Trade-displaced or trade-stuck? Self-employment, gendered outside options and trade shock adaptation

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Abstract

Do trade shocks still displace workers when they are self-employed and thus have decision-making power over job exit? The answer matters for low-income countries, where self-employment rates are highest. In this paper, I study an import tariff shock affecting self-employed retailers in Rwanda using censuses of formal and informal establishments and job-level data. Workers exposed to the shock do not leave their jobs despite sizeable hourly earnings decreases. Instead, they implement specific adjustment strategies like reallocating hours across multiple jobs. I rationalize these novel responses into a model of time allocation with multiple job holdings. It predicts that reallocation depends on the quality of outside employment options, which I test by examining gender heterogeneity, after showing that women retailers have worse outside options than men. Consistently, while men shift hours away from affected jobs toward other paid occupations, women abandon other jobs to increase hours at the affected job and face persistent negative income effects. Stressing the outside options channel, men in more vulnerable situations - whose usual job alternatives are less numerous locally, operating in low-opportunity areas, or working several casual jobs pre-shock - are less mobile in the face of the shock. Although self-employment protects workers from trade-driven displacement, it keeps the most vulnerable groups stuck in declining sectors, making trade adjustment assistance crucial.

JEL: F13, F16, J22, J46, J62, O12

Keywords: Self-employment, Trade policy, Labor market power, Labor supply, Occupational mobility

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Sub-Saharan Africa is the region of the world with the lowest share of salaried workers: 24.5% in 2019 (ILOSTAT). While trade policy is a strategical pillar or regional development, as the African Continental Free Trade Area discussions show, research on trade and labor markets has been focused on salaried workers' outcomes and little is known about the way that trade impacts the majority of workers in the sub-continent: the self-employed. This paper offers to fill this gap. Using a tariff shock that weighed on self-employed retailers in Rwanda, and comprehensive data on formal and informal workers and establishments, I answer this question: How do the self-employed adjust to trade shocks in low-income countries?

Trade adjustment is more relevant than ever in a world where protectionist policies are on the rise, as in the case I study. In 2016, the East African Community (EAC) announced the implementation of prohibitive import tariffs on used clothing, a North-South trade that represents a sizable share of urban households' clothing consumption (around 75% for Tanzania [Foundation, 2017]). Faced with threats of exclusion from the African Growth Opportunity Act, a free trade agreement with the United States, all EAC countries abandoned the project, except for Rwanda which increased its tariffs tenfold in June 2016. The apparel sector's exclusion from AGOA followed in 2018. The measure aimed to recapture domestic demand and develop the apparel industry. Its most immediate effect, however, was to dramatically decrease used clothes imports and to increase their price for local wholesalers and ultimately retailers - a workforce almost entirely made up of self-employed workers[1]. The impacts of the shock are not easily predicted from existing works, as self-employed workers cannot be fired, control their working hours, and are more likely to be holding several jobs at once than wage earners - their adaptation strategies differ from the standard reallocation framework.

The context that I investigate and the data that I leverage to do so both allow me to bring novel evidence to the question of labor market adjustment to trade shocks in low-income countries. First, the shock that I study affects an overwhelmingly self-employed workforce from the service sector, in contrast with trade liberalization shocks that often affect larger, manufacturing firms and their employees. Most works in that field put forward mechanisms leading to reallocation either from [McCaig and Pavcnik, 2018, Erten and Keskin, 2021] or to [Ponczek and Ulyssea, 2021, Dix-Carneiro and Kovak, 2019] informality and unemployment. These results imply that trade-driven shocks to wages or firm productivity lead to reallocation, which is not as likely to be the case when affected labor markets are entirely self-employed. Formal wages are more rigid than informal ones [Corbi et al., 2021, Dix-Carneiro et al., 2024], but some downward rigidity remains [Kaur, 2019] even in informal salaried work and is eliminated in self-employment: faced with the same wage-decreasing shock, self-employed workers are thus less likely to exit their jobs than even informal wage-earners. Reflecting this conceptual difference, I find evidence that in contrast with studies showing that even the informally wage-employed experience decreases in employment rates from trade shocks [Ponczek and Ulyssea, 2021, Dix-Carneiro and Kovak, 2017, 2019, Bas and Bombarda, 2023], self-employed workers do not leave their affected jobs, even when their earnings are growing significantly slower than less affected workers. This results in a limited informality response: informality does not have to be an "unemployment buffer" [Ponczek and Ulyssea, 2021] if workers are not losing their jobs[2]. I show this in sectors outside of

[1] 89% both pre-and post-shock (IHLCS)

[2] In the sector of interest, self-employed retail, 90% firms were not declared to the Rwanda Revenue Authority pre-shock (IHLCS

manufacturing and in Sub-Saharan Africa, where evidence has been scarce due to data unavailability [McCaig and McMillan, 2020], and through a protectionist shock, providing timely insights on trade wars.
The data that I use allows me to go further into the exploration of informal workers' adaptation strategies, notably through the use of privately accessed establishment censuses for both formal and informal plants. In contrast to works using formal-only panels (Dix-Carneiro and Kovak [2017, 2019], although informality is explored as an adjustment margin at the regional level), I do not have to assume that informal workers and establishments are similar in their trajectories to formal ones. This assumption is also dropped in McCaig and Pavcnik [2018] or Dix-Carneiro et al. [2024], but such data has lacked thus far in Sub-Saharan Africa. and that time allocation across multiple jobs is exogenous to shock. Fine-grain licensed survey data allowed me to quantify workers' outcomes at the ISIC-3 digit level for all of their jobs throughout the year. Quantifying reallocation at a lower scale than the individual level matters, because a sizeable share of the Rwandan workforce - about 28% in 2016[3] and 36% of the self-employed - holds several jobs at once, shedding doubt on the assumption that time allocation across different jobs within the week stays constant in the face of a job-specific shock. Dropping this assumption allows me to shed new light on several novel patterns of substitution across jobs within the week.

My empirical strategy utilizes an index of pre-shock exposure to used clothing trade built with Census data for all establishments, formal and informal, similar to numerous works on regional impacts of trade policy [Dix-Carneiro and Kovak, 2017, 2019, Ponczek and Ulyssea, 2021, McCaig and Pavcnik, 2018, Autor et al., 2023, Topalova, 2010, Bas and Bombarda, 2023]. Because zones more exposed to the shock could be different in a variety of aspects, I further introduce variation in being a job or having had a job, in self-employed retail starting before the shock. I study common adjustment margins: first, earnings and hours worked at the job level, before turning to earnings and hours across all jobs in a given week, which allows me to explore time reallocation across jobs in the context of prevalent multiple job holding. I then study reallocation across sectors, occupations, and the number and duration of jobs per year or week. I also consider migration. I develop a simple framework to speak to my results and test with quadruple-difference disentangling outcomes by gender.

-The first set of results speaks to the literature on the effect of trade policy on developing countries' labor markets. Most striking is the absence of displacement, which comes in contrast to most case studies of trade-induced earnings shocks in developing countries [Dix-Carneiro and Kovak, 2017, 2019, 2023, Ponczek and Ulyssea, 2021, Erten and Keskin, 2021, McCaig and Pavcnik, 2018]. I find that a) self-employed retailers in more exposed areas are not more or less likely than those less exposed to become inactive or unemployed. This is the case even though b) their earnings from retail are negatively affected, through slower turnover growth, and even though c) this translates into their income across earnings sources, which also decreases relatively to retailers in protected areas, with effects remaining even more than a year after the shock. Rather than going into unemployment or even decreasing hours at the affected job, d) workers tend to increase total

2013). Informality is defined as not being registered to the administration for self-employed workers, and as not being covered by health insurance by one's employer for the wage employed, as in Ulyssea [2023].

[3] Source: Integrated Household Living Conditions Survey 2016

hours worked during the week at other jobs to maintain income and e) overlap their multiple jobs to a higher extent: they have the same number of jobs throughout the year, but these jobs tend to last longer, indicating longer periods where jobs overlap. Finally, while f) there is no spatial reallocation, g) workers also reallocate across jobs, with fewer of these workers likely to do unpaid family work and evidence of more choosing to do wage farm work and sales work outside of retail, leading to h) a slight increase in the likelihood of doing formal activity throughout the week or as a main job. These results illustrate self-employment-specific adaptation margins: first, although the import tariff resulted in higher per-unit clothing costs, the channel through which profits decrease is through sales, not expenditures, indicating price pass-through or decrease in quantities sold on the part of retailers. Second, workers are not abandoning their retail jobs: they increase the total hours worked during a week and months worked at each job, overlapping them more. These are channels that are less likely to be exerted within the boundaries of a salaried job.

I rationalize these findings in a model of time allocation with a production-constrained retail sector and another option, part-time by nature, informed by the used clothes supply chain and the characteristics of the labor market workers operate in. It predicts different reallocation patterns conditional on the quality of available outside options, which I test by looking at trajectories for men and women.

I uncover striking heterogeneity in adaptation strategy across genders. I find although i) all retail job wages grow slower in more affected areas, ii) women's retail jobs are subject to an additional negative impact. While iii) the impact on earnings in men's jobs is no longer significant once one allows for gender-dependent trends iv) women's jobs are persistently hit, at the weekly level but even more so when considering hourly earnings. Indeed, the null results on hours worked at retail jobs were masking contrary trends: while men are decreasing hours worked at retail jobs, women are v) increasing them to mitigate income losses, leading to vi) a decrease in hourly income relative to men, compensated for by more hours worked. This surprising result suggests a limited capacity to reallocate toward more lucrative activities. While nobody is abandoning the retail jobs, vii) patterns in take-up of new jobs are also opposed: when women work more at their affected jobs, they do so by giving up on their other employment, often unpaid family work. On the contrary, men are reallocating hours in retail toward other, paid jobs. There is no unemployment and no formality response once one allows for gender-dependent trajectories, and the results match works describing self-employment as a potential "trap" [Blackburn et al., 2023].

Two additional exercises suggest that the cause for heterogeneous reallocation is outside options inequalities rather than gender in itself: in districts where men's usual alternatives are less present, or when they retail jobs are more precarious, their trajectories follow women's. My results suggest that the least mobile segments of the workforce get stuck in declining sectors after trade shocks, suggesting exclusion from other opportunities and indicating involuntary entrepreneurship. The abandonment of unpaid family jobs, especially as it does not impact consumption, indicates that the abandoned tasks were bringing non-pecuniary utility either to women themselves or to other members of the household, entailing broader consequences.

My paper relates to the literature on the effects of trade on regions, firms, and workers. Seminal works about the "China Shock" [Autor et al., 2013] found that US labor markets initially more exposed to import competition from China experienced higher unemployment lower labor force participation rates, and reduced wages. Such displacement has also been shown in developing countries exposed to trade competition, like in Brazil [Dix-Carneiro and Kovak, 2017, 2019] where workers initially employed in the tradable sector became unemployed and reallocated to lower-paid jobs. In developing countries, informality is another important margin, and works have related it to trade in two ways: the first approach studies the impact of trade on informality rates, for example through bigger export markets for formal firms [McCaig and Pavcnik, 2018], better access to inputs [Bas and Bombarda, 2023], or distress because of import competition [Wang et al., 2021]. The second addresses how the effects of the trade itself are changed by the presence of informality [Dix-Carneiro et al., 2021], as "The effects of trade policy on labor market outcomes depend on relevant labor market frictions within a country" [Goldberg and Pavcnik, 2016]. With prevalent informal sectors, unemployment responses tend to be muted, as informality acts as an "unemployment buffer" [Ponczek and Ulyssea, 2021]. With limited regulatory enforcement, workers go into informality rather than unemployment. When they cannot, they will be unemployed for longer, but without more cumulative earnings losses [Ponczek and Ulyssea, 2021]. I further these approaches by showing that the mechanisms put forward above linking displacement to trade policy are not automatic in settings with prevalent self-employment. These are novel results partly because the existing literature has been mostly focused on Latin America [Dix-Carneiro and Kovak, 2023], mostly for data reasons. Evidence on the Sub-Saharan African region is scarce (as noted in McCaig and McMillan [2020] in their study of Botswana, with this work and Erten et al. [2019] important exceptions) as are studies of protectionist shocks in developing countries [Kelishomi and Nisticò, 2023, Rotunno et al., 2023]. The data and setting that I exploit allow me to fill these gaps and to add evidence to the body of literature on retail [Atkin et al., 2018] and the textile supply chains [Boudreau et al., 2023, Grant and Startz, 2022]. Additionally, I explore several novel margins at the within-individual, within-week level, important dimensions when multiple job-holding is prevalent, as in most developing urban labor markets.

By addressing the ability to reallocate, the paper also brings value to the factor mobility literature. Reallocation following a shock is imperfect: exposed regions and individuals face earnings decreases and do not respond automatically through migration or sectoral reallocation [Topalova, 2010], leading to widening gaps between exposed and non-exposed regions as time passes [Dix-Carneiro and Kovak, 2019]. Most empirical studies find that the most immobile segments of the population are the most vulnerable ones: those with the least resources [Topalova, 2010], older workers from less internationally integrated regions [McCaig and Pavcnik, 2018], women [Mansour et al., 2022, Roche Rodriguez et al., 2023] or less skilled workers [Bas and Bombarda, 2023, Keller and Utar, 2023, Kelishomi and Nisticò, 2023]. This phenomenon is formalized in Adão [2016], in which different categories of the population have different comparative advantages schedules, influencing their resilience. Some works have linked turnover and development, finding higher turnover rates in developing countries [Donovan et al., 2023] and addressing the usefulness of these transitions for workers to climb the job ladder McCaig and Pavcnik [2021], McKenzie and Paffhausen [2019]. I reinforce existing findings that affected workers are not mobile enough to mitigate negative income effects, including a year and a half after the shock, and that women and vulnerable populations are especially at risk. I add to the literature by showing both inequalities in shock incidence - the direct shock on job-level earnings - and in resilience - the extent to which that earnings shock is translated to long-lasting losses in personal income.

A subfield of the factor mobility literature is interested in the gendered and empowerment effects of gender-neutral policy, like Erten and Keskin [2021] on liberalization in Cambodia, added worker effects and violence, or Sanin [2021] on seasonal work on coffee mills and gendered experience of violence. Other works show that women tend to have anti-cyclical reallocation patterns, joining the labor force in times of recession, while men are pro-cyclical [Alon et al., 2020]. My results speak to this literature, replicating this stylized fact at the level of hours worked and not the decision to join the labor force, consistent with the absence of displacement to unemployment and the lack of safety nets in this setting.

Finally, I bring novel evidence to two strands of the self-employment literature. In contrast with other regions where younger generations increasingly access salaried jobs, self-employment is not declining in Sub-Saharan Africa [Bandiera et al., 2022b], and it is thus crucial for informing policy to produce evidence that takes this working arrangement into account. Numerous works have tackled the question of whether self-employment is done out of entrepreneurial vocation or out of the need for a source of income [Bandiera et al., 2022b, Margolis, 2014, Gindling et al., 2016], and what determines entry and exit of these small firms [McCaig and Pavcnik, 2021, McKenzie and Paffhausen, 2019, Donovan et al., 2023]. Previous works in Sub-Saharan Africa have shown that women are over-represented in ”survivalist” firms that do not have growth prospects and are not credit-constrained [Grimm et al., 2012], and that in developed countries, the self-employed react anti-cyclically to business cycles, contrary more successful entrepreneurs Rubinstein and Levine [2020]. As countries develop and the organization of labor changes, women exit self-employment much later than men [Bandiera et al., 2022a], suggesting more exclusion from other labor markets. I show that women do not reallocate away from retail self-employment when it gets less lucrative, suggesting that their choice to be self-employed is constrained by the labor market rather than driven by entrepreneurial spirit.

Another part of that literature has addressed market inefficiencies and self-employment. Higher firm concentration in the formal sector [Amodio et al., 2022]or credit constraints Scarelli and Margolis [2021] has been shown to increase self-employment. It is also the work arrangement where earnings gender gaps are highest [Heath et al., 2015], and recent works have pointed at customer discrimination, occupational segregation [Hardy and Kagy, 2020], or differential valuation of occupational amenities like flexibility as causes for this gap. Both the natural experiment and the framework I construct show that outside options differences lead to women working in more crowded industries, being more vulnerable to shocks, and less likely to reallocate elsewhere, even in the self-employed labor market. This complements recent works on outside options in salaried markets [Sharma, 2023, Caldwell and Danieli, 2024].

The rest of the paper is organized as follows. In section 1, I describe the policy, and section 2 presents the data. The methodology is outlined in section 3 and section 4 presents the results. I develop a model in section 5 and check the validity of its predictions in section 6 through gendered results. I present robustness chekcs in section 7 and conclude in section 8.

1 Rwanda's 2016 tariff increase on $caguwa$ imports

The used clothes sector in domestic demand and Rwandan clothing trade

Used clothing, a sizeable and growing trade, flows from rich countries to poorer, mostly African ones. In 2020, 4 out of the 5 top importers of used clothes were Sub-Saharan African countries, each importing over 100 million dollars of these goods each year [Cobbing et al., 2022]. Used clothes, or $caguwa$ in Kinyarwanda[4], have alternatively been praised for offering a cheap clothing option to urban households and blamed for the underdevelopment of the textile and garment sector, with Frazer [2008] attributing up to 40% of the decrease in the apparel sector's share of manufacturing and of jobs across most countries of the continent to that trade. Other issues, such as cultural ones, have also been raised by citizens and governments eager to curb these imports supposedly crowding out traditional clothing and from which a sizeable share immediately goes from bales to landfills [Cobbing et al., 2022]. The notion of dignity was a central communication pillar when Rwanda's intent to ban *caguwa* imports was made public in 2016, through an East Africa Community[5] common project to raise tariffs on second-hand clothing imports [Wolff, 2021]. Faced with threats of exclusion from the Africa Growth and Opportunity Act[6]'s apparel section, all EAC countries abandoned the project, except Rwanda. The tariff increase[7] was implemented in 2016 and Rwanda was suspended from AGOA in 2018. In the meantime, there was no sizeable substitution of domestic production to these imports, as shown by the resolution to not implement further tariff hikes beyond 2.50 USD /kg as initially planned[8], because of the nascent quality of the Rwandan textile and garment industry.

The measure was implemented 6 months from the first EAC-wide proposal and was efficient in curbing imports of second-hand clothes: Figure 1 and Figure 2 represent, respectively, the evolution of new and used clothing imports in Rwanda (volume and value) and the ratio of clothing prices over the general consumer price index for urban and rural areas. We can see that after 2016, the volume of used clothes imported to Rwanda decreased persistently, consistently with the per kg. tariff. Unit prices for new clothes also decreased slightly for 2017, but their average unit value stayed much higher (around fourfold), meaning that new clothing does not represent a direct substitute for used clothing demand after the shock. New clothes remain on an increasing trend in terms of import volumes. As a result of the measure, we can also see that the years-long decreasing trend of clothing prices relative to other goods' prices halts. The stop is quicker in urban than in rural areas, which we can attribute to stocks depleting faster in the former or to slower supply chains for the latter. The tariff increase seems to have had impacts on country-level measures such as imports and prices. This provides strength to the argument that the shock was powerful enough to fuel adaptation response, as I later show in individual-level data.

Used clothing supply chain and the characteristics of used clothing retail work

Used clothing is a prevalent industry employing many of the urban areas' workforce in African countries.

[4] the official language of Rwanda, spoken throughout the country

[5] Customs Union comprising Kenya, Rwanda, Uganda, Burundi, Tanzania, with the DRC and South Sudan having joined after 2016

[6] AGOA, a program allowing selected African countries to export certain goods to the US duty-free

[7] From 0.5 to 5 dollars/kg on used shoes and 2.5 dollars/kg on used clothing according to the government framework, vis [2000]

[8] Strategy For The Transformation Of Textile, Apparel And Leather Sectors in Rwanda, MINICOM 2022

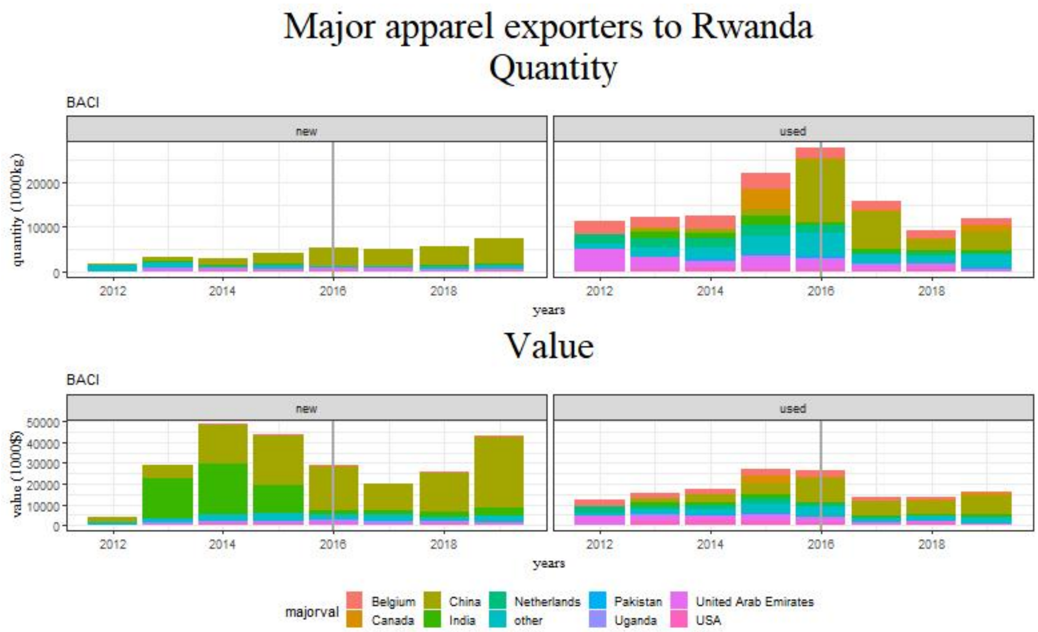

Figure 1: Import volumes and values

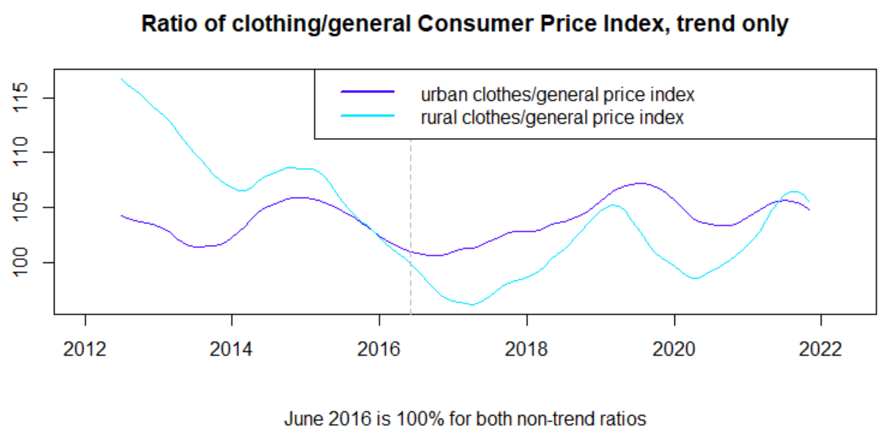

Figure 2: Prices

	Caguwa	Retail outside Caguwa	Other
Operating in market	0.81	0.18	0.05
	(0.39)	(0.39)	(0.23)
Woman manager	0.50	0.38	0.27
	(0.50)	(0.49)	(0.45)
Firm age	3.12	2.40	4.55
	(4.29)	(3.87)	(10.74)
Less than 3 workers	1.00	0.98	0.84
	(0.00)	(0.13)	(0.36)
Total workers	1.07	1.40	5.07
	(0.26)	(4.32)	(67.83)
Observations	127	90381	99780

Source: Establishment Census (2017)

Table 1: Summary statistics on Caguwa establishments

For example, 121,000 direct jobs are created from that industry in Kenya [Wolff, 2021], and my estimates based on pre-shock plant-level census data suggest that *caguwa* retail represents up to 1/8 of the retail sector in the most exposed districts before the shock. The used clothing supply chain remains to be quantified, but qualitative accounts of used clothing trade in neighboring countries [Brooks and Simons, 2012, Brooks, 2012, Mesa, 2021] or political economy studies of the measure [Behuria, 2019] all refer to clothes arriving in bulk at wholesalers, before being bought in bales by retailers. This process holds characteristics that set it apart even from new clothing retail: first, although the bales can sorted and classified by categories, the specific pieces of clothing cannot be observed before purchase, and this adds uncertainty to the retailers' livelihoods - especially when bales are not adapted to local meteorological conditions or tastes [Cobbing et al., 2022]. Most importantly, the structure of the supply chain, with plane- or truck-dependent international arrivals at wholesalers' precincts, means that supply is fragmented: replenishing stock might not always be possible once one is done with their bale, a fragmented supply chain alluded to in qualitative counts of used clothing trade in neighboring countries (Mesa [2021] in the DRC). Additionally, most *caguwa* retailers officiate at stalls and have limited power to build inventory: when Kenya installed a temporary, Covid-driven ban on *caguwa*, retailers declared only having about a month's worth of inventory, which seems to be also true of Rwanda given how fast prices rose after June 2016.

In Table 1 are summary statistics about *caguwa* firms, as compared to other firms in the retail sector and to other firms more broadly.[9] *Caguwa* firms are more likely to be women, to comprise only one worker (including the manager) and to be operating outside a formal shop.

In terms of working conditions, *caguwa* retailers are overwhelmingly self-employed, more so than other clothing retailers (in plant-level censuses, 60% of clothing retail workers are self-employed, against more than 93% of *caguwa* retail workers), and mostly, although not entirely (84% against 71% for clothing retail) informal, meaning that the corresponding individual firms are not declared to administrative or local authori-

[9] Here, the statistics are derived from the 2017 version of the Census, for which workers characteristics could be observed along with the name of the firm, allowing to isolate firms with *caguwa* in their name. It was impossible to show such statistics from the pre-shock data for data privacy reasons, but the sample for *caguwa* firms in 2013 is larger, being drawn from both the name and the main produced sold variables.

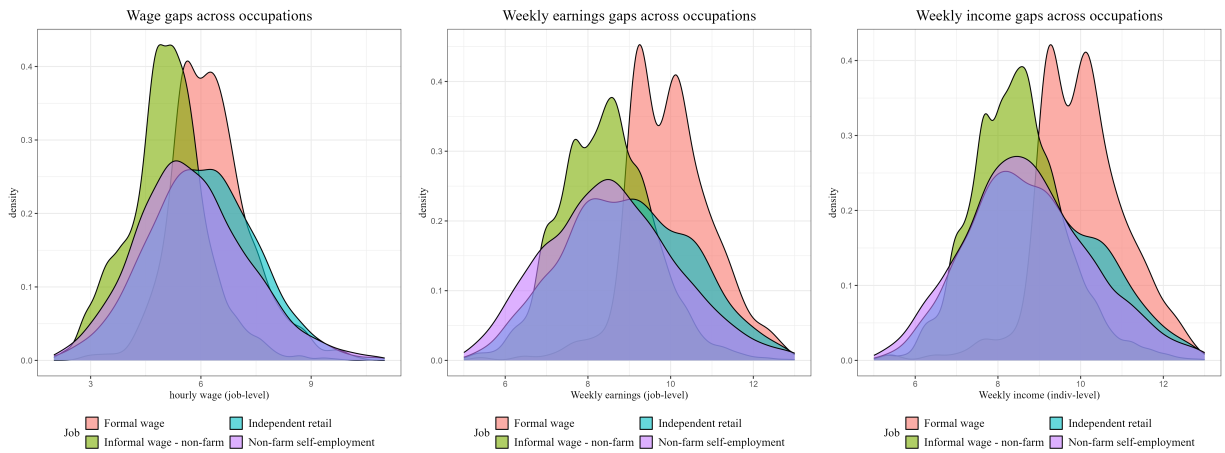

Figure 3: Self-employment in retail compared to other working arrangements

ties. In a spirit similar to McCaig and Pavcnik [2021], I compare earning in retail self-employment to formal and informal wage jobs. I first show hourly wages, then weekly earnings, and finally, income across all jobs worked during the week: this allows one to separate the profitability of a job, the ability to work many hours in a job, and the ability to work other jobs besides a job, all relevant dimensions of occupational choice in settings with prevalent multiple job holding and thin formal labor markets.

Figure 3 shows that independent retailers are earning more per hour than other non-farm self-employed workers before the shock. However, although their hourly wages could suggest that they earn the same or more than formal wage workers, the number of hours they can work this job, and the jobs that they can work besides the retail job both contribute to making their livelihoods much more comparable to informal wage than formal wage work, indicating that the formal sector might not have been an option in their occupational choice. Although retail is most retailers' main occupation of the week in 2013, they are also much more likely than the rest of the population to be working another job, paid or unpaid (Appendix D): they are not allocating their time to retail entirely, despite its lucrative aspect and possibly because of aforementioned input constraints. 81% of women and 60% of men with a secondary job outside of *caguwa* are doing agriculture. While men do other retail jobs (10%), women do not have access to that option outside of *caguwa*: around 5% of men but only less than 1% of women with a job outside *caguwa* have a salaried job in retail. Although *caguwa* provides women with one retail work option, the rest of the sector is not a possibility for all of them: the plant-level census shows that although there are as many men as women managers in *caguwa*, there are only 30% women managers in sales. Figure G the distribution of other jobs held by *caguwa* workers. I detail the survey data behind these insights in the next section.

2 Data

In my empirical strategy, I use two sources of variation: pre-shock spatial exposure to *caguwa* and having been a self-employed retailer before the shock. I first present the databases that allow me to build the spatial exposure index, the Establishment and Population Censuses, before turning to survey data for occupational variation and outcomes.

Spatial index of $caguwa$ intensity: the Establishment Censuses and the 2012 Housing and Population Census

To build a spatial index of $caguwa$ exposure, I use the Establishment Census, an administrative census of all establishments in Rwanda, whether formal or informal, collected every 3 years with 100 000 to 200 000 observations each round. $Caguwa$ retail sales is a very precise category that is not explicitly classified in the Census. however, I was able to access both the 4-digit industrial sector (ISIC) classification of the establishment and an enumerator-written description of the main economic activity for all rounds, including the 2014, the last round before the shock. Creating an indicator for whether $caguwa$ is written in the establishment description is a lower-bound for $caguwa$ retail, as enumerators often write "clothing retail" without further detail. Therefore, one can only use it assuming that, conditional on being a $caguwa$ retailer, the enumerator specifying writing $caguwa$ in the establishment description is orthogonal to other establishments characteristics we are interested in (for example, the manager's sex). Discussions with the National Institute of Statistics of Rwanda confirmed that no specific directions were given in the description of the main economic activity concerning clothing retail.

I use two other alternatives to check my results' robustness: first, I discretize the spatial exposure variable, isolating the top 10% more exposed states as this is the threshold where I see a jump in $caguwa$ prevalence, in subsection A.1. I also create an indicator for being likely to be a $caguwa$ retail establishment even though $caguwa$ is not included in the establishment description, to solve for the fact that in some small administrative zones, there might be a very small number of enumerators, leading to imprecise spatial estimates if the decision to write $caguwa$ is enumerator-dependent. Using the 2014 $caguwa$ variable, I select firms with similar characteristics[10] than the firms for which $caguwa = 1$. These characteristics match political science literature on used clothes retailers [Brooks and Simons, 2012, Brooks, 2019], and to check their validity further, I compute inclusion and exclusion error for my $caguwa$ variable. My indicator misses 5% of establishments for which the enumerator wrote $Caguwa$ and includes 3.5% of establishments for which the enumerator did not write $caguwa$ - an upper bound for inclusion error, as one establishment could be $caguwa$ without it being written. Results with these alternative indexes are similar to the main ones and are included in subsection A.4.

With my pre-shock $caguwa$ indicator, I construct a ratio of the total number of workers working in $caguwa$ establishments in a given zone over the total active population of that zone:

$$Exp = \frac{\text{Caguwa workers}(EC)_{2014}}{\text{Active population}_{HPC,2012}}$$

I construct this exposure at the scale of two administrative entities: the district, of which there are 30, and the sector, of which there are 416 in Rwanda. Figure 4 shows district-level exposure to the used clothing trade.

[10](firms that do not sell in special economic zones, whose owners are Rwandan or part of the EAC, that are sole enterprises, and that have less than 3 employees)

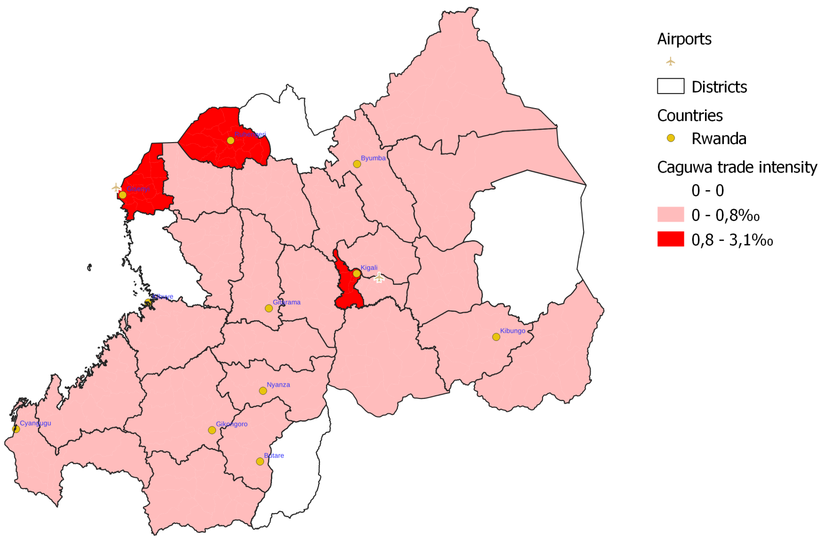

Figure 4: District-level *caguwa* exposure

We can also see that exposure is correlated to airports, major cities, and roads, but imperfectly so. Sellers' location, and thus spatial exposure to the shock is expected to be very polarized for two reasons. First, used clothing retail is usually concentrated in specific markets [Brooks and Simons, 2012]. Rwanda's very hilly geography and the socio-economic status of *caguwa* sellers make it unlikely that workers in that sector are living very far from where they work. Second and related to the more cultural aspect of the used clothing trade, taste for pre-owned garments seems to be concentrated in urban zones in most countries [Brooks, 2019]. However, *caguwa* intensity is not just a proxy for urban density: results are present while controlling for district $\times$ urban fixed effects, and replacing the *caguwa* index by district population density does not recover the same results, indicating that the index is getting at something different than purely economic activity, such as spatial discrepancy in taste in clothing.

Workers' earnings, occupational choices, and migration outcomes: the Integrated Household Living Conditions Survey

My empirical strategy relies on both spatial exposure to *caguwa* trade and belonging to the treated category of self-employed retailers[11], with a start date before the shock so that there is no reverse causality in occupational choice. I do this for two reasons: first, using a spatial index only would compare states with widely different industrial compositions, such as the size of retail, making the parallel trend assumption dubious. Additionally, my worker survey does not disaggregate to the *caguwa* level, and I thus depart from the assumption that retailers in more *caguwa* intensive areas are more likely to be *caguwa* retailers. The labor information that I use pertains to the 2013 and 2016 rounds of the Integrated Household Living Conditions Survey, a cross-sectional database that represents of 60,000 individuals (30,000 working age, 75,000 job spells) each round and collects information about migration, work history, and socio-demographic situation. The data features information on earnings (wages for salaried workers and profits, as turnover minus

[11] ISIC 2-digit category: retail sales

expenses, for self-employed workers), working status, and sector information for each job performed during the year. I denote as self-employed retailers individuals who were retailers before June 2016, even if they stopped in the meantime[12]. Another crucial aspect of that dataset is its interest in seasonality: for each round, an equal number of households are interviewed each month of the year, granting me a two-year window of observation each round. Appendix D present descriptive statistics for all the outcomes that we look at.

3 Empirical Strategy

My empirical analysis relies on a triple-difference strategy that exploits two sources of variation in shock exposure. The first one is belonging to a region more exposed to the tariff increase, in line with the regional effects of shocks literature [Topalova, 2010, Dix-Carneiro and Kovak, 2017, Kovak and Morrow, 2022]. When looking at a shock only hitting one industry, however, we might be worried that individuals in less exposed zones are not on similar trends of with respect to their earnings, their migration, or sectoral reallocation outcomes due to differences in industry composition across regions. Also, in my household data I can not disaggregate beyond belonging to retail, and am thus unable to access $caguwa$ retailers per se. For this reason, I use both spatial variation and a dummy for working in retail with a start date anterior to the June 2016 tariff shock [13]. This triple-difference design relies on the assumption that the trend in the retail-non-retail gap in more exposed zones was parallel to the trend in the retail-non-retail gap in less exposed zones, for every value of the exposure index [Olden and Møen, 2022]. With time-district fixed effects that absorb some of the triple-difference coefficients, the estimating equation is:

$$\begin{aligned} Y_{i,d,t} =& \alpha + \beta_1 Post_t \times Expo._{d(i,t-1)} \times IndRetail_i + \beta_2 Post_t \times IndRetail_i + \\ & \beta_3 Expo._{d(i,t-1)} \times IndRetail_i + \beta_4 IndRetail_i + \beta_5 X_{i,d,t} + \gamma_{t,d} + trim_t + \varepsilon_{i,d,t} \end{aligned} \tag{1}$$

For individual i living in district d at time t. $IndRetail_i$ denotes having been a self-employed retail seller within the year (as the survey asks respondents to enumerate all of their jobs throughout the past year) with a start date before the shock. $Expo._{d(i,t-1)}$ is the z-score of district-level pre-shock $caguwa$ exposure in the district individuals lived in a year ago, to avoid migration-driven reverse causality. $X_{i,d,t}$ controls include age, student, living in a rural location, and recent migrant status (except in the migration equations), education, gender, marital status, and role in the household, a dummy for being in sales and another one for being self-employed (except in equations looking at the working status and occupational code of jobs held by individuals). Trimester fixed effects (starting at the dry season in December rather than in January) avoid seasonality-related biases in earnings, migration, and labor outcomes. Finally, time-district fixed effects absorb time-variant district characteristics, and notably serve to counter concerns about smuggling.

First, I investigate individual income, aggregating over jobs in the case of multiple job holding and only

[12]That is true until June 2017, at which point individuals who stopped immediately after the shock will not be denoted $cagwua$ if they do not declare that job spell anymore, which if it is the case, would bias our coefficients on retail gap toward the null. In our results, we do not see any trend in affected workers to abandon their jobs.

[13]I chose to exclude those who started doing self-employed retail after June 2016, because it was not clear whether they did so knowing about the changed working conditions, and the link between spatial exposure and likelihood of doing $caguwa$ could have been different. The results are the same keeping them in control or dropping them

taking into account jobs worked during the interview week. Using Equation 1, I look at the log of the last weekly income and at the log of hourly income. I also consider the total hours worked this week. The reason for considering both weekly and hourly income is disentangling between who compensates for hourly wage decreases by substituting between jobs and who compensates by working more in the affected jobs. Finally, I study household-level consumption, using consumption data from the IHLCS and a similar specification as Equation 1, with $IndRetail_i$ whether any household member was a retailer starting before June 2016.

Next, I examine whether the effect on income is driven by an effect on earnings for the affected retail jobs, and not from another occupation that retailers could be doing. To do this, I leverage my triple-difference strategy and apply it to job-level data, with one observation per job-spell:

$$\begin{aligned} Y_{i,j,d,t} = &\alpha + \beta_1 Post_t \times Expo._{d(i,t-1)} \times IndRetail_{j(i)} + \beta_2 Post_t \times IndRetail_{j(i)} + \\ &\beta_3 Expo._{d(i,t-1)} \times IndRetail_{j(i)} + \beta_4 IndRetail_{j(i)} + \beta_5 X_{i,d,t} + \gamma_{t,d} + trim_t + \varepsilon_{i,d,t} \end{aligned} \tag{2}$$

With $IndRetail_{j(i)}$ whether one particular job j from individual i is in self-employed retail with a start date before the shock. I study daily wages for all job spells of the year and for respondents' most time-consuming job of the week. I also study hourly wages, which I observe only for jobs that the respondent is still working at during the interview week. I thus study hourly wages for all jobs still done at the time of the interview and for the main job of the week. Next, I study hours worked during the week for the same two categories. I also analyze still working at a job to avoid sample selection on these hourly variables, which could happen if part of the population is exiting jobs more rapidly than another.

Armed with results on the impact of the shock on the self-employed's earnings and income, I then investigate adaptation strategies: migration and sectoral reallocation, similar to Topalova [2010] although at an individual, and not region or industry, level. I exploit the same triple difference strategy and use inter-, intra-district, and return migration as my outcomes. Then, I study different patterns of reallocation. I first look at the supply of labor: inactivity, unemployment, the overlap and duration of all jobs held during the year, and the total number of all jobs and paid jobs per week and year for the active population. Finally, I investigate occupational choice: I look at the categories of employment for the main job of the week, estimating linear probability models on working as a self-employed, wage, and unpaid family worker both on and off-farm, as well as having a formal job, working in retail or working in the broader category of sales, without retail. I repeat this exercise not considering only the main job of the week, but all jobs performed this week, with the same results, in Table 37 of the Appendix.

After obtaining these results on the adaptation margins of self-employed retailers, I look at heterogeneity of responses by gender. When allowing for heterogeneity by gender g, my main specification becomes

$$\begin{aligned} Y_{i,g,d,t} = &\alpha + \beta_1 Post_t \times F_g \times Expo._{d(i,t-1)} \times IndRetail_i + \beta_2 F_g \times Expo._{d(i,t-1)} \times IndRetail_i + \\ &\beta_3 Post_t \times Expo._{d(i,t-1)} \times IndRetail_i + \beta_4 Post_t \times F_g \times IndRetail_i + \beta_5 Post_t \times IndRetail_i + \\ &\beta_6 F_g \times IndRetail_i + \beta_7 Expo._{d(i,t-1)} \times IndRetail_i + \beta_9 IndRetail_i + \beta_{10} X_{i,d,t} + \gamma_{d,t,g} + trim_t + \varepsilon_{i,g,f,t} \end{aligned} \tag{3}$$

The assumption behind this specification is that the evolution of the gender gap in retail sales in more exposed zones was parallel to the evolution of the gender gap in non-retail sales in more exposed zones, or to the evolution of the gender gap for retailers in less exposed zones. The fixed effects for the gendered specification are at the gender-district-time level, to absorb any gender-specific opportunity that might arise because of the shock in a specific district, for example, if smuggling is gendered. Standard errors are clustered to the IHLCS cluster level, according to the IHLCS survey design.

4 Results

4.1 Income and hours worked

First, I examine results on the whole population of self-employed workers living in a $caguwa$-exposed zone and working in retail prior to the shock. The coefficients associated with $Post \times IndRetail \times Expo$ denote the additional effect on self-employed retailers' trend in that outcome - the effect on the self-employed retailer premia - of living in areas 1 standard deviation[14] more exposed to $caguwa$, relative to the trend for retailers living in less exposed zones. From Table 2, we see that these retailers experienced slower personal income growth: income grew 6.4% slower for self-employed retailers retailers living in an area 1 sd. more exposed to $caguwa$ trade all things equal (col. (1)). This effect is even larger for income by hours worked during the week (col. (3)), which can be explained by the fact that these more exposed retailers also work significantly more: hours worked grew 3.5% faster for retailers living in more exposed areas than for retailers living in less exposed ones (col. (2)). The shock that we saw in imports figures seems to have been transmitted to these sellers' income. Interestingly, the shock does not seem to impact household consumption, indicating that intra-familial mitigation mechanisms might be at play. To go deeper into my findings and ascertain that the income decrease does come from a retail job, I go from this individual-level analysis to a job-level one, estimating Equation 2 on workers' main jobs of the week[15].

From the coefficient on $Post \times IndRetail \times Expo$ in Table 3, we see that self-employed main jobs of the week (henceforth, jobs, as results are similar for all jobs) in retail located in districts more exposed to $caguwa$ trade by 1 sd., all else equal, saw their earnings grow 8.5% slower. This is amplified by hourly earnings, who undergo an even larger negative effect (col. (2)). We can look more deeply at what precisely drives the effects on self-employed retailers using the business module of the survey, administered to the sub-sample of self-employed workers of the IHLCS. Retailers in more exposed areas are not seeing their earnings grow slower primarily because of increased costs (col. (4)) but because of relatively decreasing sales (col. (3)). This indicates two things: although we know that unit prices for used clothing have increased, from the imports and CPI data, retailers have been buying less of it rather than increasing expenses. Second, sales have grown slower: either some of this unit price increase has been passed through to customers, or prices stayed constant and quantity sold decreased - both phenomena likely to be at play, given the documented impact both on import volumes and local clothing prices in urban zones, and accounts in other countries

[14] around +0.07% in the ratio of caguwa workers over active population from a mean of 0.03%, keeping in mind that the measure is a lower bound for actual caguwa activity

[15] For the sake of clarity, I only focus on main jobs of the week, but results on all jobs are all qualitatively similar and of similar significance levels

	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × IndRetail × Expo	-0.064*	0.035*	-0.098***	0.002
	(0.04)	(0.02)	(0.04)	(0.02)
IndRetail	0.257***	0.027	0.178***	0.111***
	(0.04)	(0.02)	(0.04)	(0.02)
IndRetail × Expo	0.043*	-0.018	0.068***	-0.078***
	(0.02)	(0.01)	(0.02)	(0.01)
Post × IndRetail	0.065	0.041*	0.028	-0.036*
	(0.05)	(0.02)	(0.05)	(0.02)
R-squared	0.481	0.158	0.411	0.243
N	29980	53684	29969	27961
Time-district FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Samples: for (1) and (3), all jobs with non-null earnings. For (2), all jobs. For (4): all households.

Table 2: Individual-level income and hours worked, across all jobs

that retailers can split bales amongst themselves [Mesa, 2021]. However, this negative profit effect does not translate into more hours worked at these jobs (col. (5)) this is not due to selection in who keeps their job and who leaves it (col. (6))[16].

From this table I conclude, first, that the effect of the shock is driven by a negative effect on retailers' earnings from retail, and not through another job entering in the individual income aggregation. Second, the effect is persistent: the IHLCS round lasted until October 2017, 16 months after the shock, and the effect on the main job of the week is still significant. Finally, although there are negative effects on their hourly earnings that translate into their income, retailers do not leave their jobs, nor do they reduce hours worked at them, contrary to expectations and standard labor supply theory.

Interpreting the magnitude of the results In Table 2, the $Post \times IndRetail \times IndRetail$ coefficients indicate that in areas 1 s.d. more exposed to $caguwa$ trade, the income gap (resp. hourly income gap) between retailers and non-retailers grew 6.4% slower (resp. 9.8%) than in less exposed areas. To get an idea of the quantities involved, Figure 5 shows descriptive statistics of the evolution of retailer income premia in areas that are exposed vs. areas that are not. Even in raw figures without controls, we can see that although the retailers always earn more than non-retailer, that gap widened in non-exposed area and shrank in our zone of interest [17]. This matches our expectations and the regression result that we find with controls and fixed effects. I first turn to a brief discussion of the magnitude of the obtained ccoefficients, before turning to concerns about identifying assumptions.

A simplistic way that the import tariff increase would transmit to the difference in retail premia across exposed states, assuming no buyer or seller power on the part of $caguwa$ retailers and no spillover to non-$caguwa$ retail, would be first through an increase in prices at wholesalers' warehouses lowering unit profit

[16] A model with hours in logs showed qualitatively the same results but had a twice lower R^2, and is not shown here or in the gendered results

[17] A log income of 9 corresponds to around 8100 Rwandan Francs and 6,25 USD and 8 corresponds to 1980 RWF and 2.80 USD

	log(earnings)		*self-emp. sample*		*Hours this week*	*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Hours	Kept job
Post × IndRetail × Expo	-0.085**	-0.103**	-0.117***	-0.074	-0.027	-0.001
	(0.04)	(0.04)	(0.05)	(0.07)	(0.70)	(0.00)
IndRetail	0.197***	0.152**	-0.187**	-0.321***	-2.745***	-0.005**
	(0.07)	(0.07)	(0.08)	(0.11)	(0.96)	(0.00)
IndRetail × Expo	0.074***	0.089***	0.017	-0.050	-0.357	0.000
	(0.02)	(0.03)	(0.03)	(0.05)	(0.46)	(0.00)
Post × IndRetail	0.027	-0.063	-0.035	-0.243	3.601***	0.002
	(0.07)	(0.08)	(0.09)	(0.15)	(1.14)	(0.00)
R-squared	0.471	0.397	0.296	0.267	0.230	0.005
N	23638	23619	5212	3999	53429	53459
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: (1) - (2): all jobs with non-null earnings. (3) - (4): all self-employed jobs. (5)-(6): all jobs

Table 3: Job-level earnings, hours worked and abandon likelihood

Figure 5: Evolution of retail premia gap from affected areas to non-affected areas

for $caguwa$ retailers. In turn, retailers' income would decrease proportionately to the share of $caguwa$ in retail, leading to a retail premia decrease and a decrease in the difference between retail premia from exposed states to non-exposed states, which is what the $Post \times IndRetail \times Expo$ coefficient identifies, under our assumptions. To speak to whether the 10% decrease in the difference in retail premia matches the context, I would need estimates of the bale price increase at wholesalers' warehouses (Δp), the importance of costs in $caguwa$ sellers' profits ($\frac{c}{\pi}$), the size of $caguwa$ in more exposed states' retail sectors R, and the difference in retail premia growth between more and less exposed states Y. Although I lack, in the current version of this paper, the data to speak to these parameters, I can benchmark some. Governmental estimates[18] indicate that the price of used clothing imports resulted in a 30% unit price increase for wholesalers, who would transmit that increase to $caguwa$ retailers in case of perfect pass-through. The share of such retailers in the whole retail sector, in the top 10% most exposed districts, could be as high as 12,5% (Establishment Census). Finally, in raw data, we can see that the retail premia in earnings did not grow as fast in exposed areas than in non-exposed areas, resulting in a semi-elasticity coefficient that would be of higher magnitude. Setting our Δp to be 3/10 (perfect pass-through assumption) and R to be 1/8, $\frac{c}{\pi} \times \frac{1}{Y}$ would need to be around 13/10 for the triple-difference coefficient to be 0.1, which is credible knowing $\frac{1}{Y} > 1$ and that $\frac{c}{\pi}$ is not bounded by 1.

Discussion of identifying assumptions The assumption behind our triple difference model is that, for each level of exposure, if not for the policy, the trends in growth of retail premium would have been parallel. This is summarized in Olden and Møen [2022] by the fact that in triple difference, only the triple-difference coefficient needs to follow parallel trends. If something is modifying the trend in the retail premium specifically for more exposed states that is not the policy, then that would be a threat to identification. This could be the case, for example, if in areas more exposed to the policy, the retail markets were also larger, leading to more spillovers from $caguwa$ retail to non-$caguwa$ there than in less exposed states. For example, used clothing price increases could allow new clothing retailers to increase the price of their clothing, making them better off and mitigating my negative coefficient on earnings. $caguwa$ sellers could also have more outside options in markets in which other types of clothing retailers thrive, making reallocation easier in more exposed areas, and again pushing my coefficient toward the null. I argue that this is not likely to be a sizeable threat, first because $caguwa$ represents at best 1/8th of the retail sector, and a much lower share of the overall workforce: spillover effects are not likely to impact my results significantly, given the very localized quality of that trade. Also, for the workforce to reallocate more easily toward non-$caguwa$ retail in priority, it would have to be the second best option for workers in $caguwa$. However, that is not the case: if we look at secondary jobs held by self-employed retailers, they are mostly outside of retail Figure G. Still, I do test for the possibility that the size of the retail sector relative to $caguwa$ is affecting my results by changing my spatial index to be $\frac{caguwa}{retail}$ in subsection A.2, with similar results. I show in the later section that these coefficients are not driven by selection in who migrates, leaves employment altogether or this particular job. Finally, the district-time fixed effect addresses every specific opportunity that could arise in districts more exposed to the shock, for example, smuggling opportunities, mitigating these concerns for identification.

[18] Strategy For The Transformation Of Textile, Apparel And Leather Sectors in Rwanda, MINICOM 2022

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × IndRetail × Expo	0.002	0.703	0.236***	0.019*	-0.008	-0.005	-0.022
	(0.01)	(0.71)	(0.08)	(0.01)	(0.01)	(0.01)	(0.02)
IndRetail	0.001	-0.444	-0.445***	-0.031**	-0.010	-0.059***	-0.088***
	(0.00)	(0.69)	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)
IndRetail × Expo	0.006	0.834*	0.283***	-0.024***	-0.061***	-0.050***	-0.097***
	(0.00)	(0.49)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
Post × IndRetail	-0.001	2.706***	0.445***	-0.031*	-0.091***	-0.119***	-0.126***
	(0.01)	(0.89)	(0.10)	(0.02)	(0.02)	(0.02)	(0.03)
R-squared	0.047	0.226	0.365	0.232	0.330	0.237	0.235
N	61001	42018	71766	71766	71766	66232	61001
Time-district FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7)

Table 4: Reallocation - intensive margin

4.2 Reallocation channels

Our results on income and wages point to a persisting negative impact of the shock on retailers' income growth, partly compensated for by an increased growth of their working hours though not necessarily within retail employment. I will thus examine where these hours are reallocated, and with what consequences on the total labor supply. As is standard in the literature, I will also test that my estimates are not biased by selective migration patterns, which could happen if, for example, affected retailers are relocating to zones where average earnings are lower.

Table 4 reports results from estimating Equation 1 on reallocation decisions: the probability of having no job this week, total hours per job and average job duration during the year - respectively $\sum_{j=1}^{JobsWeek} \frac{hours_j}{JobsWeek}$ and $\Sigma_{j=1}^{JobsYear} \frac{months_j}{JobsYear}$ - total number of paid and overall jobs, per week and year. An important result in column (1) is that those affected by the policy are neither more nor less likely to be inactive or unemployed during the interview week. This, as mentioned in Section 1, contrasts with findings of unemployment or inactivity resulting from trade-induced negative earnings shock in richer countries, but fits the insights one would have about the self-employed population that is affected by the import tariff shock. Looking to explain the source of our positive coefficient on total hours worked per week in the previous section, we see that the average duration of employment (col. (3)), or the extent to which two jobs performed during the year will overlap or cover inactivity spells, is growing faster than in non-affected areas. Workers are remaining in jobs for longer periods or time. An increase in jobs overlap and in total hours worked within the week, as in Table 2, results in either an increase in the number of paid jobs worked within the week or in more hours worked at each of these jobs: we see that paid jobs have significantly grown faster for affected workers (col. (4)), while the coefficient on total hours per job (col. (2)) is positive but non-significant. The biggest channel for self-employed workers' reallocation patterns flowing a shock thus seems to be an increase in both the number of jobs held this week, but not this year, and an increase in duration of these jobs - more overalapping of jobs in a context of multiple job holding.

I turn to the investigation in occupational choice in Table 5. I am mostly interested in the nature of the

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × IndRetail × Expo	0.008***	0.002	-0.006	0.017*	0.010	0.003**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
IndRetail	0.046***	-0.041***	-0.063***	-0.038***	0.397***	-0.012***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
IndRetail × Expo	-0.002	-0.036***	-0.001	0.004	0.063***	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Post × IndRetail	-0.014**	-0.004	0.007	0.073***	0.028*	0.003*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
R-squared	0.077	0.237	0.170	0.205	0.425	0.012
N	71665	71665	71665	71766	71766	71766
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7)

Table 5: Reallocation - main job week

main job of the week, although table Table 37 in the Appendix explores the nature of all jobs performed this week, with similar results. W(f) and W(nf) are respectively, wage farm and non-farm employment. As a result of the shock, those with retail experience are not less likely to have retail as a main job of the week than before, relative to retailers in less exposed areas. However, they are more likely to reallocate their time toward wage employment (col. (1)), or retail-adjacent jobs (sales jobs that are not self-employed or are not retail sales, col. (6)) and turn these jobs into their main jobs of the week, while they are less likely, although not precisely estimated, to not reallocate their time toward unpaid family employment (col. (3)). This shift to wage work is important in that it is conditional on being able to access salaried employment, and thus, on having good employment prospects outside of self-employed retail work. Importantly, this reallocation results in a small increase in the likelihood of having a formal main job of the week (col. (4)), which contrasts with trade shock literature that mostly finds informality to be a common response to negative earnings shocks in developing countries, such as McCaig and Pavcnik [2018], Ponczek and Ulyssea [2021], Bas and Bombarda [2023] among many others. In this context, as the shock is hitting an overwhelmingly informal occupation, these reallocation patterns toward formal wage jobs can be rationalized, although again, these jobs are only likely to be viable outside options for a subsample of selected entrepreneurs.

Finally and in concordance with this literature [Topalova, 2010, Dix-Carneiro and Kovak, 2019, Borusyak et al., 2022], we find no migration response. These results have to be qualified in the light of recent debates [Borusyak et al., 2022] as they do not necessarily mean that migration is not a potential reallocation response: if the shock entails negative earnings prospects everywhere for affected segments of the population, it simply means that there is no advantage in moving.

	Migrant	Infra-distr. move	Return migrant
Post × IndRetail × Expo	-0.001	0.006	-0.006
	(0.01)	(0.01)	(0.00)
IndRetail	0.011**	-0.000	0.005**
	(0.01)	(0.01)	(0.00)
IndRetail × Expo	-0.006	0.006	-0.001
	(0.00)	(0.01)	(0.00)
Post × IndRetail	-0.008	0.007	-0.002
	(0.01)	(0.01)	(0.00)
R-squared	0.058	0.065	0.031
N	66232	66232	66232
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-3).

Table 6: Migration

5 Theoretical framework

In this section, I build a simple theoretical framework to aid in thinking about my results. I begin with a simple model of time allocation between leisure, self-employment in retail, and other jobs. Motivated by my imperfect reallocation results and by qualitative evidence of the used clothing supply chain, I introduce input constraints on potential jobs. The model formalizes a setting in which a decrease in hours worked would not automatically follow a decrease in hourly wages from an occupation: by introducing production constraints into our retailer time allocation program, we can thus explain the inelasticity of labor supply to hourly earnings decreases. I then discuss the implications of having better or worse employment options outside of self-employed retail. After presenting suggestive evidence that there are gendered differences in the quality of available outside options, I check the framework's predictions by studying the change in men's and women retailers' trajectories, and other geographical and individual sources of unequal outside options.

I begin with a basic setup: our agent is in retail, and has time $\bar{T}$ to allocate between leisure and work: retail (r) and, potentially, another job (o), respectively paying profit $pF(l_r, \iota) - g\iota$ (ι bales of clothing) or w_o[19]. The remaining time that they have is considered leisure. The agent maximizes utility from consuming a unitary good with a price of 1, and leisure:

$$\begin{aligned} \underset{c,z,l_r,l_o,\iota}{max}\ U(c,z)\ \ s.t.\ c = pF(l_r,\iota) - g\iota + wl_o \\ \bar{T} = z + l_r + l_o,\ \ c \geq 0,\ z \geq 0\ , l_r > 0, l_o \geq 0 \end{aligned} \tag{4}$$

In that unconstrained setting, labor supply at the self-employed retail job (and at wage work if chosen)

[19] I don't account for the fact that workers can leave their self-employed retail job, which they never do in the results. This is equivalent to saying that the first unit of work in retail is always more profitable than an hour at wage w

will be such that marginal utilities of each are equated to that of leisure:

$$\frac{\delta F}{\delta l_r} = \frac{\delta U}{\delta z} / \frac{\delta U}{\delta C} \times \frac{1}{p} \;\; (= \frac{w}{p} \text{ if extra wage job chosen}) \tag{5}$$

The predictions from this simple setting are that if the marginal productivity of self-employed retail decreases:

1. The chances the worker gets an extra wage job increase
2. Regardless of whether there is an extra job or not, labor supply at the firm decreases

This intuition matches the fact that workers do increase the amount to which they overlap jobs during the week, but does not match the fact that they do not reduce the amount of hours worked at the retail job l_r. Hence, I incorporate the context described in section 1. Sellers buy bales of used clothing in bulk at a given period, and before the next arrival, it is unsure whether they can refurnish their stocks once they have sold everything. I introduce this in the model as a constraint on inputs, in a similar spirit to Hardy and Kagy [2020] but where it is one input and not customer demand that is constrained. If agents can only buy $\bar{\iota}$ quantity of used clothing per period (45 kgs in [Brooks, 2012]), with p the mean unit price of clothing, they can only sell $pF(\bar{l_r^*}, \bar{\iota})$ and gain maximum total retail earnings $pF(\bar{l_r^*}, \bar{\iota}) - g\bar{\iota}$. This assumes that retailers are price takers for their bale and that they cannot build inventory, consistent with sellers working at open stalls or temporary premises.The optimization program thus becomes

$$\begin{aligned} &\max_{c,z,l_r,l_o,\iota} U(c,z) \;\; s.t.\; c = pF(l_r, \iota) - g\iota + wl_o \\ &\bar{T} = z + l_r + l_o, \;\; c \geq 0, \; z \geq 0\,, l_r > 0, l_o \geq 0, l_r \leq \bar{l_r^*}, \iota \leq \bar{\iota} \end{aligned} \tag{6}$$

Resolution depends on whether $\bar{\iota}$ binds or not. If does not, then solution is as in Equation 5. If $\bar{\iota}$ is binding ($l_r^* > \bar{l_r^*}$), then the agent will work retail until reaching the constraint, and then will either consume less than they wanted to or start working at the wage job sooner than they wanted to.

$$\begin{aligned} &\max_{c,l_o,z} U(c,l) \;\; s.t.\; c = pF(\bar{l_r^*}, \bar{\iota}) - g\bar{\iota} + wl_o \\ &\bar{T} = z + \bar{l_r^*} + l_o, \;\; c \geq 0, \; z \geq 0\,, l_o \geq 0 \end{aligned} \tag{7}$$

We now turn to a situation in which, as in our context, a tariff shock makes retail less profitable. The tariff increase, through bale prices increasing and some tariff pass-through, increases unit clothing prices, as can be seen with the CPI, with negative impacts on demand that makes $\frac{\delta F(l_r,\iota}{\delta l_r}$ decrease for a given level of ι - our agent is selling less clothing per hour. Our framework predicts that in this case:

1. if agents were previously input-constrained, the $\bar{\iota}$ constraint will be less likely to bind, or if still binding, make it so that agents reach it using more l_r (our agent will finish going through a bale in more time total): *in the presence of input constraints, a shock decreasing labor productivity will not necessarily decrease labor supply in that occupation.*

2. If opportunities outside of retail are few, or low-paying ($\frac{\delta F}{\delta l_r} = \frac{w}{p}$ reached relatively late), the shock can make workers with low opportunity leave their outside job to put their hours in the retail job, even when retail profitability decreased: *input constraints and low outside opportunities can make workers leave other jobs to focus on the one whose productivity is decreasing*.

With regards to the two labor supply responses we consider - supply of hours at the affected job and at a potential extra job - workers' reactions thus depend on two margins: whether they were input-bound[20] at first opens the possibility of null of even negative retail labor supply elasticity to labor supply productivity at the retail job, $\mathcal{E}_{l_r,\frac{\delta F}{\delta l_r}}$. Whether they have good outside options (O.O) post-shock - that is, whether they prefer $U(c, z|l_o > 0)$ to $U(c, z|l_o = 0)$ determines if some of their labor supply is redirected at the other job, which mitigates potential negative labor supply wage elasticity responses ($\mathcal{E}_{l_r,\frac{\delta F}{\delta l_r}}|good\ O.O > \mathcal{E}_{l_r,\frac{\delta F}{\delta l_r}}|bad\ O.O$) and consumption losses.

	input-bound 1st period	not input-bound in 1st period
good OO	$\rightsquigarrow l_r, \rightsquigarrow l_o$	$\downarrow l_r, \uparrow l_o$
bad OO	$\rightsquigarrow l_r, \varnothing l_o$	$\downarrow l_r, \varnothing l_o$
	(more inelastic than good OO)	

Table 7: Summary of labor responses to a negative productivity shock

For two agents, 1 and 2 with different quality of outside options, the predictions are thus that

1. Input-bound agents with no outside options will experience Giffen-good like labor supply responses to a labor productivity decrease *at the same job*, potentially abandoning other jobs to put their labor in the declining occupation

2. These responses will be muted or inverted for agents with good outside options in the same sector, allowing them to mitigate effects on total income through the use of an additional job

To justify the construction of this model, I check these predictions relative to outside options and reallocation patterns using two populations with varying levels of outside options: men and women. Armed with descriptive statistics and insights from the gender gap in self-employment and wage employment literature focused on low-income countries, I argue that the outside option and bargaining power difference between men (m) and women (w) can lead to differential reallocation responses and notably, to sex-specific trends in hours worked in retail being less elastic to wage decreases in retail for women than for men (or even, elasticities of contrasting signs). These different reallocation responses are precisely what our results disentangled by gender show.

5.1 Descriptive evidence on gendered outside options in the labor market

Insights from the literature on gender-dependent market power Two facts describe the working environment in which most working women of the developing world operate: a universal over-representation in

[20] The same labor supply responses can be obtained by including consumption constraints in the post-shock period - the input constraint mechanism was chosen as it was more context-relevant

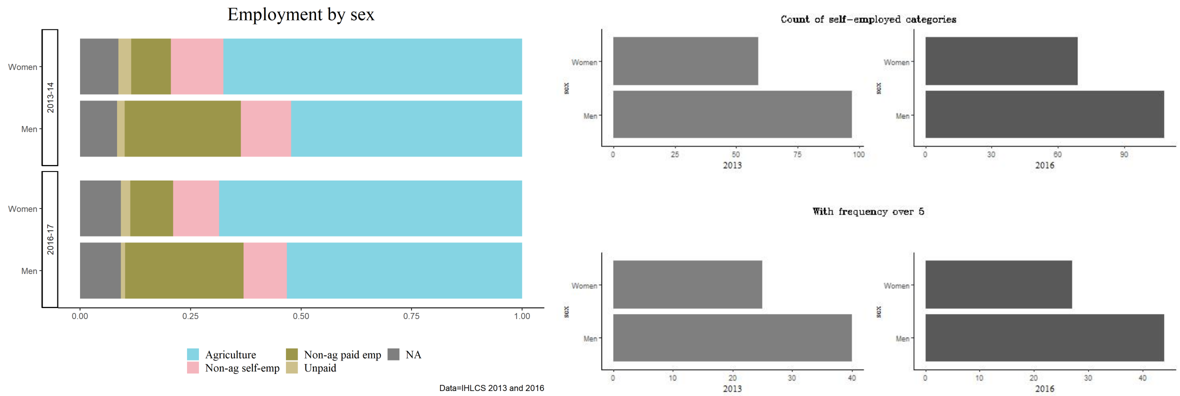

Figure 6: Type of and number of self-employment categories declared by sex (2013-2016)

self-employment, and yet, higher income gender gaps in self-employment gaps there than in any other working status [Heath et al., 2015]. I explore the causes for this gap providing descriptive evidence of women's lack of salaried employment opportunities, and higher within-industry concentration in self-employed occupations, following closely the argumentation in Hardy and Kagy [2020]. Relative to my framework, I conclude that women have a lower level of outside options in retail than men: $\frac{w_{o,w}}{w_{r,w}} < \frac{w_{o,m}}{w_{r,m}}$.

First, I argue that self-employed women having fewer outside employment options than men leave them having relatively less market power, and therefore less profits, in the labor markets they operate in, following the intuition set by Hardy and Kagy [2020]. Political science accounts of used clothes markets in other sub-Saharan African countries, such as Mozambique in Brooks [2019], mention product segmentation - women selling women's clothes - and similar labor markets such as the garments market in Ghana [Hardy and Kagy, 2020] also feature customer segmentation - women shopping from women. With either of these characteristics, the fact that women operate in more crowded markets will make a negative earnings shock weigh more on women - which we observe in our earnings regressions.

Then and in conformity with the framework's predictions, a relative lack of outside options could induce a lower ability to exit toward other occupations - a mechanism illustrated in Sharma [2023] in the case of salaried textile workers in Brazil, with men exiting the profession relatively more when wages decrease exogenously. To support this channel, I first present descriptive statistics, showing that self-employed women operate in fewer industries (cross-industry concentration) and that the industries that they do operate in are more crowded (within-industry concentration), relative to self-employed men, closely following Sharma [2023].

Descriptive evidence on gendered within- and cross-industry concentration I present job-spell level descriptive statistics, closely following Hardy and Kagy [2020] in their argumentation that women operate in more crowded industries than men.

The structure of employment differs greatly by gender, which is primarily due to lower access to paid non-agricultural employment (Figure 6). As stated in Heath et al. [2015], the higher prevalence of self-employment among women in developing countries can be partly explained is explained partly by hiring discrimination preventing them from entering non-farm wage work. In the context of Rwanda, there is a comparable share of men and women in non-agricultural self-employment job spells. However, when look-

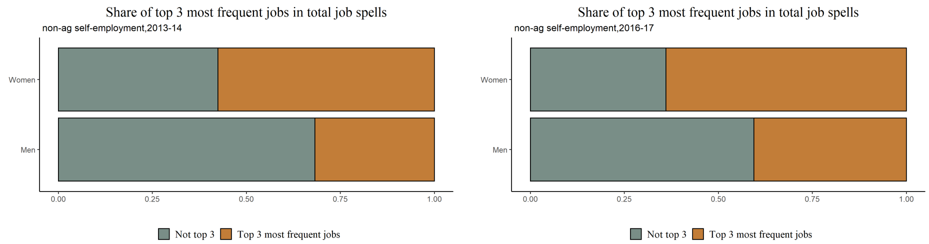

Figure 7: Share of self-employment obs held in top 3 occupations, by sex

ing at the variety of these job spells, in terms of the number of ISIC3 classifications declared (Figure 6), it appears that women operate in fewer occupations than men, and even more so when only looking at occupations where more than 5 women or men say they operate. The fact that a lower number of industries provide suitable jobs is characterized in Sharma [2023], in the case of salaried work, as a higher cross-industry concentration for women.

In our setting, while self-employed men outside of agriculture declared almost 100 occupations (40 with more than 5 men declaring to work in that sector) in 2013, only 55 (respectively 25) industries were cited by women (Figure 6). This result is constant across time.

Beyond being kept in a few sectors, the industries women do work in are relatively more crowded. Looking at the number of people declaring a to work in a given ISIC3 sector in Figure 7, we can see that more than 50% of women's non-agricultural self-employed job spells are concentrated in 3 industries only[21], while men face less polarized self-employment labor markets. As a result, in 2013, men operated in sectors where 783 other people worked, on average (2013), versus 556 for men, and in 2016, these numbers were respectively 858 and 577.

The consequence of this discrepancy in within and cross-industry crowding is, first, that men's earnings react relatively less to shocks - adverse in our case, but also to positive shocks in the case of Hardy and Kagy [2020]. Men in the self-employed retail sector are making more profits than women: although unfortunately, the IHLCS data lacks information on total capital use, Figure 10 also suggests that, for a similar level of expenses, they are generating more turnover than women. Given this initial situation, it is thus likely that they either have more customers and are operating at fuller capacity, or are able to charge more prices, because of that differential crowding and of product or customer segmentation - two plausible channels that our data does not allow us to investigate, but could mitigate the impact of a negative shock.
Secondly, this gender difference in the availability of suitable occupations implies that a given impact level has more persistence on women's income. With fewer outside options, owing either to geographical or amenities preferences or norms of ”acceptable occupations” for women [Sharma, 2023], women will not reallocate as quickly. In the event that women suffer a larger shock on their earnings (lower $1-\gamma$ in the framework) than

[21] These industries are, in order, retail sales via stalls and markets, retail sales not in stores, stalls or market, and wholesale of food, beverages, and tobacco, with retail sales of food, beverages, and tobacco also a predominant industry in 2016.

	Earnings		*Hours worked*	*Selection*
	Daily	Hourly	Hours	Kept Job
Post × IndRetail × F × Expo	-0.147**	-0.198***	3.379**	-0.003
	(0.06)	(0.07)	(1.34)	(0.00)
Post × IndRetail × Expo	-0.008	0.004	-1.897*	0.001
	(0.06)	(0.06)	(1.06)	(0.00)
IndRetail	0.372***	0.337***	-1.473	-0.006***
	(0.08)	(0.08)	(1.29)	(0.00)
IndRetail × Expo	-0.006	0.001	-0.017	-0.001
	(0.04)	(0.04)	(0.74)	(0.00)
Post × IndRetail	-0.041	-0.180*	4.931***	0.005*
	(0.10)	(0.11)	(1.82)	(0.00)
IndRetail × F	-0.355***	-0.375***	-2.239	0.002
	(0.08)	(0.09)	(1.40)	(0.00)
IndRetail × F × Expo	0.169***	0.179***	-0.252	0.003
	(0.04)	(0.05)	(0.93)	(0.00)
Post × IndRetail × F	0.158	0.260*	-2.707	-0.006*
	(0.13)	(0.14)	(2.28)	(0.00)
R-squared	0.475	0.402	0.233	0.006
N	23638	23619	53429	53459
Time-district-sex FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: (1)-(2): all main jobs of week with non-null earnings. (3)-(4): all main jobs of week.

Table 8: Daily and hourly earnings

men, which follows from the higher concentration, a lower reallocation response such as the one I shed light upon is all the more telling as to the outside options available to them.

After presenting descriptive evidence supporting considering women as having lower outside options than men, I then turn to heterogeneity results and check my model's predictions. In Appendix A, I explore two other potential channels that my results could have picked up: composition effects in skill and education driving negative results for women, the role of being the sole breadwinner, or living with a husband - a proxy for intra-household bargaining power. Overall, interacting with these explanatory variables does not change the sign and significance of our main coefficients of interest, the impact of the shock on the whole exposed retail workers population, and the additional effect on women, and the interaction with the new variables is never statistically significant.

6 The role of outside options: results on heterogeneity by gender

As in the first result section, I first investigate job-spell level earnings and individual income, discussing gendered impacts on livelihoods before turning to reallocation patterns.

Table 8 shows gendered effects of the shock on weekly earnings and hourly earnings at the job level from Equation 2. We have two ways of interpreting the results. First, $Post \times IndRetail \times Expo$ is the effect of being a man retailer in a zone 1 s.d. more exposed to $caguwa$ trade, and $Post \times IndRetail \times F \times Expo$, denotes the additional effect for women's trends. Alternatively, the difference between $Post \times IndRetail \times F \times Expo$ and $Post \times IndRetail \times Expo$ is the comparison of the trends of retail premia for women, from exposed areas to non-exposed areas. Because $caguwa$ is an occupation in which women are over-represented, women could also be disproportionately affected by the shock, leading to a gender composition effect that is netted out when comparing the trends for women retailers across zones.

When separating by gender in columns (1) and (2), it appears that the weight of the relative earnings decrease fell almost exclusively on women, with their job-level daily earnings growing less by 14.7% (19.8% for hourly earnings), while the coefficients for men's earnings in more exposed areas, $Post \times IndRetail \times Expo$. are not significant at traditional levels. Not only are women retailers in most exposed areas the only ones suffering slower earnings growth relative to less exposed zones ($Post \times IndRetail \times F \times Expo$ - $Post \times IndRetail \times Expo$), but the divergence also intensifies when looking at hourly earnings (col. (2)).

The impact of the tariff shock is thus gendered in two ways: first, earnings grow slower in more exposed zones, but especially so for women. Second, effects on women relative to men are more negative when considering the main job of the week, suggesting that men are reallocating toward other occupations during the year. Effects on hourly earnings are also stronger than effects on daily earnings, indicating that women could be working relatively more hours to mitigate their daily losses, in conformation with the simple framework of time allocation. We investigate this possibility in col. (3)-(4).

We see that the gap between the impact on daily and hourly wages is partly driven by the fact that women are working relatively more hours in affected jobs, driving these jobs to become their main jobs of the week (column (2)). If a man's main job of the week is in retail, the hours he works at that job will decrease by 1.799 hours relative to workers with a main job in retail in less exposed areas. By contrast, women with a main job in retail in more exposed areas will increase hours worked by 1.681 hours on average (the difference between the coefficients for $Post \times IndRetail \times Expo$ and $Post \times IndRetail \times Expo \times F$) compared to self-employed women retailers in less affected areas. Finally, col. (4) shows the absence of gender-dependent trends in the likelihood of still exercising an affected job, which could lead to selection in the sub-sample of jobs for which we have hour data if, for example, men leave affected jobs more often than women. While women increase hours worked in the negatively affected occupation, men decrease them, indicating different abilities to adjust to a shock.

To tie these results with individual, real-life consequences for self-employed women, Table 9 estimates impacts on weekly income at the individual level: $IndRetail$ now designates having worked in self-employed retail with a start date before June 2016, as in Equation 3. While weekly income only decreases slightly for women retailers as compared to men retailers in exposed areas (col. (1)) - hourly income decreases much more (col. (3)). Maintaining the same weekly income gap is done at the cost of working more hours for women, and these hours are worked in the affected jobs, as shown in Table 8. These adjacent facts suggest that faced with a decrease in earnings, self-employed retail women work more hours in the affected jobs to mitigate negative impacts, while men reallocate time away from these occupations, which fits the predictions of the framework delineated in prior sections. There are two ways of representing these results concretely, in line with the two interpretations of the coefficients mentioned above. We can track the evolution of the gender gap within retail from exposed areas to non-exposed areas, which tells us something about the evolution of gender inequality within a given zone, but does not alleviate concerns related to compositional effects - the fact that women were more likely to be hit in the first place. The alternative is to compare women retailers

	log(Weekly Y)	Log(tot. hours)	log(weekly Y/hour), week
Post × IndRetail × F × Expo	-0.104*	0.066*	-0.169***
	(0.06)	(0.04)	(0.06)
Post × IndRetail × Expo	-0.001	0.000	-0.004
	(0.05)	(0.03)	(0.05)
IndRetail	0.387***	0.050*	0.295***
	(0.06)	(0.03)	(0.06)
IndRetail × Expo	-0.031	-0.023	-0.012
	(0.03)	(0.02)	(0.03)
Post × IndRetail	-0.013	0.062*	-0.058
	(0.07)	(0.04)	(0.08)
IndRetail × F	-0.249***	-0.040	-0.221***
	(0.06)	(0.03)	(0.06)
IndRetail × F × Expo	0.134***	0.012	0.150***
	(0.04)	(0.03)	(0.04)
Post × IndRetail × F	0.136	-0.038	0.151
	(0.09)	(0.05)	(0.10)
R-squared	0.484	0.161	0.415
N	29980	53684	29969
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals with non-null earnings ((1) and (3)), and all individuals with a job in the interview week (2).

Table 9: Income - gender heterogeneity

in exposed areas to women retailers in non-exposed areas, categories for which norms about available jobs are not likely to play a big role. Figure 8 shows descriptive statistics (without controls or fixed effects) that support our regressions results: the income gap between women and men retailers in exposed areas widened while it was closing for all other population categories, in particular retail in non-exposed areas (left figure), and although in every other category of the population, workers in exposed areas always earn more than those in non-exposed areas, the gap entirely closed for women retailers. These workers lost income relative to the two relevant comparison points, and this is visible even in descriptive results from uncontrolled regressions.

6.1 Reallocation channels

The results on earnings and income paint a picture of both differential impact and persistence of shocks on self-employed workers in developing countries. While men and women both suffer a decrease in earnings, women's relative decrease is larger. Additionally, only women's earnings persist to be relatively smaller even during the interview week, sometime after the shock (up to 17 months), pointing to different adaptation strategies and leading to divergence in earnings and income as time passes after the policy. While men draw away from declining jobs, not only do women stay, but they become more and more invested in them in terms of working hours. Examination of income patterns reveals that affected women invest more time in these jobs to maintain total income relative to their men counterparts, at the expense of longer working hours. These findings are striking in light of standard labor theory: in response to an hourly wage decrease, hours

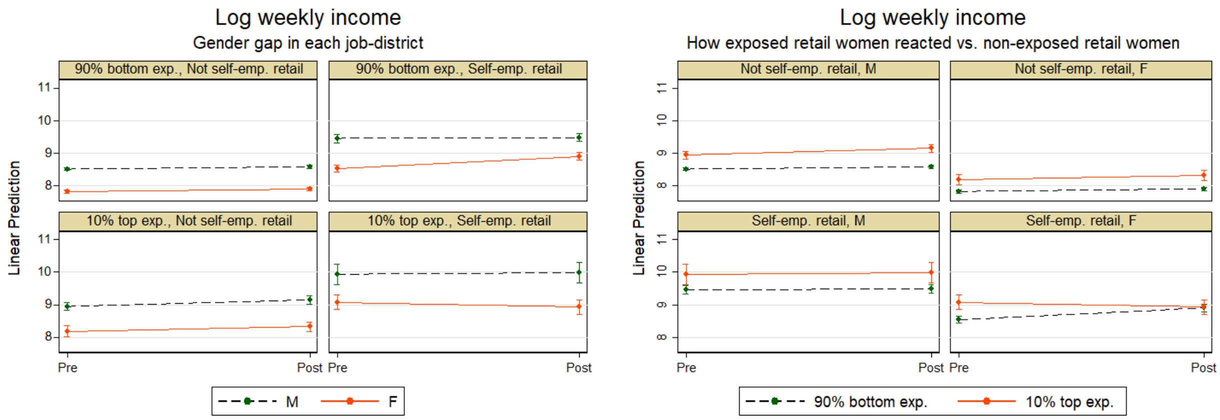

Figure 8: Evolution of income premia within retail across gender and across districts

worked should decrease and even more so for affected women for whom the relative decrease was larger. They point to limited reallocation capacity, leading to these increased working hours. While our results on total hours worked and earnings in and out of retail fit the simplistic framework that we have put forward, it is policy-relevant to examine further the occupational choices that men and women are making behind this reallocation of their working hours. I thus will focus the rest of my investigation on the mechanisms behind these theory-divergent results. First, I will explore further differences in adaptation strategy along several intensive and extensive dimensions, looking specifically at how men reallocate to draw away from affected jobs and in what ways women are not following their strategy. We have seen that there is no gender-dependent trend in leaving affected jobs altogether. Rather, men seem to be maintaining income relative to retailers in less affected areas, but working less and diminishing earnings from their affected retail jobs. Whether they redistribute time away from this job into jobs they already hold or take on new occupations, signals different reallocation mechanisms and the fact that women seem not to be doing the same entails policy implications. To explore these responses, I investigate trends on several dimensions of the intensive margin, following the results examined in the first strand of results.

Results from Table 10 reveal striking heterogeneity behind the labor supply results in Table 4. In contrast with this table, only affected retailers who are women, and not all affected retailers, are increasing the hours they work per job (col. (2)), through an increase in total hours worked coupled with a decrease in the number of jobs worked per week (col. (6)), which given the lack of results on paid jobs, indicates a decrease in the likelihood of being an unpaid worker. Men seem to thus be decreasing the number of hours worked in affected retail jobs, while not abandoning these occupations (Table 3), but are maintaining income, hours (col. (2)) and months worked (col. (3)) by diversifying and potentially acquiring another paid job (col. (4)). In contrast, women that were affected by the shock seem to be adapting, in line with our job-level estimates and our model, by increasing the number of hours they work at a job during the week but decreasing the number of jobs they work per week (col. (7)). Exploring whether men take on new occupations or substitute time away into already held jobs leads us to uncover diverging trends in how workers reallocate their time: rather than diversifying as men do, taking new jobs, women's time is polarized toward pre-existing, declining

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × IndRetail × F × Expo	0.014	3.192**	0.164	-0.009	0.005	-0.048**	-0.036
	(0.01)	(1.35)	(0.14)	(0.02)	(0.03)	(0.02)	(0.03)
Post × IndRetail × Expo	-0.004	-1.068	0.119	0.025*	-0.009	0.022	0.000
	(0.01)	(1.01)	(0.10)	(0.01)	(0.02)	(0.02)	(0.03)
IndRetail	-0.007	0.164	-0.164	-0.062***	-0.106***	-0.064***	-0.185***
	(0.00)	(1.02)	(0.12)	(0.02)	(0.03)	(0.02)	(0.04)
IndRetail × Expo	0.001	1.176	0.167**	-0.034***	-0.066***	-0.059***	-0.082***
	(0.01)	(0.76)	(0.08)	(0.01)	(0.02)	(0.01)	(0.02)
Post × IndRetail	0.003	3.041*	0.544***	-0.020	-0.111***	-0.116***	-0.136***
	(0.01)	(1.60)	(0.15)	(0.03)	(0.04)	(0.03)	(0.04)
IndRetail × F	0.011*	-0.818	-0.467***	0.056**	0.168***	0.010	0.167***
	(0.01)	(1.06)	(0.12)	(0.02)	(0.03)	(0.03)	(0.03)
IndRetail × F × Expo	0.006	-0.280	0.331***	0.016	0.001	0.021	-0.045*
	(0.01)	(0.89)	(0.11)	(0.01)	(0.02)	(0.02)	(0.02)
Post × IndRetail × F	-0.006	-0.883	-0.105	-0.022	0.028	-0.003	0.008
	(0.01)	(1.80)	(0.20)	(0.03)	(0.04)	(0.04)	(0.05)
R-squared	0.052	0.229	0.373	0.233	0.333	0.240	0.240
N	61001	42018	71766	71766	71766	66232	61001
Time-district-sex FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7), except for (2) which is all individuals with at least a job in the interview week.

Table 10: Intensive labor supply

jobs, leading them to let go of some of their unpaid occupations. In contrast with the existing literature on the impacts of trade shocks on workers, there does not seem to be an unemployment response, either on the part of all exposed workers or only for women (col. (1)) here either.

In Table 11, I explore which jobs women are abandoning. Although I focus on the main job of the week results are constant across all jobs, including those that individuals work beyond their main job of the week, as shown in Table 38 in the Appendix.

First and speaking to the literature on responses to trade shocks in developing countries, we notice the absence of an informality response for both men and women retailers: the weakly significant positive effect on take-up of formal jobs on retailers disappears when considering gender-specific trends and controlling for time-district-sex fixed effects. Contrary to Ponczek and Ulyssea [2021] or McCaig and Pavcnik [2018], changes in returns to informal jobs - characterized here as wage jobs with no fixed contract or self-employed jobs that are not registered to the Rwanda Revenue Authority, sector or district administration - do not lead to changes in the likelihood of holding a formal job. In our case, women choose to make up for the lost income not by switching jobs, but by reallocating time away from other jobs to their negatively affected retail jobs. Looking at our occupational choice results, it appears that women are drawing away from unpaid family member jobs (col. (3)), while men are increasing their participation in these jobs (col. (3), second coefficient). Men are also expanding the set of jobs they work in by starting retail-adjacent jobs (column (6)), a coefficient that is offset, although not significantly, by the negative coefficient for women. There are no gendered migration

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × IndRetail × F × Expo	0.004	-0.007	-0.028***	0.007	-0.012	-0.003
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
Post × IndRetail × Expo	0.005	0.005	0.009**	0.014	0.017	0.005*
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
IndRetail	0.020***	-0.100***	-0.049***	-0.027***	0.482***	-0.014***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
IndRetail × Expo	0.006**	-0.048***	0.002	0.003	0.047***	-0.005***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Post × IndRetail	-0.002	-0.005	-0.015	0.091***	0.006	0.006*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.00)
IndRetail × F	0.044***	0.103***	-0.023*	-0.020***	-0.140***	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
IndRetail × F × Expo	-0.013***	0.021**	0.007	0.004	0.028**	0.000
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Post × IndRetail × F	-0.023*	0.000	0.046**	-0.028	0.034	-0.005
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)
R-squared	0.078	0.242	0.188	0.207	0.434	0.014
N	71665	71665	71665	71766	71766	71766
Time-district-sex FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo.: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7)

Table 11: Occupational choice - main job week

patterns (Table 36).

The gap between men's and women's responses to a common, although not equal, decrease in earnings is illustrative of differential adaptation capacities and consequential in terms of hourly income and occupational choice. In line with predictions from the simple framework put forward in prior sections, with literature interested in self-employment in developing countries and with suggestive descriptive evidence from my Rwandan databases, I attribute these diverging adaptation paths to women's outside options being lower out of the self-employed job spells they are kept into, leading them to stay in downgrading occupations, maintaining income at the cost of their unpaid family work. Although we see no consequence of this unpaid family work abandon on household consumption in Table 9, the fact that these were not lucrative occupations could be suggesting consequences elsewhere, notably for household children - an important follow-up avenue.

7 Robustness checks

Robustness checks are presented in Appendix A for alternative specifications, and several other potential explanatory channels are presented in Appendix B.

First, I introduced the alternative spatial indexes discussed in section 2[22]. The first changes the numerator: as the $caguwa$ variable is determined by the enumerator's choice to specify that a given seller sells used clothes,

[22]For the $caguwa$ predictor and the discrete variable, I only present the main results on earnings, hours, and income, for the sake of conciseness. The other results are available on request

it is a lower bound for true $caguwa$ activity. Moreover, in areas with low prevalence of $caguwa$ sellers, the choice of a few enumerators to not specify $caguwa$ could lead to a false zero exposure being attributed to a district. I predict being a $caguwa$ firm on invariant characteristics: the procedure is detailed in the data section and has good predictive power for actual $caguwa$ establishments. Considering this spatial index in subsection A.4 does not change the direction and overall significance of the results. Changing the exposure index from a continuous variable to a discrete one denoting being in the top 10% more exposed districts, as this is where we see the biggest jump, does not change the results either. I also checked, although the results are not presented here, that the $caguwa$ index is not giving the same results as a population density index, to check that it is not just a proxy for urbanization - it is not.

Alternatively, I change the denominator and use standardized $\frac{caguwa}{retail}$ - the number of workers in the retail sector rather than the number of workers in the district - to account for the size of the retail sector in a given district. The index can be thought of as a measure of the impact of the shock on retail sectors, rather than a measure of the impact on the district as a whole. I find that while earnings, income, and reallocation results are unchanged, women do not follow significantly different trajectories than men in terms of hours reallocation anymore. Retailers are affected differently in more exposed areas compared to less exposed retailers, but the reallocation patterns become more similar between genders. As a consequence, the gendered effect ($Post \times IndRetail \times Expo. \times F$) disappears. The result supports our main hypothesis, the outside option channel: the results suggest that the districts in which trajectories were most different between men and women were those with a high $\frac{caguwa}{active\_population}$ and a low $\frac{caguwa}{retail}$ ratio, areas with both prevalent used clothing trade and big retail sectors. As stated in section 1, for men operating in $caguwa$, retail - and especially retail as wage-earners - is an outside option, while for women, it is not. It is also more likely to be a secondary job for men working in $caguwa$ than for women, as shown in Figure G. For a given level of $caguwa$ prevalence, having a smaller retail sector - leading to a larger $\frac{caguwa}{retail}$ ratio - means lower quality of outside options for men relative to women. As a result, men and women should have more similar reallocation trajectories, which the results on hours not being significant while still of the right direction illustrate. A secondary test in the same vein uses significant heterogeneity in the availability of non-farm wage jobs: in some districts, before 2016, workers are only observed working 29 different types of non-farm wage jobs, while this number is 86 for the districts with the most opportunities. We run a quintuple-difference that is Equation 3 interacted with a dummy for living in a district with more than the mean number of distinct wage occupations pre-shock, $high\_opp_i$ Gender inequality in exposure and adaptation strategies disappears when we account for local labor market opportunities. Table A.2.3 presents the results from this table: while all workers, regardless of gender or of local opportunities, are subject to slower hourly earning growth compared to retailers in less exposed areas, hourly responses are dependent on local opportunities, and not on gender anymore, whether at the job-level or across all jobs. This results in hourly income losses being larger for low-opportunities zones, regardless of gender. As such, we take these results as lending further strength to the argument that adaptation depends on available outside options, and not purely on gender-related reasons like available time, amenities of certain jobs. To go deeper in this outside option hypothesis, I use a individual variation for precariousness on the labor market: working several jobs before the shock, which could indicate an incapacity to make ends meet with only one job[23]. When disentangling by whether a worker works several jobs a week before the shock, we learn that these workers are even more vulnerable than retailers working only one job to the shock in terms of earnings, but even though they are more harmed by the shock, these workers do not decrease hours at the affected job more than workers with only one job - meaning their labor supply response to a given wage decrease is lower. Once again, this lends support to our claim that outside options, not purely gender, are guiding the results.

Finally, to check the stability of the results and check that one high-density state is not influencing all of them, I introduce a third alternative specification and I discretize the spatial exposure variable, isolating the 10% most isolated states, which are shown on the map. Results have similar significance levels and directions that the main specification.

I then check that the effects picked up by the heterogeneity analysis are not those of a different skill composition across genders or different financial burdens, that they are not driven by being in a couple, and that they do not come from women having more precarious occupations, in the form of having more paid jobs from the beginning. I do this by further differentiating my estimating equations by a dummy for having a school diploma, being the sole breadwinner of the household, living with a partner, or having many paid jobs per week before the shock. Neither of these indicator variables makes the average or gendered effects on earnings insignificant, although the income average effect sometimes is imprecisely estimated, mostly owing to my dividing the dataset to run the quadruple and quintuple differences. Coefficients attached to our heterogeneity candidates are never significant, except for the coefficient on earnings attached to having many paid jobs, which amplifies the negative earnings effects of the shock, though not in a gendered way. These results support our theory that all precarious workers, not just women, had a harder time mitigating the negative effects of the policy.

In Appendix C, I use the 2010 IHLCS wave to examine pre-trends. Although there are no outcomes for which the observed change has a same sign pre-trend from 2010 to 2013 going in the same directions, there are instances of opposite sign pre-trend. This is notably the case for earnings in the gendered specifications, where women retailers were catching up on their male counterparts before the shock, indicating that the negative effect of the shock on women's earnings could be even larger.

8 Conclusion

In this paper, I use an administrative census of formal and informal firms and job-level survey data to show the effects of trade policy when affected workers are self-employed. My results point to the specific margins available to the self-employed and under-explored in the literature: rather than being displaced by a persistent negative hourly wages shock, self-employed workers adjust quantities bought to maintain expenses, pass some of the policy through to customer prices, and adjust hours at their other jobs to mitigate income losses. These results show that, although overlapping to a great extent with informality, self-employment entails conceptually different livelihoods and adaptation mechanisms - the most important of which being that self-

[23] In this context, working several job is associated with lower total income.

employed people can decide whether to be displaced or not. Impact studies of trade shocks in countries with high self-employment prevalence such as most African countries, should allow for self-employed specific adaptation margins, ideally with job-level data as these margins are exerted across different jobs in the same period.

My framework and results also highlight the crucial importance of outside options. I uncover striking gender heterogeneity in how self-employed workers respond to shocks, along two dimensions: profit losses are borne primarily by women, suggesting a larger impact, and the impact vanishes with time only for men, indicative of longer persistence and limited reallocation capacity of women. While men are reallocating time away from affected jobs to other paid occupations, women are doing the opposite, akin to a Giffen good-type mechanism. Outside options drive this behavior, not only gender: when accounting for other factors proxying labor market tightness (the geographical prevalence of men-specific outside options other than $caguwa$, or number of distinct wage occupations available in an area) or individual lack of outside options (doing several jobs pre-shock as a symptom of precariousness on the labor market), gender inequality in adaptation strategies vanish (section 7). Women are more affected because they are overrepresented in these situations, but their lack of adaptation capacity bears some gender-specific consequences, as they abandon unpaid family jobs in order to put more hours into affected occupations, not affecting household consumption but entailing consequences on children and other household members beyond adaptation. Finally, in related work, I explore the intra-household dimension of adaptation, showing that men's disposal of unpaid feminine domestic and productive labor drives married individuals' gender inequality in shock adaptation and resilience.

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	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × IndRetail × Expo	-0.229*	-0.015	-0.201	-0.008
	(0.13)	(0.06)	(0.13)	(0.07)
R-squared	0.481	0.158	0.411	0.233
N	29980	53684	29969	27961
Time-district FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 12: Income and hours, individual level - discrete spatial exp.

	log(earnings)		*self-emp. sample*		*Hours this week*	*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Kept job	
Post × IndRetail × Expo	-0.416***	-0.374**	-0.257	0.381	-0.918	0.001
	(0.16)	(0.16)	(0.19)	(0.33)	(2.47)	(0.01)
R-squared	0.471	0.397	0.295	0.266	0.230	0.005
N	23638	23619	5212	3999	53429	53459
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 13: Earnings, hours worked and selection - discrete spatial exp.

A Robustness checks - other specifications

A.1 Alternative spatial index: discrete $caguwa$ (top 10% districts)

A.1.1 Income and earnings

	log(Weekly Y)	log(Tot. hours)	log(weekly Y/hour), week
Post × IndRetail × F × Expo	-0.529**	0.189	-0.749***
	(0.23)	(0.14)	(0.25)
Post × IndRetail × Expo	0.111	-0.118	0.250
	(0.20)	(0.11)	(0.22)
R-squared	0.484	0.161	0.415
N	29980	53684	29969
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 14: Income and hours, individual level - gender heterogeneity - discrete spatial exp.

	Earnings		*Hours worked*	*Selection*
	Daily	Hourly	Hours	Kept Job
Post × IndRetail × F × Expo	-0.711**	-0.961***	11.660**	-0.017
	(0.29)	(0.31)	(5.36)	(0.02)
Post × IndRetail × Expo	-0.010	0.186	-8.279*	0.013
	(0.26)	(0.27)	(4.47)	(0.01)
R-squared	0.475	0.402	0.233	0.006
N	23638	23619	53429	53459
Time-district FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 15: Earnings, hours worked and selection - gender heterogeneity - discrete spatial exp.

	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × IndRetail × Expo	-0.108**	0.028	-0.135***	-0.018
	(0.04)	(0.02)	(0.04)	(0.02)
R-squared	0.481	0.158	0.411	0.233
N	29980	53684	29969	27961
Time-district FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 16: Income and hours, individual level - first stage - retail denominator

A.2 $caguwa/retail$

A.2.1 Income and earnings

	log(Weekly Y)	log(Tot. hours)	log(weekly Y/hour), week
Post × IndRetail × F × Expo	-0.092	0.024	-0.123
	(0.07)	(0.04)	(0.08)
Post × IndRetail × Expo	-0.044	0.019	-0.061
	(0.06)	(0.03)	(0.07)
R-squared	0.484	0.161	0.415
N	29980	53684	29969
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 17: Income and hours, individual level - gender heterogeneity - retail denominator

	log(earnings)		*self-emp. sample*		*Hours this week*	*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Kept job	
Post × IndRetail × Expo	-0.195***	-0.220***	-0.164**	0.085	0.410	-0.000
	(0.05)	(0.05)	(0.06)	(0.11)	(0.84)	(0.00)
R-squared	0.471	0.398	0.295	0.267	0.230	0.005
N	23638	23619	5212	3999	53429	53459
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 18: Job-level earnings, hours and selection - retail denominator

	Earnings		*Hours worked*	*Selection*
	Daily	Hourly	Hours	Kept Job
Post × IndRetail × F × Expo	-0.171*	-0.195*	1.868	-0.003
	(0.10)	(0.10)	(1.74)	(0.00)
Post × IndRetail × Expo	-0.098	-0.111	-0.607	0.002
	(0.08)	(0.08)	(1.45)	(0.00)
R-squared	0.475	0.402	0.233	0.006
N	23638	23619	53429	53459
Time-district FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 19: Earnings, hours worked, selection - gender heterogeneity - retail denomiator

A.2.2 Migration

	Migrant	Infra-distr. move	Return migrant
Post × IndRetail × Expo	-0.004	0.001	-0.001
	(0.01)	(0.01)	(0.00)
R-squared	0.058	0.065	0.031
N	66232	66232	66232
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 20: Migration - retail denominator

	Migrant	Infra-distr. move	Return migrant
Post × IndRetail × F × Expo	0.004	0.012	-0.012
	(0.01)	(0.02)	(0.01)
Post × IndRetail × Expo	-0.007	-0.006	0.006
	(0.01)	(0.02)	(0.01)
R-squared	0.059	0.067	0.032
N	66232	66232	66232
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 21: Migration - gender heterogeneity - retail denominator

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × IndRetail × Expo	0.001	0.154	0.295***	0.047***	-0.004	0.010	-0.027
	(0.01)	(0.75)	(0.08)	(0.01)	(0.02)	(0.02)	(0.02)
R-squared	0.047	0.223	0.364	0.232	0.330	0.237	0.234
N	61001	42098	71766	71766	71766	66232	61001
Time-district FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 22: Reallocation - intensive - first stage - retail denominator

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × IndRetail × F × Expo	0.008	2.327	0.073	-0.008	-0.007	-0.044	-0.048
	(0.01)	(1.69)	(0.16)	(0.03)	(0.04)	(0.03)	(0.04)
Post × IndRetail × Expo	-0.004	-1.292	0.243*	0.053**	0.002	0.040	0.006
	(0.01)	(1.42)	(0.12)	(0.02)	(0.03)	(0.03)	(0.04)
R-squared	0.051	0.226	0.372	0.234	0.333	0.239	0.239
N	61001	42098	71766	71766	71766	66232	61001
Time-district FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 23: Reallocation - intensive - gender heterogeneity - retail denominator

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × IndRetail × Expo	0.018***	0.003	-0.019**	0.017	0.016	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R-squared	0.077	0.236	0.170	0.222	0.417	0.011
N	71665	71665	71665	71766	71766	71766
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 24: Reallocation - main job week - retail denominator

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × IndRetail × F × Expo	-0.002	0.002	-0.058***	0.017	0.009	-0.003
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)
Post × IndRetail × Expo	0.019**	0.000	0.018**	0.005	0.010	0.004
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
R-squared	0.078	0.241	0.188	0.225	0.426	0.014
N	71665	71665	71665	71766	71766	71766
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. IndRetail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 25: Reallocation - main job week - gender heterogeneity - retail denominator

A.2.3 Reallocation

A.3 test for local wage options

	Hourly earnings, j		*Hours, j*		*Hourly income*		*Log Total hours*	
Post × SES × ZDE	-0.412	-0.638*	10.881*	8.144*	-0.291	-0.353*	0.211**	0.184**
	(0.38)	(0.36)	(6.38)	(4.66)	(0.26)	(0.18)	(0.09)	(0.07)
Post × SES × F × ZDE	-0.722		-5.697		-0.061		-0.040	
	(0.65)		(9.87)		(0.36)		(0.13)	
Post × SES × high_opp=1 × ZDE	0.431	0.548	-14.310**	-8.849*	0.303	0.268	-0.256***	-0.179**
	(0.39)	(0.36)	(6.49)	(4.74)	(0.26)	(0.19)	(0.10)	(0.08)
Post × SES × F × high_opp=1 × ZDE	0.526		10.399		-0.112		0.129	
	(0.66)		(9.99)		(0.37)		(0.14)	
R-squared	0.40	0.40	0.24	0.24	0.41	0.41	0.16	0.16
N	23619	23619	53429	53429	29969	29969	53684	53684
District-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓	✓

	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × IndRetail × Expo	-0.070*	0.048**	-0.118***	0.007
	(0.04)	(0.02)	(0.04)	(0.02)
R-squared	0.481	0.158	0.411	0.234
N	29980	53684	29969	27961
Time-district FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. Indretail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 26: Income and hours, individual level - $caguwa$ predictor

	log(Weekly Y)	log(Tot. hours)	log(weekly Y/hour), week
Post × IndRetail × F × Expo	-0.105*	0.049	-0.142**
	(0.06)	(0.04)	(0.07)
Post × IndRetail × Expo	-0.009	0.022	-0.038
	(0.05)	(0.03)	(0.05)
R-squared	0.484	0.161	0.415
N	29980	53684	29969
Time-district FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. Indretail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 27: Income and hours, individual level - gender heterogeneity - $caguwa$ predictor

A.4 Alternative spatial index: $caguwa$ predictor

A.4.1 Income and earnings

	log(earnings)		*self-emp. sample*		*Hours this week*	*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Kept job	
Post × IndRetail × Expo	-0.100**	-0.127***	-0.129***	-0.143*	0.315	-0.000
	(0.04)	(0.04)	(0.05)	(0.08)	(0.74)	(0.00)
R-squared	0.471	0.397	0.296	0.268	0.230	0.005
N	23638	23619	5212	3999	53429	53459
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Expo: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. Indretail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 28: Job-level earnings, hours worked and selection - $caguwa$ predictor

	Earnings		*Hours worked*	*Selection*
	Daily	Hourly	Hours	Kept Job
Post × IndRetail × F × Expo	-0.167**	-0.191**	2.452*	-0.003
	(0.07)	(0.08)	(1.47)	(0.00)
Post × IndRetail × Expo	-0.011	-0.024	-0.990	0.001
	(0.06)	(0.06)	(1.17)	(0.00)
R-squared	0.475	0.402	0.233	0.006
N	23638	23619	53429	53459
District-time FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. Indretail: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 29: Job-level earnings, hours worked and selection - gender heterogeneity - $caguwa$ predictor

B Alternative hypotheses

Education and skill

	Earnings				*Income*	
	All jobs		*Main job of the week*			
P × SES × ZDE	-0.037	-0.145***	0.036	-0.066	-0.019	-0.062
	(0.08)	(0.05)	(0.08)	(0.06)	(0.07)	(0.06)
P × SES × F × ZDE	-0.178*		-0.205**		-0.081	
	(0.09)		(0.10)		(0.09)	
P × SES × Diploma × ZDE	-0.068	0.028	-0.066	0.000	-0.005	0.000
	(0.10)	(0.06)	(0.10)	(0.07)	(0.09)	(0.07)
P × SES × F × Diploma × ZDE	0.178		0.152		0.026	
	(0.12)		(0.13)		(0.13)	
R-squared	0.35	0.34	0.44	0.43	0.38	0.38
N	58469	58469	23932	23932	30364	30364
Time-district FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to $caguwa$ at t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 30: Impact of having any education on earnings and income

No other breadwinner

Having more jobs before the shock

C Pre-trends tests

In Table 34 I include the 2010 wave of IHLCS to test for pre-trends[24] in the job-level and individual-level main outcomes: hours worked this week, earnings, hourly earnings, the likelihood that the individual kept the job, total hours, income and hourly income across all jobs. All coefficients are relative to the year 2010. In the absence of pre-trends, the coefficients on 2013 × $IndRet$ × ZDE and 2013 × $IndRet$ × $Female$ × ZDE should be non-significant (nothing happening to the retail premia, or the retail gender gap premia, from exposed to non-exposed areas from 2010 to 2013), and the coefficients on 2016 × $IndRet$ × ZDE and 2016 × $IndRet$ × $Female$ × ZDE should be the same as in the main specification. This is for example the case for *Hours* in

[24]The three-period regression is not the main specification because of several differences in the data collection, notably a change in the urban/rural divide, an absence of trimester, and missing outcomes, that would allow for less credibility and less results than in just showing the 2-waves tables

	Earnings		*Income*	
	Main job of the week			
Post × IndRetail × Expo	-0.025	-0.103**	-0.024	-0.091**
	(0.06)	(0.05)	(0.06)	(0.04)
Post × IndRetail × F × Expo	-0.148**		-0.105	
	(0.07)		(0.07)	
Post × IndRetail × No help=1 × Expo	0.072	0.089	0.139	0.141*
	(0.14)	(0.09)	(0.12)	(0.08)
Post × IndRetail × F × No help=1 × Expo	0.035		-0.021	
	(0.15)		(0.15)	
R-squared	0.48	0.47	0.48	0.48
N	23638	23638	29980	29980
District-Time FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 31: Impact of being the only working household member

	Hourly earnings, j		*Hours, j*		*Hourly income*		*Log Total hours*	
Post × SES × ZDE	0.015	-0.084**	-2.001*	-0.066	-0.009	-0.093**	-0.006	0.029
	(0.06)	(0.04)	(1.05)	(0.72)	(0.05)	(0.04)	(0.03)	(0.02)
Post × SES × F × ZDE	-0.183***		3.580***		-0.150**		0.066*	
	(0.07)		(1.33)		(0.06)		(0.04)	
Post × SES × M=1 × ZDE	-1.096***	-0.727***	-6.955	-1.231	-0.089	-0.123	0.127	0.100
	(0.36)	(0.19)	(7.20)	(3.72)	(0.18)	(0.14)	(0.08)	(0.08)
Post × SES × F × M=1 × ZDE	0.637		1.381		-0.022		-0.119	
	(0.43)		(7.99)		(0.24)		(0.16)	
R-squared	0.40	0.40	0.23	0.23	0.42	0.42	0.16	0.16
N	23619	23619	53429	53429	29969	29969	53684	53684
District-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 32: Effect change with having more paid jobs before the shock

the regression that disentangles by gender (col. 5). However, on average, from 2010 to 2016, hours worked for retail vs. non-retail workers grew relatively slower in exposed areas (2016 coefficient of col. (1)), which was not the case in the main specification. With respect to earnings variables, there is a positive pre-trend on women's income relative to men within retail as compared to non retail across districts of exposure: women were catching up on their male colleagues' earnings before the shock, which means that the negative shock they undergo from 2013 to 2016 is canceled out in the $2016 \times IndRet \times Female \times ZDE$ coefficient. We reject the hypothesis of no pre-trends in earnings, but they are going in the opposite direction of the effect that we get in the main regressions, and the fact that we observe data every 3 years makes the hypothesis of a simple reversal to the mean implausible: there seems to have been an interrupted catch-up of women retailers to men, rather than a shock to earnings evolving in parallel. Figure 9 shows this graphically for daily earnings at the job level and hourly income at the individual level.

	Average effects				Gendered effects			
	Hours	Daily Y	Hourly Y	Kept this job	Hours	Daily Y	Hourly Y	Kept this job
2013 × IndRet × ZDE	-1.021	0.035	0.066*	0.001**	-0.637	-0.047	-0.011	0.003***
	(0.71)	(0.04)	(0.04)	(0.00)	(1.09)	(0.05)	(0.05)	(0.00)
2016 × IndRet × ZDE	-1.288*	-0.051	-0.033	0.001**	-2.532**	-0.062	-0.015	0.003***
	(0.76)	(0.04)	(0.04)	(0.00)	(1.03)	(0.06)	(0.05)	(0.00)
2013 × IndRet × F × ZDE					-0.874	0.153**	0.149**	-0.003*
					(1.31)	(0.07)	(0.07)	(0.00)
2016 × IndRet × F × ZDE					2.279*	0.025	-0.030	-0.003*
					(1.32)	(0.08)	(0.08)	(0.00)
R-squared	0.246	0.423	0.363	0.019	0.244	0.421	0.361	0.017
N	80574	35384	35218	80604	80574	35384	35218	80604
district-time F E	✓	✓	✓	✓	✓	✓	✓	✓

Table 33: Effects with the 2010 wave - job-level outcomes

	Total income		Total hours		Total income/total hours	
2013 × IndRet × ZDE	-0.054	0.018	-0.039	-0.041**	-0.023	0.047
	(0.05)	(0.03)	(0.02)	(0.02)	(0.05)	(0.03)
2016 × IndRet × ZDE	-0.059	-0.042	-0.041*	-0.010	-0.027	-0.042
	(0.05)	(0.04)	(0.02)	(0.02)	(0.05)	(0.04)
2013 × IndRet × Female × ZDE	0.118*		-0.013		0.122*	
	(0.07)		(0.04)		(0.06)	
2016 × IndRet × Female × ZDE	0.029		0.049		-0.029	
	(0.07)		(0.04)		(0.07)	
R-squared	0.448	0.444	0.140	0.137	0.372	0.368
N	44650	44650	80834	80834	44554	44554
district_urban FE	✓	✓	✓	✓	✓	✓

Table 34: Effects with the 2010 wave - individual-level outcomes

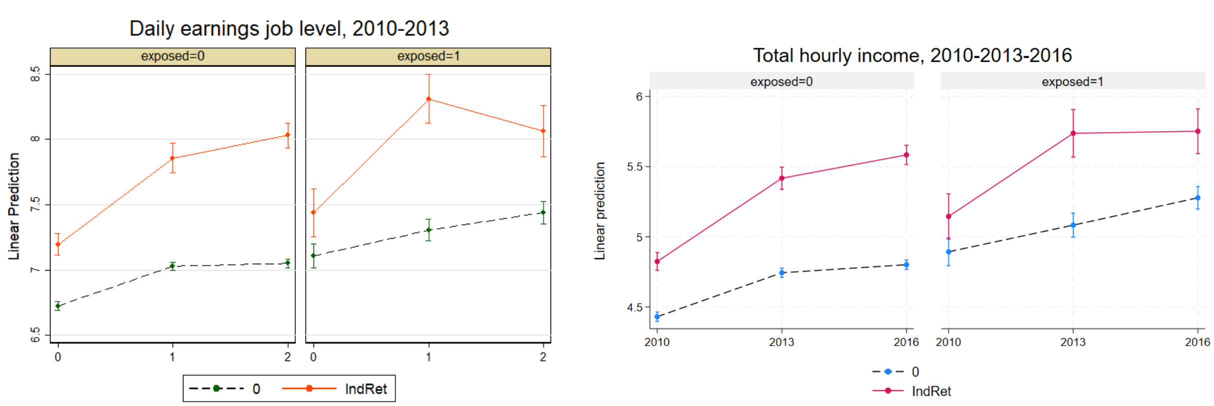


Figure 9: Pre-trends in job-level wages and individual-level income

D Descriptive statistics

	Men				Women			
	not SES		SES		not SES		SES	
	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd
Hours worked (weekly, per job)	28.19	28.37	36.53	37.12	22.74	22.25	27.45	28.77
	(20.59)	(21.77)	(25.89)	(27.26)	(15.48)	(17.00)	(21.43)	(24.72)
Earnings	7.04	7.12	7.98	8.25	6.60	6.75	7.33	7.72
	(1.11)	(1.04)	(1.63)	(1.61)	(0.97)	(0.89)	(1.55)	(1.41)
log_turnover	8.00	8.10	8.43	8.60	7.17	7.55	7.70	8.09
	(1.68)	(1.64)	(1.57)	(1.48)	(1.63)	(1.57)	(1.51)	(1.36)
log(non-L expend.)	6.55	6.46	6.58	6.52	5.82	5.89	5.80	6.20
	(2.05)	(1.97)	(2.08)	(1.95)	(1.98)	(1.95)	(2.12)	(1.91)
Tot. hours/week	30.32	29.88	42.70	42.10	23.01	22.79	31.13	31.24
	(23.83)	(24.14)	(26.06)	(25.22)	(18.36)	(19.38)	(21.82)	(23.27)
Hourly earnings	5.24	5.26	6.39	6.45	4.92	4.94	5.95	6.08
	(1.20)	(1.13)	(1.60)	(1.55)	(1.09)	(1.02)	(1.44)	(1.40)
Observations	29598	28449	977	1013	29446	29248	1674	1539

	Men				Women			
	not SES		SES		not SES		SES	
	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd
log(week Y)	8.58	8.66	9.63	9.52	7.91	8.00	8.83	8.98
	(1.31)	(1.28)	(1.62)	(1.59)	(1.26)	(1.22)	(1.57)	(1.48)
Observations	8219	8172	550	564	5582	5950	724	705

	Men				Women			
	not SES		SES		not SES		SES	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
migrant	0.05	0.05	0.04	0.04	0.04	0.05	0.04	0.04
move	0.21	0.20	0.17	0.16	0.14	0.13	0.13	0.14
return migrant	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01
Observations	16306	16172	694	680	18102	17901	1123	1074

E Migration responses

	Men				Women			
	not SES		**SES**		**not SES**		**SES**	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Tot. hrs/job (wk)	27.80	29.00	34.92	35.40	21.00	21.64	25.55	28.53
	(23.01)	(23.99)	(28.18)	(29.42)	(17.11)	(18.89)	(24.83)	(27.31)
log(Tot hrs/job)	2.88	2.92	3.05	3.04	2.67	2.67	2.64	2.74
	(1.07)	(1.07)	(1.18)	(1.21)	(0.95)	(0.97)	(1.23)	(1.26)
Job switching								
paid jobs/w	0.56	0.55	0.93	0.93	0.33	0.36	0.76	0.74
	(0.60)	(0.58)	(0.56)	(0.50)	(0.51)	(0.51)	(0.58)	(0.57)
paid jobs/y	0.97	0.94	1.47	1.41	0.64	0.67	1.36	1.37
	(0.87)	(0.85)	(0.75)	(0.70)	(0.71)	(0.70)	(0.59)	(0.60)
Jobs/y	1.93	1.89	2.10	1.97	1.70	1.71	2.05	2.02
	(0.93)	(0.89)	(0.96)	(0.92)	(0.74)	(0.72)	(0.84)	(0.86)
Jobs/w	1.00	1.16	1.34	1.33	0.96	1.11	1.25	1.21
	(0.74)	(0.63)	(0.70)	(0.65)	(0.71)	(0.63)	(0.76)	(0.73)
Av. job dur.	6.89	6.54	8.35	8.43	7.52	6.81	8.22	7.67
	(4.27)	(4.28)	(3.26)	(3.33)	(4.33)	(4.29)	(3.27)	(3.35)
No job (wk)	0.24	0.26	0.06	0.07	0.25	0.27	0.15	0.15
	(0.43)	(0.44)	(0.24)	(0.25)	(0.44)	(0.44)	(0.35)	(0.36)
Wage (wk)	0.42	0.43	0.11	0.14	0.24	0.28	0.12	0.11
	(0.49)	(0.50)	(0.31)	(0.35)	(0.43)	(0.45)	(0.33)	(0.31)
Ind. f (wk)	0.31	0.29	0.32	0.34	0.20	0.22	0.17	0.19
	(0.46)	(0.46)	(0.47)	(0.47)	(0.40)	(0.42)	(0.38)	(0.39)
Formal (wk)	0.17	0.18	0.40	0.40	0.07	0.08	0.19	0.18
	(0.37)	(0.38)	(0.49)	(0.49)	(0.26)	(0.27)	(0.39)	(0.38)
Main job of the week								
Self-emp	0.08	0.07	0.59	0.57	0.04	0.04	0.42	0.44
	(0.27)	(0.25)	(0.49)	(0.50)	(0.20)	(0.19)	(0.49)	(0.50)
Wage	0.35	0.37	0.08	0.11	0.17	0.21	0.07	0.07
	(0.48)	(0.48)	(0.27)	(0.31)	(0.37)	(0.41)	(0.26)	(0.25)
W(f)	0.10	0.11	0.01	0.04	0.09	0.12	0.05	0.05
	(0.29)	(0.32)	(0.11)	(0.20)	(0.29)	(0.33)	(0.22)	(0.22)
W(nf)	0.26	0.26	0.07	0.07	0.07	0.09	0.02	0.02
	(0.44)	(0.44)	(0.25)	(0.25)	(0.26)	(0.29)	(0.13)	(0.12)
Indep. f	0.23	0.22	0.20	0.21	0.17	0.19	0.12	0.13
	(0.42)	(0.41)	(0.40)	(0.41)	(0.37)	(0.39)	(0.33)	(0.34)
Unp. fam.	0.09	0.08	0.06	0.04	0.36	0.29	0.23	0.21
	(0.28)	(0.28)	(0.23)	(0.20)	(0.48)	(0.45)	(0.42)	(0.41)
Unp. f	0.08	0.08	0.06	0.04	0.35	0.28	0.23	0.21
	(0.28)	(0.27)	(0.23)	(0.20)	(0.48)	(0.45)	(0.42)	(0.41)
Unp. nf	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01
	(0.07)	(0.06)	(0.00)	(0.05)	(0.11)	(0.11)	(0.06)	(0.07)
Formal	0.15	0.17	0.34	0.33	0.07	0.08	0.16	0.15
	(0.36)	(0.37)	(0.48)	(0.47)	(0.25)	(0.27)	(0.37)	(0.36)
Observations	16306	16172	694	680	18102	17901	1123	1074

Table 35: Descriptive statistics - occupation and reallocation

	Migrant	Infra-distr. move	Return migrant
Post × IndRetail × F × Expo	0.010	0.014	-0.013
	(0.02)	(0.02)	(0.01)
Post × IndRetail × Expo	-0.008	-0.001	0.001
	(0.01)	(0.01)	(0.01)
IndRetail	0.013*	-0.018	0.004
	(0.01)	(0.01)	(0.00)
IndRetail × Expo	-0.002	0.014	0.003
	(0.01)	(0.01)	(0.01)
Post × IndRetail	-0.010	-0.019	-0.000
	(0.01)	(0.02)	(0.00)
IndRetail × F	-0.003	0.030**	0.003
	(0.01)	(0.01)	(0.00)
IndRetail × F × Expo	-0.008	-0.016	-0.005
	(0.01)	(0.01)	(0.01)
Post × IndRetail × F	0.003	0.042*	-0.002
	(0.01)	(0.02)	(0.01)
R-squared	0.059	0.067	0.033
N	66232	66232	66232
Time-district-sex FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 36: Migration responses

F Reallocation responses - employment during the week

G Additional descriptive statistics

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × IndRetail × Expo	0.012*	-0.005	0.016*	0.003	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
IndRetail	0.002	-0.065***	-0.041***	0.619***	-0.625***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
IndRetail × Expo	-0.037***	-0.010**	0.003	0.022***	-0.007**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Post × IndRetail	-0.025**	-0.004	0.090***	0.023	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R-squared	0.173	0.192	0.204	0.613	0.616
N	71766	71766	71766	71766	71766
Time-district FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Expo: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. IndRetail =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. * p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 37: Reallocation - all jobs this week

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × IndRetail × F × Expo	0.006	-0.026***	0.014	-0.011	-0.006
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Post × IndRetail × Expo	0.008	0.009*	0.008	0.009	0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
IndRetail	-0.105***	-0.083***	-0.028***	0.671***	-0.615***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
IndRetail × Expo	-0.036***	-0.003	0.002	0.020**	-0.010**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Post × IndRetail	0.005	-0.016	0.121***	0.026	0.003
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
IndRetail × F	0.183***	0.032**	-0.023***	-0.088***	-0.015**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
IndRetail × F × Expo	-0.003	-0.002	0.004	0.005	0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Post × IndRetail × F	-0.050**	0.032	-0.050**	-0.007	-0.010
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
R-squared	0.177	0.210	0.207	0.616	0.617
N	71766	71766	71766	71766	71766
Time-district-sex FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

[2] * p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 38: Occupational responses - employment during the week - gender heterogeneity

	Men				**Women**			
	not SES		**SES**		**not SES**		**SES**	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
diploma	0.44	0.45	0.44	0.50	0.40	0.43	0.39	0.44
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)	(0.50)
no_help	0.06	0.07	0.09	0.09	0.09	0.10	0.12	0.15
	(0.23)	(0.26)	(0.28)	(0.28)	(0.29)	(0.30)	(0.33)	(0.36)
Observations	16507	16317	493	535	18393	18133	832	842

Table 39: Statistics on education and household help

	Men				Women			
	not SES		**SES**		**not SES**		**SES**	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
last_daily_profits	33579.67	18426.41	10543.41	12282.10	3522.78	5007.04	4889.58	5980.88
	(1288037.05)	(207879.34)	(32670.64)	(73203.87)	(25025.15)	(25255.85)	(16577.75)	(16657.80)
log_last_profit	7.51	7.76	7.98	8.25	6.72	7.21	7.33	7.72
	(1.65)	(1.61)	(1.63)	(1.61)	(1.62)	(1.56)	(1.55)	(1.41)
last_daily_turnover	42502.92	24156.08	15153.35	18179.36	5529.77	7319.47	6689.78	8419.75
	(1408004.29)	(214108.44)	(39473.84)	(66263.79)	(29952.70)	(34679.00)	(22545.33)	(22669.22)
log_turnover	8.00	8.10	8.43	8.60	7.17	7.55	7.70	8.09
	(1.68)	(1.64)	(1.57)	(1.48)	(1.63)	(1.57)	(1.51)	(1.36)
last_daily_non_labor_exp	736.95	277.78	4273.63	5453.82	128.87	113.36	1694.62	2254.13
	(42723.37)	(6638.32)	(16308.00)	(52110.61)	(3147.97)	(4058.81)	(12776.49)	(13810.41)
log_nonLexp	6.55	6.46	6.58	6.52	5.82	5.89	5.80	6.20
	(2.05)	(1.97)	(2.08)	(1.95)	(1.98)	(1.95)	(2.12)	(1.91)
Formal	2.60	2.55	2.50	2.39	2.82	2.85	2.78	2.70
	(0.69)	(0.96)	(0.63)	(0.90)	(0.42)	(0.64)	(0.51)	(0.71)
Observations	29598	28449	977	1013	29445	29248	1672	1539

Table 40: Statistics on individual businesses

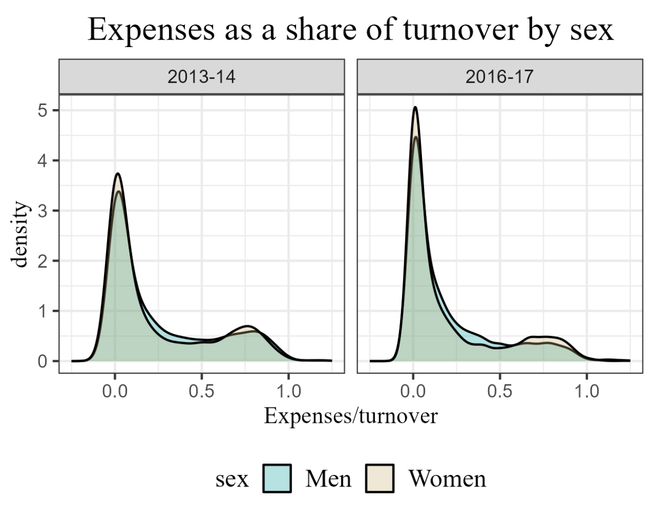
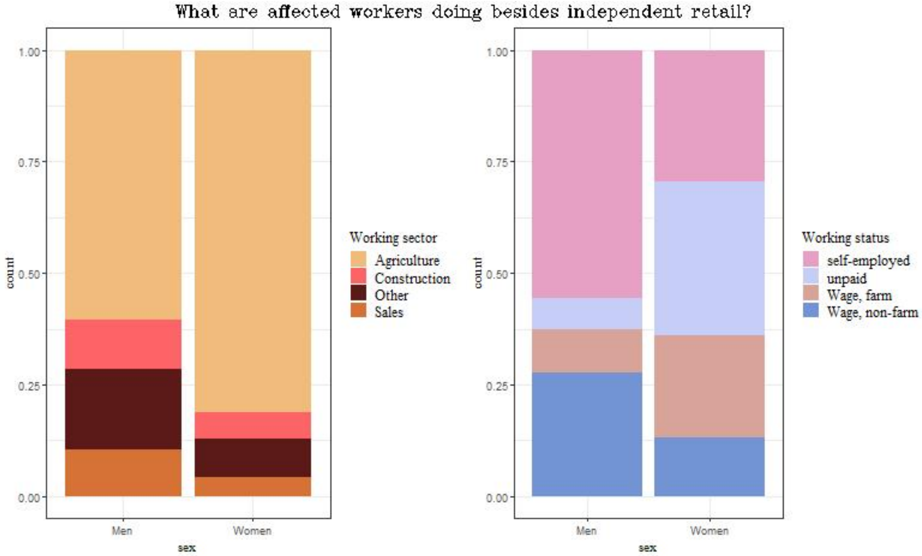


Figure 10: Turnover/expenses

What are affected workers doing besides independent retail?



Jobs held by independent retailers in affected areas that are not the affected job