, 2021; Zhang, Cai and Shi, 2021). Marketers deploy a variety of promotion tactics, including advertising and price promotion, among others. Several studies detail the long-term consequences of promotions (Pauwels, Hanssens and Siddarth, 2002). We make three main contributions to the product promotion literature. First, unlike traditional product promotion strategies, we examine a product promotion policy by the government. This allows us to examine a holistic promotion strategy by the government which has a broader social objective. Second, we demonstrate a novel macro impact of product promotion by the government on the local labor market. Due to the paucity of product promotion by the government, marketing study is usually limited to understanding product promotion policy primarily through the lens of marketing outcomes and at a micro scale. We are able to analyze both immediate and long-term effects as well as effects on a larger scale because of the breadth of the program. This is also one of our major points of differentiation. Moreover, we demonstrate a novel migration channel.

Our paper also contributes to the migration literature in the context of developing countries (Bryan, Chowdhury and Mobarak, 2014; Bryan and Morten, 2019; Morten, 2019; Imbert et al., 2022). Our research is based on internal migration because we have evidence of intra-industry inter-district labor mobility. Our key findings are consistent with the literature's assertion that internal migration tends to have a greater negative impact on wages at the destination. For example, Sousa and Poncet (2011), Ge and Yang (2014), and Imbert et al. (2022) have shown a negative impact of the migrant labor supply shock on worker earnings. According to our knowledge, this paper is the first to demonstrate the migration channel of the effect of government product promotion on the labor market.

Our research also relates to the extensive literature on the influence of government-led industrial policies and interventions on regional economic growth (Kline and Moretti, 2014).[2] Studies show the significance of government in formulating policies that support small-scale businesses (Amizade, 2011), so contributing to poverty reduction, household incomes, and employment (Hadiyati, 2015). The ODOP is essentially a local economic policy with the social goal of fostering traditional industries. In contrast to the usual clustering method that governments often use, the government assumed the role of the traditional marketer under ODOP.

This paper unfolds as follows. Section 2 provides background on the ODOP program. The third section presents the sources of our data. The fourth section discusses the empirical framework, including identification strategy, methodology, and pre-policy analysis. The fifth section analyzes and presents the main results at the aggregate and individual industry levels. Then we discuss the potential mechanism. The seventh section presents the evolution of the program's impact through an event study. The eighth section consists of various checks to test the robustness of the main results. The last section concludes.

2 Background

Uttar Pradesh, India's fourth-largest state in terms of land area, is home to a wide variety of indigenous arts and crafts. In addition, while taking into account the number of seats in the Indian Parliament, Uttar Pradesh is one of the most politically influential states in India. Each district within the state possesses its own localized, specialized products that have been produced by the natives for generations. For instance, the regions of Agra, Kanpur, and Hamirpur exhibit specialization in the field of leather and footwear industries; Siddharthnagar excels in its ancient and nutritious 'Kala namak' rice; Bahraich is specialized in its exceptional wheat-stalk craft. However, traditional products are facing

[2]See Agrawal, Hoyt and Wilson (2022) for a review.

significant challenges as a result of intensified competition from large-scale industrialized production hubs. These challenges primarily stem from their restricted distribution networks and lower visibility. Furthermore, the absence of standardized quality measures for these locally produced, unbranded products contributes to consumer uncertainty regarding their authenticity and availability. In recognition of the necessity to compete in the global market, the government acknowledges the imperative for small and medium-sized industries engaged in the production of these goods to undertake modernization efforts, while concurrently focusing on the promotion and rebranding of these indigenous products to amplify their visibility and stimulate sales.

The government of Uttar Pradesh established the "One-District-One-Product" (ODOP) initiative with the objective of focusing on a single product in a specific district to foster specialized products from all 75 districts of the state and mitigate the aforementioned challenges. In accordance with the policy, the program is a transformative step towards realizing the true potential of a district, as it will stimulate economic growth for Micro, Small & Medium Enterprises (MSME) and create jobs in Uttar Pradesh.[3] The state government has allocated Rs. 2.5 billion for the program's implementation and has set a goal of employing 2.5 million unemployed candidates in Uttar Pradesh through this program.

The government has identified a specific product, based on traditional economic activities, to be promoted as part of the One District One Product (ODOP) initiative in each district. In order to promote and enhance the sales of the selected One District One Product (ODOP) products, the state government extends comprehensive assistance to artisans, production units, and associations involved in the production of these products in their respective districts. This support encompasses all aspects of the 4Ps of marketing, including the development of a micro plan to enhance the product, ensuring fair pricing, establishing a distribution network, and facilitating advertising and branding opportunities. To effectively achieve the set goals and provide support to workers, the state government

[3] http://odopup.in/en/page/vice-president

has entered into multiple memoranda of understanding (MOUs). These MOUs include agreements with organizations such as 'Quality Control of India' to ensure product quality, General Electric for technical assistance, Amazon for product placement and marketing, Wipro for leveraging IT solutions, and others with the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) to assist businesses in raising capital.[4].

The program involves conducting research to explore production, development, and marketing possibilities for the ODOP products, followed by providing general and technical training to eligible workers based on the research findings to improve the products. To ensure quality certification, the government has signed an MOU with 'Quality Control of India' (QCI), which will enhance consumer confidence. Furthermore, local businesses will receive technical assistance from General Electric, which will enhance their competitiveness in the global market. Financial assistance is granted to eligible participants for showcasing and selling their ODOP products at national and international fairs/exhibitions. This enables eligible workers to become aware of market prices for their ODOP products and obtain fair prices. Additionally, the government has collaborated with the NSE and BSE, the two leading stock exchanges in India, to connect ODOP businesses with investors who are interested in supporting the growth of the program. This will provide ODOP businesses with the necessary capital to scale up their operations and expand into new markets. Regarding the placement of the products, the state government has made significant investments to establish a distribution network and value chain for the selected ODOP products. Through an MOU with Amazon, the government provides a platform for local businesses to sell their products online. Furthermore, an MOU with Wipro allows local businesses to leverage IT solutions, thereby expanding their global reach. To promote ODOP products, the state government facilitates advertising, publicity, and branding opportunities for eligible individuals at the district, state, national, and international levels. Moreover, the branding of products is improved by

[4] http://odopup.in/en/page/goal

connecting the production of these products with tourism through live demonstrations and retail outlets.

Although the initiative was introduced in January 2018 to mark the importance of Uttar Pradesh Diwas (Foundation Day), the program was fully executed at the ODOP summit held in August 2018 by distributing financial benefits to qualified individuals.[5] During the time between the launch of the program and the ODOP summit, Rs. 4600 billion were raised through an investors' meet[6], and MOUs for training[7] and product marketing were planned and prepared[8]. During the summit, MOUs were signed, and benefits were distributed to qualified individuals in the presence of the President of India, the Governor, and the Chief Minister of the state. During the summit, technical sessions were held, financial assistance amounting to Rs 10.07 billion was dispersed, and toolkits were provided to program beneficiaries.

In sum, in comparison to conventional product promotion tactics, the government adopted a more comprehensive strategy. Importantly, the scope of the policy permits us to investigate the effects of product promotion on a broader scale.

3 Data

Our data comes from the Center for Monitoring Indian Economy (CMIE), which runs a comprehensive, ongoing survey called Consumer Pyramids Household Survey (CPHS). A significant feature of the CPHS data is its vast geographical coverage, as the survey includes 98.5% of India's landmass population. It provides data from over 232,000 sample households and 1.19 million individuals frequently surveyed throughout time, making it the biggest household panel survey in the world.

[5] http://odopup.in/site/writereaddata/UploadNews/corrigendum/pdf/C\201905031825266297.pdf

[6] https://indbiz.gov.in/uttar-pradesh-investor-summit-attracts-critical-investments/

[7] https://odopup.in/en/page/meeting-minutes

[8] https://odopup.in/en/page/meeting-minutes

The CPHS is a longitudinal survey of Indian families designed to measure household well-being in India. Every person is surveyed three times each year with a four-month interval (referred to as a quadrimester). It includes information on household consumption expenditures, household assets, perceptions, and decisions on the purchase of assets or investments. For each household member, it also gathers identifying information and essential features such as gender, age, education level, marital status, and relationship to the household head. It provides detailed income statistics and information on each household member's occupation, nature of work, and industry of operation, as well as the duration and structure of their employment, for every earning member of the family.

We utilize the CPHS-based data acquired between 2016 and 2019. In August of 2018, the ODOP program became fully operational. Consequently, the data from January 2016 to August 2018 is utilized for pre-program analysis, whereas the data from September 2018 to December 2019 is used for post-program analysis. Since CMIE began collecting employment-related data in 2016, we began our analysis in 2016.[9] The employment and industry-related information recorded in the CMIE dataset enables us to identify program beneficiaries for each ODOP-approved product. We restrict our analysis to the pre-covid period.

Table 1 shows the summary statistics of the overall dataset used in our main analysis, as well as a breakdown of the industries whose products have been designated by the state government under the ODOP program.

4 Empirical Framework

4.1 Identification Strategy

We use the plausibly exogenous district and product level variation resulting from the execution of the ODOP program. Recall, under the ODOP program, the government of

[9] See https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9288665/

Uttar Pradesh has designated specific items for each of the state's 75 districts. To identify the aggregate impact of the program, we perform an industry-wise comparison of workers and report the pooled results for all industries.

As an illustration of our identification method of industry-wise comparison, let's consider, for example, the promotion of textile products. The state government has chosen three districts in Uttar Pradesh based on their traditional "know-how" in textile products to develop the textile products. These three districts would henceforth be known as textile-promoted districts: Ambedkar Nagar, Etawah, and Barabanki. We treat the ODOP program as a non-experimental nature of intervention in order to evaluate the effect of the promotion of textile products in our simple example on the income of eligible persons, i.e., textile workers employed in textile-promoted regions.

The use of the Ordinary Least Squares (OLS) approach to assess the influence of ODOP may have significant limitations due to the non-experimental nature of the ODOP initiative, wherein the decision to assign a product to a district is not random; it is based on the district's historic specialization. We may compare one sample of persons to another using the OLS model. However, such a comparison may not provide us with a meaningful causal effect of the program, as there may be pre-existing variations between the two groups, and our endpoint estimations will be susceptible to these changes. There may be unobservable elements that contribute to omitted variables bias if we employ OLS. For instance, if we merely compare textile workers employed in textile-promoted districts with textile workers employed in other districts, it is plausible that textile workers in the promoted districts exhibit a higher income in comparison to their counterparts in non-promoted districts owing to the prevalence of traditional economic activities within the promoted district. Furthermore, it is important to acknowledge that there might be latent disparities between districts arising from distinct local beliefs and cultural practices, which could potentially bias our findings. Similarly, if we compare the post-implementation income level to the pre-implementation income level for textile workers employed in textile-promoted districts, the results may still be skewed, as the difference over time may be attributable to multiple factors, such as changes in the macroeconomic environment. Consequently, comparing the income of textile workers and non-textile workers in textile-promoted districts may not yield valid results because textile employees and non-textile workers can differ greatly. Various sectors involve varying levels of education, physical labor, mental acuity, and skill sets, which may contribute to these discrepancies.

In order to tackle the aforementioned challenges and evaluate the true causal impact of textile product promotion under the ODOP program, we employ a difference-in-differences (DiD) methodology, which is widely recognized as one of the most prevalent techniques in the field of social sciences for estimating causal effects in non-experimental contexts. In our case, the treated districts are Ambedkar Nagar, Etawah, and Barabanki, which are textile-promoted districts. Due to their geographical proximity, cultural similarity, and economic standing, the remaining districts of Uttar Pradesh serve as a suitable comparison group for the experimental districts.

To assess the effect of textile sector promotion, we limit our sample to persons from Uttar Pradesh's textile industry. As only the textile industry is eligible for benefits in textile-promoted districts under the ODOP program, we only included individuals employed in the textile industry in our aggregate dataset for textile-promoted districts. To ensure a fair comparison, we restrict our sample in the control districts to those employed in the textile industry. Individuals in the same industry are assumed to be more similar than those in different industries. Therefore, the workforce employed in the textile industry constitutes the dataset utilized to analyze the effects of textile product promotion. In this dataset, textile workers in treated districts (textile-promoted districts) represent the treated group, while textile workers in the remaining districts represent the control group. We compare these two groups over time using a difference-in-differences design. This method effectively accounts for the pre-existing time-invariant disparities between the groups, thereby allowing us to isolate and estimate the causal effects attributable to the program (Roth et al., 2023).

Similarly, we undertake an analogous analysis for additional products identified under the ODOP program, in which we map the ODOP products from various districts to a specific product industry reported in the CMIE dataset. We are able to extend this analysis to five industries in total: the textile industry, footwear and leather industry, food processing industry, metal industry, and handicraft industry. The appendix contains a list of the government-selected mapped ODOP products with registered industries in the CMIE dataset and their respective promoted districts (Table A2 of the Appendix). We conduct this industry-by-industry analysis to report the aggregate impact on the workers employed in the production of a state-identified ODOP product in the district chosen by the state government to promote that particular ODOP product. They are henceforth referred to as "eligible" individuals or "eligible" workers. In the subsequent section on methodology, we provide a detailed description of our empirical framework.

4.2 Methodology

We estimate the causal impact of product promotion using the difference-in-differences (DiD) technique, which is widely used in non-experimental interventions. DiD assumes there are no systematic, time-varying, unobserved differences between the treatment group and the control group. Due to the geographical proximity between districts and the fact that all districts are located in Uttar Pradesh, the aforementioned assumption is reasonable. Moreover, all districts are governed by the same government, which implements the same policies and programs throughout the state. Additionally, we are comparing individuals in the same industry, which may provide additional support for the assumption of parallel trends underlying DiD. Our estimates are interpreted as intent-to-treat. We estimate the following specification for each individual i employed in an industry producing the promoted product p in district d during the time period t:

$$Y_{i,p,d,t} = \alpha_d + \mu_p + \beta_1 Eligible_{p,d} * Post_t + \beta_2 Eligible_{p,d} + \beta_3 Post_t + \gamma_i X_i + \epsilon_{i,p,d,t} \quad (1)$$

where $Y_{i,p,d,t}$ is an individual's monthly income of individual i working for the product p in district d surveyed in time t. This is our outcome of interest. The dummy variable $Eligible_{p,d}$ takes a value 1 for individuals working in the ODOP product's industry in the district selected for promotion of that particular ODOP product. For example, a textile industry worker working in state-identified textile-promoted districts would take value 1 for this '$Eligible_{p,d}$' dummy, and rest all textile workers working in other districts would take value 0. Similarly, a footwear and leather industry worker working in state-identified footwear and leather industry promoted districts would take value 1 for this '$Eligible_{p,d}$' dummy, and rest all footwear and leather industry workers employed in other districts would take value 0. Based on the program implementation details mentioned in the policy background section, the $Post_t$ dummy variable has a value of 1 for survey rounds conducted after August 2018 and a value of 0 for survey rounds conducted prior to August 2018. $Eligible_{p,d} * Post_t$ is the interaction term which takes value 1 for workers producing the ODOP product in the state-selected district for promotion of that particular ODOP product surveyed after program implementation and 0, otherwise. The terms α_d and μ_p represent district and industry-fixed effects, respectively. The former accounts for average differences between districts, and the latter ensures the comparison of individuals engaged in the same industry. X_i represents the set of individual-level controls. These controls are an individual's age, gender, a dummy to indicate whether an individual is literate or not, the number of years that an individual has spent in employment, the self-assessed status of an individual being healthy or not, a dummy to indicate whether an individual has a bank account or not, a dummy to indicate whether an individual is self-employed or working for some employer. Standard errors are adjusted for district level clustering. The parameter of interest is β_1, which captures the average intention to treat effect of the ODOP program on the monthly income of eligible workers. Interpreting the estimated regression coefficient in this framework yields the change in the average monthly income of those who were exposed to the policy versus those who were not after the implementation of the program. The identifying assumption implies that the estimated coefficient would be statistically insignificant in the counterfactual scenario, as demonstrated in the next subsection.

4.3 Pre-policy Analysis

Before reporting the results of the preceding analysis as the causal effect of program implementation, it is essential to demonstrate that the program impact did not exist prior to the implementation of the ODOP program in our difference-in-differences setup. Due to the promotion of ODOP products, it is hypothesized that the average income of treated workers will change as a result of the ODOP program. Therefore, during the pre-program analysis, prior to the implementation of the ODOP, this hypothesis should not hold true. In other words, there is no apparent reason why the difference in income between eligible and ineligible individuals would change over time, barring a policy intervention affecting these differences in the selected product's industry in selected districts (such as the ODOP program).

We demonstrate that there was no significant difference between the average incomes of eligible and ineligible workers prior to the introduction of the ODOP program, thereby ensuring the reliability of our empirical design's identifying assumption. For this purpose, we utilize CPHS pre-program data from 2016, 2017, and 2018 rounds (till August, as the program was fully implemented in that month). Since there are observations spanning 34 months in the pre-program data, we classify half of them as an untreated period (17 months) and the other half as a treatment period (17 months). Using the same regression framework described in the Methodology section, we assign the value 1 to the dummy variable $Post_t$ for observations from May 2017 to August 2018 and 0 for January 2016 to April 2017. The remaining independent variables remain unchanged. Table 2 presents the findings of this analysis.

We observe that the coefficient of the interaction term is statistically insignificant and thus cannot be statistically distinguished from 0. Before the implementation of the ODOP program, the change in the average income of eligible workers was not significantly different from that of non-eligible workers. Therefore, we can conclude that the promotion of products by the government had no effect on eligible workers in their selected product industries in selected districts prior to the program. In addition to this, another customary procedure in difference-in-difference studies entails presenting empirical support for common pre-trends in outcome variables between the treated and control groups over time. Following this established approach, we present in Figure 1 the trends in our outcome variable for both ODOP-eligible and ineligible workers over time, thereby illustrating the parallel trends preceding the implementation of the policy. We observe that prior to the policy's enactment, the raw means of the proposed outcome variable exhibit synchronous movement across successive time periods for both groups and display an upward trajectory. However, the introduction of the program alters the trajectory of the eligible group, while the ineligible group continues to follow the upward trajectory. This examination, coupled with pre-policy empirical findings, instills confidence in the validity of our study's identification assumption and bolsters our confidence in the obtained results.

5 Results

In this section, we show the causal effect of the ODOP program on the average income of ODOP-eligible workers (Table 3). In the regression specification explained in the Methodology section, we assign value 1 to the dummy variable $Post_t$ for the post-program period, i.e., from September 2018 to December 2019, and 0 for the pre-program period, i.e., from January 2016 to August 2018. Rest all other independent variables remain the same. Column 3 is our preferred estimate.

Post-implementation of the program, the average monthly income of ODOP-eligible workers has decreased by approximately Rs.1,759 compared to that of non-eligible workers. This decline accounts for approximately 20% of the sample mean. This outcome is statistically significant at the 95% confidence interval. Since the pre- and post-program periods utilized in our analysis are not balanced, we conducted the analysis using an alternative regression framework that included a time fixed effect to ensure comparisons within the same time periods and to control for all time unit-specific effects. The similarity between this alternative regression framework and our primary regression specification provides additional assurance in our findings (Results are reported in Table A1 of the Appendix).

5.1 Results for individual industry

Our primary empirical model estimates the average impact of the ODOP program by combining data from all industries, while ensuring comparisons between individuals from the same industry. There is cause for concern that one of the industries may have experienced a setback in its government-selected promoted districts, thereby affecting the average results. To address this concern and examine the program's impact on each industry separately, we run our main analysis for each industry separately (Results are reported in Table 4, with each column depicting results for a specific industry). To accomplish this, we apply the main regression model to subsamples of individuals from one industry at a time. For instance, in order to estimate the impact of the ODOP on the textile industry in three districts chosen for textile product promotion, the main regression model is run on a subsample of textile workers (Results are in column 1 of Table 4). Similarly, to determine the impact on the footwear and leather industry, we analyze a subsample of workers from the footwear and leather industries (Results are in column 2 of Table 4). For estimating the impact on the food processing industry, the regression is conducted on a subsample of food processing employees (Results are in column 3 of Table 4). Similarly, Column 4 of Table 4 contains the results for the metal industry, while Column 5 contains the results for the handicraft industry.

We observe that all industries promoted by the state government experienced a similar negative outcome, indicating that the income of ODOP-eligible workers decreased due to the implementation of the program, regardless of industry. This indicates that our results are not skewed by the poor performance of a single industry in its promoted districts; rather, all ODOP-eligible workers were negatively impacted immediately after the program's implementation. It allows us to confidently generalize the short-term negative effects of product promotion on eligible workers who produce the promoted products in the region where the product has been promoted.

6 Mechanism

Our results indicate that the promotion of ODOP products had a negative impact on the incomes of eligible workers. Economic theory predicts that such a product promotion could expand market access and will eventually benefit employees (Donaldson and Hornbeck, 2016). A plausible reason for the negative consequences could be that the commencement of the ODOP program resulted in a massive influx of promoted industrial workers in their particular government-selected areas, hence intensifying labor market competition. The negative effect of increasing competitive pressure in the labor market may lower workers' pricing power, resulting in a decline in the income of eligible workers following the introduction of the program. This is especially true when demand cannot match supply shocks. This is consistent with the literature's conclusion that internal migration may have substantial detrimental wage consequences in developing economies

(Kleemans and Magruder, 2018; Imbert and Papp, 2020). Extensive literature on the migration of workers also suggests that the influx of immigrants will substantially reduce native wages (Grossman, 1982; Greenwood and McDowell, 1986; Borjas, 1987; Lalonde and Topel, 1991).

Although it was anticipated that the ODOP program would grow the labor force. The initiative's primary purpose in fact was to employ 2.5 million unemployed workers in Uttar Pradesh. In the short term, one possibility is that this increase in the number of workers overwhelmed the promoted industries in their respective selected districts; thus, the average income of eligible workers decreased relative to that of non-eligible workers.

The ODOP initiatives that lured workers to promoted industries in their respective districts may have been the result of inter- or intra-industry migration. Intra-industry migration refers to the movement of workers from non-selected districts to selected districts within the same promoted industry, which is more likely than within-district inter-industry migration. This is due to the costs associated with inter-industry migration, where a worker needs to acquire new skills when transitioning between different industries. To support this argument, Table 5 provides evidence that the proportion of workers from the promoted industry in their respective selected districts increased by an average of 34 percentage points. Conversely, their proportion in other non-selected districts decreased by approximately 20 percentage points. This indicates a significant influx of workers from non-selected districts to the selected ones within the same industry. Furthermore, the data shows that the proportion of workers in non-promoted industries remained unchanged. This finding rules out the possibility of within-district inter-industry migration, where workers from non-promoted industries within the same district would have switched to the selected industry to become eligible for ODOP. Therefore, the observed migration patterns primarily involve workers from non-selected districts joining the promoted industries in selected districts. Additionally, it is important to note that the ODOP program places particular emphasis on traditional craftsmanship, which requires considerable time to learn. Consequently, the likelihood of inter-industry migration is highly improbable when considering the specialized skill sets associated with traditional craftsmanship alone.

To supplement our descriptive data, we use inferential analysis to corroborate the hypothesis of an influx of promoted industrial workers in their respective promoted districts. We utilize the "eligible" dummy variable as the dependent variable in our primary regression equation, retaining all controls and fixed effects. The results of this examination, detailed in Table 6, demonstrate a notable augmentation in the count of eligible workers subsequent to the initiation of the program. To be specific, we find that the number of promoted industry workers in their respective designated districts has increased by 4 percentage points since the program's inception. This, along with our descriptive results, indicates that the ODOP initiatives led to a massive influx of promoted industry workers from other districts into the corresponding selected districts, suggesting intra-industry inter-district mobility.

Understanding who will lose out in the short term — natives or migrants — is another intriguing avenue to explore. A significant body of literature explores the aforementioned issue (Borjas, 2018; Dustmann and Preston, 2019). We run the main regression equation separately for native and migrant workers as part of a heterogeneity check to examine the impact of the ODOP program on each group separately. The findings are shown in Table A4 in the Appendix. The point estimates imply that, following the program's adoption, the income of native eligible workers experienced a comparatively more adverse effect in comparison to the income of migrant ODOP product workers who relocated to the respective selected districts. Despite the marginal disparity in the point estimates, these findings suggest that the program's adoption had a relatively more pronounced immediate impact on native workers, thus contributing to the overall negative consequences of the program. Nevertheless, subsequent analysis indicates that the impact of the migration shock is transient, manifesting primarily in the immediate aftermath of program implementation when migrants may not have possessed complete knowledge regarding forthcoming wage conditions in the designated districts. However, over an extended duration, we observe a restoration of wages among eligible individuals, a phenomenon elucidated in the subsequent section of the paper.

7 Evolution of the program effect

We demonstrate that the migratory pressure is likely to have detrimental consequences for qualified workers. However, the demand pressures are likely to catch up with the supply shocks in the long run for at least two reasons. First, the brand-building exercise and product placements in the value chain may require some time to accomplish. Consequently, demand is likely to have increased over time. Second, even if demand has not increased, migratory shocks are likely to slow down. This is due to the fact that potential migrants who have not yet moved may incur large migration costs and be hesitant to do so. For a comprehensive understanding of the migration channel, a dynamic study is required.

Till now, when analyzing the impact of ODOP on the earnings of eligible workers, we have viewed the entire post-program period as a single time unit. We demonstrate that the introduction of the ODOP program caused the labor market to become oversaturated, resulting in a decline in earnings for eligible workers. However, instead of evaluating the entire post-program period as a single time unit, we can apply a dynamic difference-in-differences strategy to an event study to determine how the influence of ODOP changes over time. We utilize a period of 4 months (referred to as a quadrimester) as the unit of time for our analysis since every household in the CMIE dataset is re-surveyed in each quadrimester. Figure 2 displays the point estimates for the effect of ODOP on the income of eligible workers using the second quadrimester of 2018 as the comparison period in our dynamic DiD model. We pick the second quadrimester of 2018, i.e., May 2018 to August

2018, as the reference period because it is the quadrimester immediately preceding the ODOP program summit. The point estimates are computed using the primary regression specification (equation 1), which includes fixed effects and controls. The graph displays that immediately following the commencement of the ODOP program, there was a large negative impact on the income of eligible workers. In the subsequent quadrimesters, the income of eligible workers recovers, which may imply a reduction in labor market congestion. This is consistent with research findings indicating that time mitigates labor market disruptions caused by external interventions such as government policy or other macroeconomic shocks (McLaren, 2022).

8 Robustness

In this section, we undertake a number of robustness checks on our main results. Initially, we run a falsification test and evaluate the impact of the ODOP program on a fictitious treatment group. Then, we run a randomization test to ensure that our estimates of the causal impact of the ODOP program are not influenced by random differences between the treatment and control groups. Finally, we run our primary regression specification on a winsorized sample to ensure that our results were not exclusively influenced by dataset outliers.

8.1 Falsification

A potential concern with our difference-in-differences design is that the results are spurious and are being picked up by our empirical specification due to some other general differences between the treatment and control groups, rather than the ODOP program's causal effect. Specifically, it is possible that the income of all workers in selected districts for the promotion of some product, regardless of the industry in which they are employed, fell after the implementation of the program due to some macro-level factor.

We conduct a falsification exercise to address this concern.

We replace our actual treated group with an untreated group within government-selected districts to promote ODOP products. Since the ODOP program would have affected only eligible workers, it is reasonable to assume that non-eligible workers will not be affected by the implementation of the program.

To empirically test this, we apply our primary regression specification to non-eligible workers. For our treated group, we take non-eligible workers from government-selected districts promoting ODOP products, and for our control group, we take non-eligible workers from the remaining non-selected districts. Table 7 displays the results.

This falsification exercise demonstrates that the ODOP program has no statistically significant effect on non-eligible workers. We observe that the average income change of non-eligible workers is statistically indistinguishable from zero. As a result, we have some level of confidence that our calculations of the ODOP program's causal effect on the average income of eligible workers are not spurious.

8.2 Test of exact randomization

Next, we undertake a test to ensure that our estimates of the program's causal impact are not random. To confirm that our main results are not random, we randomly assign all the workers in our sample to treated and control groups and run our main regression specification using these randomly generated treated and control groups. We run 1000 such simulations for the outcome variable - average income and collect 1000 estimates of β_1 from these simulations. If our results detected some random variation between treated and control groups, then these simulated estimates should produce similar results. Figure 3 plots the percentage occurrence of the 1000 simulated coefficient β_1 on the Y-axis and the simulated coefficient 1 on the X-axis for the outcome variable. These random outcomes are distributed around zero, indicating that this random assignment produces both good and negative outcomes throughout a broad range of values. Our point estimate from

Table 3, plotted with a vertical green line, is to the far left. This gives us confidence that our empirical strategy identified the true causal effect of the ODOP program and did not pick up any random variation between the treated and control group.

8.3 Correcting for Outliers

We then adjust our primary results for likely outliers. Our empirical model analyses the effect of the ODOP program on the annual income of textile workers in an intent-to-treat context. Therefore, there is a risk that the point estimate of the change in income may be confounded by outliers in the data set. Assume that there are extreme values on both ends of the data set. As outliers influence point estimates, it is possible that the estimated effect of the program is biased. Following a standard approach (Jensen and Johannesen 2017; Matsusaka 2009), we winsorize the outcome variable annual income at the 1st and 99th percentile of the distribution of each variable to address the concerns of outliers contaminating our estimation. In this process of replacing the extreme values of the dataset to reduce the effect of possibly spurious outliers, we made sure to winsorize the outliers for both the treatment and control groups independently. The summary statistics of the outcome variable before and after transformation are presented in Appendix Table A3, confirming the presence of outliers in our original data set.

Table 8 displays the outcomes following winsorization of the data. We find that the effect is still statistically significant along with the negative coefficient of the interaction term. It shows that the negative impact on the income of eligible workers is unlikely to be the result of outliers.

9 Conclusion

Countries and their leaders have been attempting to accomplish the 17 Sustainable Development Goals (SDGs) established by the United Nations.[10] Promoting equitable and sustainable economic growth and ensuring productive employment are vital to achieving these objectives (SDG 8). Frequently, the government takes the initiative and creates advantageous conditions, particularly for small businesses.

In this paper, we assess the labor market impact of a government-led product promotion, one district one product (ODOP), in the Indian state of Uttar Pradesh. Product promotion has historically been the responsibility of marketers. Rarely do governments act as conventional marketers. The government's comprehensive approach under the ODOP and its larger social focus enables us to evaluate the impact of the promotion program on affected workers on a broader scale. Although marketing literature has studied the impact of product promotion on marketing results, we do not know how those who work for the product are affected when the government promotes a product.

Several of our findings are novel to the literature. First, we see a decline in the average income of eligible workers shortly following the commencement of the program. Second, we discover that the government product promotion program caused intra-industry inter-district migration of workers, resulting in labor market congestion. This is in line with the existing literature on migration in developing countries. Third, labor market congestion may result in a short-term decline in the average earnings of workers, but in the long run, demand factors will likely catch up with the supply of skilled migrants. We observe that the adverse effects diminish progressively. Together, we provide suggestive evidence that initial supply shock is the primary mechanism responsible for the negative effects on eligible workers.

Governments allocate billions to business assistance initiatives. Scholars from a variety of disciplines dispute whether government efforts are advantageous or detrimental

[10] `https://sdgs.un.org/goals`

to achieving its broader social objectives (Agrawal, Hoyt, and Wilson, 2022). We pose the fundamental question: by promoting a product, can the government as a marketer assist workers of the promoted products? In our case, despite the Uttar Pradesh government's efforts in employment generation under the program, for which approximately 75 billion Rs. have been allocated (until August 2020) and approximately 28,000 job opportunities have been created,[11] our results indicate that the program immediately attracted more migrant workers than opportunities created, resulting in an overcrowded labor market for promoted products in their respective districts. Workers suffer a loss in income as a result. Although, with such persistent government efforts in product promotion, the oversaturation of the labor market is gradually lessening, as seen by the gradual growth in the income of qualified workers.

Consequently, our findings imply that even if the government and corporations have a novel purpose in a policy aimed at rural entrepreneurship through product promotion, they must consider the early negative effects on workers. Migration is frequently viewed as a risk mitigation technology in the context of developing countries (Bryan, Chowdhury and Mobarak, 2014). Such a migration shock is inescapable for any large-scale industrial promotion program. However, it appears that the administration can achieve its goal over time. Nevertheless, we expect that governments and corporations engaged in collaborative efforts or undertaking independent similar initiatives for corporate citizenship in emerging countries would take note of our research findings and should consider implementing measures to mitigate the early negative effects of a large-scale product promotion initiative.

[11] https://www.businessworld.in/article/-One-District-One-Product-scheme-given-boost-to-traditional-industries-UP-govt/08-11-2020-340673

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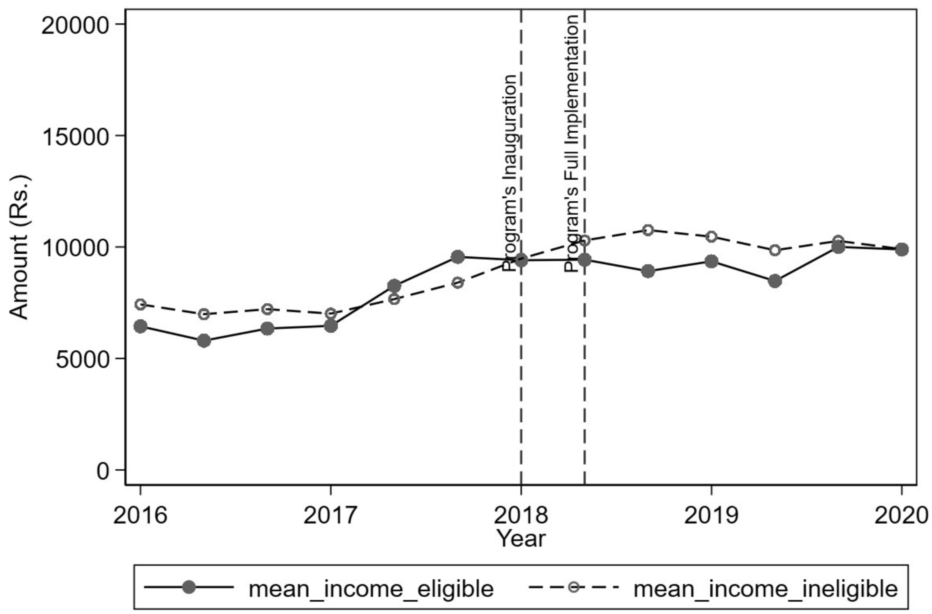
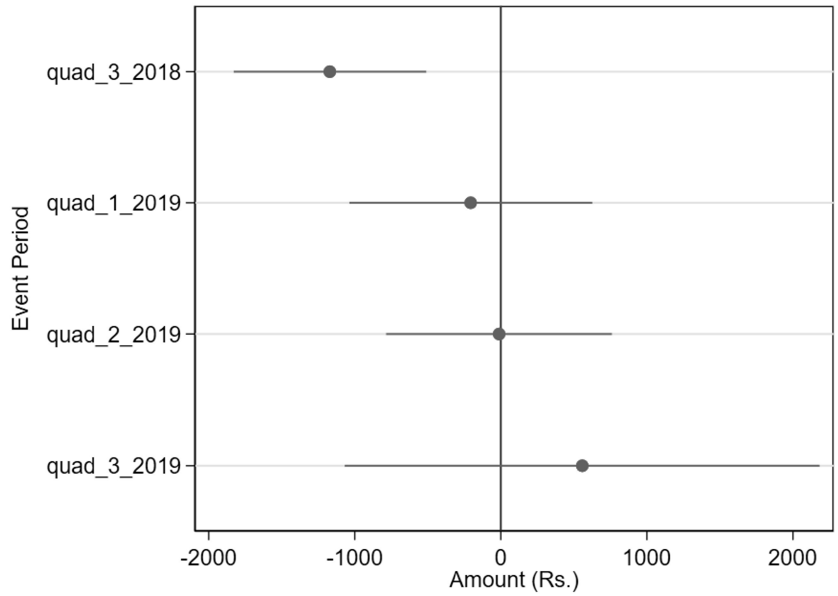
Figures and Tables

Figure 1: ***Trends in Outcome variable for Eligible and Ineligible workers***



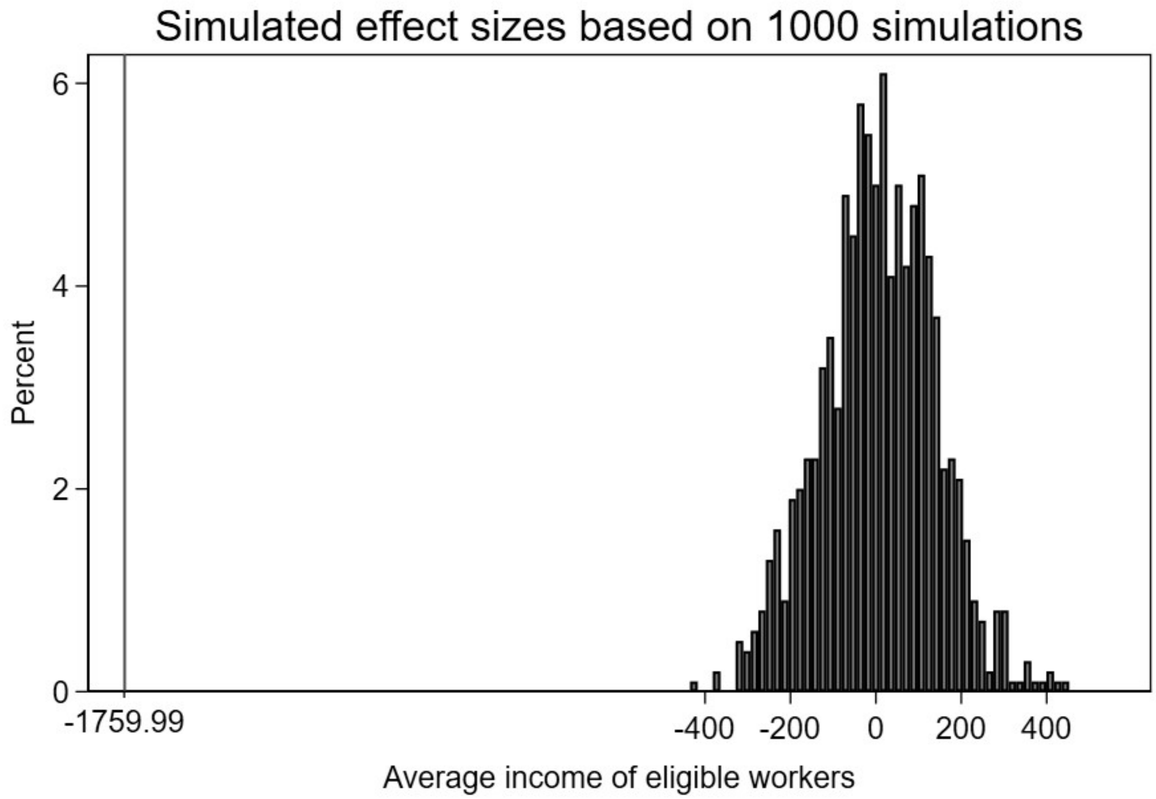
Note: The figure above depicts the trends observed in our outcome variable for both Eligible and Ineligible workers. The solid and dashed trend lines represent the average monthly income of Eligible and Ineligible workers, respectively, based on the dataset at hand. The left vertical dashed line indicates the moment when the ODOP policy was announced, while the right vertical dashed line signifies the complete implementation of the ODOP policy.

Figure 2: ***Event Study: Impact of ODOP on eligible workers' income***



Note: The figure plots the point estimates (solid bullets) for the impact of the ODOP on the income of eligible workers for different quadrimesters by considering 2nd quadrimester of 2018 as the reference period for comparison in our dynamic DiD model. The dynamic DiD model is based on the main regression specification (equation 1) including fixed effects and controls, by assigning the value 0 to the dummy variable $Post_t$ for data points belonging to the reference period. The horizontal lines indicate the 95% confidence intervals.

Figure 3: ***Results from random assignment***



Note: The figure shows the distribution of coefficients from the 1000 simulated regressions based on randomly assigned district-based treatment status among workers. We observe that the coefficients are centered around zero, and the true causal estimate of the ODOP from the main analysis (Table 3) is to the far left (indicated by a vertical green line). It gives us confidence that our empirical strategy identified the true effects rather than picking up any random variation between the treated and control group.

Table 1: *Summary Statistics*

	Full Sample		Industry: Textile		Footwear & Leather		Food Processing		Metal		Handicraft	
Variables	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean
Outcomes:												
Monthly Income	99,746	8748.23	34,025	7917.01	16,748	8774.22	17,592	9500.40	24,093	9538.93	7,288	8139.65
(Rs.)		(7143.74)		(6631.05)		(5958.97)		(9021.53)		(7450.11)		(4961.93)
Explanatory Variables:												
Age	100,346	36.07	34,227	36.69	16,865	33.73	17,782	38.04	24,184	35.18	7,288	36.68
(Years)		(12.41)		(12.56)		(11.78)		(12.44)		(11.99)		(13.24)
Gender	100,346	0.95	34,227	0.93	16,865	0.98	17,782	0.96	24,184	0.97	7,288	0.92
(Percent Male)		(0.21)		(0.26)		(0.13)		(0.18)		(0.15)		(0.26)
Literacy	100,346	0.95	34,227	0.96	16,865	0.96	17,782	0.96	24,184	0.92	7,288	0.94
(Percent Literate)		(0.21)		(0.18)		(0.20)		(0.18)		(0.25)		(0.21)
Bank Account	95,855	0.96	33,275	0.97	15,796	0.97	16,975	0.97	23,196	0.95	6,613	0.94
(Percent holding a Bank account)		(0.19)		(0.18)		(0.18)		(0.18)		(0.21)		(0.22)
Health status	92,503	0.98	31,998	0.99	15,129	0.98	16,673	0.99	22,135	0.98	6,568	0.97
(Percent Healthy)		(0.12)		(0.11)		(0.12)		(0.11)		(0.12)		(0.16)
Duration of employment	80,173	13.80	26,642	14.13	13,943	11.63	13,722	15.12	20,202	13.50	5,664	15.21
(Years)		(10.40)		(10.58)		(9.70)		(10.40)		(10.26)		(11.14)
Employment arrangement	59,598	0.35	18,292	0.51	10,704	0.13	10,676	0.49	15,234	0.16	4,692	0.57
(Percent Self-employed versus those employed by others)		(0.48)		(0.50)		(0.34)		(0.50)		(0.36)		(0.49)

Note: This table shows the summary statistics. The table also reports the summary statistics for all five industries for which products have been state-identified under the ODOP program. The table contains summary statistics for the outcome variable and all the explanatory variables used in the study. We have reported the summary statistics for the data used in our primary analysis from the year 2016 to 2019. Each subsample's first and second columns represent the number of observations and the variable's mean value for that subsample, respectively. Standard errors are reported in parentheses.

Table 2: ***Pre-policy Analysis***

	Monthly Income		
	(1)	(2)	(3)
Effect of ODOP	1089.07	-715.16	-942.90
	(620.36)	(960.89)	(1183.91)
Observations	62,355	29,946	29,946
R-squared	0.031	0.167	0.277
Industry FE	Yes	Yes	Yes
Controls	No	Yes	Yes
District FE	No	No	Yes

Note: This table reports the results from regression equation (1) after assigning value 1 to the dummy variable $Post_t$ for the observations from May 2017 to August 2018 and 0 for the observations from January 2016 to April 2017. This way, using CPHS (Consumer Pyramids Household Survey) dataset, we are analyzing the impact of product promotion on the income of eligible workers before the implementation of the ODOP program. We have three different specifications in three different columns. Column 1 represents the analysis from equation (1) without using district fixed effects and controls. Column 2 represents the analysis from equation (1) with household-level controls, but without district fixed effects. Column 3 represents the analysis from equation (1) using district fixed effects and controls. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ for three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, column 3. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively, in three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, and column 3. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Table 3: ***Primary Results***

	Monthly income		
	(1)	(2)	(3)
Effect of ODOP	-1107.12	-1933.46	-1759.99
	(824.67)	(750.45)	(738.22)
Observations	99,746	59,354	59,354
R-squared	0.027	0.153	0.229
Industry FE	Yes	Yes	Yes
Controls	No	Yes	Yes
District FE	No	No	Yes

Note: This table reports the results from the main regression specification described in the Methodology section. This way, using CPHS (Consumer Pyramids Household Survey) dataset, we are analyzing the impact of product promotion by the government on the income of eligible workers after the implementation of the ODOP program. We have three different specifications in three different columns. Column 1 represents the analysis from equation (1) without using district fixed effects and controls. Column 2 represents the analysis from equation (1) with household-level controls such as an individual's age, gender, a dummy to indicate whether an individual is literate or not, the number of years that an individual has spent in employment, the self-assessed status of an individual being healthy or not, a dummy to indicate whether an individual has a bank account or not, and a dummy to indicate whether an individual is self-employed or working for some employer, but without district fixed effects. Column 3 represents the analysis from equation (1) using district fixed effects and controls. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ for three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, column 3. The interaction term is our variable of interest as it represents the impact of the ODOP program on the income of eligible workers, post-program implementation. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively, in three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, and column 3. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Table 4: ***Individual Industry Results***

	Monthly income				
	Textile Industry	Footwear and Leather Industry	Food Processing Industry	Metal Industry	Handicraft Industry
Effect of ODOP	-2088.61	-2332.78	-3373.03	-1608.58	-1159.68
	(892.46)	(844.42)	(1715.61)	(748.44)	(706.76)
Observations	18,208	10,628	10,656	15,174	4,688
R-squared	0.306	0.224	0.246	0.261	0.281
Industry FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results by running the main regression specification described in the Methodology section on a subsample of workers from one industry at a time. This way, using the CPHS (Consumer Pyramids Household Survey) dataset, we analyze the program's impact separately on each of the five industries identified by the government for promotion under the ODOP. The impact has been estimated for all five industries using the main specification, including fixed effects and controls. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ using equation (1) for each industry separately. The interaction term is our variable of interest as it represents the impact of the ODOP program on the income of eligible workers, belonging to an industry. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Table 5: ***Mechanism: Descriptive Analysis***

	Promoted industry workers in their respective selected districts	Promoted industry workers in their non-selected districts	Non-promoted industry workers in the ODOP selected districts	Non-promoted industry workers in the districts not selected for ODOP
Growth in the proportion	34.00%	-19.14%	-0.19%	0.28%

Note: This table shows the descriptive statistics of the full dataset used for the main analysis to indicate the movement of workers between districts and across industries. We have reported the growth in the proportion of each group of workers by comparing the pre-program period with post-program period.

Table 6: ***Mechanism: Inferential Analysis***

	Probability of promoted industry workers being in their respective selected districts		
	(1)	(2)	(3)
Effect of ODOP	0.040	0.031	0.005
	(0.022)	(0.018)	(0.010)
Observations	1,00,346	59,354	59,354
R-squared	0.264	0.298	0.717
Industry FE	Yes	Yes	Yes
Controls	No	Yes	Yes
District FE	No	No	Yes

Note: This table reports the results after considering the 'eligible' dummy as the dependent variable in the main regression specification described in the Methodology section, keeping all other controls and fixed effects unchanged. This way, using CPHS (Consumer Pyramids Household Survey) dataset, we are analyzing the increase in the number of eligible workers, post-program implementation. We have three different specifications in three different columns. Column 1 represents the analysis without using district fixed effects and controls. Column 2 represents the analysis with household-level controls such as an individual's age, gender, a dummy to indicate whether an individual is literate or not, the number of years that an individual has spent in employment, the self-assessed status of an individual being healthy or not, a dummy to indicate whether an individual has a bank account or not, and a dummy to indicate whether an individual is self-employed or working for some employer, but without district fixed effects. Column 3 represents the analysis using district fixed effects and controls. Row 1 represents the point estimate of the variable of interest for three specifications depicted in three different columns, viz, column 1, column 2, and column 3. The point estimate represents the impact of the ODOP program on the number of promoted industry workers (eligible workers) in their respective selected districts. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively, in all three specifications depicted in three different columns, viz, column 1, column 2, and column 3. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Table 7: ***Results on a Placebo Group***

	Monthly income		
	(1)	(2)	(3)
Effect of ODOP	-1912.26	193.79	-57.21
	(1355.94)	(1254.99)	(1315.50)
Observations	1,15,283	69,104	69,104
R-squared	0.108	0.198	0.260
Industry FE	Yes	Yes	Yes
Controls	No	Yes	Yes
District FE	No	No	Yes

Note: This table reports the results from the falsification exercise. We run our regression equation (1) for individuals from government-selected districts for the promotion of ODOP products, but are not eligible workers as they are employed in industries other than the promoted industry for their district. This way, using the CPHS (Consumer Pyramids Household Survey) dataset, we are analyzing the impact on the income of ineligible workers after implementing the ODOP program. We have three different specifications in three different columns. Column 1 represents the analysis from equation (1) without using district fixed effects and controls. Column 2 represents the analysis from equation (1) with household-level controls such as an individual's age, gender, a dummy to indicate whether an individual is literate or not, the number of years that an individual has spent in employment, the self-assessed status of an individual being healthy or not, a dummy to indicate whether an individual has a bank account or not, and a dummy to indicate whether an individual is self-employed or working for some employer, but without district fixed effects. Column 3 represents the analysis from equation (1) using district fixed effects and controls. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ for three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, column 3. The interaction term is our variable of interest as it represents the impact of the ODOP program on the annual income of non-textile workers in state-identified textile cluster districts. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively, in three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, and column 3. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Table 8: ***Results from Winsorizing***

	Monthly Income		
	(1)	(2)	(3)
Effect of ODOP	-1039.28	-1869.27	-1702.29
	(781.16)	(705.57)	(697.91)
Observations	99,746	59,354	59,354
R-squared	0.029	0.176	0.270
Industry FE	Yes	Yes	Yes
Controls	No	Yes	Yes
District FE	No	No	Yes

Note: This table reports the results from winsorizing exercise. We run our regression equation (1) on the winsorized sample as described in this section. We have three different specifications in three different columns. Column 1 represents the analysis from equation (1) without using district fixed effects and controls. Column 2 represents the analysis from equation (1) with household-level controls such as an individual's age, gender, a dummy to indicate whether an individual is literate or not, the number of years that an individual has spent in employment, the self-assessed status of an individual being healthy or not, a dummy to indicate whether an individual has a bank account or not, and a dummy to indicate whether an individual is self-employed or working for some employer, but without district fixed effects. Column 3 represents the analysis from equation (1) using district fixed effects and controls. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ for three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, column 3. The interaction term is our variable of interest as it represents the impact of the ODOP program on the income of eligible workers. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively, in three specifications using equation (1) depicted in three different columns, viz, column 1, column 2, and column 3. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Appendix

Table A1: Primary Results with alternate specification

	Monthly income	
	(1)	(2)
Effect of ODOP	-1759.99	-1756.10
	(738.22)	(735.92)
Observations	59,354	59,354
R-squared	0.229	0.229
Industry FE	Yes	Yes
Controls	Yes	Yes
District FE	Yes	Yes
Time unit-specific FE	No	Yes

Note: This table reports the results from the alternate regression specification by adding time unit-specific fixed effects in the described in Methodology section. In this table, using two different regression specifications on CPHS (Consumer Pyramids Household Survey) dataset, we are reporting the results of the impact of product promotion by the government on the income of eligible workers after the implementation of the ODOP program. Column 1 represents the analysis from equation (1) with controls and District FE as described in the Methodology section, which is our main empirical framework. Column 2 represents the results from the alternate regression specification by adding time unit-specific fixed effects in equation (1) mentioned in the Methodology section. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ for both the specifications depicted in two different columns, viz, column 1 and column 2. The interaction term is our variable of interest as it represents the impact of the ODOP program on the income of eligible workers, post-program implementation. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively, in both specifications. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.

Table A2: Mapping of ODOP products with the industries registered in the CMIE dataset

Industry in CMIE Dataset	ODOP Product	Selected District
Textile Industry	Textile Products	Ambedkar Nagar
	Textile Products	Etawah
	Textile Products	Barabanki
Footwear and Leather Industry	Leather Products	Agra
	Leather Products	Kanpur Nagar
	Shoes	Hamirpur
Food Processing Industry	Food Processing (Desi Ghee)	Auraiya
	Food Processing (Pulses)	Balrampur
	Food Processing (Pulses)	Gonda
	Food Processing (Banana)	Kaushambi
	Asafoetida (Hing)	Hathras
	Food Processing (Aamla)	Pratapgarh
	Food Processing (Kala Namak Rice)	Siddharthnagar
Metal Industry	Brassware Craft	Sant Kabir Nagar
	Metal Craft	Moradabad
	Aluminium Utensils	Kanpur Dehat
	Ankle Bells (Ghungroo), Bells and Brass Products	Etah
	Iron Arts	Shamli
Handicraft	Wheat-Stalk Handicrafts	Bahraich
	Terracotta	Gorakhpur
	Horn-Bone Handicraft	Sambhal
	Handmade Paper Art	Jalaun
	Moonj Products	Sultanpur
	Moonj Products	Allahabad/Prayagraj
	Moonj Products	Amethi
	Jute Wall Hanging	Ghazipur
	Tribal Craft	Lakhimpur Kheri
	Banana Fiber Products	Kushinagar
	Black Pottery	Azamgarh
	Ceramic Product	Bulandshahar
	Tribal Craft	Shravasti
	Tarkashi Art	Mainpuri
	Decorative Products	Deoria
	Wood Craft	Basti
	Wood Craft	Bijnor
	Wood Crafting	Saharanpur
	Wood Work	Raebareli
	Furniture	Maharajganj
	Wooden Toys	Chitrakoot
	Shazar Stone Craft	Banda
	Gaura Stone Craft	Mahoba

Table A3: Winsorizing

	(1)	(2)	(3)	(4)	(5)	(6)
	Obs.	Winsor	Mean	Std. Dev.	Min.	Max.
Income of workers	99,746	N	8748.23	7143.74	0	120000
		Y	8567.14	6323.72	0	55000

Note: This table reports the summary statistics of the winsorized data. For our outcome variable, income of workers, we first report the statistics from the original dataset, without winsorizing. In the next row, we report the statistics for the winsorized data. Column 1 represents the number of observations in the dataset across treatment and control districts. Column 2 identifies whether the reported statistics are for the original dataset (N) or for the winsorized dataset (Y). Column 3 reports the mean of the outcome variable. Column 4 reports the standard deviation of the outcome variable. Column 5 represents the minimum value in the dataset for the outcome variable. Column 6 represents the maximum value in the dataset for the outcome variable.

Table A4: Effect of ODOP on native and migrant incomes

	Monthly income	
	Native Workers	Migrant Workers
	(1)	(2)
Effect of ODOP	-1853.60	-1481.13
	(729.76)	(707.12)
Observations	58,470	24,942
R-squared	0.232	0.242
Industry FE	Yes	Yes
Controls	Yes	Yes
District FE	Yes	Yes

Note: This table reports the heterogeneity results by running the main regression specification described in the Methodology section separately for native and migrant workers. Column 1 represents the analysis from equation (1) with controls and District FE as described in the Methodology section, which is our main empirical framework, on native eligible workers who were already in the treated districts and employed in their respective treated industries, even before the implementation of the program. Column 2 represents the analysis from equation (1) with controls and District FE as described in the Methodology section, which is our main empirical framework, on migrant workers of the ODOP products who sifted to their respective treated districts, after the program implementation. Row 1 represents the point estimate β_1 for the interaction term, $Eligible_{p,d} * Post_t$ for both the specifications depicted in two different columns, viz, column 1 and column 2. The interaction term is our variable of interest as it represents the impact of the ODOP program on the income of eligible workers, post-program implementation. Row 2 and 3 represent the total number of observations used and the value of R-squared, respectively. Robust standard errors clustered at the district level, which is the level of variation, are reported in parentheses.