Food and Agriculture
Organization of the
United Nations

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FAO AGRICULTURAL DEVELOPMENT ECONOMICS
WORKING PAPER 20-02

ISSN 2521-1838

October 2020

Coffee in crisis offers a lesson in resilience: evidence from Guatemala

Elena Serfilippi
Economist, Instituto de Estudios Peruanos (IEP), Committee on Sustainability Assessment (COSA)

Carlos De Los Rios
Economist, Instituto de Estudios Peruanos (IEP), Committee on Sustainability Assessment (COSA)

Marco d'Errico
Economist, Agrifood Economics Division, FAO

Food and Agriculture Organization of the United Nations

Rome, 2020

Required citation:

Serfilippi E., De Los Rios C. & d'Errico M. 2020. *Coffee in crisis offers a lesson in resilience: evidence from Guatemala.* FAO Agricultural Development Economics Working Paper 20-02. Rome, FAO. https://doi.org/10.4060/cb1350en

ISSN 2664-5785 [Print]

ISSN 2521-1838 [Online]

ISBN 978-92-5-133409-6

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Abstract

The idea that resilience plays a role in mitigating the effects of disaster and climate change is becoming widespread across the development community. Consequently, the concept of resilience has been translated into actionable metrics. In this paper, we use panel micro-data from coffee farmers in Guatemala severely affected by a widespread attack of *Hemileia Vastatrix* (leaf rust). This covariate (and exogenous) shock provides a unique opportunity to a) check if greater resilience capacity is associated with better reaction to exogenous shock; and b) explore the key drivers of response mechanisms. Ultimately, this paper looks at how resilience-enhancing and agroecological interventions must be combined to reduce the negative effects of leaf rust.

Findings show a negative impact of the shock on households' well-being; the strategic role of resilience in mitigating those negative effects; and provide evidence on how an approach that enhances both absorptive and adaptive capacity, can be beneficial for coffee producers. This paper provides policy indications to prepare a response mechanism that supports farmers in facing a recurrent, although unpredictable, shock.

Keywords: resilience, shock, leaf rust, risk, vulnerability, sustainability, household income, poverty.

JEL codes: D10, Q18, I32, O54.

Acknowledgements

The authors would like to thank colleagues and friends for their contribution. In particular, we would like to thank Rebecca Pietrelli, Daniele Giovannucci and Professor Mark Constas for their comments and inputs.

The authors are thankful to the ESA Working Paper Editorial Board who provided very useful insights; the paper highly benefitted and improved. The authors are also grateful to Daniela Verona for her editorial and layout support.

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Corresponding author: marco.derrico@fao.org

1 Introduction

Farmers face a myriad of risks that affect their agricultural output, assets, consumption, and well-being. Indeed, the high risk associated with agricultural production is one of its most salient features; there is no other productive sector facing such a combination of simultaneous and inter-related risks (Timmer, 1988). Further, in recent years, these risks have become more intense and less predictable due to climate change, economic volatility, and political instability (Barrett and Constas, 2014). In response, international development agencies and non-governmental organizations (NGOs) have turned to analyze the concept and components of resilience hoping it can help to face these risks.

During the 150-year history of Leaf Rust, the evolving agronomic and ecological conditions, together with the evolving pathogen itself, made this a challenging pathosystem both for the economy and the science (Talhinhas *et al.,* 2017). Coffee rust epidemics have affected several countries: Colombia, from 2008 to 2011; Central America and Mexico, in 2012–13; and Peru and Ecuador in 2013 (Avelino *et al.,* 2015; ICO, 2016).

Guatemala has exported coffee since 1856 (Hoffman, 2014). Small farmers represent around 97 percent of the producers and 47 percent of the total coffee production (GAIN, 2018). Coffee currently represents around 2 percent of national GDP (down from a high of 5 percent), is planted in approximately 300 000 hectares, and employs more than 300 000 families (GAIN, 2018).

Coffee is an important source of income for 20 of the 22 departments in Guatemala. However, smallholders coffee farming faces strong productivity and competitiveness challenges. Coffee production in Guatemala was affected by a widespread attack of *Hemileia Vastatrix* (leaf rust fungus) that severely impacted coffee production in Guatemala. By the end of 2012, the Guatemalan National Association of Coffee (ANACAFE) estimated that around 70 percent of the total coffee area was affected.

This paper looks at how different resilience-enhancing initiatives can be integrated to reduce the negative effects of leaf rust on well-being and income. In general, we demonstrate that greater resilience capacity is associated with less negative effects. In particular, this paper shows that the best policy mechanisms should reinforce both absorptive and adaptive capacity while combining resilience-enhancing and agroecological interventions. These findings enable policymakers to plan interventions to better support households that are coping with leaf rust.

Interestingly, our findings demonstrate that while reinforcing resilience components through specific interventions, policymakers should also reinforce the agroecological response *per se* (i.e. enhancing scientific efforts toward new genes). It is the combination of the two mechanisms that enable a better response, without limiting the development of a more efficient production system, and without promoting unsustainable solutions.

2 Background

Together, Central America and Mexico produce around a fifth of the world's arabica, a higher-quality variety favored by most top-end roasters. Unfortunately, one of the most devastating coffee diseases has attacked Guatemala during the last few years. Nearly 40 percent of Guatemala's roughly 677 000 acres (274 000 hectares) of planted coffee land has been affected by the disease. Leaf rust is a well-known fungal disease that affects wheat, barley, and rye stems, leaves, and grains. It causes serious epidemics in North America, Mexico, and South America, and it is a devastating seasonal disease in India. It is particularly aggressive against coffee plants, causing losses of one to two billion US dollars annually (McCook, 2006). Leaf rust is an airborne pathogen whose spores are spread by wind over long distances (CropWatch, 2020). The spores spread locally within fields and nearby fields, particularly fast under certain meteorological conditions (like moderate nights and warm days).

Leaf rust was first recorded by an English explorer in 1861 near Lake Victoria (East Africa) (Berkeley and Broome, 1869; Talhinhas *et al.*, 2017). Its effects are well known (Eskes, 1983); and there is ample evidence in the literature. Coffee leaf rust (CLR) is one of the main limiting factors of Arabica coffee (Coffea arabica) production worldwide (Talhinhas *et al*., 2017). Bigirimana *et al.* (2012) find that the level of affection varies with the altitude of coffee plantation, in Rwanda. Yield losses per year due to leaf rust can range from 30 to 90 percent of the product depending on the environmental conditions (Sera, 2005).

Few solutions have been proposed. Silva *et al*. (2006) suggest that growing genetically resistant varieties is the most appropriate cost-effective mean of managing plant diseases and is one of the key components of crop improvement. Different types of resistance available for Arabica coffee were discussed and the possibilities of combining them to achieve higher durability of resistance were explored (Santaram, 2017). Local characteristics specific to each plantation are associated with the intensity of coffee rust epidemics, whereas meteorological factors (e.g. rainfall) are less relevant (Avelino *et al*., 2006).

Plant breeders have tried to improve yield quantities in crops, by identifying numerous single genes for leaf rust resistance. The leaf rust resistance gene (an effective adult-plant gene that increases the resistance of plants) is normally combined with other genes[1]. It is normal practice to use crossed genes.

One of the most adopted good farming practices is the timely application of foliar fungicides, on top of the use of resistant genes. Since, however, leaf rust occasionally produces new races which are capable of attacking varieties that were resistant when they were first released, seeds treatments, adoption of foliar fungicides, and other cultural practices (such as heavy grazing or the use of herbicides during autumn to remove self-sown seeds) will reduce the amount of rust in following crops. One of the key challenges is to develop coping strategies that are both ecologically and economically sustainable. Farmers across the affected regions who applied appropriate fertilizers are normally less affected by rust. That is to say that more resilient plantations are more resistant to this shock. Normally, farmers indicated shade management as the most important measure to sustain coffee productivity.

[1] The resistance gene against *Puccinia recondita* infections (UVPrt2 or UVPrt13), is normally combined with genes Lr13 and gene Lr34 (Kloppers and Pretorius, 1997). Lr37 originates from the French cultivar VPM1 (Dyck and Lukow, 1988). The line RL6081, developed in Canada for Lr37 resistance.

The Coffee Trust has discovered that effective micro-organisms, as a specific mixture of beneficial anaerobic bacteria, help to fight the leaf rust (The Coffee Trust, 2020). They can kill the fungus making it starving and out-competing for nutrients.

A mobile phone application has been also adopted to support technical assistants and producers. Technical assistants no longer have to visit the field, but they educate producers on how to collect the data that they will then analyse. It is a more efficient system and, therefore, more effective way to get advanced warnings about leaf rust outbreaks (Perfect Daily Grind, 2018).

Others created an “Anti-Rust Brigades” that employs technologically efficient, motorized sprayers to combat the fungus in the most afflicted areas using natural botanical fungicides to avoid damaging other fauna and flora in the surrounding forests (Fair Trade, 2020). This environmentally friendly product has been used on conventional and certified organic coffee crops.

Several studies approach the coffee crisis, mainly looking at price contraction and its consequences. Eakin *et al.* (2010) show the severity of the impact, particularly in the Mexican and Guatemalan communities, while indicating that the existence and development of local networks among farmers, service providers, and information sources may be critical for facilitating adaptation and reaction.

3 Resilience conceptual framework

Innovative approaches to sustainability are urgently needed to deal with rapid large-scale changes and build resistant social-ecological systems (Westley *et al*., 2013). One of these is resilience. Definitions of resilience vary from concise to comprehensive, from coherent to internally contradictory, from precise to vague, and from descriptive to normative to predictive; the resilience vocabulary does not fit into the social sciences, whereas core concepts and theories in social science – such as agency, conflict, knowledge and power – are absent from resilience theory (Olsson *et al*., 2015). Although some question its applicability to social systems (Davidson, 2010), a resilience lens has been largely adopted from the international community working on humanitarian and development assistance.

Different definitions of resilience have been used over time to describe how socio-economic systems react to perturbations generated by shocks and/or stressors. In this paper, we adopt one of the most widely used definitions: "*Resilience is the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences*" (FSIN, 2014a, 2014b). This approach considers resilience as a multidimensional framework, conceptualized at different scales (households, communities, and systems), that emerges as a reaction to specific disturbances (shocks and stressors) that undermine the stability of a system, increasing its vulnerability. It considers resilience not as an end, but rather as an instrument to achieve the ultimate goal of limiting vulnerability and promoting long-term sustainability and improved well-being. Finally, resilience must be benchmarked against an outcome of interest, like food security, poverty, or income.

There are two main approaches to measure resilience. On the one hand, the *capital approach* is grounded on the belief that people require a range of assets to achieve positive livelihood outcomes. This vision is inspired by the Sustainable Livelihood Framework (DFID, 2000) and it is based on five main capitals: natural, human, socio-political, financial, and physical on which individuals depend. On the other hand, the capacity approach[2] is based on the idea that resilience is not a static concept that concerns capital, but rather a more dynamic one, that mainly relies on human behavior (Béné *et al.,* 2012; Béné, Frankenbergerger and Nelson, 2015). This approach considers resilience as the fruit of the interaction between the capacity to absorb the shock through short-term mitigation and preparedness strategies, to adapt to it through the development of long-term responses to social, economic, and environmental shocks and stressors (e.g., livelihood diversification, asset accumulation, improved social and human capital) and to transform, as a result of the shock, by enhancing governance and enabling conditions to make households and communities more resilient. Resilience is related to (but it does not have to be confused with) adaptive capacity. Practical adaptation initiatives tend to focus on risks that are already problematic; and adaptations are mostly integrated or mainstreamed into other resource management, disaster preparedness, and sustainable development programs (Smith and Wandel 2006).

In this paper, we embrace the capacity approach initiated by Béné (2012, 2015), and followed by Frankenberg and Smith (2018), Serfilippi and Ramnath (2017); Knippenberg *et al.* (2019). In this approach, absorptive capacity is a household's ability to absorb the impacts of shocks in

[2] This approach allows the analytical framework adopted by FAO and framed in d'Errico *et al.* (2018) where the pillars analyzed are Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN) and Adaptive Capacity (AC).

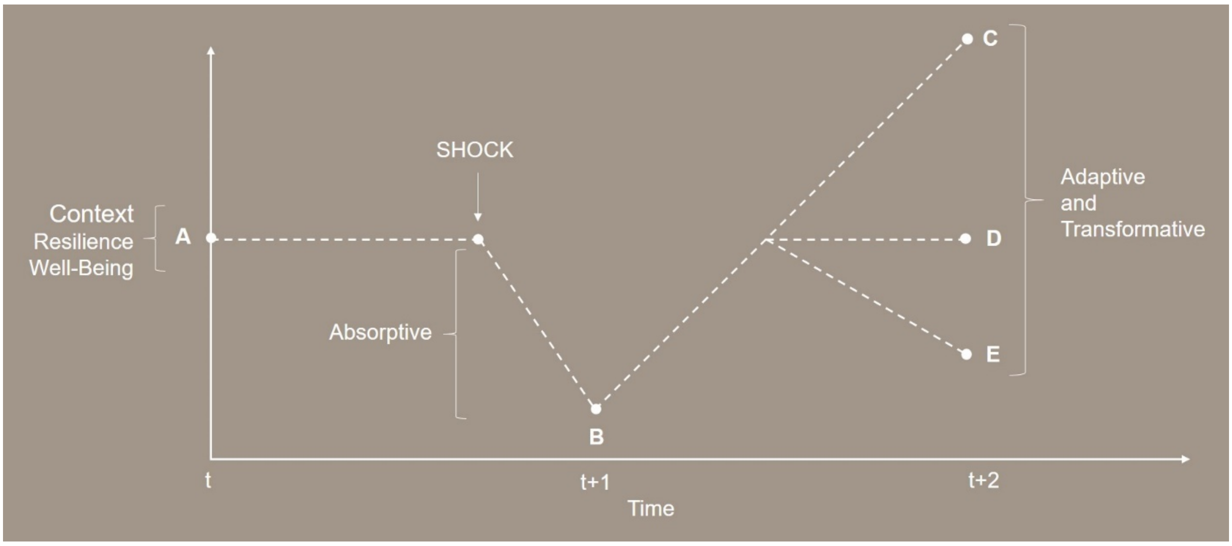
the short-run. Adaptive capacity reflects the ability to respond to long-term social, economic, and environmental impacts of shocks through specific adaptation strategies. Transformative capacity refers to structural changes in the structure and function of the system caused when the adaptive capacities of the household, community, or ecosystem are overwhelmed by the magnitude of the shocks.

In the presence of a shock, resilience is the result of the interaction of those three capacities over time; it is also indexed against a measure of well-being (e.g. food security). Each farmer enjoys a specific measure of well-being and resilience at time *t-1*. Assuming that farmers experience a shock at time *t*, they will reach different levels of well-being at time *t+1* depending on their resilience capacities. In particular, the absorptive capacity represents the ability to reduce both risks of exposure to shocks and stressors (preparedness) and to absorb the impact of shocks in the short term (mitigation). This capacity influences the "length of the fall" from the original level of well-being (A) to a lower level of well-being brought by the shock (B). The adaptive and transformative capacities play a crucial role after the shock (long-term responses) since they reflect the farmer's ability to adapt to the new situation and determine whether the farmer's well-being is better (C), worse (E), or the same (D) after the shock as before it. The transformative capacity is represented by structural changes in the system caused when the adaptive capacity is not enough to overcome the magnitude of shocks. For some systems, vulnerabilities and risks may be so sizeable that they require transformational rather than incremental adaptations (Kates *et al*., 2012). Transformative capacity also produces non-linear changes in systems (Pelling *et al*., 2014) that are necessary for migrating to a new (post-shock) equilibrium. Finally, transformative capacity looks at both incremental and transformational adaptation, focusing on contesting and creating alternatives to climatic changes rather than on accommodating them (O'Brien, 2011).

The interaction between these capacities guarantees the stability, flexibility, and change of a system after a large covariate shock (Serfilippi and Ramnath, 2017). The ideal outcome of the absorptive capacity is to offer resistance to a shock. When the absorptive capacity is exceeded, the adaptive capacity will jump in allowing for long-term recovery to the shock. Finally, when the shock is large enough and the adaptive capacity is exceeded by the size of the shock, the overall system will change.

Following Béné (2012), we use a set of indicators to estimate the absorptive, adaptive, and transformative capacities using factor analysis. As mentioned before, the difference between these capacities lies in the temporal dimension. The absorptive capacity represents the "ability to reduce both risks of exposure to shocks and stressors (preparedness) and to absorb the impacts of shocks in the short term (mitigation)" (Serfilippi and Ramnath, 2017). On the other hand, the adaptive and transformative capacities represent longer-term responses to changes caused by large covariate shocks, being the transformational response represented by structural changes in the system originated when the adaptive capacities are not enough to overcome the magnitude of the shocks.

Figure 1. Resilience conceptual framework



Source: Serfilippi and Ramnath, 2017.

3.1 Resilience capacity indices

As summarized in Table 1, for the absorptive capacity, we group all indicators related to mitigation and preparedness strategies. In this sense, we chose indicators associated to access to liquidity (TLU, farm area, access to credit) to allow for immediate reaction to the shock (mitigation); and, indicators associated to good agricultural practices (soil and water management, integrated pest management, pruning, renovation, inputs use), and income diversification, representing the degree of preparedness of farmers to the coming shock.

For the adaptive capacity, we consider indicators associated with knowledge and ability to use technology and innovation skills to overcome the shock as long-term responses once the absorptive tools are exceeded by the shock. In this sense, we consider indicators, such as education and training as a proxy for the ability to adapt and access technology and market information as proxies for the level of farmers' knowledge.

For the transformative capacity, we consider all indicators that enhance governance and enable conditions for resilience and transformation, as access to services and infrastructure and inclusion. Unfortunately, the number of variables available for measuring transformation is limited and we can only give a general sense of this capacity. In future investigations, we will enrich the list using different indicators covering all basic services, infrastructure, and measures of good governance. In the Annex, we offer the descriptive statistics associated with those three capacities.

Table 1. Components of the three capacities

	Social	Environmental	Economic
Absorptive		▪ Fertilizer use ▪ Pesticide use ▪ Integrated pest management practices ▪ Soil, water conservation	▪ Good agricultural practices ▪ Tropical Livestock Unit ▪ Diversification ▪ Credit
Adaptive	▪ Education ▪ Training		▪ Market information ▪ Access to technology
Transformative	▪ Electricity ▪ Safe water ▪ Participation		▪ Access to markets

Source: Authors' own elaboration.

4 Data and methods

4.1 Data

Data used in this paper belongs to a study developed to evaluate an initiative to improve the sustainability of Guatemalan coffee farmers' livelihoods by building their technical and organizational capacities. The project reached 4 500 farmers from 33 producer organizations distributed among eight departments in two regions: *Oriente* and *Alta y Baja Verapaz*. For the project, producer organizations were classified into three groups based on their organizational capacity, productivity, and access to infrastructure. The 378 farmers considered in this paper are a randomly selected subsample of the total farmers. They were interviewed both in 2012 and in 2015.

In 2012, after the baseline survey, farmers in our sample were affected by a widespread attack of *Hemileia Vastatrix* (leaf rust fungus) that severely impacted coffee production in Guatemala.[3] By the end of 2012, the Guatemalan National Association of Coffee (ANACAFE) estimated that around 70 percent of the total coffee area was affected. Around 98 percent of farmers in our sample reported being affected. Leaf rust caused severe economic losses amongst coffee farmers across Guatemala. Between 2012 and 2015, the coffee yield dropped 40 percent on average in our sample. In addition to decreased yields, farmers noted a 45 percent decrease in income. It is in this context that we analyze the level of farmers' resilience capacities and their impact on households' income.

Table 2. Leaf rust

	Mean	S.D.
Households affected with leaf rust	98%	13%
Average of plants affected by leaf rust	66%	33%
Average of plants dead by leaf rust	11%	18%
Total household net income 2012 (GTQ)	57 071	127 204
Total household net income 2015 (GTQ)	312 424	71 283
Average coffee yields 2012 (GBE/ha)	12.5	9.5
Average coffee yields 2015 (GBE/ha)	7.4	8.5

Source: Authors' own elaboration.

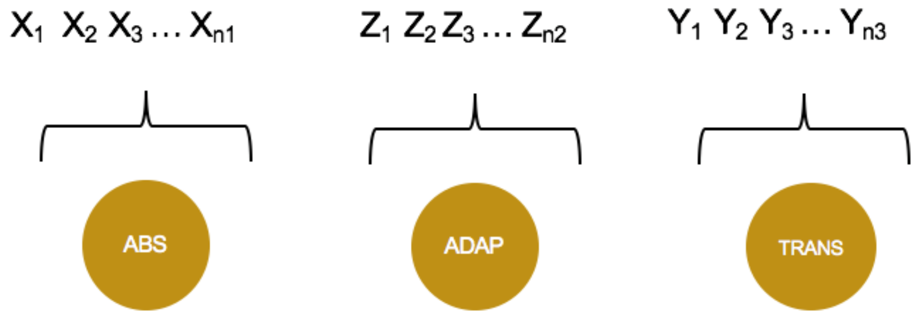
4.2 Measuring resilience

This section describes the methodology followed under a panel data scenario with the presence of a large covariate shock between the baseline and end-line data collection.

To estimate resilience, we first estimate each capacity (unobserved) by following a latent variable approach (Alinovi *et al.*, 2009, 2010). We operationalize Béné's conceptual framework, by using a set of widely accepted indicators at the household level and estimate each capacity using factor analysis.

[3] All Guatemalan coffee production is recovering from the rust epidemic of 2012 when 20 percent of the coffee production was lost to the disease, but the recovery and growth of the sector have been slow (GAIN, 2018).

Figure 2. Estimating each capacity



Source: Authors' own elaboration.

As with poverty,[4] given the multi-dimensional nature of capturing and aggregating the parts of resilience, there is a consensus in the literature that an index is a best-fit tool for measurement (Barrett and Constas, 2013; FSIN, 2014a, 2014b; USAID, 2013; Cissé and Barrett, 2016). This means that resilience must be considered as a function of several dimensions or characteristics that can be context and time-specific (FAO, 2015; FSIN, 2014a).

If resilience is to be conceived as a multidimensional index, an aggregative procedure should be defined. There are two broad categories of aggregative procedure: those that seek to explain the role of each variable when defining the final index, and those that do not. The most commonly used procedures in the former group are multivariate models; the latter typically adopt a moment-based approach (FSIN, 2016). This paper will follow an aggregative procedure based on multivariate models since the interest is to seek the role of each component of resilience in explaining changes of well-being over time and responses to shocks.

In this sense, we estimate resilience as a combination of the three capacities using a latent variable approach and use this resilience metric to estimate its relationship to well-being. For this process, we will follow two distinct approaches that have been used in recent literature (Brück, d'Errico and Pietrelli, 2018; d'Errico and Pietrelli, 2017; d'Errico, Romano and Pietrelli, 2018; d'Errico *et al.*, 2019; Jones and d'Errico, 2019; Smith and Frankenberg, 2018). Other, more recent, approaches seem to be disconnected with actual data available in the field and more interested at vulnerability than resilience measurement (Cissé and Barret, 2018); or specifically designed for using high-frequency data (Knippenberg *et al.*, 2019).

First approach: two-steps factor analysis

The first step consists in estimating the resilience index through factor analysis on the three estimated capacities; and following, use fixed-effects modeling to assess the relationship between the resilience metric and a well-being measure, as income.

We use the three estimated capacities for the formation of the Resilience Index. The resulting index is a weighted average of the factors generated using Bartlett's scoring method; and the

[4] The measurement needs faced by the resilience agenda have been compared by Cissé and Barret (2016) to the poverty aggregation needs to be faced by Sen (1979) when he states the need for both poverty "identification" (e.g., identification of who is poor) and "aggregation" (e.g., defining how characteristics of the poor can be combined into an aggregate indicator) to guide policy.

weights are the proportions of variance explained by each factor. This is the simplest method to weigh each resilience capacity to create the latent variable "Resilience". We acknowledge that other weighting methods can be applied, but prefer this method as it avoids *ad hoc* weighting practices and cut-offs.

$$R_{i0} = f(ABS_{i0}, ADAP_{i0}, TRANS_{i0}) \tag{1}$$

We then implement the resilience index (R) in a simple panel regression analysis to assess its relationship with a well-being measure (Y).

$$Y_{it} = f(R_{it}) \tag{2}$$

This simple approach takes advantage of the panel nature of the data allowing for time-invariant observables and non-observables affecting both dependent and independent variables to cancel-out over time. However, this first approach faces its challenges. The most relevant one is related to the simultaneity bias amongst the resilience measure and the well-being measure. We cannot disentangle which one comes first. It can be the case that the wealthier or better-off are thus more resilient or it can also be that being more resilient contributed to making households better off after the shock. The second issue facing this approach is that in building the resilience index, some well-being measures could have been incorporated into the resilience metric, and thus generating an endogeneity problem.

Second approach: Multiple Indicators Multiple Causes (MIMIC) pooled modeling

The MIMIC approach can be used following the RIMA-II approach to resilience measurement (FAO, 2016). Under this method, resilience is simultaneously estimated using structural equation models (SEM) by its causes (capacities) and outcomes (well-being), overcoming the simultaneity bias of the first approach.

While this method overcomes some of the endogeneity issues of the first approach, it ignores the panel nature of the data allowing for potential time-invariant un-observables variables (e.g. ability) that can create some "omitted variables" endogeneity issues, solved by the fixed effects of the first methodology.

Following Buehn and Schneider (2008) the mathematical representation is:

$$y = \lambda R + \epsilon \qquad\qquad R = \gamma x + \zeta \tag{3}$$

where (*y*) represents the vector of outcome variables and *x* the observables (i.e. absorptive, adaptive, and transformative capacities) that are causes of our latent variable R.

The MIMIC model is estimated through the Maximum Likelihood. There are two things of interest in the analysis: the structural and the measurement effect. The measurement effect captures the effect of resilience on the outcome variables, while the structural effect consists of capturing the links between the latent variable and its causes (i.e. three capacities).

4.3 Resilience index

We start the analysis building the three capacities indices that we will use in both measurement approaches.[5] The factor loadings associated with each capacity are presented in the Annex.[6] Table 3 reports the overall scores. We found that, on average, farmers exhibit low levels of absorptive capacity at the moment of the shock since the average absorptive score in 2012 is about 0.15 (scale from 0 to 1). This capacity did not change over time, signaling that those farmers should reinforce preparedness and mitigation strategies. Farmers' capacity to adapt is at a medium-low level with a slight reduction after the shock, while the ground for transformation is at a medium level, with scores around 0.50 for both years. The fact that transformative capacity did not change between years is not surprising since the time spam between baseline and end-line was very limited.

Table 3. Three capacities indices

Resilience capacities	Score			
	2012		2015	
	Mean	S.D.	Mean	S.D.
Absorptive capacity	0.15	0.09	0.15	0.12
Adaptive capacity	0.37	0.23	0.20	0.14
Transformative capacity	0.53	0.32	0.54	0.34

Notes: Indices computed with factor analysis. Scores rescaled with min-max.

Source: Authors' own elaboration.

We then run the two separate approaches to computing the resilience index. Table 4 reports the factor loadings under both approaches.[7] It emerges that adaptive capacity is the main factor affecting the resilience score.[8]

[5] To computing the indices for 2015 we use the same weights as 2012.

[6] In general, the estimation of the absorptive capacity index suggests that diversification of livelihood and access to credit have contributed the most to building strong response capabilities in the short term (i.e. higher factor loadings and lower uniqueness in the absorptive capacity index), together with preparedness strategies in the sphere of good agricultural practices, as soil and water conservation practices, and integrated pest management practices. The factors that matter the most to define adaptability have been mostly driven by access to technology devices together with the level of education of the household head. Finally, the transformative capacity shows a high farmers' ability to transform based on access to infrastructures, as electricity and water, and active inclusion in producer organizations (i.e. voting power in producer organizations).

[7] In the two-steps factor analysis, we use the same factor loadings between the two years. This means that the factor loadings for 2012 were used to compute the resilience index for 2015.

[8] In the MIMIC model, the effect of adaptive capacity on resilience indicates that a one standard deviation increase in adaptive capacity leads to an increase in the magnitude of the Resilience Index by 0.45 standard deviations.

Table 4. Resilience index

Resilience index	Factor loadings	
	Factor analysis	MIMIC_POOLED
Absorptive capacity	0.71	0.14
Adaptive capacity	0.85	0.45
Transformative capacity	0.77	0.15
Resilience Index Score	0.28	0.50

Note: Resilience index scores rescaled with min-max.

Source: Authors' own elaboration.

5 Identification strategy

We now want to assess the mitigation role of resilience on farmers' well-being after the leaf rust attack. The main objective is to test the hypothesis that more resilient farmers show a higher ability to recover from the income losses experienced as a result of the shock. We will then look at what determinants of resilience have been the most effective in reducing the negative effect of the leaf rust. Tables 5 and 6 report the results of the two methodologies, respectively the two-steps factor analysis, and the MIMIC pooled model.

5.1 Two-steps factor analysis

Following the first methodology, we use the resilience index computed with factor analysis in a fixed effect estimation accounting for all the individual characteristics (α_i) that are not changing over time (e.g. regions, gender). We thus determine the effect of resilience on income (Y_i) controlling for the presence of a shock.[9]

$$\ln(Y_i) = \alpha_i + \alpha_1 resilience_i + \alpha_2 shock_{it} + u_i \qquad (4)$$

As expected, the effect of the shocks on income is negative, while resilience positively contributes to the income increase (see column 1 of Table 5). This means that more resilient people experienced fewer income losses. To further develop the analysis and study the effect of shocks on income for various values of resilience, we interact the two variables (shock and resilience) and found that resilience is a strong explanatory variable when there is a significant shock affecting farmers' incomes and assets. Results are shown in columns 2 and 3 (Table 5).

Table 5. Fixed effects of two-steps factor analysis

	1	2	3
Resilience	0.34**	0.15	0.15
	(0.06)	(0.37)	(0.31)
Shock		-0.86***	-0.86***
		(0.00)	(0.00)
Shock*resilience		0.26**	0.26**
		(0.09)	(0.04)
Constant	10.00***	9.92***	9.92***
	(0.00)	(0.00)	(0.00)
Observations	756	756	756
Individual FE	YES	YES	YES
Robust SE			YES

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Source: Authors' own elaboration.

[9] The variable *shock* is equal to 0 when farmers did not experience a shock severely affecting their incomes and assets, and equal to 1 when farmers experienced respectively one or more shocks.

Through a marginal effect analysis, we let resilience varying between zero and 1 with increments of 0.3. It results in a more negative effect of the shock on income decreases (i.e. less negative) for each resilience increase, as reported in Table 6.

Table 6. Marginal effects

1. Shock		
Resilience	**Coeff**	**P>|z|**
0	-0.86	0.00
0.3	-0.78	0.00
0.6	-0.7	0.00
0.9	-0.62	0.00

Source: Authors' own elaboration.

In conclusion, our results show a positive correlation between resilience and income and a mitigation role played by resilience. If we assume that no unobservable characteristics are changing over time, the results of this fixed effect estimation imply a causal relation. A limitation of this model is that we do not consider income in the formation of the resilience index to avoid endogeneity problems related to the fact that resilience is explained by its causes and consequences. In the next section, we see how the MIMIC pooled analysis confirms the results obtained through factor analysis overcoming the endogeneity issue.

5.2 MIMIC pooled

The MIMIC pooled model confirms the results of the factor analysis, showing that adaptive capacity is the variable contributing the most to the formation of the resilience index (see Table 7).

Turning to the relationship between income and resilience, given the coefficient of yields constrained to 1, the coefficient of income indicates that an increase in Resilience Index of one standard deviation increases income by 0.78 standard deviations. This result confirms the correlation between income and resilience captured by the fixed-effect model and it is confirmed if we use robust standard errors (see column 2 of Table 7).

Table 7. MIMIC pooled model

	1		2	
Structural Model	**Coefficients**	**Z-score**	**Coefficients**	**Z-score**
Absorptive	0.14***	3.52	0.14***	2.72
Adaptive	0.45***	11.24	0.45***	9.61
Transformative	0.15***	3.74	0.15***	3.91
Measurement model				
Income	**0.78*** **	26.88	**0.78*** **	21.05
Yields GBE	1		1	
Observations	756		756	
Individual FE	NO		NO	
Year FE	NO		NO	
Robust SE	NO		YES	
Chi2	8.28			
p-value	0.01			
RMSEA	0.06			
prob(RMSEA<0.05)	0.237			
CFI	0.99			
TLI	0.96			

Notes: *** significative at 99 percent; ** significative at 95 percent; * significative at 90 percent.

Source: Authors' own elaboration.

The test of goodness of fit to different methods is displayed at the bottom of Table 6. The Root Mean Square Error of Approximation (RMSEA) evaluates the fit of the model based on the deviance between the estimated and the real covariances. Brown and Cudeck (1993) assume that RMSEA values close or lower than 0.05 imply a good model fit, which corresponds to a p-close near to unity. The two fit indexes suggested by Bentler (1990) are the Confirmatory Fit Index (CFI) and Tucker–Lewis Index (TLI). They indicate a good model fit with values close to unity Hu and Bentler (1999).

5.3 Unpacking the smoothing effect of resilience capacity

We regress now a more specified model that includes every variable employed in the estimation of resilience capacity. The algebraic notation is:

$$\ln \left({}_{Yi}\right) = \alpha_i + \alpha_1 R_i + \alpha_2 shock_{it} + u_i \qquad (5)$$

Where R_i represents the vector of variables specified in the section on data and methods.

The truncated output of (5) is reported in Table 8, while the complete list of results is in Table A5.

Table 8. Unpacking resilience

Variables	Model 1	Model 2

Shock	-0.947***	-0.215
	-0.116	-0.195
Voting in PO		0.413**
		-0.165
Number of training hours		-0.00536*
		-0.00289
TLU		0.0714***
		-0.0243
Land size (manzanas)		0.0336***
		-0.0129
The area under chemicals (manzanas)		-0.000298*
		-0.000157
Number of integrated pest management practices		0.315**
		-0.159
Diversification of livelihood Index		2.106***
		-0.396
Access to credit		0.376**
		-0.18
Constant	10.00***	7.855***
	-0.0785	-0.448
Observations	756	756
R-squared	0.115	0.295
Number of keys	378	378
Country FE	YES	YES

Notes: *** significative at 99 percent; ** significative at 95 percent; * significative at 90 percent.

Source: Authors' own elaboration.

Results shown in Table 8 demonstrate that people with an active inclusion in producer organizations (i.e. voting power in producer organizations), or better access to credit are more capable of smoothing the negative effects of leaf rust. Similarly, those who have a diversified portfolio of options available for making a living, can eventually relax budget constraints and face that challenge more effectively. Finally, those who have access to pest management practices are more capable of tackling this issue. We found therefore three main channels for reducing the negative effects of leaf rust: better technology (i.e. pest management practices); better social inclusion (access to credit, active participation); and diversified livelihood strategies.

6 Conclusions and discussion

The food supply of a large portion of the world's population comes from smallholder farmers, many of whom face increasing risks from external forces like volatile markets, climate change, and conflict. These same households are also among the world's most vulnerable populations, with the highest incidence of people living below the poverty line. The idea of resilience in response to disaster and climate-change phenomena is becoming increasingly prevalent in the development community as a means to face risks. Different efforts have been made to translate the concept of resilience into actionable measurement metrics.

This paper contributes to the literature on coffee farming, with a case study in Guatemala, and to that on resilience measurement by demonstrating that i) the occurrence of an exogenous shock such as a plant disease has a negative effect on income; ii) those who are more resilient can cope with the shock much better than those who are not; iii) those who have greater social inclusion, diversified livelihoods, and better production technology, are more capable of handling leaf rust risks; iv) these findings are consistent when using (slightly) different measurement approaches, and v) the combined effect of resilience-enhancing initiatives with genetic and agroecological interventions, are more effective in smoothing or reducing negative effects on income and well-being. Since there are two forms of capacity to adapt to shocks (such as global change or plant diseases): those associated with fundamental human development goals (generic capacity), and those necessary for managing and reducing specific climatic threats (specific) (Eakin, Lemos and Nelson, 2014), it seems crucial that policymakers can have context-specific reaction mechanisms to put in place.

Guatemala's small producers are particularly poorly equipped to combat the effects of climate change and the spread of crop disease. Farmers continue to be threatened with reduced yields, lower bean quality, diminished resilience, and increased production costs. Guatemalan farmers' yields are 60 percent lower on average than the global average (TechnoServe, 2017). Overcoming these challenges of production is crucial to improving the food and economic security of Guatemala’s 120 000 smallholder coffee farmers.

As presented above, the largest part of the response mechanisms refers to the Absorptive capacity, as producers normally adopt new technology (i.e. new improved, genetically manipulated, seeds) to cope with Leaf Rust (see Silva *et al*. (2006) and Santaram (2017)).

However, the outbreak of leaf rust disease has also highlighted the socioeconomic fragility of the coffee sector (Avelino *et al*., 2015). This calls for a socio-economic approach to find the most appropriate policies and supporting activities. McCook and Vandermeer (2015) state that the main challenge for researchers (on Leaf Rust) is to develop rust control strategies that are both ecologically and economically viable for coffee farmers, in the context of the volatile, deregulated coffee industry, and with the additional challenge of climate change. We concur and propose some key socio-economic indicators that must be addressed to reinforce coffee producers' resilience to leaf rust outbreak. In particular, our study demonstrates that those who have better-producing technology, a more diversified portfolio of livelihoods strategies, and greater social inclusion, are better off in facing the challenges from leaf rust.

In other words, our paper demonstrates that adaptive capacity is important too. In particular, we argue that the best response mechanisms policymakers should adopt integrates absorptive and adaptive capacities. Response mechanisms should reinforce on one side the ability to absorb the impacts of shocks in the short term, for instance adopting genetically manipulated species.

On the other side, mechanisms are required to diversify the portfolio options, reinforce the capacity to adapt to new situations and strengthen supporting mechanisms (such as access to credit).

One of the added value of a resilience analysis is its holistic approach. What we are arguing with this paper is that policymakers need to adopt a multidimensional response framework when such a thorough shock occurs, that can intervene on a different level of the socio-economic texture.

This paper provides also insights that strengthen the linking role of resilience interventions in bridging humanitarian and development approaches. A household equipped with adequate means to sustain and recover from shocks can allocate resources and efforts to a development plan; this will ultimately translate into greater capacity to pave the way out of poverty and finally improving living conditions. In particular, the disaggregated analysis of resilience determinants showed that greater inclusion, valid technology, and diversified portfolio of income sources, may trigger a better response mechanism. This calls for a supportive environment that could invest in these elements to strengthen producers' reaction capacity.

As possible ways forward for this paper, further analysis employing simplified versions of the above-mentioned approaches can be envisaged. Otherwise, replication of the same exercise can reinforce the evidence of consistency between similar methods.

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Annex

Table A1. Descriptive statistics of three capacities

	2012		2015		
	Mean	**S.D.**	**Mean**	**S.D.**	**ttest: p-value**
Adaptive capacity					
Years of schooling of household's head	3.61	4.06	3.7	4.28	0.77
Number of training hours	6.35	10.25	17.99	28.36	0.00
Number of market information [0–7]	1.57	0.7	1.33	0.67	0.00
Number of technology devices (TV, radio, telephone)	1.87	1.11	1.74	1.16	0.12
Absorptive capacity					
Chemical fertilizer expenditure per Manzana (GTQ)	1.581	1.907	1.236	1.428	0.00
Pesticide expenditure per Manzana (GTQ)	32.65	92.21	345.6	487.67	0.00
Percentage of plants renovated	6.2	19.21	7.73	22.01	0.31
Total Livestock Units (TLU)	1.33	5.29	0.63	3.06	0.03
Total farm area (manzanas)	6.09	10.7	7.54	16.2	0.15
Number of soil and water conservation practices [0–12]	1.77	1.09	0.82	0.64	0.00
Number of Integrated Pest Management practices [0–6]	0.92	0.39	0.31	0.48	0.00
Diversification Index (Composite Entropy Index)	0.34	0.22	0.29	0.21	0.00
Percentage of households with credit	0.45	0.5	0.25	0.43	0.00
Percentage of households practicing shade management and/or pruning	0.8	0.4	0.87	0.33	0.01
Transformative capacity					
Percentage of households with access to electricity	0.72	0.45	0.72	0.45	1.00
Percentage of households with access to safe water	0.88	0.32	0.52	0.5	0.00
Altitude	1203	319	1203	319	1.00
Percentage of households voting in PO	0.47	0.5	0.53	0.5	0.08

Source: Authors' own elaboration.

Table A2. Factor loadings

Absorptive capacity	Factor 1 loading	Factor 2 loading	Factor 3 loading	Factor 4 loading	Uniqueness
Pesticide expenditure per Manzana (GTQ)	0.58				0.52
Number of integrated pest management practices [0–6]			0.69		0.32
Chemical fertilizer expenditure per Manzana (GTQ)	0.44			-0.56	0.42
Percentage of households practicing shade management and/or pruning	0.68				0.46
Percentage of households with credit	0.77				0.39
Percentage of plants renovated			0.47		0.67
Tropical Livestock Units (TLU)		0.87			0.22
Total farm area (Manzanas)			0.67		0.48
Number of soil and water conservation practices			0.80		0.36
Diversification Index (Composite Entropy Index)				0.87	0.22
The determinant of the correlation matrix	0.4780				
Bartlett test of sphericity					
Chi-square	275.197				
Degrees of freedom	45				
p-value	0.0000				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.594				
Absorptive capacity score	**0.15**				

Notes: Principal component factor method used in the analysis of the correlation matrix. Same factor score coefficients for both years based on 2012. The absorptive capacity score was rescaled with min-max. Blanks represent abs(loading) <0.4.

Source: Authors' own elaboration.

Table A3. Factor loadings

Absorptive capacity	Factor loading	Uniqueness
Years of schooling of household's head	0.73	0.46
Number of training hours	0.43	0.81
Number of market information [0–7]	0.62	0.80
Number of technology devices (TV, radio, telephone)	0.88	0.22
The determinant of the correlation matrix	0.6710	
Bartlett test of sphericity		
Chi-square	148.621	
Degrees of freedom	6	
p-value	0.0000	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.673	
Absorptive capacity score	**0.37**	

Notes: Principal component factor method used in the analysis of the correlation matrix. Same factor score coefficients for both years based on 2012. The adaptive capacity score was rescaled with min-max.

Source: Authors' own elaboration.

Table A4. Factor loadings

Absorptive capacity	Factor loading	Uniqueness
Percentage of households with access to electricity	0.68	0.54
Percentage of households with access to safe water	0.61	0.62
Percentage of households voting in POs	0.80	0.35
Altitude (a proxy of access to services and infrastructures)	0.70	0.50
The determinant of the correlation matrix	0.8110	
Bartlett test of sphericity		
Chi-square	92.459	
Degrees of freedom	6	
p-value	0.0000	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.63	
Transformative capacity score	**0.53**	

Notes: Principal component factor method used in the analysis of the correlation matrix. Same factor score coefficients for both years based on 2012. The transformative capacity score was rescaled with min-max.

Source: Authors' own elaboration.

Table A5. Unpacked resilience analysis

Variables	-1	-2
	Model 1	Model 2
Shock	-0.947***	-0.215
	-0.116	-0.195
Access to electricity		-0.144
		-0.289
Voting in PO		0.413**
		-0.165
Access to water		0.312
		-0.191
Years of schooling		0.0211
		-0.0382
Number sources of market information		-0.0728
		-0.129
Number of new technologies		-0.0027
		-0.139
Number of training hours		-0.00536*
		-0.00289
Plants renovated		0.000914
		-0.00309
Tropical Livestock Units (TLU)		0.0714***
		-0.0243
Land size (manzanas)		0.0336***
		-0.0129
The area under chemicals (manzanas)		-0.000298*
		-0.000157
The area under fertilization (manzanas)		0.000101
		-6.53E-05
Number of soil and water management practices		0.0897
		-0.08
Number of integrated pest management practices		0.315**
		-0.159
Soil and pest management practices		-0.0357
		-0.305
Diversification of livelihood Index		2.106***
		-0.396
Access to credit		0.376**
		-0.18
Shock = o,		-
Constant	10.00***	7.855***
	-0.0785	-0.448
Observations	756	756
R-squared	0.115	0.295
Number of keys	378	378
Country FE	YES	YES

Source: Authors' own elaboration.

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Economic and Social Development – Agrifood Economics
Food and Agriculture Organization of the United Nations (FAO)

www.fao.org/economic/agricultural-development-economics
www.fao.org/economic/esa
ESA-Director@fao.org

ISBN 978-92-5-133409-6 ISSN 2664-5785

9 789251 334096
CB1350EN/1/10.20