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Greenhouse farming and employment: Evidence from Ecuador[☆]

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ABSTRACT

The transforming agri-food sector is an important contributor to employment generation in rural areas of lower-income countries. However, little attention has been paid to the question of how technology affects the quality and quantity of employment in the sector. In this paper, we provide the first empirical evidence of how the rise in greenhouse farming changes labor demand (i.e., the number of employees), using large-scale and nationally representative agricultural survey data from Ecuador between 2014 and 2021 and pseudo-panel as well as event-study estimation techniques. Contrary to fears that more technologically advanced production methods displace large shares of the workforce, we find that greenhouse farming is associated with higher labor demand. Specifically, greenhouse farms hire more female workers and workers on permanent contracts.

1. Introduction

The agri-food system remains key for tackling challenges such as un- and under-employment and poverty, especially in rural areas of many lower-income countries (Christiaensen et al., 2021). While a large share of the population in lower-income countries works as self-employed smallholder farmers, the importance of wage jobs increases as countries grow wealthier and as their dietary patterns and food systems transform (Christiaensen and Maertens, 2022). At the same time, population growth and climate change will require more efficient agricultural production to secure sustainable food production globally (Smith et al., 2014; Benke and Tomkins, 2017; Engler and Krarti, 2021). Technologies such as greenhouse farming play an important role in raising agricultural productivity and decoupling production from land use (Shamshiri et al., 2018). While it has long been feared that the use of new agricultural technology will displace labor on farms in lower-income countries (Pingali et al., 1987; Pingali, 2007), it remains unclear how greenhouse farming affects socioeconomic outcomes and employment.

In this paper, we address this gap and provide first empirical evidence of how greenhouse farming affects labor demand on farms. Over the past years, greenhouse farming has grown rapidly, especially in higher-income countries, urban areas in Asia, and in the production of nutritious foods such as fruits and vegetables globally (Barrett, 2021). Data from a nationally representative agricultural survey from Ecuador between 2014 and 2021 allows us to analyze whether greenhouse farms hire different levels of workers compared to non-greenhouse farms and whether differences are larger for certain groups of workers, such as household and hired labor or male versus female workers. While the data at hand are a repeated cross-section, we are able to aggregate the data to very small geographic units—namely 17,000 so called segments—and thereby make use of pseudo-panel estimation techniques (Deaton, 1985; Verbeek, 2008; Khan, 2021).

In contrast to other agricultural practices, greenhouse farming has

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received very limited attention in the academic literature, even though adoption is growing and it is becoming more important in providing healthy diets. Greenhouses are often used to produce fruits and vegetables—nutritious products that are under-consumed by many of the world's consumers, often because of their relatively high price and limited seasonal availability (Hirvonen et al., 2020).[1] A major advantage of greenhouse production is its year-round productive capacity and smaller exposure to environmental risks, as it reduces the dependency on, and disruptions by, natural factors and cycles, such as temperature and light, water and rain, and pests and diseases (Lansink and Ondersteijn, 2006; Bergstrand, 2010; McCartney and Lefsrud, 2018). Empirical studies on greenhouses have mostly focused on conditions favoring greenhouse adoption (Guarderas, Smith and Dufrene, 2022). Qualitative studies have shed light on the resilience of greenhouses to climatic conditions (Knapp, 2017) and the consequences for water and pesticide use (Franze and Ciroth, 2011; Mena-Vásconez et al., 2016). A few studies also look at pesticide exposure of workers and individuals living in proximity to greenhouses (Friedman et al., 2020; Nassar and Ribeiro, 2020; Suarez-Lopez et al., 2020). There are no quantitative but a few qualitative studies focusing on employment. Knapp (2017) documents that greenhouse production in Ecuador created employment opportunities and prevented outmigration while exhibiting comparatively good working conditions. Raynolds (2012, 2014) highlights the potential of standards and certification to improve working conditions and to reduce the use of harmful pesticides in greenhouses used for flower production in Ecuador.[2] The main reason that there is little empirical evidence—despite the large academic and general interest in the topic of technological change in agricultural—is the lack of large-scale data, especially outside of high-income countries (Daum and Birner, 2020).

This paper contributes to the broader literature on technological change and structural transformation in the agri-food sector and its importance for employment creation (Christiaensen, Rutledge and Taylor, 2021; Yi et al., 2021; Barrett et al., 2022; Bellemare et al., 2022) in three distinct ways. First, we provide novel empirical evidence on the effects of greenhouse farming on labor demand based on nationally representative longitudinal data. We find that greenhouse farming is positively associated with the demand for hired labor, especially for workers on permanent contracts. The results are robust to several alternative specifications, including different levels of aggregation or repeated cross-sectional analysis, and results are unlikely to be biased by omitted variables or by existing pre-trends prior to greenhouse adoption. Second, we add evidence to the literature investigating how the adoption of technology can have gendered implications, especially in societies where agricultural tasks and responsibilities are gender-specific (Doss, 2002; Quisumbing and Doss, 2021). For example, agricultural machinery has been found to substitute for specific manual tasks that are predominantly carried out by women (Caunedo and Kala, 2021; Afridi, Bishnu and Mahajan, 2022). Our analysis shows that women appear to gain from jobs created by greenhouse farming, which is relevant as women's access to off-farm employment and wage income has far-reaching consequences for women's empowerment, food security, and child education (Maertens and Verhofstadt, 2013; Van den Broeck and Maertens, 2015; Krumbiegel et al., 2020). Third, the existing literature on agricultural labor focuses on smallholders, leaving out the "hidden middle", despite the importance of post-farm sectors in creating wage employment (Reardon, 2015; Yi et al., 2021). Our data include farms of different sizes, which are often liked to higher-value markets. As discussed, studies on the effects of agricultural technologies on employment using larger-scale data outside of high-income countries are rare (Daum and Birner, 2020). Although Ecuador is an upper-middle income country, much of its relatively high per capita income stems from the oil sector, and the country is characterized by a high poverty rate, especially in rural farming areas.[3]

The rest of the paper is structured as follows. In the following section, we develop a conceptual framework outlining potential effects and mechanisms through which greenhouse farming could alter labor demand, highlighting the main and unique characteristics of greenhouse farming. Section 3 provides an overview of the dataset and the empirical strategy, discussing potential threats to identification. Empirical results are presented in section 4. We also run several robustness tests, including testing for pre-trends (de Chaisemartin and D'Haultfœuille, 2020; Borusyak, Jaravel and Spiess, 2022) and for sensitivity to omitted variables (Oster, 2019; Diegert et al., 2022). Section 5 discusses the results and highlights implications for policy. Section 6 concludes and offers directions for future research.

2. Conceptual framework

In what follows, we offer conceptual considerations regarding our two key research questions, namely, (i) how greenhouse farming might affect employment and (ii) how it affects the composition of workers, based on gender and contractual arrangements. While there is no empirical evidence as to how greenhouse technology affects the number of workers on a farm to date, we draw from previous theoretical and empirical evidence in related areas.

There are several ways through which greenhouse farming could affect labor demand. First, one of the major advantages of greenhouse farming is that it reduces the dependency on seasonal cycles and enables year-round production (Forkuor et al., 2022). Bustos et al. (2016) show that a new maize variety led to higher labor demand in Brazil because it enabled growing maize in a second season during the year. Similar properties of greenhouse farming can be expected to have similar effects on labor demand. Moreover, stable and higher-value production can create linkages between farms and downstream firms—for instance, in processing or retail—and thus more stable output demand, which can increase production and labor demand (Neven et al., 2009; Rao and Qaim, 2011; Meemken and Bellemare, 2020).

Second, greenhouse farms typically focus on higher-value-added production of flowers and horticulture and, depending on the context, delivery to the export market with higher food safety and quality standards (Nicola, Tibaldi and Fontana, 2009; Berkers and Geels, 2011; Codron et al., 2014; Forkuor et al., 2022). While there is little empirical evidence on the interlinkage between employment and greenhouse farming in particular, several studies show how such characteristics increase farms' productive capacity and output, and thereby labor demand. This holds especially when higher quality and safety standards have to be met. For instance, farms focusing on floriculture, horticulture, and export markets have been shown to raise their revenues (Maertens

[1] There are broad discussions about the environmental impact of greenhouse agriculture, which is heavily dependent on the structural type and production techniques (Engler and Krarti, 2021). In the context of climate change, this kind of production entails substantial trade-offs: on the one hand, greenhouses contribute to large parts of agricultural CO_2 emissions in advanced economies (Wainwright et al., 2014). On the other hand, they may save water due to reduced evapotranspiration (Czyzyk et al., 2014; O'Connor and Mehta, 2016; Nicola et al., 2020). With technological advances, greenhouses are becoming more energy-efficient and less water-intensive (Lansink and Ondersteijn, 2006; Bergstrand, 2010).

[2] These findings resonate with the broader literature on the relation between sustainability standards and the quality and quantity of employment (Schuster and Maertens, 2016; Krumbiegel et al., 2018; Meemken et al., 2019, 2021).

[3] The poverty rate declined substantially between 2000 and 2014, then stagnated at around 23%, and increased again to 33% between 2018 and 2020 (World Bank, 2022). Poverty rates are substantially higher in rural areas, with 42% in 2019, where the vast majority of agricultural labor is concentrated (Bertelsmann Stiftung, 2022).

and Swinnen, 2009; Minten et al., 2009; Miyata et al., 2009; Wang et al., 2009), productivity, and investments (Dries and Swinnen, 2004; Asfaw et al., 2009; Dries et al., 2009; Carletto et al., 2011).[4] Increases in productivity and higher value-added production often increase the demand for hired labor, thus, creating jobs, especially for vulnerable populations (Van den Broeck et al., 2017). Therefore, it is likely that greenhouse farms hire more workers.

Third, because greenhouses range from mere plastic covers to fully automated production entities, certain elements of these technological packages might be labor-saving while others increase the demand for labor (Codron et al., 2014). In higher-income countries, technologies are often employed to reduce labor demand, although the empirical evidence suggests that technology often does not reduce the overall demand for low-skilled labor but rather shifts labor demand to new activities (Autor, 2015; Dauth et al., 2021). In the context of lower-income countries and Ecuador, it is however unlikely that investments in technologies are driven primarily by the goal of saving labor costs (Engler and Krarti, 2021). Labor, especially in rural areas, is abundant since more-formal production units pay higher wages and offer more additional non-wage benefits than smallholder farmers. Furthermore, even if technology is labor-replacing, it can have a positive effect on employment if it increases productivity more than it displaces labor, which likely holds in countries with lower levels of technology adoption (Bonfiglioli et al., 2020).

Our second research question is how greenhouse production affects the composition of the workforce. We hypothesize that greenhouses hire more workers on permanent contracts (than on a seasonal basis, on casual contracts, or informally) given its year-round production capacity. Further, we hypothesize that higher labor demand on greenhouse farms creates wage employment especially for women. Greenhouse farming is predominantly used for horticulture and floriculture, where the share of female labor is high (Barrientos et al., 2000; Van den Broeck and Maertens, 2015). More generally, technology adoption and agro-industrial production can have gendered implications, depending on the existing gender division of labor in agriculture (Doss, 2002; Maertens and Swinnen, 2012; Quisumbing and Doss, 2021), and the type of tasks that any given technology affects. For instance, in the context of agricultural machinery as the technology, the adoption of tractor-driven equipment on Indian farms has led to a significantly greater decline in women's than men's labor input (Caunedo and Kala, 2021; Afridi, Bishnu and Mahajan, 2022).[5] This was driven by the substitution of specific manual tasks that are predominantly carried out by women. Yet other types of technology, for instance, mobile technology and internet, have been shown to improve labor market outcomes, especially for women, as they reduce market frictions and barriers (Suri and Jack, 2016; Bahia et al., 2020; Viollaz and Winkler, 2022). Although greenhouse technology differs from these technologies, its characteristics resonate with modern agro-industrial production. Agroprocessing companies and other entities within modern supply chains hire large shares of female workers, with comparatively good working conditions (Maertens and Swinnen, 2012; Van den Broeck et al., 2017). As greenhouse farming is more formalized than non-greenhouse farming, similar effects for female employment can be expected.

[4] Such developments can however also exclude smallholder farmers and result in distorted power relations (Handschuch et al., 2013; Schuster and Maertens, 2013).

[5] Naturally, not only the type of technology matters. For instance, Daum and Birner (2020) show that the correlation of both animal-based machinery and tractor use on hired labor depends on the country within Sub-Saharan Africa that they study.

3. Data and empirical strategy

3.1. Data

We use Ecuador's Continuous Area and Agricultural Production Survey (ESPAC) data, which are collected by the National Institute of Statistics and Census (INEC). ESPAC covers a variety of agricultural topics, including crop choice, input use, yields, agricultural employment, and technology adoption. INEC divided the country into segments, defined as squares of land between 0.1 and 5.8 square kilometers. Each segment, whose size depends on the intensity of agricultural production in the area, is characterized by homogeneous agroecological conditions (Castillo, Boucher and Carter, 2016).[6] Within these segments, representatives of so-called agricultural production units—which we label as farms for simplicity—are surveyed.[7] The data also include expansion factors (sampling weights) and contain information on the province (ADM1), canton (ADM2), and parish (ADM3) that each segment lies in. As there are over 1,500 parishes in Ecuador, we have a relatively precise idea of the segment's location. Due to the sampling design, data are only representative at the segment, province, and country level, but not at the parish and canton level. Overall, we observe 18,741 different segments in the data for an average of 2.5 years each. Unfortunately, it is not possible to track the agricultural production units (farms) over time.

3.2. Empirical strategy

To capture the relationship between greenhouse farming and labor demand, we use fixed effects and pseudo-panel regression models. As the farm identifiers are not traceable over time, we take advantage of the survey's sampling design, which splits the country into small homogenous geographical units or segments. Segment identifiers are the same across years, which allows us to construct a pseudo-panel by aggregating our data to this level, while applying sampling weights. Pseudo-panel methods are most often used to aggregate individuals into cohorts, which can be tracked over time (Deaton, 1985; Verbeek and Nijman, 1992; Verbeek, 2008). As our data is representative at the segment level, there is no issue of sampling bias upon aggregation, even though the number of observations within segments is relatively small (Khan, 2021).[8] On average, there are 5 farms within a segment (the median number is 3).

We estimate regressions of the following type:

$$L_{spt} = \beta_0 + \beta_1 G_{spt} + \beta_2 X_{spt} + \delta_s + \rho_{pt} + u_{spt}, \tag{1}$$

where L_{spt} is the average number of workers—including both hired and household labor—on farms in segment s and province p. The data also allow us to disaggregate labor into different categories: household workers, workers on permanent contracts, and workers on casual contracts. Moreover, for each of these categories, we know the number of male and female workers. As worker counts are not normally distributed, we transform the outcome variable using the inverse hyperbolic sine (henceforth *arcsinh)* to account for outliers, while allowing for zero-values (Bellemare and Wichman, 2020). As a robustness test, we also show results using different variants of measuring our outcome—i.e., in

[6] Segment size is inversely proportional to cropping intensity. For instance, in areas where cropping intensity is only 20%, the segment size goes up to 5.8 square kilometers. When the cropping intensity is above 60%, the segment size is as small as 0.09 square kilometers.

[7] Although each farm may include several plots used for different crops, information on employment is only available at the farm level. Thus, we aggregate all other variables to the farm level.

[8] Local-labor market approaches are other contexts in which firm-level data is aggregated to the regional level (Autor et al., 2013; Kis-Katos and Sparrow, 2015; Dix-Carneiro and Kovak, 2017; Stemmler, 2019).

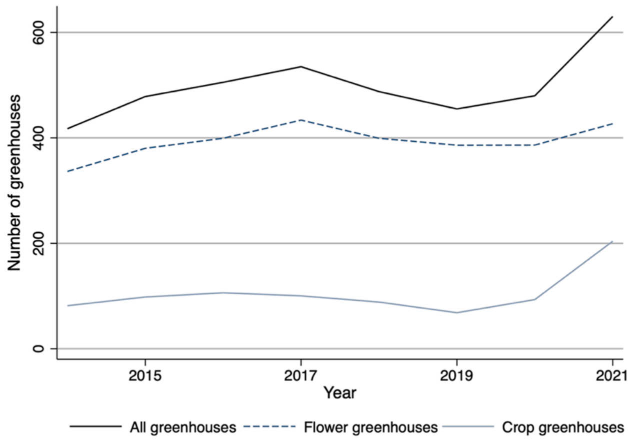

Fig. 1. Number of greenhouses in Ecuador over time. *Notes:* This figure displays the average number of plots with greenhouses per segment in Ecuador between 2014 and 2021.

absolute numbers and workers per hectare of agricultural land—and estimation techniques. The main coefficient of interest, β_1, is the estimated effect of greenhouse adoption (*G),* which corresponds to the share of plots that use greenhouse structures for farming within a segment.[9] The coefficient β_1, therefore, captures whether greenhouses are used as well as the intensity of greenhouse farming. We control for total agricultural land size within the segment, the number of farms in the segment (both *arcsinh* transformed), and the main crop grown in the segment (based on agricultural land size), which are subsumed in the vector X_{spt}. By including segment fixed effects, δ_s, we capture idiosyncratic variation within segments over time, conditional on the other controls related to agricultural characteristics. Province-year fixed effects, ρ_{pt}, account for all unobserved broader developments in provinces, such as changes in policies or economic growth. The remaining error term is denoted by u_{ispt}.

Although we control for multiple levels of fixed effects, results could be biased if the effect of greenhouse adoption on employment is correlated with the error term. Conditional on our included control variables and fixed effects, our estimation strategy relies on the assumption that greenhouse usage is not correlated with other time-varying factors that affect employment conditions. However, this identifying assumption would be violated if greenhouse adoption was more or less likely in segments where employment changed because of other factors. To study whether such effects are prevalent, we employ an alternative estimation approach, namely an event study design. This approach allows us to analyze pre-treatment trends of greenhouse farming. Relatively few regions had any greenhouses in 2014, and this number grew thereafter (see Fig. 1 and Fig. A-1). We assign segments to be treated whenever any of its plots use a greenhouse.[10] The validity of standard difference-in-difference (DiD) assumptions in staggered treatment assignments has recently been contested (de Chaisemartin and D'Haultfœuille, 2020; Callaway, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak, Jaravel and Spiess, 2022). For instance, due to staggered rollout, the comparison group of segments with later treatment would include segments that had already been treated before, distorting the resulting weights of treatment effects. Therefore, we employ the imputation method by Borusyak, Jaravel and Spiess (2022), which accounts for heterogeneous timing in greenhouse adoption. The estimation procedure uses all untreated segments (never and not yet treated) as comparison groups. In the first step, segment and province-year fixed effects, as well as a set of controls, are fitted for untreated observations only (i.e., those without any greenhouses and those without a greenhouse yet) and the estimated coefficients are used to impute a counterfactual outcome for treated segments:

$$L_{st}(0) = \alpha_1 X_{spt} + \delta_s + \rho_{pt} + \varepsilon_{spt}.$$

In the second step, an estimated treatment effect is obtained by subtracting imputed from actual outcomes:

$$\widehat{\tau}_{st} = L_{st} - \widehat{L}_{st}(0)$$

Finally, the average treatment effect for each period is derived:

$$\widehat{\tau}_h = \frac{1}{S_h}\sum_{s\in S_h}\widehat{\tau}_{sh}$$

where h denotes the period of treatment (e.g., 1 year after greenhouse adoption). S_h represents the number of segments observed in that period. Hence, for each segment and period, the imputation method computes difference-in-difference coefficients in relation to before the segment was treated, and in relation to other segments which were not treated in the same period.

In addition, we use a number of alternative specifications to verify the results, including additional control variables and other sets of fixed effects. Segment-level estimation, aside from permitting the creation of a pseudo-panel, accounts for unobserved local labor market effects (e.g. labor moving from one farm to another within the same segment). As a robustness test, we also run cross-sectional farm-level estimations to verify that results are not biased by aggregation.

Furthermore, we test for omitted variable bias based on the selection on observed and unobserved variables (Altonji et al., 2005; Oster, 2019; Diegert et al., 2022). The method developed by Oster (2019) infers how large the selection on unobservables would have to be to fully explain the estimated coefficients. Comparing changes in coefficients with changes in the explanatory power of the model (R-squared) when control variables are included, allows us to assess the sensitivity of our estimates to omitted variable bias. Following Oster (2019), we estimate $\delta \approx \left(\frac{\widetilde{\beta}}{\dot{\beta}-\widetilde{\beta}}\right)\left(\frac{\widetilde{R}-\dot{R}}{R^{max}-\widetilde{R}}\right)$, where $\dot{\beta}$ and $\dot{R}$ are the estimated coefficient and R^2 in a regression without any controls (short-regression), and $\widetilde{\beta}$ and $\widetilde{R}$ correspond to regressions with covariates and fixed effects (long-regression). R^{max} is defined as 1.3 times $\widetilde{R}$, with a maximum value of 1. Values of δ larger than 1 are typically interpreted as evidence against omitted variable bias. We also employ the test of Diegert et al. (2022), which relaxes some assumptions of the Oster (2019) selection test. Most importantly, it allows for endogenous controls, i.e., that omitted variables can be correlated with included covariates. The test calculates bounds of the estimated coefficient of our main variable of interest in relation to the magnitude of how large the selection on unobservables relative to observables would have to be to overturn the statistical significance of this coefficient (see Diegert et al. (2022) for more details).

4. Results

In what follows, we present descriptive statistics of the main variables, the results of our empirical analysis, as well as several extensions and robustness tests.

4.1. The rise of greenhouses

Greenhouse farming in Ecuador already existed in the 1980 s, when the export of cut flowers and somewhat later of vegetables began to boom (Gasselin, 2001). Fig. 1 shows how the average number of

[9] We also provide estimation results with different measurements of greenhouse farming, namely agricultural land size under greenhouse farming, the number of greenhouses in a segment in levels, and the number of greenhouses in a segment transformed by inverse hyperbolic sine.

[10] As we cannot observe farms over time, the treatment status reflects employment also of plots without greenhouses, which is likely to result in a downward bias our results.

Table 1
Descriptive statistics (farm level, pooled 2014–2021).

	Mean	Median	Min	Max	SD
No. of greenhouses	0.03	0	0	18	0.25
No. of crop greenhouses	0.01	0	0	9	0.12
No. of flower greenhouses	0.02	0	0	18	0.22
Land size (ha)	27.71	2.2	0.01	34913.4	289.05
Irrigation (0/1)	0.29	0	0	1	0.44
Use of organic fertilizers (0/1)	0.18	0	0	1	0.37
Use of chemical fertilizers (0/1)	0.44	0	0	1	0.48
Use of organic pesticides (0/1)	0.02	0	0	1	0.13
Use of chemical pesticides (0/1)	0.48	0.37	0	1	0.48
Total no. of workers	8.3	2	1	5000	56.71
No. of male workers	6.17	1	0	4500	48.37
No. of female workers	2.13	1	0	1371	14.67
No. of household workers	1.78	1	0	36	1.1
No. of permanent workers	5.23	0	0	4999	49.52
No. of casual workers	1.28	0	0	3812	24.01
Total workers per hectare	4.17	1.52	0	2513.44	16.03
Male workers per hectare	2.43	0.95	0	1977.98	10.15
Household workers per hectare	1.74	0.12	0	1211.3	7.41
Household workers per hectare	3.09	1.03	0	248.62	5.31
Permanent workers per hectare	0.61	0	0	2509.12	14.59
Casual workers per hectare	0.48	0	0	487.8	3.49
Observations	140,707				

Notes: This table presents descriptive statistics of the main variables used in the analysis. All variables are measured on the farm level.

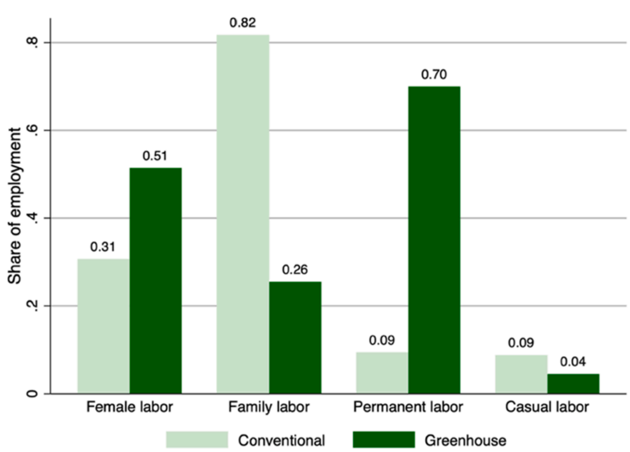

Fig. 2. Share of labor type by farming practice. *Notes:* This figure displays the average share of workers by conventional (i.e., non-greenhouse) or greenhouse farming.

greenhouses in segments in Ecuador has increased between 2014 and 2021. The majority of greenhouses are found in the highlands of Ecuador, given favorable climatic conditions and better infrastructure, (Knapp, 2017). Fig. A-1 in the appendix displays the geographic dispersion of greenhouses. Some regions used greenhouses more intensively in 2021 compared to 2018, and several regions only began greenhouse cultivation after 2014. The share of the total agricultural area used for greenhouse production is relatively small (Fig. A-2 in the appendix), which makes intuitive sense: Greenhouses are more often used for flower and vegetable production than for e.g., cereal or staple crop production, and the latter make up the largest share of agricultural land use (in Ecuador and globally).

Table 1 shows descriptive statistics. The average number of greenhouses on a farm is 0.03, which corresponds to 2% of farms in our sample using greenhouses. The average agricultural land size is 28 ha, though the median size of 2 ha shows that the majority of farms are small. About a third of farms irrigate their lands, 43% apply chemical fertilizers, and 47% chemical pesticides.

The average number of workers on farms is 8, though there is considerable heterogeneity with the median number of workers being 2. Overall, employment in agriculture is male-dominated, and the average number of male workers is three times as high as that of female workers. Most workers are contracted permanently (5.2 on average), which is four times the number of casual workers, and more than half of the farms have no permanent workers at all. Most farms use household labor, but only 1.8 workers on average. On average, three workers work on one hectare of land. Table B-1 in the appendix displays mean comparisons in the main variables of interest between farms with and those without greenhouses. Non-greenhouse farms farm more land, while greenhouse farms farm their land more intensively, using irrigation and other inputs. The latter also employ more workers (besides casual workers) and use less household labor. The larger standard deviation in the number of workers in greenhouse farms reflects the smaller sample size of greenhouse farms.

Fig. 2 visualizes the composition of workers, differentiating between conventional (i.e. non-greenhouse) and greenhouse farms (see also Table B-1). Women make up only a third of the workforce on non-greenhouse farms but half of the workers (including household and hired labor) on greenhouse farms are female. Greenhouses use substantially less household labor and employ more permanent workers compared to conventional farms. This descriptive finding is consistent with our hypothesis that greenhouses provide year-round production and employment opportunities. Fig. A-3 shows the geographical distribution of the average number of total workers (panel a) and of permanent workers (panel b) on farms. Regions with more total and permanent workers are clustered in regions where more greenhouses are used and in Western and South-West Ecuador.

Naturally, not all non-greenhouse farms are comparable to greenhouse farms. We, therefore, turn to the empirical estimation in the following section, where we control for various observable and unobservable factors that could confound the effect of greenhouses on employment.

4.2. *Greenhouses and employment*

We begin our analysis with estimating equation (1), showing how greenhouse adoption changes labor demand within segments. Table 2 presents results. We start with estimating the effect of greenhouses on the average number of workers—including household and hired labor—on farms within segment (column 1).[11] The coefficient of interest is positive and statistically significant at the 5% level (column 1) and even when controlling for all changes over time on the province level (column 2). Column 3 adds the number of plots in a segment, accounting for endogenous selection in and out of segments, and the overall farm size (both *arcsinh* transformed). The coefficient of greenhouses remains statistically significant at the 5% level, and the effect size is substantial: a 1 percentage point larger share of greenhouses is associated with a 0.8 percent larger number of workers on the farm.

In column 4, we add a control for the main crop produced on the farm[12], as different types of crops require different labor input. We find that crop choices do not drive our results. In the last two columns, we differentiate between household and hired labor, which reveals that the positive coefficient of greenhouse farming on labor demand comes from farms hiring more non-household workers (column 6).

[11] Standard errors are clustered on the level of provinces, to account for possible correlation of standard errors on the regional level.

[12] We group crops into 11 categories: Maize & Cereals, Cocoa, Coffee, Rice, Fruit, Flowers, Forage & Fodder, Vegetables, Pulses, Sugar and Other.

Table 2
Greenhouses and employment in segments.

Outcome (*arcsinh*):	Average number of farm workers				Household	Hired
	(1)	(2)	(3)	(4)	(5)	(6)
Greenhouse use (share of plot)	0.831***	0.782**	0.827***	0.805***	−0.108	0.862**
	(0.280)	(0.283)	(0.258)	(0.266)	(0.069)	(0.316)
No. of farms in segment (*arcsinh*)			−0.059*	−0.060*	0.047***	−0.096***
			(0.029)	(0.030)	(0.008)	(0.030)
Land size of the segment (*arcsinh*)			0.118***	0.119***	−0.011*	0.141***
			(0.020)	(0.020)	(0.006)	(0.023)
Observations	18,242	18,242	18,242	18,242	18,242	18,242
Year FE	Yes					
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE		Yes	Yes	Yes	Yes	Yes
Main Crop FE				Yes	Yes	Yes

Notes: The outcome variable is the average number of workers on farms within a segment, transformed by inverse hyperbolic sine. Greenhouse use represents the share of plots in a segment that use greenhouses. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

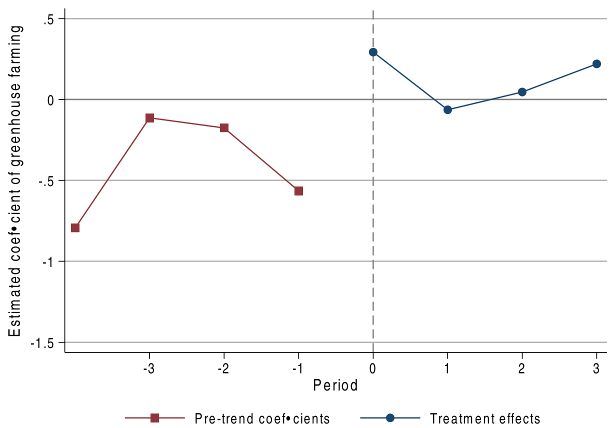

Fig. 3. Greenhouse usage – staggered DiD. *Notes:* This figure displays estimation results following the imputation method developed by Borusyak, Jaravel and Spiess (2022). The treatment variable here is dummy variable indicating whether the segment adopted at least one greenhouse. The outcome variable is the number of hired workers (*arcsinh*). We controls for segment, year, and main crop fixed effects, as well as farm size and the number of plots (*arcsinh*). Confidence intervals represent the 10% significance level. Standard errors are clustered on the province level.

While our estimations control for time-invariant segment-level characteristics and for changes over time at the provincial level, they cannot rule out the possibility that the number of hired workers was increasing before greenhouse adoption. For instance, segments that experienced output growth could hire more workers and be more likely to use greenhouses. To test for the presence of such pre-trends, we switch to an event study type estimation. Here, we observe how employment changed before and after the adoption of greenhouse farming in a segment. As shown in Fig. A-1 in the appendix, few regions had greenhouses in 2014, and this number grew over time. Instead of measuring the share of plots with greenhouses within a segment, we define a segment as 'treated' if there is at least one greenhouse. As explained (see Section 3.2), we use the estimator developed by Borusyak, Jaravel and Spiess (2022), which accounts for heterogeneity in the uptake of greenhouses. Fig. 3 shows the results, where the outcome is the average number of non-household workers on a farm within segments. We focus on the group of hired workers, as we did not see a positive effect on household workers (see Table 2). There are no pre-trends in greenhouse usage.[13] Segments that adopted greenhouses display a negative employment trend before adoption. Also, we see a persistent but decreasing effect of greenhouse farming on employment after adoption. It should be noted that the number of rounds per segment is limited and persistency effects are, thus, only indicative. These findings nevertheless suggest that our results are not biased by heterogeneity in treatment timing or by factors that affected greenhouse uptake and employment before adoption.

Table 3
Greenhouse use and disaggregated employment.

Workers (*arcsinh*):	Total		Household			Hired, permanent			Hired, casual		
	Male	Female	All	Male	Female	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Greenhouse use (share of plots)	0.735***	0.846**	−0.108	0.005	−0.190*	0.994**	0.915**	0.962**	−0.203**	−0.260**	−0.046
	(0.247)	(0.303)	(0.069)	(0.049)	(0.100)	(0.425)	(0.338)	(0.418)	(0.089)	(0.105)	(0.102)
Observations	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are the average number of workers, transformed by inverse hyperbolic sine. Greenhouse use represents the share of plots in a farm that use greenhouses. All columns control for segment and province-year fixed effects. Control variables are the number of plots and average agricultural land size in a segment. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

These findings confirm our first hypothesis: greenhouse farms hire more workers, which is in line with previous evidence on other technologies. Mechanization, formalization, and professionalization have been shown to lead to higher demand for hired workers as compared to the number of household workers on farms (Caunedo and Kala, 2021; Christiaensen, Rutledge and Taylor, 2021).

[13] Note that for the estimations to be valid, we have to exclude segments which switched from being treated to untreated within our period of observation, which however make up only 0.39 percent of observations.

Table 4
Greenhouses and farm employment in segments.

Outcome:	Average number of farm workers (*arcsinh*)			
	(1)	(2)	(3)	(4)
Greenhouse use (share of plots)	0.707**	0.733**	0.723**	0.973**
	(0.277)	(0.336)	(0.334)	(0.362)
No. of farms (*arcsinh*)	−0.056*	−0.049*	−0.049*	−0.084**
	(0.028)	(0.027)	(0.027)	(0.036)
Land size of the segment (*arcsinh*)	0.117***	0.117***	0.117***	0.155***
	(0.019)	(0.019)	(0.019)	(0.027)
Share of plots irrigated	0.119*	0.109**	0.111**	0.151**
	(0.063)	(0.049)	(0.049)	(0.060)
Share pesticides (plots)	0.130***	0.121***	0.121***	0.086***
	(0.016)	(0.018)	(0.018)	(0.025)
Share fertilizer (plots)	0.109***	0.097***	0.097***	0.156***
	(0.018)	(0.018)	(0.019)	(0.035)
Tractor use (share of plots)				0.031***
				(0.011)
Observations	18,243	17,965	17,965	9100
Segment FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes			
Main Crop FE	Yes	Yes		
Canton-Year FE		Yes	Yes	Yes
Main GH crop			Yes	Yes

Notes: The outcome variable is the average number of workers on farms within a segment, transformed by inverse hyperbolic sine. Greenhouse use represents the share of plots in a segment that use greenhouses. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Greenhouses and the composition of employment

We turn to our second question, namely whether greenhouse farming has compositional effects on hired labor. Table 3 provides evidence for greenhouse farming causing such shifts. Here, we use the same fixed effects specification (equation #1) as in columns 3–5 of Table 2 above. The coefficient of greenhouse use is statistically significant both for male and female workers, though it is larger and more precisely estimated for the latter (columns 1 and 2), indicating that women benefit more in terms of employment than men. This is in line with our hypothesis and findings of previous studies (Van den Broeck and Maertens, 2015). Moreover, there are fewer female household members working on greenhouse farms, which does not hold for male household workers.

In the following columns, we disaggregate hired workers further into different contractual types and by gender. In line with our hypothesis that year-round production in greenhouses leads to more stable working arrangements, the number of permanent workers is substantially larger than in non-greenhouses (see Table 3). Similar to overall employment, the difference is larger for female workers. Lastly, we see that fewer casual workers are hired, though here the reduction coming from fewer male workers.

Taking the previous results together, greenhouse farms hire more workers—and especially more female workers—than to non-greenhouse farms, which differentially benefits women. Moreover, higher employment is solely driven by a larger number of workers on permanent contracts.

4.4. Extensions and robustness tests

In this section, we provide several sensitivity tests and alternative specifications. First, as outlined above, we have aggregated the data to the segment level, to construct a pseudo-panel and account for unobserved time-invariant factors. In Table B-2 we run the estimations at the farm level, again including segment and province-year fixed effects, and controlling for the farm's land size. The advantage of the specification is that we estimate changes in the number of workers at the same level in which we observe greenhouses. Therefore, resulting coefficients are not diluted by aggregation with farms that do not use greenhouses. The results of the repeated cross-sectional estimations at the farm level are very similar to the panel estimations at the segment level (Table 2). The coefficient of greenhouse farms in estimations on the number of workers is large and positive. This is, again, driven by a larger number of workers with permanent contracts, while there is a reduction in household workers. The only difference is that at the farm level, the coefficient of workers on casual contracts is positive and statistically significant, though much smaller than that of permanent workers.

As the level of aggregation for our pseudo-panel analysis could bias the estimation, we test whether aggregating farm-level data to other geographical units alters results. In Table B-3 in the appendix we run pseudo-panel estimations on more aggregate levels, namely parishes (ADM3, panel A) and cantons (ADM2, panel B).[14] The results are fairly similar to the main results presented in Table 3: the coefficient of greenhouse farming is statistically significant at both levels for overall employment, permanent employment, and employment disaggregated by gender, as well as for casual employment at the parish and household employment at the canton level.

Next, we vary how we define the dependent and independent variables in Table B-4 and Table B-5 in the Appendix. First, we redefine the dependent variable from the inverse hyperbolic sine transformation of the average number of workers to the average number of workers in absolute numbers in columns 1 and 2—and to the number of workers per hectare in columns 3 and 4 of Table B-4.[15] With both modifications, our main variable of interest, the share of plots with greenhouses, remains statistically significant. A 1 percentage point increase in the share of greenhouses is associated with 69 more workers overall or 13 workers per hectare. The results are also robust to how we measure greenhouse farming. Table B-5 displays regression results for the area of agricultural land in a segment used for greenhouse farming (columns 1 and 2), the number of greenhouses in a segment in levels (columns 3 and 4), and using the hyperbolic sine transformation (columns 5 and 6).

Using our main approach (i.e., segment-level estimations as in Table 2), Table 4 provides several alternative specifications. In column 1, we add controls for farm-specific input choices, including the share of plots that are irrigated and on which both pesticides and fertilizers are used. In column 2, we change our included fixed effects to the canton-year level, which is a smaller geographical unit than provinces. The coefficient of greenhouse use remains statistically significant, which strengthens our confidence that we identify unbiased effects. Third, we change our measure of the main crop that is grown in the segment. As greenhouse farms are on average smaller than non-greenhouse farms, using land size to determine the segment's main crop could under-represent the crop type of greenhouses. We therefore define the crop of the largest greenhouse or, if no greenhouse exists, the crop with the largest agricultural land size as the main crop, which does not change the results. Lastly, we add another control that indicates the level of mechanization on farms, which is the use of tractors.[16] The coefficient of greenhouse use is still statistically significant.

Additional alterations to our main specification are provided in Table B-6 in the appendix. First, instead of estimating Eq. (1) via OLS, we use Poisson estimations in the first two columns to account for the fact that our outcome variable could be seen as a 'count' variable (Wooldridge, 2010). Accordingly, we do not use the inverse hyperbolic sine transformation but the number of workers in levels in these specifications. Second, we exclude segments with the highest number of workers, to verify that our results are not driven by outliers. Specifically, we

[14] As noted above, the data are not representative on these geographical levels. Results should therefore only be interpreted qualitatively, in terms of robustness of the main results.

[15] Workers per hectare are defined as the total number of workers divided by the total agricultural land size in a segment.

[16] The variable comes from an add-on survey to ESPAC, which however is not available for all farms. The number of observations therefore drops.

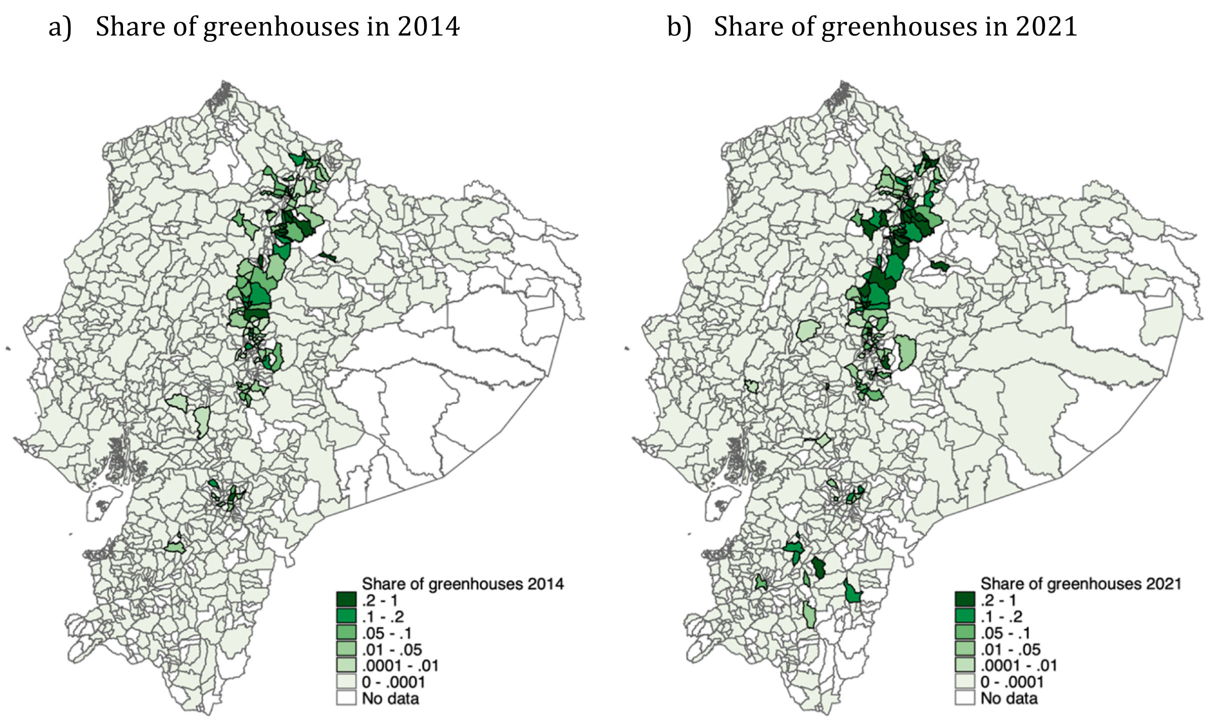

Fig. A-1. Geographical distribution of greenhouse and tractor usage. *Notes:* The figure displays the share of plots using greenhouses in 2014 (a) and 2021 (b) within parishes (ADM3). Areas in white represent regions without survey data or regions with changing IDs that could not be matched. Note that the data is not representative at the level of parishes, but a graphical representation of segments is not possible.

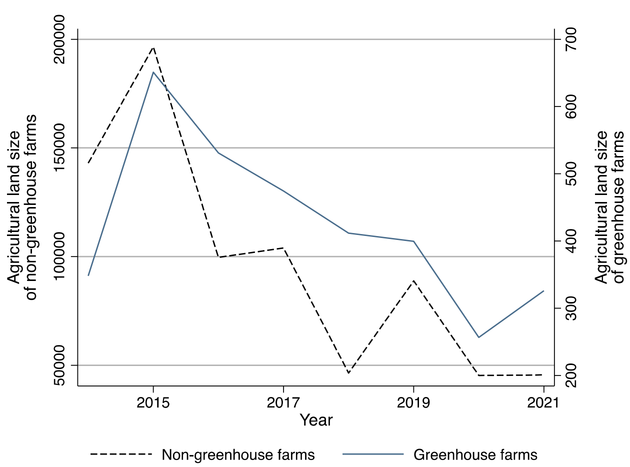

Fig. A-2. Total agricultural land size of non-greenhouse and greenhouse farms in hectares (2014–2021). *Notes:* This figure displays the total agricultural land size (in hectares) of plots without greenhouses (dashed line) and of plots with greenhouses (solid line) in Ecuador between 2014 and 2021.

remove segments with over 100 farm workers on average from the sample, which corresponds roughly to the top 1% of observations. Third, we cluster standard-errors on the level of cantons instead of provinces. None of these alterations substantially changes our results. Excluding the outlier regions reduces the coefficient size, while clustering standard errors on the canton level yields tighter confidence intervals. As a next step, in Table B-7, we disaggregate greenhouses into those that are used to produce flowers and those that produce other crops (which is mostly horticulture).[17] In the first four columns, agricultural entities are aggregated to the segment level, while in the latter four columns, cross-sectional farm-level estimations are run (as in Table B-2). For floriculture greenhouses, the coefficient is statistically significant with and without segment fixed effects. For crop greenhouses it is only not distinguishable from zero when segment fixed effects are included in column 4, which is likely attributable to the small sample size. Segment fixed effects minimize the variation in the coefficient in the respective estimation. On the farm level, the respective estimate remains statistically different from zero (column 8).

Lastly, we perform two tests on omitted variable bias, based on the selection on observable and unobservable covariates following Oster (2019) and Diegert et al. (2022). Both tests relate included controls to the stability of coefficients, as explained in more detail in Section 3.2. Table B-8 in the appendix displays results of the Oster (2019) test, of four model variants of our main estimations results, including both the beta coefficient and R^2 of the model with controls (denoted as $\tilde{\beta}$ and $\tilde{R}^2$) and without any controls (denoted as $\dot{\beta}$ and $\dot{R}^2$). Following Oster (2019), we set the maximum R^2 to 1.3 times the R^2 of the respective estimation (up to a value of 1). The value of δ (reported at the bottom of the table) indicates how much larger the selection on unobservables must be compared to the selection on observed covariates to fully explain the estimated results. A rule of thumb is that values of δ above 1 are indicative of robust treatment effects, which is the case in all specifications. The results also show how much of unobserved variation is picked up in estimations with segment fixed effects (column 2) as we here do not define fixed effects as nuisance parameters. It is difficult to imagine any unobserved variables having the same impact on the model as fixed effects. Therefore, we take the parameters as evidence against omitted variable bias. The results of the test developed by Diegert et al. (2022) point to in a similar direction and are presented in Fig. A-4. As a comparison to the Oster test (2019) detailed above, we here include segment and year fixed effects as nuisance parameters. Hence, the comparison of the long- and short-regression is carried out on the basis of the included control variables, the number of observations per segment, the average agricultural land size, average irrigation use,

[17] This classification is based on the main crop that is produced on the plot of the greenhouse. Crop greenhouses include all that do not produce flowers.

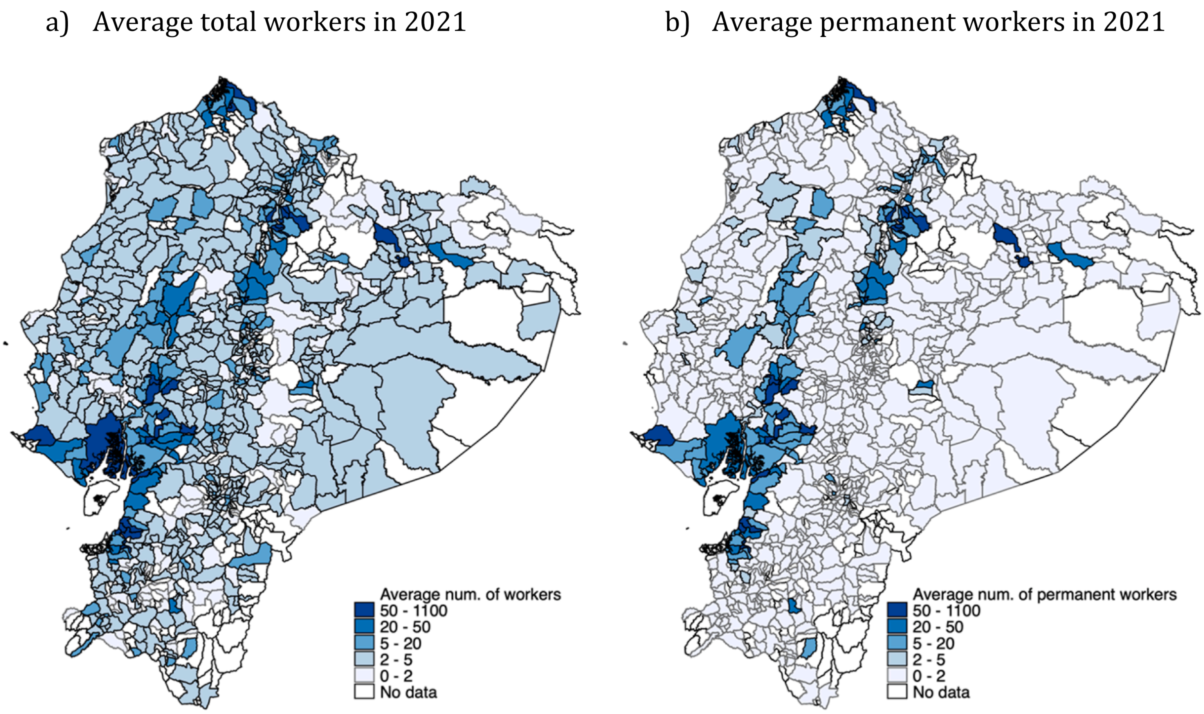

Fig. A-3. Geographical distribution of employment. *Notes:* The figure displays the average number of total workers (a) and average number of workers with permanent contracts (b) on farms within parishes (ADM3). Areas in white represent regions without survey data or regions with changing IDs that could not be matched. Note that the data is not representative at the level of parishes.

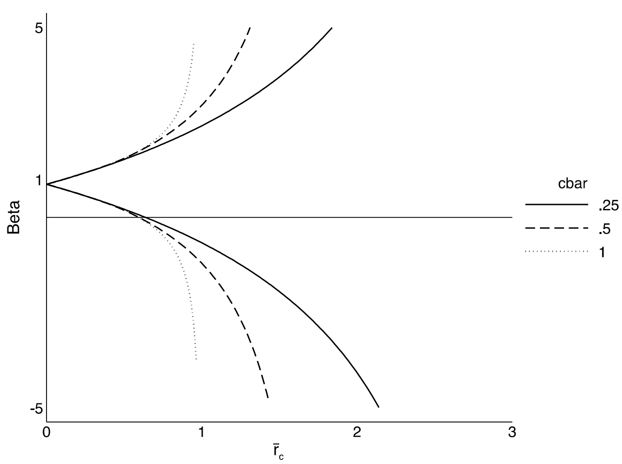

Fig. A-4. Selection and coefficient stability following Diegert et al. (2022). *Notes:* The figure displays the sensitivity of Diegert et al. (2022). The presented bounds reflect values of the estimated coefficient in the fully specified model with all controls (β_{long} in Diegert et al. (2022)). The values of $\bar{r}_c$ represent the magnitude of how large the selection on unobservables relative to observables would have to be to overturn our results. The different line patterns indicate different levels of assumed endogeneity between included controls and omitted variables (cbar). The dotted line is the strictest setting, with full endogeneity assumed. The intersection here lies at 0.61, indicating that our baseline results are statistically different from zero, if selection on unobservables is at most 61% as large as selection on observables. Segment and year fixed effects here are excluded from the comparison.

Table B1
Mean comparisons between greenhouse and non-greenhouse farms.

	Non-greenhouse farms		Greenhouse farms		
	Mean	SD	Mean	SD	T-Stat.
Land size (ha)	28.07	291.92	9.87	26.45	3.29
Irrigation (0/1)	0.28	0.44	0.97	0.15	−83.32
Use of organic fertilizers (0/1)	0.16	0.36	0.83	0.35	−96.22
Use of chemical fertilizers (0/1)	0.43	0.47	0.9	0.27	−51.63
Use of organic pesticides (0/1)	0.01	0.1	0.42	0.48	−181.62
Use of chemical pesticides (0/1)	0.47	0.48	0.91	0.25	−48.31
Total no. of workers	6.81	53.75	81.79	117.82	−70.32
No. of male workers	5.53	47.9	37.81	59.4	−35.04
No. of female workers	1.28	10.29	43.98	62.02	−166.41
No. of household workers	1.79	1.11	1.37	0.89	19.69
No. of permanent workers	3.74	45.95	79.3	117.11	−81.64
No. of casual workers	1.29	24.21	1.12	10.18	0.36
Total workers per hectare	3.85	14.75	20.08	44.28	−53.46
Male workers per hectare	2.29	9.7	9.79	22.17	−38.85
Female workers per hectare	1.56	6.58	10.29	23.64	−62.39
Household workers per hectare	3.05	4.97	4.89	13.97	−18.12
Permanent workers per hectare	0.33	13.3	14.17	42.43	−50.05
Casual workers per hectare	0.47	3.42	1.02	5.98	−8.3
Observations	137,919		2788	Total: 140,707	

Notes: This table presents mean comparisons of the main variables used in the analysis between greenhouse and non-greenhouse farms. All variables are measured on the farm level.

average pesticide use and average fertilizer use. As our fixed effects are high-dimensional and explain a lot of unobserved variation, we treat fixed effects as given. It is very unlikely for any omitted variable to have similar explanatory power (Diegert et al., 2022). The test compares our baseline results without any additional controls to estimations with the full set of controls. In Fig. A-4, we include three different lines of possible endogeneity between included controls and omitted variables (cbar). In the strictest setting, with full endogeneity assumed, the estimated breakdown point lies at 0.61. Thus, the selection on unobservables

Table B2
Farm-level estimations (repeated cross-section).

Workers (*arcsinh*):	Total			Household			Permanent			Casual		
	All	Male	Female	All	Male	Female	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Greenhouse use (share of plots)	0.855***	0.680***	0.962***	−0.031	0.015	−0.063**	0.962***	0.729***	1.009***	0.088**	0.060**	0.055
	(0.124)	(0.103)	(0.156)	(0.022)	(0.018)	(0.027)	(0.164)	(0.128)	(0.170)	(0.041)	(0.028)	(0.033)
Observations	140,707	140,707	140,707	140,707	140,707	140,707	140,707	140,707	140,707	140,707	140,707	140,707
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are the average number of workers (*arcsinh*). Greenhouse use represents the share of plots on a farm that use greenhouses. All columns control for segment and province-year fixed effects and for land size. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B3
Parrish- and Canton-level estimations (pseudo-panel).

Workers (*arcsinh*):	Total			Household			Permanent			Casual		
	All	Male	Female	All	Male	Female	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Parrish-level												
Greenhouse use (share of plots)	1.520***	1.235***	1.901***	−0.507***	−0.407*	−0.652***	1.620***	1.383***	1.645***	0.153	−0.025	0.499
	(0.342)	(0.364)	(0.368)	(0.138)	(0.202)	(0.202)	(0.405)	(0.380)	(0.442)	(0.301)	(0.228)	(0.322)
Observations	6255	6255	6255	6255	6255	6255	6255	6255	6255	6255	6255	6255
Panel B: Canton-level												
Greenhouse use (share of plots)	4.165***	3.429***	5.328***	−0.095	−0.227	0.268	8.160***	7.084***	9.601***	0.883*	0.430	2.783***
	(0.842)	(0.890)	(1.112)	(0.353)	(0.383)	(0.332)	(0.570)	(0.690)	(1.137)	(0.476)	(0.544)	(0.690)
Observations	1660	1660	1660	1660	1660	1660	1660	1660	1660	1660	1660	1660
Parrish/Canton FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In Panel A, agricultural entities are aggregated to the level of parishes and in Panel B to the level of cantons. The outcome variables are the average number of workers (*arcsinh*). Greenhouse use represents the share of plots in a parrish/ canton that use greenhouses. All columns control for parrish/ canton and province-year fixed effects and for land size. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4
Farm workers in levels and per hectare (segment level).

Farm workers:	Levels		Per hectare	
	All	Hired	All	Hired
	(1)	(2)	(3)	(4)
Greenhouse use (share of plots)	51.470***	51.770***	22.435***	16.397**
	(17.681)	(17.730)	(7.206)	(6.409)
Observations	18,243	18,243	18,243	18,243
Segment FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: The outcome variable is the average number of workers on a farm within segments in levels in columns 1 and 2, and the number of workers per hectare of farm land in columns 3 and 4. Greenhouse use represents the share of plots in a segment that use greenhouses. Control variables are the number of plots and average agricultural land size in a segment. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

would have to be at least 61% as large as the selection on observables to overturn the statistical significance of our results.

5. Discussion and policy implications

Our analysis shows that greenhouse farming can contribute to much-needed employment opportunities in lower-income countries. Many studies in agricultural and development economics have highlighted the importance of wage employment, both on– and off-farm, for development and poverty reduction (Barrett et al., 2001; Haggblade and Hazell, 2010; Haggblade, Hazell and Reardon, 2010; Christiaensen, Rutledge and Taylor, 2021). Agriculture will remain an important source of employment in lower-income countries, even when structural transformation shifts larger shares of the workforce to other sectors (Christiaensen, Rutledge and Taylor, 2021; Bellemare et al., 2022). Greenhouse farming contributes to the creation of jobs in the higher value agri-food sectors in lower-income countries, where wage employment has been shown to improve incomes and welfare of households (Maertens et al., 2011; Herrmann and Grote, 2015; Van den Broeck et al., 2017). As the expansion of land is becoming less and less feasible and desirable, investments in greenhouses (which can use land more efficiently) can be useful to facilitate the production of particularly nutritious foods—as well as the generation of wage jobs. To reap these benefits, policies could target factors that incentivize and enable greenhouse farming, such as access to infrastructure, irrigation, and higher-value and export markets. To promote such shifts, farmers also need to receive necessary information, financing options, and targeted agricultural extension services to build related knowledge and skills.

Our analysis also shows that women benefit more (in terms of employment) from greenhouse technology. These results are in line with previous studies suggesting that higher-value supply chains are more inclusive towards women (Maertens and Swinnen, 2012; Fabry, Van den Broeck and Maertens, 2022), which has far-reaching consequences, e.g., for food security (Van den Broeck et al., 2018), fertility rates (Van den Broeck and Maertens, 2015), and children's education (Maertens and Verhofstadt, 2013; Quisumbing and Doss, 2021).

With the data at hand, we however cannot observe wages and

Table B5
Agricultural land under greenhouse farming, number of greenhouses in levels and number of greenhouses *arcsinh* transformed segment level).

Farm workers (arcsinh):	All	Hired	All	Hired	All	Hired
	(1)	(2)	(3)	(4)	(5)	(6)
Agri. land under greenhouses (*arcsinh*)	0.228**	0.266**				
	(0.088)	(0.105)				
Number of greenhouses (levels)			0.008**	0.010**		
			(0.003)	(0.004)		
Number of greenhouses (*arcsinh*)					0.161**	0.188**
					(0.077)	(0.085)
Observations	18,378	18,378	18,378	18,378	18,378	18,378
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the average number of workers on a farm within segments (*arcsinh*). Greenhouse use represents the share of plots in a segment that use greenhouses. Control variables are the number of plots and average agricultural land size in a segment. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B6
Alternative specifications.

	Poisson		Excl. Outlier		Canton s.e. clustering	
	All	Hired	All	Hired	All	Hired
	(1)	(2)	(3)	(4)	(5)	(6)
Greenhouse use (share of plots)	0.945***	1.039***	0.644***	0.658***	0.805***	0.862**
	(0.237)	(0.209)	(0.181)	(0.212)	(0.222)	(0.316)
Observations	18,243	14,072	17,963	17,963	18,243	18,243
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the average number of workers on a farm within segments, in levels in columns 1 and 2, and transformed by inverse hyperbolic sine thereafter. Excluded outliers reflect the top 1% of segments with most workers. Greenhouse use represents the share of plots in a segment that use greenhouses. Control variables are the number of plots and average agricultural land size in a segment. Standard errors, in parentheses, are clustered on the province level in columns 1–4, and on the canton level in columns 5 and 6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B7
Greenhouse types and farm workers.

Average num. of farm workers (arcsinh):	Segment-level				Farm-level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flower greenhouses (share of plots)	3.173***	1.397***			2.254***	1.341***		
	(0.146)	(0.197)			(0.263)	(0.217)		
Crop greenhouses (share of plots)			0.920***	−0.030			0.465***	0.279***
			(0.176)	(0.133)			(0.065)	(0.059)
Observations	18,243	18,243	18,126	18,095	140,707	140,707	137,927	137,881
Segment FE		Yes		Yes		Yes		Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the average number of workers on a farm within segments, transformed by inverse hyperbolic sine. The first four columns depict estimation results on the segment- and the latter four columns on the farm-level. Greenhouse use represents the share of plots in a segment/ farm that use greenhouses, for flower and for crop production, respectively. Segment fixed effects are included in every second, and province-year fixed effects throughout. Control variables are the number of plots and average agricultural land size in a segment/ farm. Standard errors, in parentheses, are clustered on the province level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

working conditions. Discriminatory working conditions have been documented for instance in the horticulture sector, which could prevent the above-discussed benefits from materializing (Staritz and Reis, 2013). Additionally, health issues related to high pesticide use have been emphasized in previous studies (Nassar and Ribeiro, 2020). Therefore, it is essential that good working conditions, including occupational heath and safety standards, and fair wages are enforced. Ideally, governments would introduce and enforce public, mandatory labor standards. A complementary option is private sustainability standards, such as GlobalGAP and Fairtrade, which also have stringent labor and safety standards (e.g., on safe pesticide application) (Schuster and Maertens, 2016; Krumbiegel et al., 2018; Meemken et al., 2021).

Lastly, our results show that greenhouse farms hire more workers on permanent contracts (likely because greenhouses reduce seasonality of agricultural production), which has important implications. Households living in uncertain environments exhibit lower savings and investment rates, hindering long-run development (Hallegatte et al., 2012; Brooks and Donovan, 2020). Generally, seasonal employment is a key driver in hunger and poverty in many regions dominated by agriculture (Khandker, 2012; Bryan et al., 2014; Cedrez et al., 2020; de Janvry, Duquennois and Sadoulet, 2022). Reducing seasonal poverty, therefore, is of immanent importance to improve livelihoods. While there are several strategies through which seasonal poverty can be reduced, such as providing access to credit or migration opportunities, their

Table B8
Selection and coefficient stability following Oster (2019).

	(1)	(2)	(3)	(4)
$\tilde{\beta}$	2.29	0.84	0.76	0.77
$\tilde{R}$	0.35	0.80	0.82	0.82
$\dot{\beta}$	2.66	2.66	2.66	2.66
$\dot{R}^2$	0.05	0.05	0.05	0.05
Rmax	0.45	1	1	1
δ (β = 0)	17.70	1.72	1.13	1.14
Observations	29,140	18,243	18,243	18,243
Long regression covariates:				
Controls	Yes	Yes	Yes	Yes
Segment FE		Yes	Yes	Yes
Province-Year FE			Yes	Yes
Main Crop FE				Yes

Notes: This table presents the degree of selection on unobservables that is required to fully explain our estimated results (δ), following Oster (2019). In the first row, $\tilde{\beta}$, the estimated coefficient of greenhouse farming of the 'long' regression, is presented, followed by $\tilde{R}^2$ of the same regression in column 2. Controls and fixed effects are included in each model as specified on the bottom of the table. The third and fourth row display the statistics for the estimation without any controls. The coefficient $\dot{\beta}$ relates to the 'short' regression, without any controls. R^{max} is defined as 1.3 times the R^2 of the model with controls. In column 1, all control variables as in column 1 of Table 4 without fixed effects are included. Column 2 adds segment fixed effects, column 3 province-year fixed effects, and column 4 crop fixed effects.

implementation remains difficult (Bryan et al., 2014). Greenhouse farming can be an important avenue in directly generating year-round employment opportunities in rural areas, where off-season labor opportunities are scarce.

6. Conclusion

Many lower-income countries have been experiencing a proliferation of high-value agricultural production. A large body of literature explores implications for smallholder farmers. Yet evidence on wage labor remains thin, despite the importance of wage employment for poverty reduction in rural areas (Jacoby, 2016; Christiaensen, 2017). We contribute to the emerging literature on agrifood labor by analyzing how greenhouse farming affects employment, differentiating between different types of workers. For this purpose, we use unique nationally representative pseudo-panel data from Ecuador. Our results indicate that greenhouse farms hire more workers—and especially more workers hired on permanent contracts—than non-greenhouse farms. This resonates with a key factor of greenhouse technology: it reduces the vulnerability of agricultural production to seasonality and other external factors. The higher number of hired workers goes hand in hand with fewer household members working on the respective farms, which is in line with other studies on agricultural mechanization and commercialization (Bellemare and Bloem, 2018; Adu-Baffour et al., 2019). We also find that greenhouse farms hire more female workers than non-greenhouse farms, which is important to reduce existing labor market inequalities.

With the data at hand, we are not able to inspect important aspects related to job quality, such as wages or working conditions. Here remain interesting gaps for future research. For instance, analyzing how greenhouse farming affects workers' wages but also non-wage benefits, such as social security or safety-related aspects and exposure to hazardous chemicals, are intriguing questions left to be answered. Other aspects, that are not directly related to labor, are also under-researched and important when evaluating the overall performance of greenhouse farming. For instance, greenhouse farming could increase water use and thereby further reduce access to water among less power-full and vulnerable populations in locations plagued by water scarcity (Tilman et al., 2002; Mena-Vásconez et al., 2016). Yet technological advances can also help increase water use efficiency in greenhouse farming (Czyzyk et al., 2014; O'Connor and Mehta, 2016; Nicola et al., 2020). Holistic approaches are necessary to evaluate whether greenhouse farming reduces or increases trade-offs in promoting socio-economic and environmental sustainability goals.

CRediT authorship contribution statement

Henry Stemmler: Conceptualization, Methodology, Software, Formal analysis, Validation, Investigation, Data curation, Writing – original draft. **Eva-Marie Meemken:** Conceptualization, Methodology, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Figures

(See Fig. A1, Fig. A2, Fig. A3, Fig. A4).

Appendix B

Tables

(See Table B1, Table B2, Table B3, Table B4, Table B5, Table B6, Table B7, Table B8).

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