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To Sew or Not to Sew?

Assessing the Welfare Effects of the Garment Industry in Cambodia

Carolina Mejía-Mantilla
Martha Tesfaye Woldemichael

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Poverty and Inequality Team
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Abstract

This paper uses the 2011 Cambodia Socio-Economic Survey to analyze the relationship between participation in the garment industry and household welfare. The analysis relies on propensity score matching estimators to investigate whether households that have at least one member employed in the textile and apparel sector are better off than those who do not participate in the garment industry, in terms of several monetary and non-monetary welfare indicators. The findings show that garment households are less likely to experience self-reported food insufficiency, and their children are more likely to be enrolled in school. Yet, the positive effect of the treatment is restricted to the bottom 40 percent of the consumption distribution, possibly due to the nature of garment jobs, and the fact that they represent an attractive alternative for the poorest households but not necessarily for the better-off. Using instrumental-variables, the analysis also shows that remittances originating from the textile and apparel sector relax household budget constraints, increasing expenditures in education, health, and investments in agricultural activities.

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To Sew or Not to Sew? Assessing the Welfare Effects of the Garment Industry in Cambodia*

Carolina Mejía-Mantilla† Martha Tesfaye Woldemichael‡

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†East Asia Pacific Region, Poverty and Equity Practice, World Bank. Email: cmejiamantilla@worldbank.org

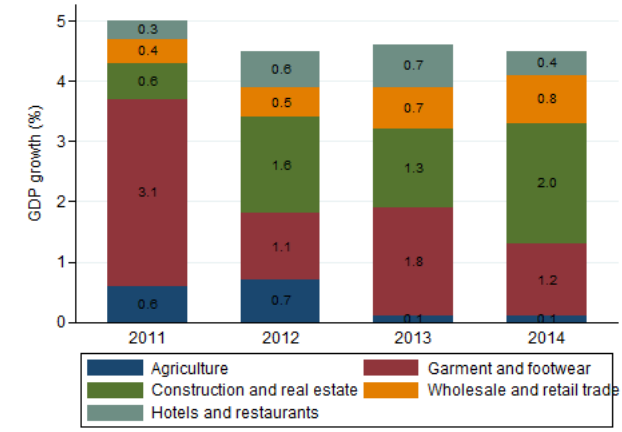
‡CERDI, Université Clermont Auvergne. Email: martha.t.woldemichael@gmail.com

1 Introduction

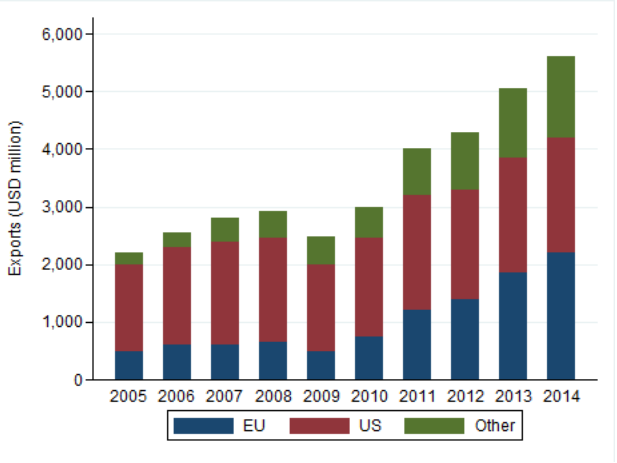
The garment industry has been one of the pillars of Cambodia's impressive economic growth in the past fifteen years, as well as the most important source of industrialization of the country. In 2014, it was the second highest contributor to GDP growth after the construction sector, accounting for 1.2 percentage points out of a total of 7.1 percentage points (Figure 1a). The value of garments exports reached USD 1.4 billion in 2015, representing around 75 percent of the country's total exports and constituting the main source of foreign direct investment. The primary destination of garment exports in 2015 was the EU market followed by the US, with a share of 40 and 30 percent respectively (Figure 1b). Although it has faced some challenges in recent years, including the appreciation of the US dollar[1] and the emergence of other Asian competitors such as Myanmar and Bangladesh, it is projected to remain a key engine of the economy for the foreseeable future.

Figure 1: Stylized Facts on the Garment Industry in Cambodia

(a) Sector Contribution to GDP Growth



(b) Main Destination Markets of Garment Exports



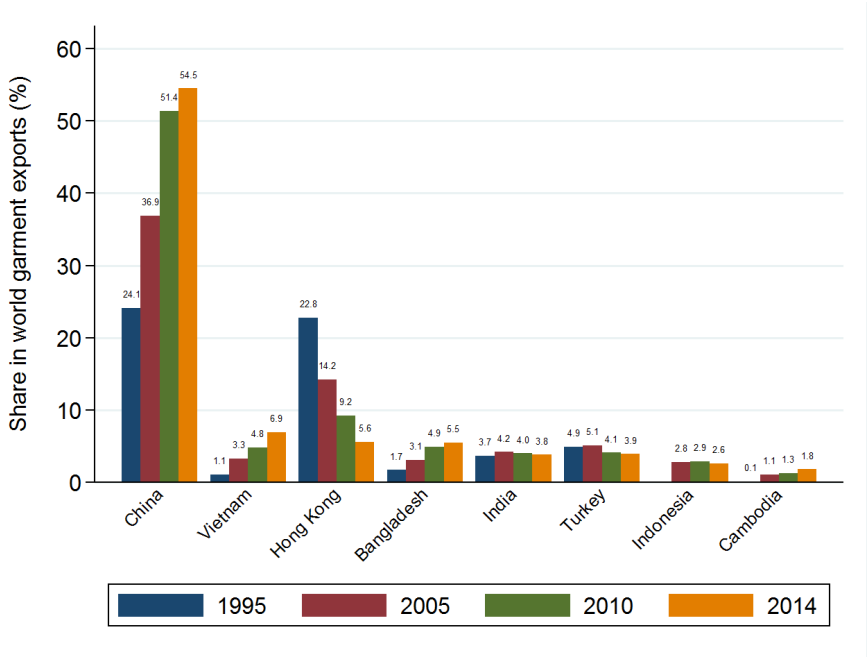
Notes: (a) Adapted from figures provided by Cambodian authorities. (b) Adapted from World Bank (2015). Exports are expressed in millions of USD. EU: European Union; US: United States.

The industry took off in 1999, with the bilateral textile agreement between the US and Cambodia, which granted Cambodia access to the US market for three years under the Multi-Fiber Agreement (MFA) quota system, and with the privileged access the EU granted to Cambodian apparel exports. Under the MFA, the initial quotas granted by the US to Cambodia were the most generous for any country (in per capita terms) and the agreement established that the quotas would increase annually if the country's firms and factories accepted to comply with internationally agreed labor standards, as well as the country's labor law. This initiative, initially known as the Better Factories Cambodia was the genesis of the Better Work Program, which currently operates in seven additional countries (Lopez-Acevedo and Robertson, 2012; Kotikula, Pournik, and Robertson, 2015). The MFA was extended for another three years in 2001 and it finally ended in 2005. Cambodia's access to the EU has continued under the Everything but

[1]The appreciation of the US dollar negatively affects Cambodian textile and apparel exports in a setting where most garment firms' costs are in dollars.

Arms Initiative (EBA), established in 2001 (Savchenko and Lopez-Acevedo, 2012) and, as mentioned, is nowadays the main garment export destination for the country. Access to both the US and the EU textile markets was a major incentive to investors from China; Hong Kong SAR, China; and the Republic of Korea, and the industry boomed in the country. Between 1995 and 2014, the contribution of Cambodia's garment exports to the world's garment exports increased from 0.1 percent in 2000 to 1.8 percent in 2014 (Figure 2).

Figure 2: Main Garment Exporters in the World



Notes: Adapted from UNCTAD (2015). Top 8 garment exporters in the world, ranked in descending order based on their 2014 performance. Indonesia's value for 1995 is missing.

Along with being an engine of economic growth, the garment industry in Cambodia is seen as a source of job opportunities for low-skilled workers, who usually belong to the poorest households and whose alternatives are the agricultural sector and/or informal economic activities. As of 2015, the garment sector employs approximately 600,000 workers, accounting for the lion's share of the total manufacturing labor force (Kotikula, Pournik, and Robertson, 2015). Jobs in the garment sector usually pay higher wages and are considered to be more stable over time, allowing households to enhance their acquisitive power and increase their well-being and savings over time (Robertson, Brown, Pierre, and Sanchez-Puerta, 2009). Moreover, 80 percent of textile and apparel workers in Cambodia are young women, mostly migrants from rural areas. Thus, garment manufacturing is considered to contribute to enhancing the socio-economic status of women in the country, with positive externalities on human capital investment through children's education (Kotikula, Pournik, and Robertson, 2015).

Despite its economic and social relevance, the garment industry in Cambodia has also received significant negative attention from the international community because of the working conditions that its employees face. Despite the existence of the Better Work Program, NGOs and international organizations still report concerns related to the poor working conditions, health and safety standards and child

labor (Cambodian Center for Human Rights, 2014). Strikes organized by the garment trade unions are common and headlines of confrontation between workers and official authorities often fill the pages of national and international newsletters.[2] Similarly, although the garment industry is the only sector in the economy for which there is a minimum wage,[3] workers often complain that wage increases are often met with steep increases in rents and food costs.

Against this background, this paper contributes to the contentious debate on the socio-economic advantages of the garment industry in Cambodia. It uses a rigorous empirical approach to explore the benefits of household participation in the textile and apparel sector. Instead of focusing on the labor market outcomes or the working conditions of garment workers, as most studies have, it explores the relationship between garment participation and monetary and non-monetary welfare indicators at the household level. More specifically, the study uses propensity score matching (PSM) estimators to identify the effect of having at least one household member employed in the garment sector[4] on a wide array of household level welfare-related measures using data from the Cambodia Socio-Economic Survey (CSES) collected in 2011. Monetary dimensions of welfare include consumption per capita, poverty and extreme poverty status, including the poverty gap, and asset ownership; while non-monetary indicators comprise the proportion of children aged 6-14 attending school and the self-reported incidence of food insufficiency.

In the absence of a good instrument for garment sector participation, we resort to PSM, an approach that has been widely used to estimate causal treatment effects in the evaluation literature. Its applications include, among others, the evaluation of labor market policies (Dehejia and Wahba, 1999; Bryson, 2002) and, closer to this paper, the identification of the effects of migration and remittances on household outcomes (Acosta, 2011; Cox-Edwards and Rodríguez-Oreggia, 2009; Jimenez-Soto and Brown, 2012; Bertoli and Marchetta, 2014). PSM estimators have the advantage of not requiring the introduction of functional forms of the relationship between household characteristics, participation in the garment sector and the measures of welfare. Our preferred specification uses kernel weights and estimates the standard errors using bootstrap, which provides a valid inference given that the estimator is asymptotically linear (Abadie and Imbens, 2008). However, since there is an on-going debate on whether the methodology can consistently produce unbiased estimates in the absence of an experimental approach (Dehejia and Wahba, 1999, 2002; Dehejia, 2005; Smith and Todd, 2001, 2005,b), Rosenbaum's bounding sensitivity test is used to assess the robustness of the estimates to unobserved heterogeneity (Rosenbaum, 2002, 2010).

Results suggest that garment households are 0.9 percentage point less likely to exhibit food insufficiency and 3.3 percentage points more likely to have children attending school relative to households who are not involved in the textile and apparel industry. Surprisingly, garment participation appears to be negatively associated to consumption and asset ownership. Nonetheless, the sign of these point estimates is reversed when we exclusively analyze the treatment effects for the bottom 40 percent of the consumption distribution. Amongst the poorest households, participation in the garment sector raises per capita consumption by 3 percent and enhances asset ownership by 2.6 percentage points. Benefits in

[2] "Violent Clash as Garment Strike Intensifies" The Phnom Penh Post, 12/28/2013; "Cambodia Garment Workers Killed in Clashes with Police" BBC News, 01/03/2014.

[3] As of January 2016, the minimum wage in the garment sector is USD 140 per month.

[4] Not necessarily living in the same household.

terms of food insufficiency and increased school enrollment appear even larger for this sample. Results are robust to different specifications of the selection model and to the use of alternative PSM techniques. Following Dehejia (2005), the covariates are balanced for both the full sample and the sub-sample of the bottom 40 percent of the distribution.

In other words, participation in the garment sector enhances the welfare of the poorest, while this is not true for the well-off households. A possible explanation for this result lies in the nature of the majority of textile and apparel jobs: while these low-skilled jobs represent an outstanding opportunity for the poorest households, they might actually be the last resort for the better-off. The majority of the firms operating in the garment sector are foreign-owned, and also, most top and middle managers as well as technically skilled workers and supervisors are foreigners (Lopez-Acevedo and Robertson, 2012). These results complement the findings of the studies that uncovered significant wage premiums and higher labor participation for low-skilled workers (particularly of rural extraction) employed in the apparel industry (Mammen and Paxson, 2000).

Moreover, we explore the remittances channel as a mechanism through which participation in the garment sector enhances well-being. Using an instrumental variables (IV) methodology, we find that garment remittances increase households' aggregate consumption per capita, as well as expenditures in education, health and agricultural productive inputs, such as fertilizer and pesticide. Overall, we conclude that the garment sector seems to be a positive factor in enhancing monetary and non-monetary welfare of households, particularly for those in the lower end of the distribution, adding to the results of Heath and Mobarak (2015) and De Hoyos, Bussolo, and Núñez (2012). However, these results should be interpreted as additional evidence on the benefits of the garment industry in a developing country, and not as an excuse to overrule or ignore concerns related to the working conditions or over-specialization of the labor force.

The main contributions of this paper are as follows. First, it complements the existing literature by analyzing the effect of garment participation at the household level on a wide range of welfare indicators, using a rigorous econometric approach. Second, it contributes to the on-going debate on the benefits and drawbacks of the garment sector in Cambodia; which is not only informative for the country but also for other countries in the East Asia Pacific region, such as Myanmar, where this sector is expanding. Finally, it contributes to the strand of literature that looks at the effects of remittances on poverty reduction and productive agricultural investments by exploring the welfare-enhancing effect of remittances in the Cambodian context.

The rest of the paper is organized as follows. Section 2 links this paper to the existing literature on the effects of the expansion of export-led sectors on development outcomes, to the literature on the effects of the garment sector on the labor outcomes of its workers in Cambodia and other countries, and finally to the literature that goes beyond labor market outcomes. Section 3 presents the data and some descriptive statistics, while Section 4 introduces the methodological approach. The empirical results are presented in Section 5, while Section 6 explores the remittances channel using instrumental variables. Section 7 concludes.

2 Review of Existing Studies

Since the early examples of the United Kingdom and the United States, industrialization and, more specifically, the textile sector, has been considered as a gateway to economic development. Garment and apparel manufacturing provide job opportunities for the low-skilled and contrary to other sectors, it enhances the labor participation and other labor outcomes of women (Keane and te Velde, 2008; Fukunishi, Murayama, Yamagata, and Nishiura, 2006; Yamagata, 2009; Fukunishi and Yamagata, 2013). Most of the studies that have analyzed the benefits of an expanding garment sector have indeed focused on the labor market outcomes of their workers. Several quantitative studies have shown the existence of a wage premium for garment and apparel workers, while qualitative studies have analyzed the non-wage working conditions of workers (Kotikula, Pournik, and Robertson, 2015). Robertson, Brown, Pierre, and Sanchez-Puerta (2009) report the existence of a wage premium in the garment sector in four out of five country-cases (Honduras, Cambodia, El Salvador, Madagascar; the exception being Indonesia) and indicate that the larger the foreign direct investment in the sector, the larger the wage premium. Interestingly, the highest wage premium reported for all countries corresponds to Cambodia, standing at around 35 percent. Similarly, Lopez-Acevedo and Robertson (2012) explore how apparel exports, employment, and wages changed after the end of the MFA in 2005 for various countries. As expected, the results vary by country: total employment and wage premium increased in Bangladesh, India, Pakistan and Vietnam, while they declined for Sri Lanka, Honduras and Mexico. For Cambodia, the end of the MFA resulted in a 20 percent increase of total employment while the garment wage premium declined, although it recovered in the following years.

In the specific case of Cambodia, Savchenko and Lopez-Acevedo (2012) use the Cambodia Socio-Economic data and Mincer wage equations to determine that the garment sector premium was around 28 percent during the 2004-2009 period. Similarly, they conclude that the expansion of the garment sector coincided with a narrowing of the gender wage gap in the country, supporting the hypothesis that this sector is beneficial for female unskilled workers. Finally, they find that the phasing out of the MFA negatively affected the working conditions in the garment sector, as measured by an average index of no-child labor and no-mandatory or unpaid overtime work. Similarly, Kotikula, Pournik, and Robertson (2015) report that amongst the workers employed in garment factories, there is no statistically significant difference between the self-reported wages of female and male workers, despite the fact that women are often concentrated among the lower-skilled occupations (such as sewer). In other words, they conclude that there is no gender wage gap within the garment industry, contrary to what is observed in other economic sectors.

However, few rigorous studies have explored how the benefits of the garment sector extend beyond labor market outcomes. In the case of Cambodia, Kotikula, Pournik, and Robertson (2015) present some summary statistics indicating that poverty in households that are not associated with the garment sector is slightly higher than in household that are, but there is no further analysis. Similarly, they present some evidence that a girl whose mother works in the garment sector has higher chance to attend school compared to a girl whose mother works in comparable sectors. This paper is closer to De Hoyos, Bussolo, and Núñez (2012) and Heath and Mobarak (2015), who carefully analyze the welfare implications of

the garment sector in Honduras and Bangladesh. The first study concludes that the maquila sector in Honduras not only has contributed to curb the gender gap in terms of wages but it also helped to reduce poverty. By setting the maquila wage premium to zero in wage income micro-simulations, they estimate that on average, the maquila premium by itself accounted for 0.31 percentage points in the reduction of the poverty incidence, and 0.44 percentage points when allowing for gender-specific effects. Similarly, Heath and Mobarak (2015) find that the rise of the garment industry in Bangladesh is associated with a lower risk of early marriage and childbirth for girls, both because girls postponed marriage and stayed in school to enhance their human capital. By taking advantage of the variation in the dates in which garment firms opened in the country, as well as the distance to the households from which data were collected, they estimate hazard models for age at marriage and age at first birth for girls with different exposure to factory jobs.

This paper also relates to a large body of literature that explores the relationship between labor outcomes and export-led growth in developing countries. As summarized nicely in Bernard, Jensen, Redding, and Schott (2007), export-oriented sectors are beneficial for economic development. Not only do they create more employment (particularly in low-income countries as suggested by Mammen and Paxson (2000)) and pay higher wages (Alvarez and Lopez, 2005; Arnold and Hussinger, 2005; Van Biesebroeck, 2005; De Loecker, 2007 and Sinani and Hobdari, 2010), they are also more productive and a source of innovation and technological progress.

3 Data and Descriptive Statistics

The data used in the analysis are drawn from the Cambodian Socio-Economic Survey (CSES), a comprehensive household survey collected by the National Institute of Statistics (NIS) to measure the living conditions of the population. It contains data on characteristics of the household, its consumption and various sources of income as well as individual-level data on education, economic activities, and health, among other factors. The survey is representative at the national level, and it is used both by the government and the World Bank to calculate poverty estimates. We use the 2011 wave of the CSES, as this is the latest year with a migration module, containing detailed information on the sector of employment and whereabouts of the migrants. This is key to our identification strategy given the profile of the workers employed in the garment sector: young females who migrate from rural areas to Phnom Penh, where most of garment firms are located (Kotikula, Pournik, and Robertson, 2015). This is confirmed in our sample where in 32 percent of the households that participate in the garment sector, the household member employed in the garment sector is a migrant.

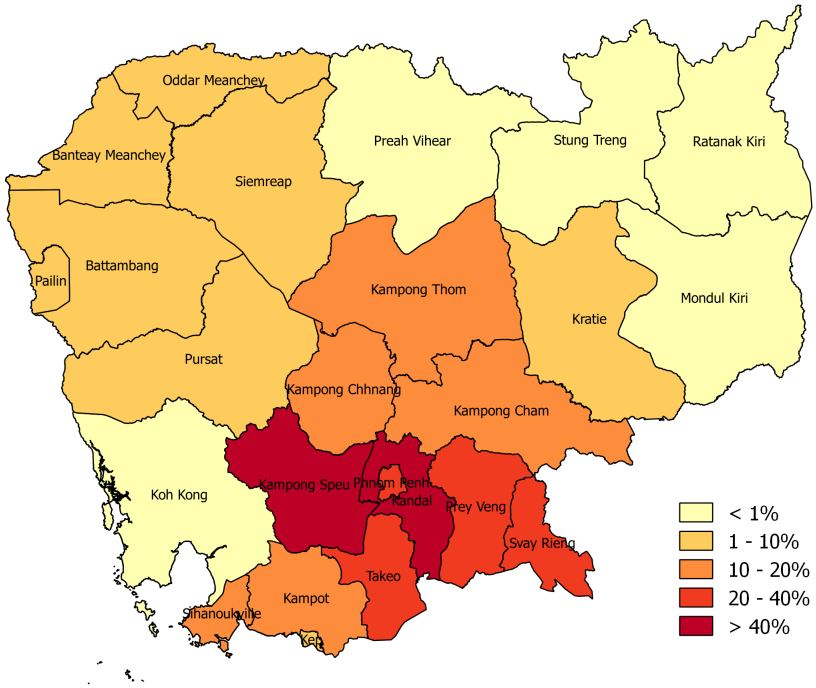
The data were collected from a sample of 3,518 households across Cambodia. Of those, 19 percent participate in the garment and apparel sector, where participation is defined as having at least one member of the household (migrant or living in the household) employed in the garment sector.[5] These garment households are identified on the basis of NIS-specific occupation codes,[6] when the member of

[5]The retained sample remains close to the original CSES 2011 comprising 3,592 households of which 74 (only 2 percent of households) were dropped due to missing values for some covariates of interest.

[6]Individuals whose occupation is described with the following NIS codes are identified as garment workers: 737 Rope

the household is a migrant, and of the International Standard Industrial Classification of All Economic Activities (ISIC)[7], when the member still lives in the household. Figure 3 depicts the distribution of garment households across Cambodian provinces.

Figure 3: Distribution of Garment Households across Provinces



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. The map displays the percentage share of treated households across Cambodian provinces. Figures are computed using sampling weights. Tbong Khmum province, which was only formed in 2013 when Kampong Cham Province was split in two, was merged with the latter to reflect the administrative provinces prevailing in 2011.

In addition, the following monetary and non-monetary welfare indicators are used in the analysis:

- *Monthly consumption per capita*: the consumption aggregate used here is the same used by the World Bank to estimate the poverty incidence in the country. It includes the following expenses: house services, housing, food, communication, personal, entertainment, school, health, durables, and other expenses. For durable goods, it uses the monthly use value of durable goods purchased in the last 12 months. Similarly, when households own the dwelling place in which they reside, the monthly use value of the house was estimated based on the characteristics and location of the household. The consumption aggregate is adjusted by a spatial price index to account for the price differences between households living in Phnom Penh, other urban areas and rural areas.

- *Asset index*: it is computed as the percentage of goods owned out of a list of 15 agricultural and non-agricultural durable goods accumulated to date by the household. These are: radio, television, bicy-

makers; 738 Handloom weavers, handicraft workers in textile, leather and related material; 754 Tailors, dress makers, furriers and hatters; 755 Garment and related trade workers; 756 Pelt, leather and related trades workers; 815 Textile, fur and leather products machine operators.

[7]Garment households have at least one member working in one of the following ISIC Revision 4 industry divisions: 13 Manufacture of textile; 14 Manufacture of wearing apparel; and 15 Manufacture of leather and related products.

cle, motorcycle, video/VCD/DVD recorder or player, refrigerator, electric fan, electric kitchen or gas stove, cell phone, electric iron, desktop or laptop computer, plough, harrow/rake/hoe/spade/axe, batteries and bed sets (bed mattress).

- *Poverty status*: a household is considered to be poor when its monthly consumption per capita is below the national poverty line, which includes a food component based on a minimum caloric intake recommended by the FAO, and a non-food allowance. In the case of Cambodia, three poverty lines[8] are used depending on the geographical location of the household. For 2011 the poverty lines were 182,935 Cambodian Riels (CR) for households residing in Phnom Penh, 146,846.94 CR for those living in other urban areas and 134,507.02 CR for those in rural areas. The poverty gap indicator, which measures the average shortfall of poor people, is also used. It is defined as the average distance of household consumption to the poverty line as a proportion of the poverty line (for the non-poor the distance is considered to be zero). The indicator is usually interpreted as the average amount that would have to be transferred to the poor to bring their expenditure up to the poverty line as a proportion of the poverty line.

- *Extreme poverty status*: similarly, a household is considered extremely poor when its monthly consumption per capita falls below the food component of the poverty line. As of 2011 the food component for Phnom Penh, other urban areas and rural areas was: 118,444.51 CR, 97,986.32 CR and 89,752.28 CR respectively.

- *Food insufficiency*: it is computed as the percentage share of the last 12 months during which the household reported not having enough food.

- *Children in school*: it refers to the proportion of children aged 6-14 attending school.

Table 1 presents the summary statistics of key variables used in the analysis, comparing garment households to their non-garment counterparts.[9] Garment households seem to display a lower level of per capita consumption, but the data also suggest they have accumulated more durable goods with an asset index of around 45 percent versus 42 percent for non-garment households. Poverty incidence is also less prevalent at 19 percent, compared to 21 percent for non-garment households. Similarly, the poverty gap index stands at 3.7 and 4.3 percent for garment and non-garment households respectively. The latter report experiencing food insufficiency about 2.68 percent of the last 12 months, while the corresponding figure for households participating in the textile and apparel industry is lower at 1.40 percent. Garment households also enjoy a higher rate of school enrollment for children aged 6-14 years (92 percent versus 88 percent).

[8] Poverty lines were determined in 2011 using 2009 data. A detailed description of the poverty methodology can be found in World Bank (2013).

[9] Descriptive statistics are computed using sampling weights.

Table 1: Descriptive Statistics by Treatment Status

	All HHs		Garment HHs		Non-Garment HHs	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Head's Characteristics						
Age of household head (years)	46.50	14.93	50.90	13.08	45.47	15.01
Schooling of household head (years)	5.12	4.20	5.02	3.77	5.14	4.29
Male headship	0.82	0.43	0.81	0.41	0.82	0.43
Married head	0.83	0.40	0.82	0.40	0.84	0.40
Employed head	0.91	0.32	0.89	0.35	0.92	0.31
Khmer ethnicity	0.97	0.18	0.98	0.15	0.97	0.19
Household Characteristics						
Urban residence	0.20	0.38	0.23	0.41	0.20	0.37
Household size	5.28	2.46	5.66	2.99	5.19	2.29
Dependency ratio (% working-age members)	73.72	81.05	50.03	59.39	79.21	83.45
Number of working female members	1.52	1.21	2.05	1.34	1.39	1.12
House ownership	0.97	0.14	0.97	0.12	0.98	0.14
Wall	0.15	0.35	0.14	0.35	0.15	0.35
Access to electricity	0.38	0.55	0.44	0.57	0.36	0.54
Access to water	0.46	0.58	0.49	0.58	0.46	0.58
Access to sanitation facilities	0.47	0.58	0.53	0.59	0.45	0.57
Primary education	0.64	0.55	0.69	0.52	0.63	0.55
Secondary education	0.66	0.55	0.81	0.44	0.63	0.56
Tertiary education	0.11	0.32	0.12	0.38	0.10	0.31
Welfare Indicators						
Consumption per capita (monthly, riels)	302,276	174,044	281,447	137,442	307,105	181,127
Asset index (% ownership of 15 durable goods)	42.47	19.80	45.03	18.01	41.88	20.06
Poverty	0.21	0.52	0.19	0.52	0.21	0.52
Extreme poverty	0.04	0.26	0.03	0.22	0.04	0.27
Poverty gap	0.04	0.14	0.04	0.13	0.04	0.14
Food insufficiency (% months)	2.44	13.64	1.40	7.55	2.68	14.67
School enrollment (% children aged 6-14)	88.48	31.53	92.33	26.08	87.73	32.41
Migration and Remittance Receipt						
Number of migrants	0.82	1.65	1.37	1.94	0.69	1.53
Share of migrant households	0.35	0.56	0.56	0.58	0.30	0.54
Share of remittance-recipient households	0.28	0.52	0.48	0.59	0.23	0.49
Remittances from all migrants (riels)	173,307	712,328	365,807	1,022,836	128,674	612,147
Remittances from employed migrants (riels)	161,770	673,416	338,623	920,066	120,766	596,253
Remittances from non-garment migrants (riels)	129,035	615,643	164,700	693,023	120,766	596,253
Observations	3,518		667		2851	

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. *Garment HHs* are households with at least one member (migrant or current member) working in the garment sector; *Non-Garment HHs* are households included in the control group; while *All HHs* combines both. Descriptive statistics are computed using sampling weights. For *school enrollment*, descriptive statistics are computed over a total sample of 1,799 households, among which 289 are treated and 1,510 are not involved in the garment industry. Variables: *Schooling of household head*: number of years of education of the head; *Male headship*: dummy equal to 1 if head is male; *Khmer ethnicity*: dummy equal to 1 if head is Khmer; *Urban residence*: dummy equal to 1 if urban household; *Household size*: number of household members; *Dependency ratio*: the ratio between dependents (children who are 14 years old and younger, and seniors who are 65 years and older) and working-age members (aged 15-64); *House ownership*: dummy equal to 1 if household owns the dwelling unit in which it resides; *Wall*: dummy equal to 1 if the primary construction material of the dwelling unit's walls is of superior quality (i.e. if made out of concrete, brick, stone or cement/asbestos); *Acess to water*: dummy equal to 1 if 1 if household has access to an improved water source both in wet and dry seasons; *Primary/Secondary/Tertiary education*: dummy equal to 1 if household has at least one working member who has completed some level of primary/secondary/tertiary education at most; *Welfare Indicators*: a detailed description is available in Section 3.

Furthermore, households that participate in the textile and apparel industry appear to be headed by older (51 versus 45 years old), less educated individuals (5.02 of education versus 5.14 years) who have a higher probability (0.82 versus 0.81) of being a man. Heads of garment households are also less likely to be married (82 percent versus 84 percent) or employed (89 percent of them have a job against 92 percent in the case of non-garment heads). In addition, garment households are larger in size (5.66 individuals versus 5.19), exhibit lower dependency ratios (50 percent against 79 percent), and host on average 2.05 female members (against 1.39 for non-garment households), consistent with the fact that the garment industry is intensive in female labor as documented in Section 2. In terms of housing conditions, 44 percent of garment households enjoy access to electricity, 53 percent have sanitation facilities and 49 percent benefit from an improved water source whereas corresponding figures for non-garment households are lower and stand at 36 percent, 45 percent and 46 percent respectively.

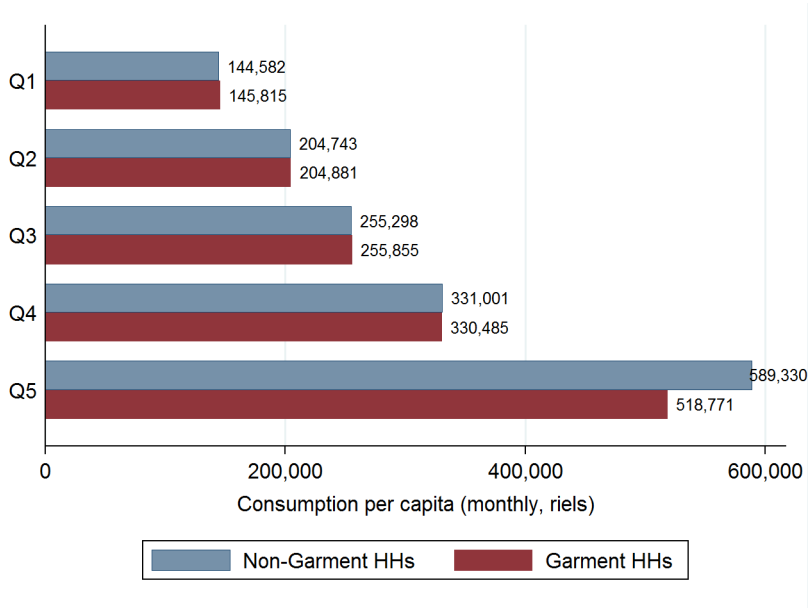
A closer look at the difference in consumption per capita between garment and non-garment households suggests that the full-sample result is driven by the top 20 percent of the distribution (Figure 4a). In other words, consumption is lower only for the richest households who are involved in the textile and apparel sector. Once households from quintile 5 are trimmed, consumption per capita turns out to be higher for garment households, with a mean difference of +3,424 CR. The gap even widens to +5,580 CR and is statistically significant at the 15 percent level when the analysis is further restricted to quintiles 1 and 2 which refer to the bottom 40 percent of the distribution. Combined with the observation that the poor and extremely poor are concentrated in the bottom 40 percent of the distribution,[10] this explains why a lower poverty incidence coincides with a lower level of consumption per capita for garment households compared to their non-garment counterparts in the complete sample.

A breakdown of the asset index by quintile portrays a similar picture, as only garment households from quintile 5 display lower asset accumulation with respect to non-garment households (55 percent against 58 percent respectively). On the contrary, the difference in means favors garment households across the remaining quintiles (Figure 4b). Garment households from the top 20 percent of the distribution also seem less likely to host a member who has completed tertiary education (22 percent against 31 percent) whereas the inverse holds across the remaining quintiles (Figure 4c). These stylized facts indicate that the differences between garment and non-garment households for the richest quintile are reversed in comparison with other quintiles. More specifically, for the richest quintile, households that participate in the textile and apparel industry consume less, own fewer durable goods, and are less likely to have at least one member who has completed tertiary education. In other words, they seem to be worse-off than their non-garment counterparts. This might be related to the nature of the jobs available in the garment sector and the fact that these possibly represent a "second best" or constrained choice for individuals in the richest households. Given their social and human capital characteristics, the wealthiest households would have earned more and been better-off in alternative non-garment occupations. It is worth noting that households in the richest quintile represent only 16 percent of households participating in the garment sector, while those in the bottom 40 percent of the distribution make up 42 percent of garment households (Figure A1).

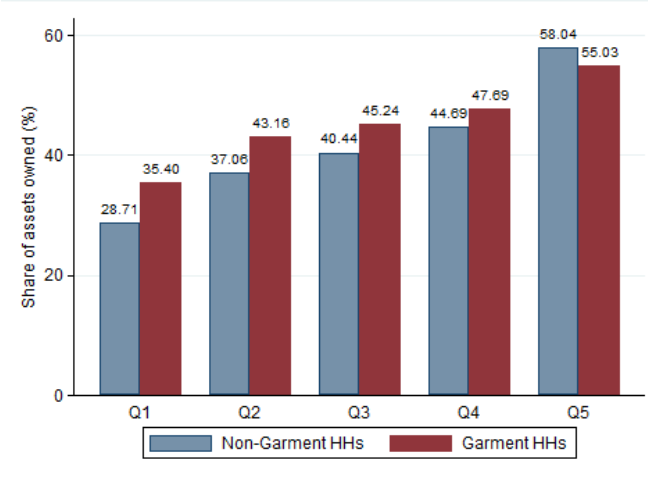
[10] Quintile 1 hosts all 82 extremely poor garment households whereas the 501 poor garment households are distributed over quintiles 1 and 2.

Figure 4: Quintile Distribution of Selected Variables

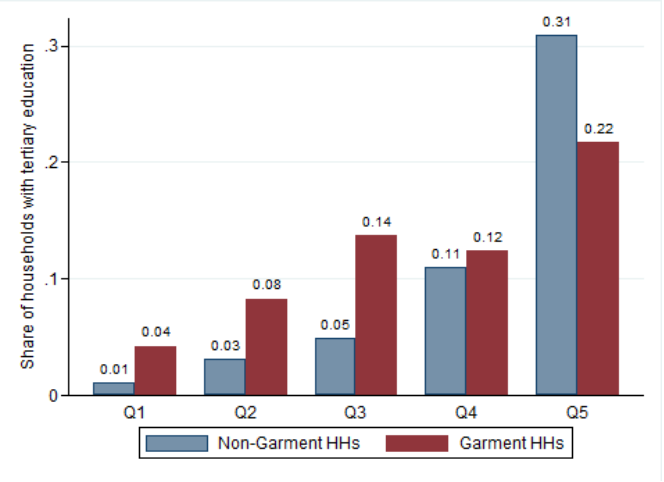
(a) Consumption per capita



(b) Asset index



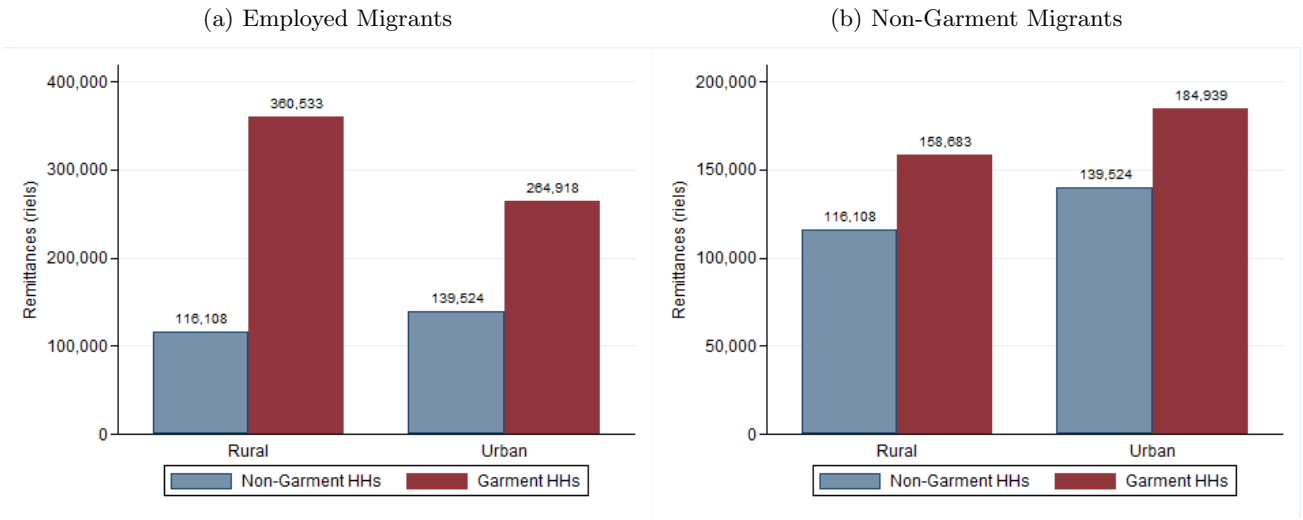
(c) Tertiary education



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Figures are computed using sampling weights. *Garment HHs* are households with at least one member (migrant or current member) working in the garment sector, while *Non-Garment HHs* are households included in the control group. *Consumption per capita* is total monthly per capita consumption in Phnom Penh prices. *Asset index* is the percentage share of goods owned out of a list of 15 agricultural and non-agricultural durable goods accumulated to date by the household, including i) radio; ii) television; iii) bicycle; iv) motorcycle; v) video, VCD or DVD recorder or player; vi) refrigerator; vii) electric fan; viii) electric kitchen kitchen or gas stove; ix) cell phone; x) electric iron; xi) desktop or laptop computer; xii) plough; xiii) harrow, rake, hoe, spade or axe; xiv) batteries and xv) bed sets. *Tertiary education* is the share of households with at least one working member who has completed tertiary education. *Q1* to *Q5* refer to quintiles 1 (poorest or least educated households) to 5 (richest or most educated households) of the variable's distribution. Difference in means is statistically significant for (a) the 5^{th} quintile only; (b) all quintiles; and (c) the 3^{rd} and 5^{th} quintiles only.

Table 1 also reports summary statistics pertaining to migration and remittances. It shows that the average number of migrants in garment households is 1.37, twice the figure reported for those that do not participate in the textile and apparel sector. Similarly, garment households receive on average more remittances from their employed migrants (Table 1), although the difference in means is statistically significant for rural households only (Figure 5a).[11] They also seem to be more dependent on migrant transfers, with remittances representing 3 percent of aggregate consumption, against 1 percent in the case of non-garment households.[12] Also, it is worth noting that by definition, total remittances channeled to households participating in the textile and apparel sector may originate from both garment and non-garment sectors (and possibly from unemployed migrants), whereas non-garment households can only receive non-garment remittances (and again, transfers from unemployed migrants).[13] Subsequently, it is crucial to disentangle the effect of remittances originating from garment workers and those sent by non-garment workers, especially in the case of hybrid households who host both types of migrants. In our case, the data do not seem to support any confounding effect of non-garment remittances as their amount does not statistically differ across garment and non-garment households, even after considering a further rural/urban breakdown (Figure 5b).[14]

Figure 5: Remittances Received by Rural and Urban Households



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Figures are computed using sampling weights. *Garment HHs* are households with at least one member (migrant or current member) working in the garment sector, while *Non-Garment HHs* are households included in the control group. Remittances are expressed in riels: (a) total amount of remittances received from employed migrants, whatever their occupation; (b) total amount of remittances received from migrants employed outside the garment sector. Difference in means is statistically significant for (a) rural households only; (b) neither rural, nor urban households.

[11] This result still holds even when the amount of remittances received is normalized by the number of remitters or by the size of the household.

[12] This difference in the remittances-to-consumption ratio holds for both rural and urban households.

[13] 2.4 percent of garment households receive remittances from unemployed migrants whereas the corresponding figure lies at 1.3 percent for households who are not involved in the textile and apparel sector. Unemployed migrants possibly send remittances out of their savings or the earnings of their spouse. The report by the Cooperation Committee for Cambodia (2005) indicates that amounts sent home sometimes include borrowed money.

[14] The same analysis holds for remittances sent by unemployed migrants.

Restricting the sample to households that participate in the textile and apparel sector seems to further highlight the importance of garment remittances. An average garment household typically has 2.5 times more non-garment migrants than garment migrants. Yet, the average ratio of garment-to-non-garment remittances stands at 1.2, suggesting that migrants working in the garment industry send more remittances than their non-garment counterparts. This is particularly true for rural garment households. Remittances received by a garment household from its migrants working in the textile and apparel sector represent 1.7 percent of its aggregate consumption, against 1.3 percent in the case of transfers originating from non-garment workers.[15]

Overall, garment households seem to be better-off when compared to their non-garment counterparts in most of the welfare dimensions being analyzed. Nonetheless, these comparisons do not account for selection into participation in the garment sector. Using propensity score matching estimators, this paper addresses the selection bias based on observable characteristics. Since the aim is to obtain a relationship between welfare and garment participation that is close to a causal inference, the methodology is complemented with sensitivity analyses based on Rosenbaum bounds, so as to measure how robust the results are to unobserved heterogeneity bias.[16]

4 Methodology

4.1 Setting the Framework

Let D_i be the treatment status dummy, which in this case takes the value of one if household i has at least one household member (migrant or current member) working in the garment sector. The value of the observed outcome of interest when $D_i = 1$ is equal to $Y_{i1(D=1)}$, whereas $Y_{i0(D=1)}$ is the potential outcome of the same household i if it had not participated in the garment industry. The average treatment effect on the treated (henceforth ATT), is defined as follows:

$$ATT = E[(Y_{i1} - Y_{i0}) \mid D_i = 1] = E[Y_{i1} \mid D_i = 1] - E[Y_{i0} \mid D_i = 1] \tag{1}$$

It measures the difference in the outcome of interest as a result of the treatment for household i. In practice, the observational rule for Y_i precludes the estimation of ATT as $Y_{i0(D=1)}$ cannot be observed. In an experimental scenario $E[Y_{i0} \mid D_i = 1] = E[Y_{i0} \mid D_i = 0]$, so the observed outcomes for the untreated observations can replace those of the treated observations to estimate the counterfactual. However, in a non-experimental scenario, this does not hold true, as the assignment into the treatment can be influenced by factors also affecting the outcome Y. In the specific case of this study, it could be that households residing in Phnom Penh are more likely to have a current member working in the textile and apparel sector as garment factories are concentrated in the capital city, and they are also more likely to register a higher economic status than their rural counterparts. Thus, the estimation of the ATT requires finding a proxy for the mean welfare outcome of garment households if they had not been treated.

[15] The ratio of garment remittances-to-consumption for rural households is twice the figure for urban households (2 percent and 1 percent respectively).

[16] More specifically, they determine how strongly an unmeasured variable must influence the selection process in order to undermine the results of propensity score matching estimators.

Matching estimators typically assume that there exists a set of observable characteristics X_i such that the outcomes are independent of assignment to treatment conditional on X_i. This is known as the unconfoundedness or conditional independence assumption (CIA). Formally:

$$Y_i \perp D_i \mid X_i \tag{2}$$

where Xi is the vector of covariates that jointly influence garment participation and welfare. This way, once controlling for confounding observables, systematic differences in the outcome of interest between treated and control households with the same values of covariates X_i are attributable to the treatment (Caliendo and Kopeinig, 2008).

Since conditioning on all relevant covariates is not straightforward in the case of a high dimensional vector of covariates X_i – *the curse of dimensionality* – matching is performed on a single dimension which summarizes the information given by X_i. Hence, the second key assumption for the propensity score matching methodology is that for all values of X_i, there is a positive probability $p(X)$ of assignment to treatment for both treated and untreated observations, known as the propensity score.[17] This *common support* or overlap condition ensures that there are comparable non-treated households for each treated household.

$$0 < Pr(D_i = 1 \mid X_i) < 1 \tag{3}$$

As Rosenbaum and Rubin (1983) demonstrated, if $p(X) \subset (0, 1]$ this implies that:

$$Y_i \perp D_i \mid p(X_i) \tag{4}$$

which in turn implies that the expected value of the unobserved outcome for treated observations $Y_{i0(D=1)}$ coincides with the expected value of the observed outcome for untreated observations $Y_{i1(D=1)}$, conditional on $p(X_i)$. Thus, if the conditional independence assumption and the common support conditions are met, then the counterfactual for the unobserved outcomes of treated observations can be proxied with the observed outcomes of the untreated observations.

Hence the ATT can be estimated as follows:

$$ATT = E[Y_{i1} \mid D_i = 1, p(X_i)] - E[Y_{i0} \mid D_i = 0, p(X_i)] \tag{5}$$

When both unconfoundedness and overlap are verified, the treatment is said to be strongly ignorable and allows proper identification of the ATT (Rosenbaum and Rubin, 1983).

4.2 Specifying and Estimating the Propensity Score Model

The estimation of the propensity score model is an essential step of the process as the omission of key variables can bias the estimated treatment effect (Heckman, Ichimura, and Todd, 1998; Dehejia and

[17] Formally, the propensity score is defined as $p(X_i) = E(D_i \mid X_i) = Pr(D_i = 1 \mid X_i)$ and is simply the probability of a household of having at least one member working in the garment industry given its observed characteristics X_i.

Wahba, 1999). As mentioned in Section 4.1, the covariates included in the vector X_i should influence both the probability of a household participating in the garment industry and the welfare outcomes of interest (Sianesi, 2004; Smith and Todd, 2005). Moreover, variables that are directly affected by participation in the garment sector should be excluded to avoid a reverse causality problem. As Caliendo and Kopeinig (2008) suggest, the aim is not to estimate the true propensity score as accurately as possible but to obtain treatment probabilities $p(X_i)$ that balance the covariates across treated and untreated households (in this case between garment and non-garment households). Achieving this balancing property may require the inclusion of higher-order and/or interaction terms among the selected household characteristics.

Given that the treatment is binary, the propensity score is estimated using a logit model:

$$p(X_i) = Pr(D_i = 1 \mid X_i) = \frac{e^{\beta X_i}}{1 + e^{\beta X_i}} \tag{6}$$

4.3 Choosing the Matching Method

To estimate the ATT, the counterfactual for the unobserved outcomes of the treated observations are proxied with the observed outcomes of the untreated observations. More specifically, the welfare outcome Y_i of each household i belonging to the set of treated households C_1 is matched to a weighted average of welfare outcomes of neighboring households from the pool of untreated households C_0 lying within the common support region. Following Dehejia and Wahba (2002), the region of common support is identified based on the minima and maxima criterion which consists in discarding households whose propensity score is smaller than the minimum and larger than the maximum in the opposite group. A credible range of the common support ensures comparable garment and non-garment households, hence minimizing off-support inferences.

Matching methods differ in how the neighborhood is defined. The weight w_{ij} attached to each untreated household j is proportional to the closeness of its observables to those of i proxied by the distance between their propensity scores. In our baseline specification, we rely on Epanechnikov-kernel weights following Heckman, Ichimura, and Todd (1998). Therefore, given the common support restriction, the ATT is calculated as follows:

$$ATT = \sum_{i \in C_1} [Y_{i1} - \sum_{j \in C_0} w_{ij} Y_{j0}] N_T^{-1} \tag{7}$$

where $w_{ij} \propto K[\frac{p(X_i) - p(X_j)}{h}]$, with $\sum_{j \in C_0} w_{ij} = 1$. h is the bandwidth parameter[18] and N_T stands for the number of matched garment households in the sample. As common in the literature (Heckman, 1997; Lechner, 2002; Black and Smith, 2004; Sianesi, 2004), standard errors of treatment effects are computed by bootstrapping with 500 replications. Bootstrapping is not inconsistent with kernel matching (Abadie and Imbens, 2006, 2008, 2011) and accounts for both sampling errors in the propensity score estimates and errors due to multiple matches for a single treated household (Johar, 2009).

Several alternative matching techniques are used to check the robustness of the baseline estimates derived from kernel weights matching: i) local linear regression matching, a method similar to kernel

[18] A large bandwidth reduces variance at the cost of increased bias. We use the default value $h = 0.06$.

matching except for the fact that it includes a linear term in the weighting function; ii) nearest-neighbor matching with replacement, in which each treated observation is matched with its n closest neighbors from the untreated observations, with a number of neighbors $n = 1$, 3 and 5; and finally iii) radius matching, where a tolerance level – the caliper - is imposed on the maximum propensity score distance; all untreated households within the caliper are used as matches (Dehejia and Wahba, 2002). A narrow ($r = 1\%$), medium ($r = 5\%$) and wide ($r = 10\%$) radius is alternatively used.

4.4 Assessing the Matching Quality

The quality of the matching procedure depends on how well the estimated treatment assignment probabilities balance the distribution of covariates across the treated and untreated groups. In this particular context, the matching is successful if there are no differences in observable characteristics between garment and non-garment households after conditioning on the propensity score (Imbens, 2004). A common approach to investigating the quality of the matching is to exploit the standardized bias indicator proposed by Rosenbaum and Rubin (1985). For each covariate, the standardized bias is computed as the difference of sample means in the treated and matched control sub-samples as a percentage of the square root of the average of sample variances in both groups (Caliendo and Kopeinig, 2008; Lechner, 1999):

$$SB = 100 \times \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{0.5[V_1(X) + V_0(X)]}} \tag{8}$$

where $X_1(V_1)$ is the mean (variance) in the treatment group and $X_0(V_0)$ is the mean (variance) in the control group. The standardized bias after matching should be less than 5%. t-tests for equality of means in the treated and untreated groups can also complement the assessment of the matching quality: they should be non-significant after matching to support the validity of the CIA. Following Sianesi (2004), another procedure consists in estimating the propensity score on both the unmatched sample (original sample) and the matched sample (i.e. on garment households and their matched non-garment counterparts), so as to compare the pseudo R^2s before and after matching.[19]

4.5 Assessing the Sensitivity of Estimates to Unobserved Heterogeneity

As described in Equation 2, one of the key identifications underlying PSM is conditional independence or selection on observables. The methodology does not account for possible hidden bias that might arise in the presence of unobservable characteristics affecting both the treatment and the outcome (Rosenbaum, 2002). Since it is unrealistic to completely rule out selection bias on unobservables in the context of this study, we carry out sensitivity analyses to assess the robustness of ATT estimates to departures from the conditional independence assumption.

Let u_i be an unmeasured confounder which determines household participation in the garment sector along with the vector of observable confounders X_i so that the propensity score model is now defined as

[19]Given that the pseudo R^2 measures how well the covariates explain the probability of garment participation in the logit model, the estimated treatment probabilities act as good balancing scores if the distributions of covariates across the two groups are similar, hence entailing a lower pseudo R^2 after matching. This is similar to rejecting the corresponding likelihood-ratio test of the joint significance of all covariates in the logit model of the propensity score after matching.

follows:

$$p(X_i, u_i) = Pr(D_i = 1 \mid X_i, u_i) = \frac{e^{\beta X_i + \gamma u_i}}{1 + e^{\beta X_i + \gamma u_i}} \tag{9}$$

The parameter γ reflects the extent to which unobservable confounders affect the probability of a household of having at least one member working in the garment industry. It implies that two households with similar observed covariates can still feature different probabilities of being treated due to unobserved heterogeneity. Rosenbaum (2002) shows that the odds ratio that these two households are involved in the garment sector is bounded within the interval $[e^{-\gamma}, e^{+\gamma}]$. Both households have the same probability of treatment if $e^{\gamma} = 1$, entailing the absence of unobserved selection bias. Subsequently, we rely on Rosenbaum (2002) bounds sensitivity tests to investigate the size of the hidden bias that jeopardizes the validity of the matching procedure. More specifically, we consider incremental levels of e^{γ} to determine how large the unmeasured confounder u_i can be before the significance of the estimated ATT is rejected. The higher the threshold, the more robust the point estimates are.[20]

5 Results

5.1 Selection Model

Recall that the treatment status for a household is to have one or more members, migrants or current residents, employed in the garment industry. The vector of covariates chosen for the baseline propensity score model includes variables pertaining to the household head, namely gender, age, years of education (in level and squared) and employment status. These characteristics of the household head are expected to influence both garment participation and welfare indicators. Similarly, they are considered stable over time and are not likely to be affected by the treatment status. The vector of covariates also comprises the size of the household, the total dependency ratio expressed as the ratio between dependents (defined as children who are 14 years old and younger, and seniors who are 65 years and older) and working-age members (individuals aged 15-64), as well as binary variables for urban residence, access to electricity and house ownership. We also include a dummy variable indicating whether the primary construction material of the dwelling unit's walls is of superior quality.[21] As a robustness check, the selection model is sequentially augmented with dummy variables reflecting household access to an improved water source during both wet and dry seasons, the marital status of the household head and ethnicity. In all cases, the overall results of the baseline model are robust to the inclusion of additional variables.

Results from the logit estimation of the propensity score are reported in Table 2. The treatment probabilities supporting our empirical approach are derived from the model displayed in Column 1 while the remaining specifications are used for robustness purposes. The coefficients on the regressors do not have a behavioral interpretation (Dehejia and Wahba, 2002; Bertoli and Marchetta, 2014), but it is worth noting that most of them are significant and bear the expected sign. The hump-shaped relationship

[20] Becker and Caliendo (2007) provide an implementation of the Rosenbaum bounding approach in the case of binary-outcome variables. We use DiPrete and Gangl (2004)'s *rbounds* Stata routine which extends to continuous-outcome variables.

[21] Walls are deemed of superior quality if they are primarily made out of concrete, brick, stone or cement/asbestos.

between participation in the garment sector and the years of education of the household head suggests that once the threshold of 5.5 years is reached, additional years of education decrease the likelihood of participation. This is likely related to the fact that an educated individual will probably opt for higher-skilled jobs. Female headship and the age of the household head are positively correlated with the dependent variable, although the employment status of the head does not seem to exert any significant influence. This is not surprising as there is little variation in the employment status of household heads, as only 9 percent of them are unemployed.

Table 2: Propensity Score Estimation

	(1)	(2)	(3)	(4)
Head's years of education	0.132***	0.131***	0.131***	0.129***
	(0.035)	(0.035)	(0.035)	(0.035)
Head's years of education^2	-0.012***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Male headship	-0.249**	-0.350*	-0.246**	-0.243**
	(0.113)	(0.194)	(0.113)	(0.113)
Head's age	0.015***	0.016***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
Head's employed	-0.001	-0.005	-0.001	0.013
	(0.152)	(0.152)	(0.152)	(0.152)
Household size	0.104***	0.101***	0.104***	0.104***
	(0.024)	(0.024)	(0.024)	(0.024)
Urban	-0.180	-0.178	-0.180	-0.234*
	(0.127)	(0.127)	(0.127)	(0.131)
Dependency ratio	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
House ownership	-0.816***	-0.823***	-0.819***	-0.796***
	(0.189)	(0.189)	(0.189)	(0.189)
Wall	-0.275**	-0.276**	-0.277**	-0.314**
	(0.128)	(0.128)	(0.128)	(0.129)
Electricity	0.341***	0.341***	0.344***	0.336***
	(0.117)	(0.117)	(0.117)	(0.118)
Head's married		0.128		
		(0.202)		
Khmer ethnicity			0.150	
			(0.294)	
Access to water				0.216**
				(0.099)
Constant	-1.575***	-1.595***	-1.713***	-1.674***
	(0.334)	(0.336)	(0.432)	(0.338)
Observations	3,518	3,518	3,518	3,518
Pseudo R^2	0.051	0.051	0.051	0.053

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Logit estimates. The dependent variable is a dummy for household participation in the garment sector. Standard errors are given in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. Section 5.1 provides a detailed description of included variables.

Dummies for house ownership and superior quality of the dwelling unit's walls are negatively related with garment participation, while the inverse is true for households who have access to water and electricity. The coefficient on the dummy for urban residence is negative but not significant, except in Column 4, probably reflecting the fact that rural households are more likely to participate in the apparel and textile industry by sending a member to work in garment factories located in the cities.[22] Finally, an increase in the size of the household raises the likelihood of participating in garment whereas a high dependency ratio reduces it due to the lower number of working-age members with respect to dependents.

5.2 Results from the Matching Estimators

Table 3 presents ATT estimates of participating in the garment sector on the welfare indicators of interest at the household level: consumption per capita, poverty, extreme poverty, poverty gap index, asset index, food insufficiency, and school enrollment. Results from the kernel matching suggest that the share of the past 12 months for which households declare having experienced food insufficiency is 0.9 percentage points lower for garment households. Similarly, the proportion of children aged 6-14 attending school is 3.3 percentage points higher among garment households relative to the control group. While the size of the effect is modest, the ATT estimates on school enrollment range from 4.7 to 5.8 percentage points and are slightly larger when considering the nearest-neighbor matching methodology but they convey the same qualitative message that children aged 6-14 years enjoy higher school enrollment rates when at least one adult in the household works in garment factories. This result is line with Heath and Mobarak (2015) who show that exposure to garments jobs promotes the educational attainment of girls, contributing to close the gender enrollment gap. Likewise, it also complements the evidence presented by Kotikula, Pournik, and Robertson (2015) showing that working in the textile and apparel industry raises school attainment. Turning to monetary measures of welfare, the ATT estimates on poverty, extreme poverty and the poverty gap bear the expected negative sign but are statistically insignificant. However, garment participation appears to be negatively associated with consumption per capita and asset ownership, with coefficients of 9 percent and 1.1 percentage points respectively (using kernel matching).

Nonetheless, the sign of the point estimates on consumption and asset ownership is reversed when the treatment effect is analyzed for households in the bottom 40 percent of the consumption distribution, the reference population for *shared prosperity*.[23] The results for this subset of the total sample are summarized in Table 4. For the poorest households, participation in the garment sector raises per capita consumption by 3 percent and enhances asset ownership by 2.4 to 3.2 percentage points. As expected, benefits in terms of reduced exposure to food insufficiency and increased school enrollment appear even larger for the least well-off: food insufficiency is 1.7 percentage points lower for garment households, while school enrollment is 9.3 percentage points higher. While the size of the effect on consumption, assets and food insufficiency is modest, the one on school enrollment is substantial. As before, nearest-neighbor matching yields the largest ATT estimates, with coefficients on school enrollment ranging from 12.9 to 13.6 percentage points.

[22] 77 percent of treated households reside in rural areas. Rural concentration of garment households is even starker when the treatment variable is restricted to garment participation through a migrant member: in this case 90 percent of garment households are rural dwellers. The corresponding figure unsurprisingly falls to 73 percent when the treatment excludes participation to garment via migration and solely focuses on garment workers who are currently residing in the household.

[23] This indicator is defined by the World Bank as the consumption growth of the bottom 40 percent of the distribution.

Table 3: Propensity Score Matching Estimates, Full Sample

	Kernel matching	Local linear matching	Radius matching			Nearest-Neighbor matching		
			r = 1%	r = 5%	r = 10%	n = 1	n = 3	n = 5
ATT, *Consumption per cap.*	-0.091***	-0.093***	-0.091***	-0.090***	-0.087***	-0.094***	-0.083***	-0.087***
	(0.015)	(0.017)	(0.018)	(0.016)	(0.016)	(0.034)	(0.028)	(0.024)
Median bias	0.5	1.2	1.2	0.5	3.0	1.2	2.2	2.3
Pseudo R^2	0.001	0.002	0.000	0.001	0.007	0.002	0.002	0.001
LR test (p-value)	1.000	0.967	0.570	1.000	0.352	0.967	0.979	1.000
Rosenbaum test	1.5	1.5	1.5	1.5	1.5	1.3	1.5	1.5
ATT, *Asset index*	-1.091*	-1.705***	-1.428**	-1.043*	-0.456	-0.718	-1.262	-1.159
	(0.584)	(0.607)	(0.639)	(0.593)	(0.586)	(1.197)	(0.961)	(0.899)
Median bias	0.5	1.2	1.2	0.5	3.0	1.2	2.2	2.3
Pseudo R^2	0.001	0.002	0.000	0.001	0.007	0.002	0.002	0.001
LR test (p-value)	1.000	0.967	0.570	1.000	0.352	0.967	0.979	1.000
Rosenbaum test	1	1.1	1.1	1	1	1	1	1
ATT, *Poverty*	-0.009	-0.012	-0.007	-0.010	-0.012	0.003	-0.004	-0.004
	(0.013)	(0.013)	(0.013)	(0.014)	(0.012)	(0.023)	(0.019)	(0.017)
Median bias	0.5	1.2	1.2	0.5	3.0	1.2	2.2	2.3
Pseudo R^2	0.001	0.002	0.000	0.001	0.007	0.002	0.002	0.001
LR test (p-value)	1.000	0.967	0.570	1.000	0.352	0.967	0.979	1.000
Rosenbaum test	3	3	3	3	3	1	3	3
ATT, *Extreme Poverty*	-0.007	-0.007	-0.008	-0.007	-0.008	-0.019*	-0.008	-0.007
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.010)	(0.008)	(0.008)
Median bias	0.5	1.2	1.2	0.5	3.0	1.2	2.2	2.3
Pseudo R^2	0.001	0.002	0.000	0.001	0.007	0.002	0.002	0.001
LR test (p-value)	1.000	0.967	0.570	1.000	0.352	0.967	0.979	1.000
Rosenbaum test	>3	>3	>3	>3	>3	1.4	>3	>3
ATT, *Poverty gap*	-0.003	-0.003	-0.003	-0.003	-0.003	-0.005	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
Median bias	0.5	1.2	1.2	0.5	3.0	1.2	2.2	2.3
Pseudo R^2	0.001	0.002	0.000	0.001	0.007	0.002	0.002	0.001
LR test (p-value)	1.000	0.967	1.000	1.000	0.352	0.967	0.979	1.000
Rosenbaum test	>3	>3	>3	>3	>3	1	2.1	2.7
ATT, *Food insufficiency*	-0.871***	-0.919***	-0.849***	-0.874***	-0.889***	-1.072*	-0.725	-0.832*
	(0.279)	(0.273)	(0.311)	(0.271)	(0.255)	(0.615)	(0.468)	(0.427)
Median bias	0.5	1.2	1.2	0.5	3.0	1.2	2.2	2.3
Pseudo R^2	0.001	0.002	0.000	0.001	0.007	0.002	0.002	0.001
LR test (p-value)	1.000	0.967	0.570	1.000	0.352	0.967	0.979	1.000
Rosenbaum test	>3	>3	>3	>3	>3	1.1	>3	>3
ATT, *School enrollment*	3.337**	3.321*	3.765**	3.263**	3.317**	5.353**	5.755**	4.695**
	(1.559)	(1.699)	(1.700)	(1.606)	(1.508)	(2.713)	(2.298)	(1.991)
Median bias	1.0	1.6	1.4	0.9	3.8	1.6	1.7	1.8
Pseudo R^2	0.001	0.005	0.001	0.001	0.007	0.005	0.002	0.001
LR test (p-value)	1.000	0.972	0.660	1.000	0.889	0.972	1.000	1.000
Rosenbaum test	>3	>3	>3	>3	>3	1.4	>3	>3
Observations	3,518	3,518	3,518	3,518	3,518	3,518	3,518	3,518
# of Treated Obs.	667	667	667	667	667	667	667	667
# of Control Obs.	2,851	2,851	2,851	2,851	2,851	2,851	2851	2851

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Bootstrapped standard errors based on 500 replications are reported in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. *ATT*: Average Treatment effect on the Treated. *Median bias*: median post-matching absolute bias. *Pseudo* R^2: pseudo R^2 derived from the estimation of the propensity score on the sample of garment households and their matched non-garment counterparts. *LR test (p-value)*: p-value of the likelihood-ratio test of the joint significance of all covariates in the logit model of the propensity score after matching. *Rosenbaum test*: the level of e^{γ} (see Section 4.5) beyond which the ATT is no longer significant at the 10% confidence level.

Table 4: Propensity Score Matching Estimates, Bottom 40 percent

	Kernel matching	Local linear matching	Radius matching			Nearest-Neighbor matching		
			r = 1%	r = 5%	r = 10%	n = 1	n = 3	n = 5
ATT, *Consumption per cap.*	0.030*	0.029*	0.037**	0.029*	0.030*	0.031	0.031	0.031
	(0.016)	(0.017)	(0.019)	(0.017)	(0.016)	(0.029)	(0.025)	(0.022)
Median bias	2.4	8.7	3.7	2.3	3.7	8.7	2.0	4.6
Pseudo R^2	0.001	0.019	0.004	0.001	0.004	0.019	0.007	0.007
LR test (p-value)	1.000	0.476	0.997	1.000	0.998	0.476	0.976	0.977
Rosenbaum test	1.5	1.5	1.6	1.5	1.5	1.1	1.3	1.4
ATT, *Asset index*	2.571**	2.407**	2.583**	2.588**	3.163***	2.702	2.001	2.541*
	(1.103)	(1.107)	(1.182)	(1.053)	(1.013)	(1.891)	(1.542)	(1.368)
Median bias	2.4	8.7	3.7	2.3	3.7	8.7	2.0	4.6
Pseudo R^2	0.001	0.019	0.004	0.001	0.004	0.019	0.007	0.007
LR test (p-value)	1.000	0.476	0.997	1.000	0.998	0.476	0.976	0.977
Rosenbaum test	1.4	1.3	1.3	1.4	1.5	1.2	1.2	1.3
ATT, *Poverty*	-0.079**	-0.082**	-0.095**	-0.076**	-0.073**	-0.125**	-0.083	-0.071
	(0.040)	(0.039)	(0.045)	(0.039)	(0.037)	(0.062)	(0.053)	(0.046)
Median bias	2.4	8.7	3.7	2.3	3.7	8.7	2.0	4.6
Pseudo R^2	0.001	0.019	0.004	0.001	0.004	0.019	0.007	0.007
LR test (p-value)	1.000	0.476	0.997	1.000	0.998	0.476	0.976	0.977
Rosenbaum test	1	1	1.3	1	1	1.3	1.2	1.1
ATT, *Extreme Poverty*	-0.033	-0.032*	-0.038*	-0.033*	-0.033*	-0.030	-0.030	-0.037
	(0.021)	(0.019)	(0.023)	(0.020)	(0.020)	(0.037)	(0.030)	(0.026)
Median bias	2.4	8.7	3.7	2.3	3.7	8.7	2.0	4.6
Pseudo R^2	0.001	0.019	0.004	0.001	0.004	0.019	0.007	0.007
LR test (p-value)	1.000	0.476	0.997	1.000	0.998	0.476	0.976	0.977
Rosenbaum test	>3	>3	>3	>3	>3	1	2.4	>3
ATT, *Poverty gap*	-0.017*	-0.017	-0.023*	-0.017*	-0.018*	-0.016	-0.020	-0.020
	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)	(0.017)	(0.015)	(0.013)
Median bias	2.4	8.7	3.7	2.3	3.7	8.7	2.0	4.6
Pseudo R^2	0.001	0.019	0.004	0.001	0.004	0.019	0.007	0.007
LR test (p-value)	1.000	0.476	0.997	1.000	0.998	0.476	0.976	0.977
Rosenbaum test	1.7	1.7	1.7	1.7	1.7	1.2	1.6	1.6
ATT, *Food insufficiency*	-1.755**	-1.727**	-1.851**	-1.735**	-1.657**	-2.325	-1.398	-1.770*
	(0.770)	(0.774)	(0.847)	(0.781)	(0.788)	(1.504)	(1.220)	(1.039)
Median bias	2.4	8.7	3.7	2.3	3.7	8.7	2.0	4.6
Pseudo R^2	0.001	0.019	0.004	0.001	0.004	0.019	0.007	0.007
LR test (p-value)	1.000	0.476	0.997	1.000	0.998	0.476	0.976	0.977
Rosenbaum test	>3	>3	>3	>3	>3	1.1	2	>3
ATT, *School enrollment*	9.319***	9.079***	11.278***	9.171***	8.959***	13.491***	13.580***	12.876***
	(2.613)	(2.413)	(2.897)	(2.690)	(2.504)	(5.001)	(3.956)	(3.516)
Median bias	3.5	10.1	7.7	3.6	3.5	10.1	3.9	4
Pseudo R^2	0.001	0.025	0.010	0.003	0.004	0.025	0.003	0.005
LR test (p-value)	0.94	0.648	0.986	1.000	1.000	0.648	1.000	0.999
Rosenbaum test	>3	>3	>3	>3	>3	1.8	>3	>3
Observations	1,052	1,052	1,052	1,052	1,052	1,052	1,052	1,052
# of Treated Obs.	200	200	200	200	200	200	200	200
# of Control Obs.	852	852	852	852	852	852	852	852

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Bootstrapped standard errors based on 500 replications are reported in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. *ATT*: Average Treatment effect on the Treated. *Median bias*: median post-matching absolute bias. *Pseudo* R^2: pseudo R^2 derived from the estimation of the propensity score on the sample of garment households and their matched non-garment counterparts. *LR test (p-value)*: p-value of the likelihood-ratio test of the joint significance of all covariates in the logit model of the propensity score after matching. *Rosenbaum test*: the level of e^{γ} (see Section 4.5) beyond which the ATT is no longer significant at the 10% confidence level.

Consistent with the consumption estimates, garment participation has now a statistically significant poverty-reducing effect of around 8 percentage points. Table 4 also indicates a 3 percentage point reduction in the incidence of extreme poverty and a 1.7 percentage point reduction in the poverty gap index among the garment households of the bottom 40 percent. The statistically significant negative effect of garment participation on poverty echoes the findings of De Hoyos, Bussolo, and Núñez (2012) and Yamagata (2006), among others. Overall, our results are robust to the use of different PSM techniques. They also remain quantitatively and qualitatively similar when resorting to alternative specifications of the propensity score model (results are available upon request).

The reversal of the sign of the ATT on consumption per capita and asset accumulation suggests that the welfare-enhancing potential of the garment industry is specific to the poorest households. This is consistent with the descriptive statistics depicted in Figure 4a, which shows that consumption is significantly larger for non-garment households only in the richest quintile of the distribution. We further probe this result by plotting the density distribution of consumption per capita for both treated and control groups, revealing that garment households are not homogeneously distributed across the income spectrum and that they are particularly absent from the last fifth of the sample (Figure A2). As discussed above, for the richest households, the low-skilled jobs offered by the garment sector probably pay less than other alternatives. Our findings relate to the strand of the literature that reports significant wage premiums and higher labor participation for low-skilled workers (particularly of rural extraction) employed in the apparel industry (Robertson, Brown, Pierre, and Sanchez-Puerta, 2009; Savchenko, Lopez-Acevedo, and Robertson, 2014). Our results suggest that an expanding apparel sector is likely to help lift least well-off households out of poverty by offering them opportunities in better-earning jobs.

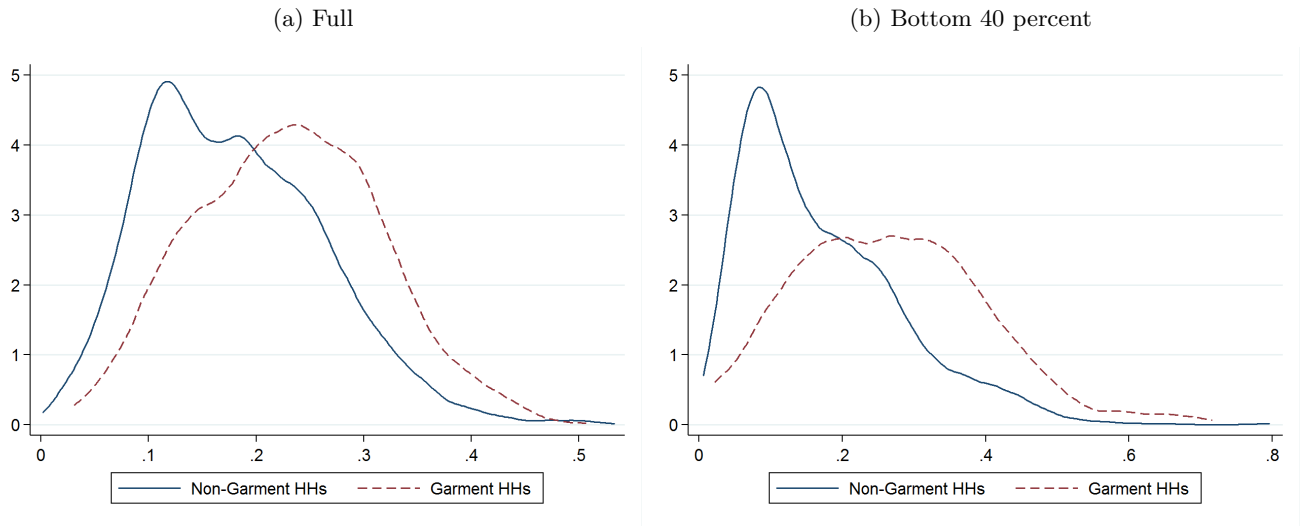
A set of graphs, statistics and diagnostic tests, introduced in Section 4.4, indicate that the quality of the matching is satisfactory for both the entire sample and the bottom 40 percent sub-sample. Figure 6 depicts the distribution density of propensity scores for garment and non-garment households over both samples analyzed. The fairly large overlapping areas reveal a rather good region of common support.[24] More importantly, the low pseudo R^2 derived from the estimation of the propensity score on the sample of garment households and their matched non-garment counterparts also indicates that the estimated treatment probabilities result in good balancing.[25] Finally, the matching was effective in building a comparable control group by reducing the extent of the covariate imbalance as further suggested in Figure 7. This is summarized by the median post-matching absolute bias reported below each ATT estimate which is less than 5 percent.[26]

[24] In the case of the bottom 40 percent, it turns out that one garment household falls outside the region of common support. The removal of this single treated household does not change the results of the analysis.

[25] Similar information is relayed by the high p-value of the likelihood ratio-test of joint insignificance of all regressors.

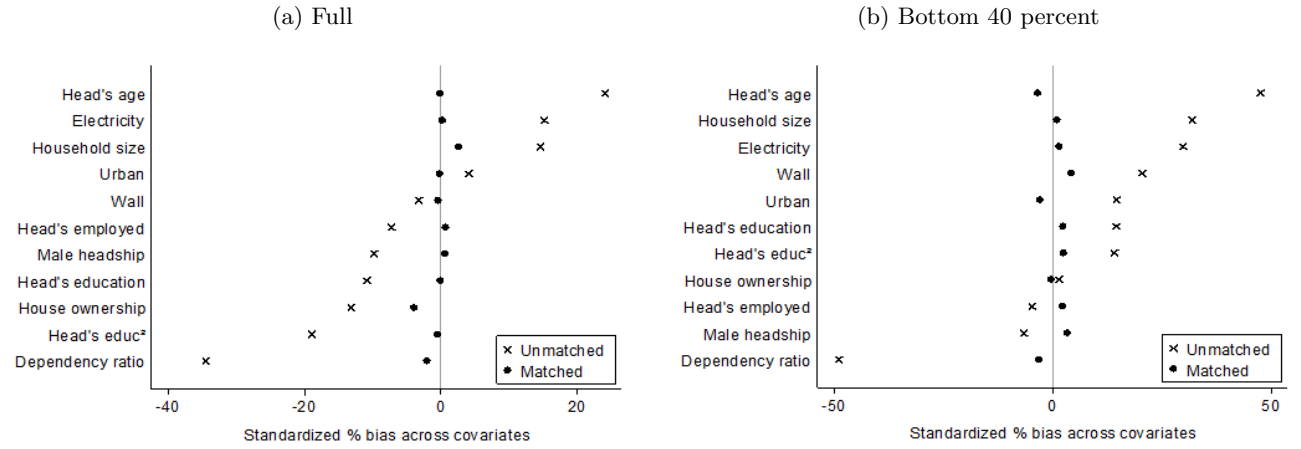
[26] The median bias is larger but inferior to 10 percent in the case of local linear matching and nearest-neighbor matching with $n = 1$ performed over the bottom 40 percent. Further details on the percentage reduction in absolute bias and the t-tests of equality of means for individual covariates are available upon request.

Figure 6: Kernel Density of Covariates



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. *Garment HHs* are households with at least one member (migrant or current member) working in the garment sector, while *Non-Garment HHs* are households included in the control group. The dashed and solid lines depict the distribution density of propensity scores for treated and untreated households respectively.

Figure 7: Covariate Balance Before and After Matching



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. The standardized bias measures the extent to which the propensity scores balance the distribution of covariates across treated and untreated households; it should be less than 5% after matching. The vector of covariates includes: i) the characteristics of the household head including gender (*Male headship*), age (*Head's age*), years of education in level (*Head's education*) and squared (*Head's educ*^{2}), and employment status (*Head's employed*); ii) the size of the household (*Household size*); iii) the ratio between dependents (children who are 14 years old and younger, and seniors who are 65 years and older) and working-age members (individuals aged 15-64) *Dependency ratio*; and binary variables for iv) urban residence (*Urban*), v) access to electricity (*Electricity*); vi) house ownership (*House ownership*); and vii) whether the primary construction material of the dwelling unit's walls is of superior quality, i.e. whether walls are made out of concrete, brick, stone or cement/asbestos (*Wall*).

Regarding the robustness of the results to unobservable heterogeneity, Tables 3 and 4 report the level of e^{γ} beyond which the ATT is no longer significant at the 10% confidence level due to hidden bias. Focusing on the bottom 40 percent, it appears that the ATT on consumption per capita is only sensitive to an unobserved heterogeneity that would raise the odds of participating in the garment industry by 50 percent. This figure stands at 40 percent in the case of the asset index. Even better, selection on unobservables would need to more than triple the probability to select into garment participation for the ATTs on non-monetary measures of welfare to become non-significant.[27] Overall, the critical values for e^{γ} are relatively large compared to figures reported in the evaluation literature (e.g. Aakvik, 2001; Clément, 2011; Bertoli and Marchetta, 2014). Although not informative on the actual presence of unobservable counfournders (Becker and Caliendo, 2007), the Rosenbaum test indicates that our ATT estimates are robust to a the possible presence of hidden bias.

6 Investigating the Remittances Channel

Given the definition of the treatment variable and the importance of garment remittances compared to non-garment transfers (Figure 5), it is very likely that the positive association between participation in the garment industry and welfare observed in our results is operating through this channel, particularly for rural households. In this section, we adopt an intensity of treatment approach and exploit the variation in the amount of remittances that households receive from their migrants employed in the textile and apparel industry. Several studies that have investigated the welfare-effects of remittances and their use have found evidence in favor of the productive use of remittances by recipient households. These include Castaldo and Reilly (2007) in the case of Albania, Taylor and Mora (2006) in the case of for Mexico and also Acosta, Fajnzylber, and Lopez (2008) who study seven Latin American countries. Similarly, there is evidence that remittances allow recipient households in rural areas to supplement non-farm income, encouraging productive investments (Rozelle, Taylor, and DeBrauw, 1999; Minot, Kherallah, and Berry, 2000; Abdoulaye and Sanders, 2005). In this section, we build on this literature and relax the CIA underlying PSM to allow for selection on unobservables. By using IV, we explore the causal effect of garment remittances on household expenditure patterns, distinguishing between food consumption, expenditures on durable goods and productive investments including health, education and agricultural inputs.

6.1 Identification Strategy

We focus on the sub-sample of 166 treated households that reported receiving remittances from migrants working in garment factories.[28] Among these, an overwhelming majority (92 percent) are rural dwellers engaged in farming activities. This motivates the choice of investigating not only the causal

[27] Considering kernel matching, the poverty variable is the only variable which appears to be highly sensitive to hidden bias, as even a 10 percent increase in unobserved heterogeneity suffices to undermine the statistical significance of the ATT estimate.

[28] Out of the 3,518 households used in the PSM section, 986 are remittance-recipient households and 175 receive remittances originating from the textile and apparel sector. However, the analysis excludes the 9 garment households that reported receiving remittances from international migrants, which sizes down the sample of interest to 166 households.

impact of remittances on recipient households' aggregate consumption per capita and its sub-components (described in Section 2)[29] but also on investments that enhance agricultural productivity. Formally we consider the following specification:

$$Y_i = \alpha + \beta Remit_{i,p} + \gamma X_i + \epsilon_i \tag{10}$$

where $Remit_{i,p}$ is the amount of remittances received by household i from its migrant(s) working in the garment industry in province p, Y_i refers to aggregate consumption per capita, one of its sub-components or investment costs pertaining to farming activities. The latter are further broken down into expenditures related to i) livestock and poultry raising activities and ii) crop cultivation, which include expenses on buying chemical fertilizers; and those related to tractors, animals, and human labor for ploughing and harrowing. We also consider a measure of labor productivity defined as kilograms of crop production per worker.[30] X_i is a vector of household characteristics comprising the age, marital status, gender and years of education of the household head, as well as the dependency ratio and dummy variables for urban residence and access to electricity. In the case of expenditures on agricultural inputs and productivity, the set of control variables includes the total plot area (in square meter), total expenditure in chemical fertilizers (in logarithm), the number of different crops grown, the size of livestock owned in the previous year,[31] the occurrence of bad harvest in the past dry and/or wet seasons at the province level and a dummy variable for urban residence. ϵ_i denotes the error term.

We anticipate garment remittances to alleviate household budget constraints (i.e. $\beta > 0$), allowing recipients to increase consumption in food and non-food items and invest more on education, health and agricultural inputs. The main challenge in identifying the causal effect of garment transfers on consumption and investment expenditures lies in addressing the possible endogeneity of remittances, which means that transfers are potentially correlated with the error term, such that $cov(Remit_{ip}, \epsilon_i) \neq 0$. Endogeneity may arise from reverse causality if migrants particularly care about the welfare status of their household of origin. For instance, a household's low consumption level and limited resources for agricultural investments may signal its poverty status, which may induce its garment migrant(s) to send higher amounts of remittances back home. This translates into downward biased estimates of β. In contrast, an omitted variable bias may lead to overestimate the true impact of garment transfers on expenditures. This can occur in a context where a common negative (positive) shock affects both migrants and their household of origin, by reducing (increasing) the ability to remit back home for the former, and by reducing (increasing) consumption and investment expenditures for the latter. To deal with biases stemming from the potential endogeneity of garment remittances, we resort to an IV methodology relying on the two-stage least squares (2SLS) estimator:

$$Remit_{i,p} = \delta + \theta Z_{i,p} + \mu_{ip}$$

$$Y_i = \alpha + \beta \widehat{Remit}_{i,p} + \gamma X_i + \epsilon_i \tag{11}$$

[29] More specifically, house services, food, communication, personal, entertainment, school, health, durables, and other expenses.

[30] The number of workers is proxied by the number of working-age individuals in the household.

[31] This includes all poultry, ovine and bovine animals owned in the previous year.

where $Z_{i,p}$ is a vector of three instrumental variables for the amount of remittances received by household i from its migrant(s) working in the garment industry in province p. For these variables to be valid instruments, they must be sufficiently correlated with the amount of garment remittances but uncorrelated with the error term.[32] Our first instrument is the average age of migrants employed in garment factories and provides variations across households. If taken as a proxy of the wage level of the migrant, it should be positively associated with the amount of remittances. This is in line with the literature showing a positive relationship between earnings and age or experience (tenure) (Mincer, 1974; Card, 1999; Lemieux, 2006). However, the average age of garment migrants could also negatively correlated with the amount of remittances sent as older migrants are more likely to get married and set up a household of their own in the city where they reside and work. In this context, remittances may decrease in size as the garment worker will need to provide for his/her own family (Dahlberg, 2006).

The remaining two instruments are computed at the province level using the district-level questionnaire provided along with the CSES 2011. First, we exploit the exogenous variations in the cost of making a domestic financial transaction in the province where the migrant resides, following a strategy similar to that of Calero, Bedi, and Sparrow (2009), who use information on the number of bank branches in the migrants country of residence as an instrument for remittances sent to households in Ecuador. Domestic transaction costs negatively affect the volume of funds transferred by textile and apparel workers, but at the same time, they are not expected to have a direct impact on households consumption and investment back home. Second, we use the price of ampicillin prevailing in the province of residence of the garment migrants. A qualitative study by Dahlberg (2006) indicates that medical fees represent a significant share of garment workers' total expenditures (after accounting for remittances, savings, and food and housing expenditures). Thus, an increase in the price of drugs in the province of destination of the migrant should be negatively correlated with the amount of remittances sent, without directly impacting the beneficiary households' agricultural or consumption decision in the province of origin.

6.2 IV Results

The results from the IV estimation of the effect of garment remittances on consumption per capita and its sub-components are presented in Table 5.[33] The first-stage estimation presented in Column (1) of Table A1 in the Appendix shows that the coefficients on the average age of garment migrants, the price of ampicillin and the transfer cost all bear a negative sign at the 5, 1 and 5 percent of statistical significance respectively.

[32] Formally, the first condition requires that the F-statistic for the joint significance of the coefficients on all excluded instruments exceed 10 (Stock, Wright, and Yogo, 2002). The second requirement implies that all instruments meet the exclusion restriction which precludes any direct impact of the instrument on the consumption or investment-related dependent variable, except through its effect on remittances. In the case of clustered standard errors and an overidentified model where the number of additional instruments exceeds the number of endogenous regressors, it can be tested using Hansen's J statistic which should not be statistically significant at the 10 percent level.

[33] Using the amount of garment remittances normalized by the size of the household or the number of remitters yields quantitatively and qualitatively similar results.

Table 5: Garment Remittances and Consumption, IV Estimates

Dependent variable	(1) Aggregate Consumption	(2) Food	(3) School	(4) Health	(5) House services	(6) Communi-cation	(7) Entertain-ment	(8) Personal	(9) Others	(10) Durables	(11) Asset index
Garment remittances	0.091***	0.075**	0.871***	1.822*	0.014	-0.239*	0.104	0.049	0.333***	-0.238	2.585**
	(0.035)	(0.036)	(0.180)	(0.942)	(0.055)	(0.128)	(0.141)	(0.144)	(0.095)	(0.411)	(1.263)
Head's years of education	0.031**	0.015	0.120***	-0.128	0.038***	0.041	0.023	0.035	0.050**	0.122	0.939***
	(0.015)	(0.009)	(0.046)	(0.207)	(0.011)	(0.029)	(0.036)	(0.031)	(0.021)	(0.123)	(0.299)
Head's age	0.004	0.002	0.049**	0.111**	-0.003	-0.005	0.009	0.004	0.016	0.009	0.379**
	(0.003)	(0.002)	(0.023)	(0.052)	(0.003)	(0.012)	(0.011)	(0.010)	(0.012)	(0.036)	(0.172)
Head's married	-0.452**	-0.352*	-2.695***	-0.192	-0.403**	-0.731**	0.651**	-0.152	-0.305	-0.131	1.661
	(0.216)	(0.204)	(0.182)	(0.722)	(0.171)	(0.287)	(0.262)	(0.163)	(0.421)	(0.468)	(2.977)
Male headship	0.223*	0.252**	1.537***	-1.486	0.081	0.882***	-0.900***	0.187	-0.007	-0.571**	6.732**
	(0.118)	(0.117)	(0.144)	(1.197)	(0.124)	(0.168)	(0.195)	(0.169)	(0.292)	(0.253)	(3.370)
Dependency ratio	-0.002***	-0.002***	-0.006**	-0.005	-0.001***	-0.001	-0.001	-0.003***	-0.002***	-0.011*	-0.048***
	(0.000)	(0.000)	(0.003)	(0.007)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.018)
Urban	0.101	0.157*	0.710	1.021	0.125	0.367	-0.340	-0.068	0.351***	-0.048	9.740**
	(0.093)	(0.083)	(0.486)	(0.752)	(0.147)	(0.239)	(0.355)	(0.144)	(0.131)	(0.758)	(4.269)
Electricity	0.138*	0.000	0.271	-0.407	0.213***	-0.065	0.461***	0.404***	0.064	-0.097	2.792*
	(0.081)	(0.067)	(0.225)	(0.813)	(0.052)	(0.116)	(0.146)	(0.125)	(0.182)	(0.252)	(1.672)
Observations	154	154	98	60	154	138	107	154	154	58	154
Root MSE	0.324	0.298	1.442	2.727	0.437	1.017	0.661	0.615	0.736	1.315	13.024
Kleibergen-Paap F-stat	24.60	24.60	8.28	2.30	24.60	9.56	17.60	24.60	24.60	2.15	24.60
Hansen J p-value	0.183	0.460	0.323	0.914	0.065	0.078	0.581	0.336	0.517	0.465	0.108
Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Standard errors are clustered at the province level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. Sampling weights are used in all regressions. Dependent variables are monthly per capita expenditures in Phnom Penh prices, in logs: (1) *Aggregate Consumption*: total consumption; (2) *Food*: food expenditures; (3) *School*: education expenditures; (4) *Health*: health expenditures; (5) *House services*: housing services expenditures, including sewage, lighting, and cooking; (6) *Communication* transport and communications expenditures; (7) *Entertainment*: recreational expenditures; (8) *Personal*: personal use goods expenditures, including clothing, soap...etc.; (9) *Others*: other expenditures such as domestic salaries, gifts received, charity; (10) *Durables*: expenditures on durables; (11) *Asset index*: percentage share of goods owned out of a list of 15 agricultural and non-agricultural durable goods accumulated to date by the household, including i) radio; ii) television; iii) bicycle; iv) motorcycle; v) video, VCD or DVD recorder or player; vi) refrigerator; vii) electric fan; viii) electric kitchen kitchen or gas stove; ix) cell phone; x) electric iron; xi) desktop or laptop computer; xii) plough; xiii) harrow, rake, hoe, spade or axe; xiv) batteries and xv) bed sets. RHS variables: i) *Garment remittances*: total value of remittances received by a household from its garment migrant(s), in riels, logs; ii) *Head's years of education*: number of years of education of the head; iii) *Head's age*: age of the head; iv) *Head's married*: dummy equal to 1 if head is married; v) *Male headship*: dummy equal to 1 if head is male; vi) *Dependency ratio*: the ratio between dependents (children who are 14 years old and younger, and seniors who are 65 years and older) and working-age members (individuals aged 15-64); vii) *Urban*: dummy equal to 1 if urban household; viii) *Electricity*: dummy equal to 1 if household has access to electricity. Instruments: average age of garment migrants, cost of domestically transferring money, price of ampicillin. *Root MSE*: root mean squared error.

All specifications include geographical zone fixed effects and standard errors are clustered at the province level (Moulton, 1990).[34] Sampling weights are also used to account for the features of complex survey data (Kish and Frankel, 1974; Holt, Smith, and Winter, 1980).

If the amount of garment remittances is doubled, then households enjoy a 9.1 percent increase in their monthly per capita consumption. Similarly, food expenditure, which accounts for 57 percent of total expenditure, also increases with remittances: a 100 percent rise in garment transfers translates into a 7.5 percent increase in food spending. For both regressions, the Kleibergen-Paap F-statistic for weak identification[35] stands at 24.60 and exceeds the Stock and Yogo critical values (9.08 percent for the maximum IV relative bias and 22.30 for the maximum IV size), rejecting the hypothesis of weak instruments. Similarly, the p-values associated with the overidentification test are above the threshold of 0.10, signaling that the instruments are exogenous. Although the magnitude of the coefficients is modest, these findings are consistent with Orozco (2003) who shows that Mexican households spend a large share of the remittances they receive on food items. However, we do not find an impact on leisure activities, as Tabuga (2007) does in the case of the Philippines. Also, miscellaneous expenditures such as contributions to funeral rituals and wedding ceremonies witness a 33.3 percent increase following a twofold rise in garment remittances (Col. 9).

Table 5 also provides evidence on the productive use of garment remittances. A 10 percent increase in transfers raises education expenditure by 8.7 percent (Col. 3). This positive effect on human capital investment is in line with Kifle (2007) who shows that remittance-recipient Eritrean households tend to spend more on education. Cardona Sosa and Medina (2006) and Adams and Cuecuecha (2010) find similar expenditure patterns for households in Colombia and Guatemala respectively. Furthermore, remittances originating from the textile and apparel industry increase health expenditures per capita by 1.8 percent (Col. 4),[36] consistent with Amuedo-Dorantes and Pozo (2011) and Valero-Gil (2009). In contrast, a doubling of garment remittances seems to deter per capita spending in transportation and communication which falls by 24 percent (Col. 6), but in this specification the quality of the instruments is not satisfactory. In addition, the impact on per capita expenditures on durables is not statistically significant but turns positive when asset accumulation is proxied by the share of durable goods owned by the household. These results broadly hold when the amount of remittances is normalized by the household size or by the number of migrants that send money.[37]

Table 6 reports the non-trivial causal effect of garment remittances on productive agricultural investments. A twofold increase in transfers raises aggregate per capita expenditures related to farming activities by 36.6 percent (Col. 1), providing additional support to the hypothesis on the productive use of remittances. Specifically, per capita costs incurred in crop cultivation and those pertaining to livestock

[34] Clustering at the province level relaxes the independence assumption of errors and requires only that households be independent across provinces. Cluster-robust standard errors are robust to both arbitrary heteroskedasticity and intra-province correlation. Several studies have discussed the implications of failure to control for within-cluster correlation (Bertrand, Duflo, and Mullainathan, 2004; Wooldridge, 2010).

[35] Since standard errors are clustered at the province level, the Cragg-Donald-based weak instruments test is no longer valid and the Kleibergen-Paap F-statistic is used instead (Baum, Schaffer, and Stillman, 2007).

[36] However, our instruments for remittances seem to perform poorly, especially for health expenditures, probably due to the reduction in sample size.

[37] Output tables were not included for the sake of space but are available upon request.

Table 6: Garment Remittances and Agricultural Investments, IV Estimates

Dependent variable	(1) Total agric. costs	(2) Crop cultivation	(3) Chemical fertilizers	(4) Draft power	(5) Livestock & Poultry	(6) Labor productivity
Garment remittances	0.366***	0.473***	0.584***	0.134	0.466***	0.280**
	(0.115)	(0.160)	(0.174)	(0.222)	(0.120)	(0.113)
Urban	-0.706***	-0.769***	-1.247***	-0.079	0.038	0.576***
	(0.242)	(0.131)	(0.095)	(0.217)	(0.265)	(0.146)
Area	0.554***	0.733***	0.872***	0.567***	0.156*	0.645***
	(0.088)	(0.110)	(0.132)	(0.133)	(0.086)	(0.106)
Bad harvest	4.418***	5.433***	8.162***	2.679		
	(1.104)	(1.915)	(1.362)	(1.778)		
Nb. of livestock & poultry	0.006				0.016**	
	(0.004)				(0.006)	
Chemical fertilizers						0.246***
						(0.044)
Crop varieties						0.187***
						(0.047)
Observations	131	122	108	107	114	105
Root MSE	0.878	0.900	1.181	0.837	1.282	0.765
Kleibergen-Paap F-stat	24.96	22.69	19.12	29.47	45.40	20.51
Hansen J p-value	0.367	0.505	0.586	0.713	0.081	0.090
Zone FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. Standard errors are clustered at the province level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. Sampling weights are used in all regressions. Dependent variables: (1) *Total agric. costs*: per capita total expenses related to agricultural activities, including crop cultivation and livestock and poultry-raising activities (riels, log); (2) *Crop cultivation*: per capita total expenses related to the production of crop, including fruits and vegetables (riels, log); (3) *Chemical fertilizers*: per capita expenses related to buying chemical fertilizers, pesticide, weedicide and fungicide for crop cultivation (riels, log); (4) *Draft power*: per capita expenses related to payment to hired draft power (tractors/animals) including human labor for ploughing/harrowing (riels, log); (5) *Livestock & Poultry*: per capita expenses of livestock and poultry-raising activities such as spending on animal feed and veterinary services (riels, log); (6) *Labor productivity*: output per worker (log). Regressors: i) *Garment remittances*: total value of remittances received by a household from its garment migrant(s), in riels (log); ii) *Urban*: dummy equal to 1 for urban households; iii) *Area*: total area in m^2 of plots owned or freely used by household (logs); iv) *Bad harvest*: dummy equal to 1 if the village experienced a bad harvest during the past dry and/or wet season; v) *Nb. livestock and poultry*: number of cattle, ovine and poultry animals owned on 31 December 2010; vi) *Crop varieties*: varieties of crops grown by household. Instruments: average age of garment migrants, cost of domestically transferring money, price of ampicillin. *Root MSE*: root mean squared error.

and poultry raising activities increase by 47.3 and 46.6 percent respectively when remittances are doubled. Although garment transfers do not seem to have an effect on expenditures for hiring draft power (Col. 4), they do increase the amount spent on chemical fertilizers and pesticides: a 100 percent rise in transfers translates into a 58.4 percent increase in this expenditure post. In addition, a twofold increase in remittances boosts agricultural labor productivity by 0.28 kilogram per worker. Overall, these findings are consistent with the literature that underlines how remittances relax the liquidity constraints of agricultural households (Minot, Kherallah, and Berry, 2000; Abdoulaye and Sanders, 2005). For instance, they allow overcoming imperfect credit and insurance markets in Burkina Faso (Wouterse and Taylor, 2008) and China (Rozelle, Taylor, and DeBrauw, 1999). In the specific case of the textile and apparel sector, our IV results also broadly echo findings from qualitative studies reporting that remittance-recipient households living in rural areas in Cambodia are able to increase their food consumption, cover health and education expenses, and invest in crop production and durable assets (Cooperation Committee for Cambodia, 2005; Dahlberg, 2006).

7 Conclusion

The garment industry is one the key engines of Cambodia's impressive economic growth in recent years, as well as the largest source of jobs in the manufacturing sector. Nonetheless, it is also associated with poor labor conditions and suboptimal health and hazard regulations. This paper seeks to contribute to the debate on the socio-economic advantages of the industry for Cambodia by exploring the benefits of participating in the textile and apparel sector. Using a rigorous econometric approach, it explores the relationship between garment participation and both monetary and non-monetary welfare indicators at the household level. More specifically, we use PSM estimators to compare households with at least one member employed in the textile and apparel sector (treatment group), with those with no participation (control group). Our preferred specification uses kernel weights and estimates the standard errors using the bootstrap method.

When considering the entire sample of households, we find that garment households have lower food insecurity and a higher proportion of children aged 6-14 attending school. However, they also have lower consumption per capita and accumulate fewer assets. But the sign of the latter point estimates is reversed when we restrict the sample to the bottom 40 percent of the consumption distribution. Among these households, participation in the garment sector raises per capita consumption by 3 percent and enhances asset ownership by 2.6 percentage points. The benefits in terms of food insufficiency and increased school enrollment appear even larger for this sample, at 1.8 and 9.3 percentage points respectively. Similarly, it decreases the poverty incidence, the extreme poverty incidence and the poverty gap index by 8, 3 and 1.7 percentage points respectively. Although the magnitude of the coefficients is modest (except for school enrollment), overall the results are robust to different specifications of the selection model and to the use of alternative PSM techniques, such as nearest neighbor, radius matching and caliper. Moreover, the quality of the matching is good, as the covariates are balanced for both the full sample and the sub-sample of the bottom 40 percent of the distribution, and the results are robust to high levels of unobserved heterogeneity.

The differences in the results when looking at the whole sample versus just the bottom 40 percent of the distribution are attributed to the differences between garment and non-garment households in the highest (richest) quintile, i.e. the top 20 percent of the distribution. For these households, participating in the garment sector is a second best, perhaps because of the profiles of the jobs available. Given their social and human capital characteristics, members of the wealthiest households would have earned more and been better-off in alternative non-garment occupations. However, and more importantly, the garment sector does enhance the welfare of the poorest households in Cambodia, allowing them to increase their consumption, accumulate more assets and invest in human capital.

A caveat to our results is that participation in the garment sector may have negative consequences for the welfare of households that are important but very difficult to quantify, such as potential psychological effects of family separation (in the case of migrants) and long-term psychological and physical effects of working long hours in harsh conditions. The objective of the study is not to undermine or ignore important issues related to the garment industry, like poor working conditions, overspecialization of the labor force and family-separation, but to bring to the debate quantitative evidence on some of the positive aspects of this industry.

The study also explores one of the potential channels through which the relationship between participating in the garment sector and well-being operates: the remittances that households receive from migrants employed in the industry.[38] Using instrumental variables, and thus controlling for unobserved heterogeneity, we provide evidence that higher garment remittances allow households to increase per capita aggregate consumption (and food consumption), as well as the amount spent in education and health. More importantly, we find that remittances enable rural households to invest in inputs that increase labor agricultural productivity.

In sum our results point that the garment sector is beneficial to the poorest households in Cambodia. Thus, the government should continue its efforts to support this sector. Specifically, it should maintain sound macro-economic and open-market policies, continue to attract foreign direct investment into the manufacturing sector, and contribute to political stability. At the same time, and in light of the increasing international competition, it should also focus on raising labor productivity and adopting better technologies in the sector. Efforts to increase the educational level and enhance the technical skills of the labor force are key to accomplish this. Similarly, investing in research and technology and providing incentives for firms to adopt new technologies should also be a priority.

At the same time, the government should push for the diversification of industrial activities beyond the textile and apparel sector, with the goal of expanding the high-value added domestic production in competitive and creative sectors like machinery, electronics, transports means, etc. The agro-industrial sector is also an area that could bring high payoffs for the welfare of Cambodians, given the rural nature of poverty. Agro-industries have a great job-creation potential, if the backward and forward linkages are fully exploited. A first step in the right direction was the launch in 2015 of Cambodia's Industrial Development Policy 2015-2025, which lays an ambitious road map to develop a stronger and more diversified industrial sector.

[38] A second channel that has been studied in the literature is the wage premium that garment workers enjoy.

Another important recommendation that stems from the results of this study is that promoting remittances can have a positive impact for the poor. Lowering the cost of remittances, both nationally and internationally, and supporting the productive use of remittances can benefit the well-being of Cambodian households. Some alternatives include promoting monetary transfers using mobile technology, developing financing products linked to remittances and introducing matching programs. These actions can act as multipliers of the positive effects of remittances on agricultural investment observed in the results of this study.

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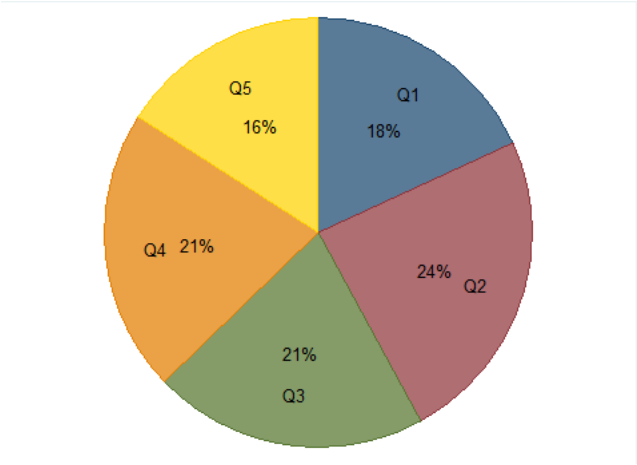
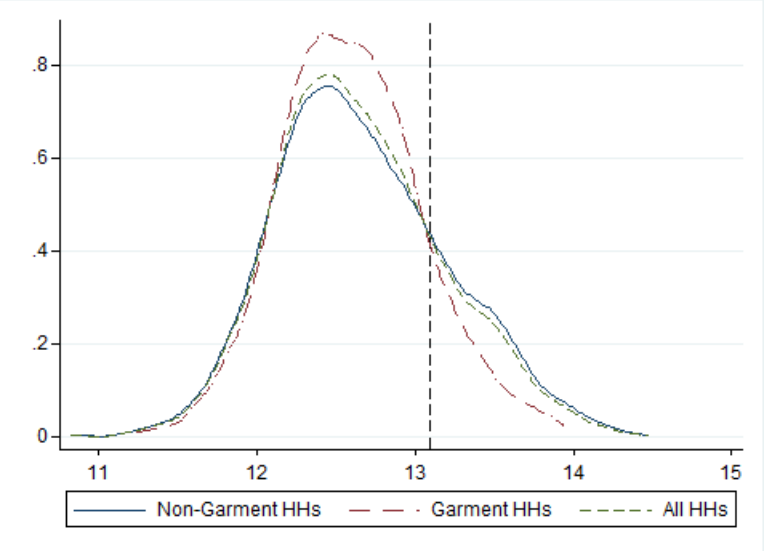
Appendix

Figure A1: Distribution of Garment Households across the Consumption Spectrum



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. *Q1* to *Q5* refer to quintiles 1 (poorest households) to 5 (richest households) of the distribution of monthly consumption per capita.

Figure A2: Density Plots of Consumption per capita



Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. *Garment HHs* are households with at least one member (migrant or current member) working in the garment sector; *Non-Garment HHs* are households included in the control group; while *All HHs* combines both. The variable of interest is monthly per capita consumption in Phnom Penh prices, in logs. The vertical line marks the 5^{th} quintile.

Table A1: First-stage Regressions

	(1)	(2)	(3)	(4)	(5)
Age of garment workers	-0.041**	-0.079***	-0.078***	-0.079***	-0.088***
	(0.015)	(0.010)	(0.010)	(0.009)	(0.012)
Price of ampicillin	-0.006***	-0.006***	-0.006***	-0.007***	-0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Transfer cost	-0.000**	-0.000	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.266	0.282	0.349	0.269	-0.650
	(0.160)	(0.176)	(0.243)	(0.184)	(0.451)
Head's years of education	-0.015				
	(0.031)				
Head's age	-0.029**				
	(0.012)				
Head's married	-0.012				
	(0.402)				
Male headship	0.221				
	(0.256)				
Dependency ratio	-0.001				
	(0.002)				
Electricity	-0.287				
	(0.217)				
Area		-0.046	-0.013	-0.029	0.199
		(0.105)	(0.100)	(0.109)	(0.212)
Bad harvest		-2.438*	-2.669*		
		(1.133)	(1.343)		
Nb. of livestock & poultry		0.008		0.009	
		(0.006)		(0.006)	
Chemical fertilizers					-0.298**
					(0.105)
Crop varieties					-0.102
					(0.200)
Constant	19.239***	19.399***	18.806***	19.408***	21.127***
	(0.834)	(1.301)	(1.548)	(1.186)	(1.538)
Observations	154	133	133	133	108
Adj. R^2	0.248	0.298	0.296	0.295	0.292
Root MSE	1.255	1.202	1.204	1.205	1.183
First stage F-stat	24.60	24.99	23.96	19.88	19.88
Zone FE	Yes	Yes	Yes	Yes	Yes

Notes: Authors' calculations based on the 2011 Cambodia Socio-Economic Survey. The dependent variable is the total value of remittances received by a household from its garment migrant(s), in riels (log). Standard errors are clustered at the province level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. Sampling weights are used in all regressions. Instruments: (i) *Age of garment workers*: average age of household's garment worker(s) in years; (ii) *Price of ampicillin*: the price of ampicillin prevailing in the province of residence of the garment migrants (riels/capsule); (iii) *Transfer cost*: cost of transferring 2,000,000 riels domestically, in the province of residence of the garment migrants (riels). *Adj.* R^2: Adjusted R^2. *Root MSE*: root mean squared error.