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CONVERTIBLE LOCAL CURRENCIES FOR THE ECONOMIC DEVELOPMENT OF SUSTAINABLE COMMUNITIES, FINDINGS FROM AN ANALYSIS OF NINE FRENCH LOCAL CURRENCIES

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ABSTRACT:

Alternative currencies have become a growing phenomenon in grassroots social innovation. Convertible local currencies are one of the main forms they take in France. Despite the abundance of theoretical literature on this subject, empirical evaluations remain scarce due to limited data availability. To address this gap, we conducted an econometric evaluation of the impact of using CLCs on firms' turnover. This evaluation employs a two-way fixed-effects model using data from the Fare file, a dataset containing tax information for all French firms from 2009 to 2019. Additionally, we selected a control group through propensity score matching in the Fare file. Our analysis reveals a 10% in turnover for small and medium-sized firms using one of the nine CLCs included in this study. Consequently, we conclude that CLCs support the economic development of a localized community of actors who are chosen for their commitment to ethical and sustainable production practices.

KEYWORDS:

Convertible Local Currency, Local Development, Sustainable Development, Two-Way Fixed Effects Model

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1. INTRODUCTION

Numerous grassroots innovations are emerging in response to the challenges of the ecological and social transition, aiming to transform production systems to make them more sustainable and resilient. Among these social innovations, monetary innovations arise in the form of alternative currencies, which have undergone a significant revival in Europe following the 2008 crisis and continue to grow in response to the environmental crisis (Seyfang and Longhurst, 2013a, 2013b). In France, convertible local currencies (CLCs) are among the most prevalent forms of these currencies. Their number soared in France in particular during the 2010s, with a tenfold increase in the number of CLCs in circulation between 2011 and 2019 (Blanc, Fare, and Lafuente-Sampietro 2022). By the end of 2019, 82 CLCs were circulating in France, covering nearly 30% of French municipalities. The extent and rapid spread of this phenomenon during the 2010s have equally sparked interest of public authorities and been further supported by the them (Magnen and Fourel, 2015) with legislation regarding the status of CLCs drafted in France in 2014. In addition, activist organizations present them as potential tools for ecological and social transition (Mouvement SOL and Cabinet Transformation Associés, 2021). This growing number of projects and the attention CLCs' garnered in France lead us to question their social, economic and environmental effects from an empirical point of view. While local currencies have already been evaluated several times for their social impact in terms of trust (Alia and Spiegelman, 2020; Richey, 2007) or social representations (Tichit, 2019), few studies have assessed their economic effects (Michel and Hudon, 2015).

Convertible local currencies are monetary instruments used for specific purposes that circulate alongside national currencies in a given territory (Blanc 2018b). They are created and managed by non-profit organizations, sometimes benefit from the support of local public authorities, and can take the form of either paper banknotes or digital payments devices. Their distinctive feature is the way they are issued: currency units are created through the exchange of national currency units for local currency units at a fixed rate. The units obtained can then be used in stores, companies, associations or institutions inside the territory that accepts it as a means of payment. The national currency units exchanged to acquire CLCs are held in a guarantee fund, allowing CLC to be converted back into national currency, subject to specific conditions set by the issuing organization. While conversion back to national currency is generally prohibited for individual users, companies are authorized to do so, albeit at the price of conversion fees or, at least, the implicit costs associated with the exchange process.

CLC's are presented as instruments to support the development of territorial economies by promoting the networking of local actors and supporting local consumption of local income (Dittmer 2013). However, while there is abundant literature on the potential economic effects of CLCs, the measurement and empirical evaluation of CLCs remain inadequate and require further investigation (Michel and Hudon, 2015). Krohn and Snyder (2008) have attempted to measure the effects of local currencies on economic development by comparing growth in US cities that have local currencies versus those that do not. However, they failed to show that local currencies had any significant impact. Nevertheless, we believe that the municipal scale they chose is too large to measure a general effect, due to the low territorial coverage of CLCs (Matti and Zhou, 2022; Michel and Hudon, 2015). Moreover, the purpose of CLCs is not necessarily to develop an entire locality but rather to foster a territorial community selected for the commitment to ethical and sustainable practices of its actors. Our study therefore focuses on this specific community that uses the CLC to assess its potential to support a targeted economic growth among actors engaged in sustainable economic practices. Our analysis is thus positioned at the microeconomic and individual level of the activity of CLC member companies.

At the microeconomic level, several studies have already demonstrated the positive effects of using an alternative currency on users' income. Colacelli and Blackburn (2009) estimates that users of Trueque, a set of inconvertible local currencies in Argentina, experienced an average income increase of $35 per month, which represented 17% of the average monthly income in Argentina at that time. Ruddick (2011) also estimates that the microentrepreneurs who are members of the Eco-pesa local currency in Kenya saw an average income increase of 22%. Therefore, positive impacts on income have already been observed. However, these currencies circulate in contexts of currency crisis, or within territories facing significant economic difficulties (Gómez, 2010; Gómez and Dini, 2016), and are a different type of alternative currencies compared to CLCs, where users are often households wearing two hats, as both consumer and producer. As such, the results of these evaluations may not be generalizable to more favorable economic contexts and to Western CLCs, whose economic impacts are currently empirically evaluated only by qualitative work that concludes from 27 interviews that CLC's have no impact on local procurement and production (Marshall and O'Neill, 2018). In this paper, we use a quantitative method to assess how CLCs support the economic development of selected producers who use them. We therefore develop a theoretical model explaining the gains producers can derive from using CLCs, and an empirical measure of these benefits.

We thus evaluate CLCs to estimate their impact on the economic activity of firms using them, measured in terms of turnover. First, we introduce a theoretical model that explains the constraint and points out mechanisms likely to lead to an increase in firms' output. We then conduct an empirical analysis at a micro level, using a public policy evaluation approach. This involves considering CLCs as instruments used by certain actors and evaluating their impact by comparing turnover variation between a test group using a CLC and a non-user control group. To this end, we accessed the business records of members from 9 French CLCs in circulation from 2012 to 2019 (n=1,700). We then collected their production information from the Fare file, a dataset from the the French General Direction of Public Finances that compiled annual tax data for all French companies in the market sector from 2010 to 2019. The file's comprehensive nature allows us to select the control group through propensity score matching, and its longitudinal data enables us to estimate the effects using a two-way fixed effects model, facilitating the econometric identification of the impact (Hoynes et al., 2016; Stevenson and Wolfers, 2006).

We obtain promising results, indicating an approximate 10% increase in sales for small and medium-sized companies due to their membership in a CLC.

We will first outline the theoretical model that details the positive effect using a CLC on firms' economic activity (2). Next, we will describe the impact identification strategy (3), the data used (4) and the process of selecting the control group through propensity score matching (5). Finally, we will present the results of our estimations (6) and discuss them in the conclusion (7).

2. THEORETICAL MODEL: THE IMPACT OF USING A CLC ON THE FIRMS' OUTPUT

In this first part, we present the constraint and signal mechanisms we have identified to support the hypothesis that using a CLC has a positive impact on companies' business activity.

The monetary boundary constraint effect

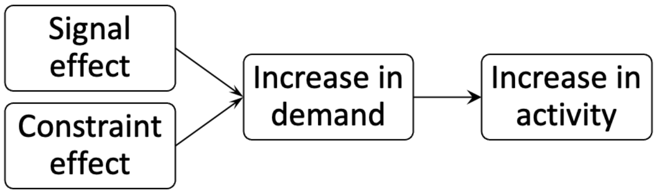
CLCs are issued when users exchange units of national currencies into local currencies. This process creates a relatively tight parallel monetary circuit[i], which imposes a constraint on users' spending behavior and compels them to exchange with each other (Fare, 2016). Indeed, while income earned in national currency can be used to purchase goods and services from any other national actor, income received in CLCs can only be used within the network of other CLCs users. To utilize the CLC units obtained from trade, users must interact with one another to spend them. Therefore, CLCs influence consumption choices by directing them toward goods and services sold or produced in the users' network. The constraint imposed by CLCs on actors' spending opportunities is therefore expected to attract new clients to CLC member firms or encourage existing clients to purchase more from them, thereby increasing demand.

The signal effect

Beyond this first mechanical effect, the acceptance of a CLC signals a distinction between firms and their competitors. Joining a CLC is not a neutral step for companies. Firms that opt to use a CLC tend to have a specific profile, especially in terms of their territorial attachment and production practices. Although there is an initial self-selection process where companies choose to join a CLC, managing organizations also ensure that applicants comply with the ethical standards they advocate, such as environmentally-friendly and sustainable production practices (Blanc and Fare 2016). Selecting company members is akin to a labeling process. Hence, accepting CLCs as a means of payment allows companies to assert their membership in a values-based community, setting themselves apart from the rest of the market and creating a distinct market segment (Akerlof, 1970). It acts as a signal, which may encourage consumers and companies with similar values to purchase from these companies rather than a competitor. This signaling effect, along with the previous constraint, should draw new customers to firms that accept CLCs as payment and thus increase demand for their products. Through the signal effect, users will potentially choose to purchase from a company because it accepts CLCs, even if they do not use CLCs to buy its products. For this reason, it also appears crucial to measure the impact of CLC use on overall turnover, not only turnover in CLCs.

The redirection of demand from CLC users to businesses within the monetary community, whether through the mechanical constraint on their spending ability or the signal sent by CLC acceptance, may result in additional demand for CLC member companies and thus enable them to increase their total turnover.

Figure 1 - Theoretical model: the effects of using a CLCs on firms' activity



Source: Author's illustration

These theoretical mechanisms are empirically corroborated by the results of an online survey of French CLCs users (Mouvement SOL and Cabinet Transformation Associés, 2021). Among the respondents, 33% of businesses (n=432) and 55.5% of individual users (n=1,417) reported having found new suppliers or providers within their CLCs members since they began using the currency. In addition, 40% of businesses and 74% of individual users indicated that they had already chosen at least one provider over another because they used the same CLC. Furthermore, 73% (n=102) of businesses reported an increase in customers since joining the CLCs, with half of them noting a significant rise. However, while this data confirms the legitimacy of the proposed mechanisms and hypotheses, it does not provide sufficient evidence to determine the full extent of these effects and their consequences for productive activity.

3. IDENTIFICATION STRATEGY

To measure the effect of using a CLC on firms' sales, we employ a two-way fixed effects model using longitudinal data. Through this approach, we aim to observe changes in firms' activity before and after they start accepting CLC as a means of payment. The two-way fixed effects model is suitable for a project with diverse entry dates and longitudinal data (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Imai and Kim, 2019). The method involves adding individual dummies to a linear model to control for all invariant and unobserved characteristics of the firms that could influence both their economic activity and their decision to join a CLC, as well as annual dummies to control for business cycle effects affecting all firms simultaneously. Fixed effects help mitigate the risk of omitted variable bias due to unchanging individual characteristics.

The estimated linear model is:

$$CA = \beta_1 \text{ IdMLC} + \beta_2 \text{ Caract}_{it} + c_i + t_t + \varepsilon_{it}$$

IdMLC is a dummy variable that takes the value 1 when the firm is a member of a CLCs and 0 when it is not. The index *i* indicates individual variation, while the index t indicates temporal variation. The variable c_i represents static individual characteristics, or the individual fixed effect, and the variable t_t represents the time fixed effect, which is consistent across individuals but variable over time. The variable ε_{it} is the error term, capturing unobserved, time-varying individual characteristics. The β terms are the coefficients of the model, with β_1 being the coefficient for *IdMLC*, the variable of interest and thus the target of the estimation. The individual, but time-varying control characteristics $Caract_{it}$ are demographic (category of firm size, sector of activity, legal status, number of full-time equivalent employees) and spatial (employment area, CLCs zone and communal density).

4. DATA PRESENTATION

In this section, we describe the data combined to build the database used for the econometric analysis: the register from 9 CLCs and the Fare file, that contains tax information for French firms from 2010 to 2019.

CLC's membership registers

To identify firms that are members of CLCs, we compiled a list of firms that had joined 9 French CLCs, including their registration dates, resulting in a total of 3,465 organizations that joined one of these CLCs between 2012 and 2021 (Table 1). We contacted the CLCs through the two main French local currency networks: the Sol movement and the MLCC network, which forwarded our request for data-sharing to their members. These 9 currencies that responded positively to our request are among the largest and most sustainable in France, falling within the top three clusters of CLC size as defined by Blanc and Lakócai (2020). They represent over 10% of French CLCs at that time and gather just over 40% of all CLC member organizations in France during this period (Blanc, Fare, Lafuente-Sampietro, 2020). Thus, while they may not be representative of the majority of CLCs, they encompass enough companies to construct a sufficiently large and reliable sample. Although two of these CLCs are experiencing serious difficulties in 2024, the others are all still circulating, including one undergoing a merger as of 2021, the time of the study.

Table 1 - List of CLCs' member companies

CLC	First year of activity	Number of organization members
Cairn	2017	561
Doume	2014	401
Eusko	2012	1,137
Florain	2017	197
Gonette	2015	557
Moneko	2015	56
Pêche	2013	141
Pive	2019	255
SoNantes	2015	160
Total	X	3,465

Source: CLCs membership registers

We obtained the official Siren[ii] identification numbers of member firms using a web scraping script. Since the Fare file covers 'market enterprises participating in the productive system with the exception of enterprises in the financial sector [...] and agriculture' (Insee 2022), non-profit organizations without commercial activities, as well as most agricultural enterprises and public administrations, were removed from the study. Their activity and accounting are not comparable to those of market companies, which explains why the Fare file excludes them from the list of other organizations. Therefore, limiting the scope to organizations with market activity allows for a more homogeneous sample of actors to compare, whose activities are more aligned with the study's objectives. As a result, the number of organizations selected and included in the Fare file and the list of CLC member organizations is 1,895.

The Fare file

The primary source of data is the Fare file, which contains tax information and consequently, production information, for French firms from 2010 to 2019. It is longitudinal and comprehensive, covering all French companies in the market sector involved in productive activity, except for those in the financial and agricultural sectors. Firms are identified in the file by their public Siren[ii] identification number. For each year, the file includes approximately 190 variables related to the statistical status of the observation, the identification and administrative details of the enterprise, and the fiscal information of the activity.

Table 2- Number of observations in the Fare file by year

Year	Observations
2010	3,340,887
2011	3,737,728
2012	3,866,486
2013	4,224,263
2014	4,385,731
2015	4,052,206
2016	4,245,075
2017	4,188,215
2018	4,290,267
2019	4,456,558
Total	43,677,123

Source: Fare file

Based on the registers of the 9 CLCs and web-scraped Siren identification numbers, we identified CLC member companies in the Fare file and labelled them as the test group. To select the control firms for the experiment, i.e., firms that are not members of CLCs, we used a propensity score matching model. We sampled firms located in the same employment zones and belonging to the same sectors of activity as those in the test sample to ensure they experienced similar economic contexts. Since CLCs' territories rarely overlap, we could be confident that unidentified firms in these areas are unlikely to be users of another CLC.

However, this approach introduces the possibility of negative externalities for the selected control group, as the decision of a tested firm to enter the CLC may negatively impact the activity of other firms in the same locality, such as through customer transfers. Nevertheless, we believe this effect to be limited given the large number of firms in the employment areas and the small size of the CLCs. And, although the measured impact accounts for this crowding-out effect, since the CLCs' aim to develop their communities even at the expense of other territorial communities, it remains an interesting outcome.

We also chose to restrict the samples to firms included in the 2019 year of the Fare file. This choice allows us to factor out firms that ceased their activity, which would result in data gaps for the most recent years that are difficult to interpret in relation to the effects of CLCs. Indeed, a large proportion of businesses, particularly small ones, have very short lifespans, as they correspond to temporary or complementary activities for their founders. On the other hand, businesses that choose to integrate a CLC typically demonstrate a commitment to a more sustainable entrepreneurial model. After applying this restriction, 1,701 firms were retained in the test group, representing 90% of the firms in the test sample. Meanwhile, the pool of potential controls, this decision resulted in retaining only 1,054,053 firms, or 53% of the firms in the sample. The restriction therefore seems to bring the profiles of the firms in the pool of potential controls and the test sample closer together, as the CLCs member firms tend to have a more extended period of activity compared to the average French firms.

Lastly, we removed imputed values for certain firms in specific years, which are particularly large for microenterprises with no employees. We also retained only observations of firms from their second year of activity onward and for the years in which their turnover is different from 0. Some firms may have been founded early in their first year and others in the last half of the year, leading to an unequal number of semesters in the comparison between the first year and subsequent years. The restriction to turnover other than 0 is based on the hypothesis that zero turnover indicates an absence of activity that year, without necessarily being linked to a production issue. This results in a final test sample of 1,268 firms, of which 1,182 have a non-imputed value in 2019.

Table 1 - Companies by years of Fare

Year	Test Group		Possible controls
	Total	Companies using a CLCs	
2010	529	0	360,121
2011	571	0	396,867
2012	629	22	423,809
2013	650	111	452,246
2014	709	159	478,718
2015	793	247	533,862
2016	872	380	575,630
2017	988	549	625,651
2018	1,053	736	668,560
2019	1,182	1,038	699,205
Observations	7,976	3,242	5,214,669

Source: Fare file, years 2010-2019

5. CONTROL GROUP SELECTION USING A PROPENSITY SCORE MATCHING MODEL

Companies that register with CLCs through self-selection and are approved by the issuing organizations have a different profile from average French companies. To control for this self-selection bias, we select a control group with observable characteristics that closely resemble those of the companies that have chosen to use CLCs. For this purpose, we use a matching method based on observed characteristics (Colacelli and Blackburn, 2009; Quantin, Bunel, and Lenoir, 2021). Given the heterogeneity in the dates of enrolment and first observations in the Fare, we applied the matching model by cohorts, defined by the first year of observation and the year preceding the test firms' enrolment in a CLC (Quantin, Bunel, and Lenoir 2021). Thus, controls are selected according to their characteristics in the year when test firms are first observe in the cohort and in the year before test firms join a CLCs. We opted for a nearest-neighbour model, with a distance measured by propensity score, which is estimated by logit regression. However, we enforced exact matching by CLCs region, sector of activity and date of business creation that is close to that of test companies. The aim of this model is not to predict a firms likelihood of joining a CLC, but to select firms with similar characteristics whose sales would exhibit comparable variation without CLC participation. The controls used to calculate the propensity score include the year firm was established, its sector of activity, legal status, employment zone, communal density, turnover in the first year of the cohort, variation in turnover between the first and last year, number of full-time equivalent employees for both periods, and profits for both periods.

We selected three times as many control firms as test firms in each cohort, based on their propensity score. When fewer firms than three times the number of test firms in the cohort obtained a sufficient score or met the restrictive conditions, only those firms that satisfied these criteria were selected. This procedure resulted in a sample of 3,368 control firms. Additionally, we selected a random control group of 3,843 companies to assess the impact of this selection method on the final results of the study.

In addition, due to the high variability of turnover at the upper distribution levels, which significantly affects the average turnover, we removed 1% of companies with the highest turnover in the first year of observation in the Fare file, i.e., those with a turnover exceeding €16,000,000. This adjustment resulted in a final sample comprising 1,268 test companies, 3,334 matched controls, and 3,821 random controls. The descriptive statistics of these samples confirm that the characteristics of the matched control sample ("PPM") are more closely aligned with those of the test sample compared to the random sample (Annexe 1, Table 4).

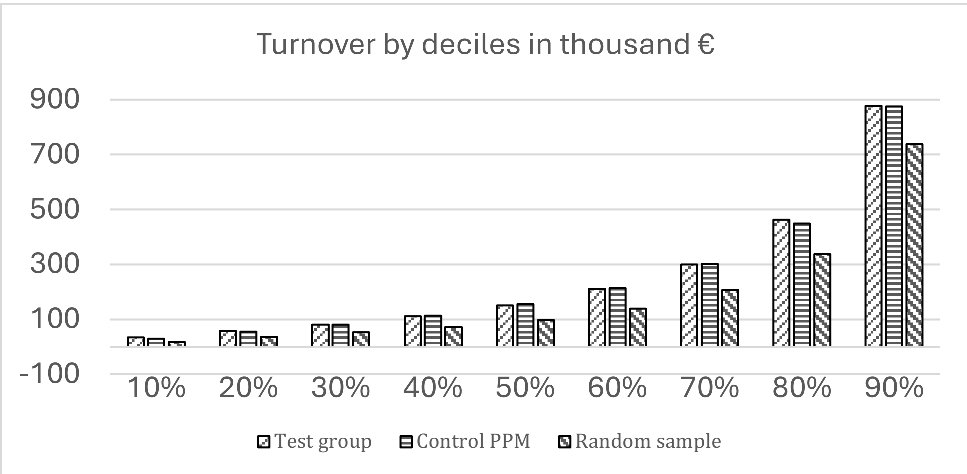
Table 4 - Turnover in the samples

Indicator	Test (n=1,268)	PPM Control (n=3,334)	Random Control (n=3,821)
Average turnover in first year	€439,857	€399,169	€361,963
Median turnover in first year	€151,385	€156,295	€97,920

Source: Fare file, years 2010-2019

Since turnover is the variable of interest in this study, we have analyzed its distribution across the different samples with greater accuracy (Figure 2).

Figure 2 - Turnover by deciles in the firms first year of observation



Source: Fare file, years 2010-2019

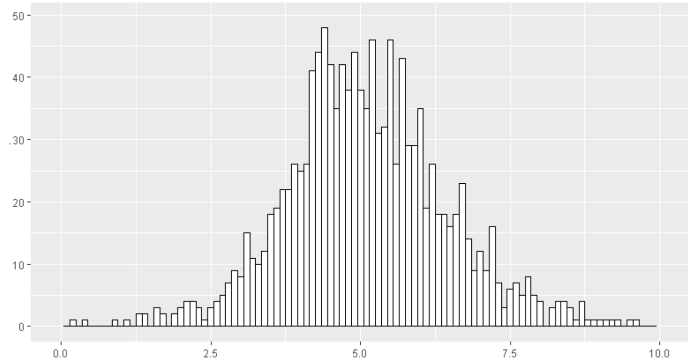
In the first year of observation, the distribution of firm turnover in the test and matched control groups is more similar than in the randomly selected control sample. The characteristics of the test and matched samples somewhat deviate in the years before joining a CLCs and show slight divergences in evolution (Annexe 2). However, because firms enter CLCs at different times, comparing turnover trends appears less meaningful, as test companies are gradually changing status, while the controls remain unchanged.

Since turnover does not follow a normal distribution, its use in the model requires logarithmization, which transforms the interpretation into relative variation. The logarithm distributions of turnovers are quite similar for the turnovers of the test and control selected by PPM samples in the first year of observation, as well as in the year before entering a CLC. In contrast, they differ more when compared to the random sample (Figure 3)

Figure 3 : Distributions of the logarithm of turnovers

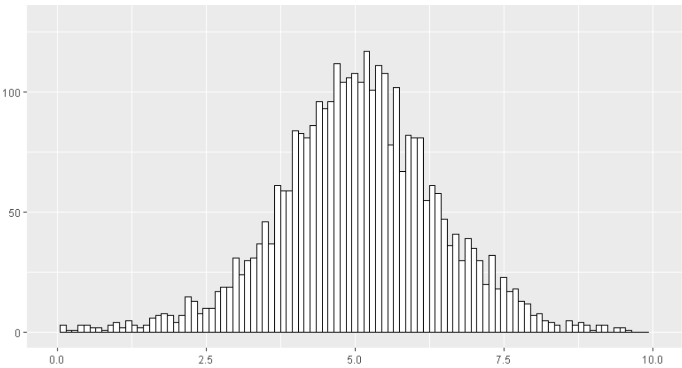
Test Group

1st year of observation



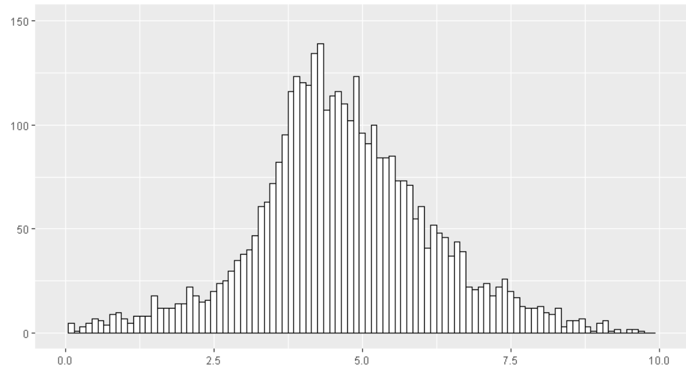
Control PPM

1st year of observation



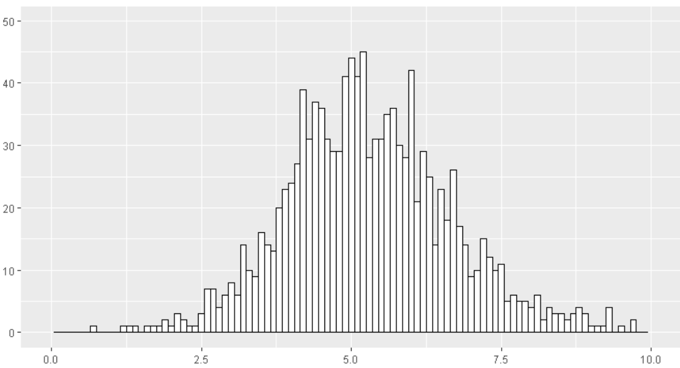
Random Sample

1st year of observation



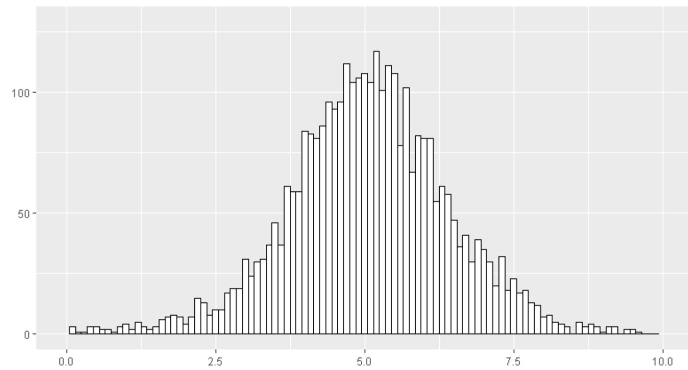
Test Group

Year before joining a CLC



Control PPM

Theoretical year before joining a CLC



Source: Fare file, years 2010-2019

6. RESULTS

In this section, we present the results of the models estimated using the plm R package (Hsiao, 2014). We begin by presenting the model estimated on the complete samples. We then perform additional analyses by estimating models for different firm categories and CLCs size. We also estimated the model by transforming turnover, which is the dependent variable, into logarithmic form to estimate the relative change in turnover.

As the data are heteroskedastic (Breusch and Pagan, 1979) and the residuals are auto-correlated, we calculated the precision of the estimated parameters using a correlation matrix that accounts for individual and temporal aggregations (Colin Cameron and Miller, 2015; Thompson, 2011) by employing the vcovDC function in the plm R package (Hsiao, 2014).

General results

The general model containing all observations yields a weakly significant result for the matched control group, estimating an increase of approximately €40,000 in turnover associated with accepting a CLC as a payment method (Table 5). This effect is tendentially positive, but the variance is too high to draw firm conclusions about its magnitude. The estimate of the relative variation in turnover is more precise. We find a 12% (exp(0.11)-1) average increase in turnover associated with the use of a CLC in the matched control sample and a 16% (exp(0.15)-1) increase in the random sample. The results for the two samples are consistent, although the matched sample yields slightly smaller effects. This difference is potentially due to the closer proximity of firm profiles to those in the test sample, which produces a finer measure of the impact.

The difference in significance between the absolute result and the percentage variation result could result from high variability in the high turnover observations, possibly unrelated to the use of a CLC, which would distort the average of the absolute effect. The change in variation via the logarithmic transformation puts all the companies on the same scale, thus reducing the weight of this type of phenomenon in the measurement.

Table 5 - General results[iii]

	Absolute turnover		Logarithm of turnover	
	Matched control group	Random control group	Matched control group	Random control group
Treatment: using a CLC	39,516 . (21,753)	49,822 (-38,357)	0.11*** (-0.02)	0.15***(-0.02)
Number of full-time equivalents	73,556*** (14,204)	80,532* (-31,303)	0.03*** (-0.01)	0.02*** (0.00)
Business category				
Large companies	-2,806,641 (5,427,174)	-639,669 (-535,686)	0.12 (-0.44)	-0.2 (-0.21)
Microenterprises	-1,595,660* (765,521)	-1,398,731* (-628,133)	-0.52*** (-0.14)	-0.32*** (-0.09)
Small and medium-sized companies	-1,357,949 . (712,146)	-1,345,945* (-679,498)	-0.3* (-0.13)	-0.07 (-0.08)
Municipal density				
Intermediate density	53,796 (41,423)	-872 (-103,230)	0.01 (-0.06)	-0.07 (-0.08)
Sparse	28,121 (67,869)	185,518 (-209,324)	-0.17* (-0.08)	0.07 -(0.09)
Very sparse	142,835** (52,221)	-247,317 (-216,509)	0.22* (-0.09)	-0.06 (-0.1)
Activity sector				
C1 Food manufacturing	1,681,015*** (205,536)	1,098,060 (-714,962)	-0.06 (-0.08)	-0.03 (-0.11)
C5 Other industrial product manufacturing	1,348,800*** (242,407)	946,043 (-635,937)	-0.07 (-0.15)	0.07 (-0.19)
FZ Construction	1,593,310*** (387,377)	1,072,689 . (-613,767)	0.11 (-0.35)	0.34 (-0.23)
GZ Trade	1,514,815*** (316,665)	956,610 (-652,027)	-0.28*** (-0.07)	-0.08 (-0.13)
HZ Transport and storage	1,505,402*** (300,999)	848,634 (-580,427)	-0.22 (-0.18)	-0.43 (-0.42)
IZ Accommodation and food services	1,452,026*** (320,847)	835,566 (-662,933)	-0.25 (-0.15)	0.07 (-0.29)
JZ Information and communication	1,444,536*** (119,966)	1,120,817*** (-242,748)	-0.73 (-0.53)	0.06 (-0.24)
KZ Financial and insurance activities	1,354,951*** (159,037)	1,480,934* (-726,143)	-0.88*** (-0.19)	-0.65** (-0.2)
LZ Real estate activities	1,363,177*** (350,708)	776,000 (-583,858)	-1.41*** (-0.14)	-0.43 (-0.3)
MN Administrative and technical services	1,327,266*** (263,911)	985,529 . (-591,260)	-0.51*** (-0.13)	-0.25 (-0.16)
OQ Administration, education, health	1,365,041*** (226,053)	972,384 . (-585,163)	-0.53** (-0.16)	0.03 (-0.3)
RU Other service activities	1,422,936*** (239,470)	845,590 (-594,062)	-0.58*** (-0.12)	-0.15 (-0.17)
Legal status				
Public right organization with commercial status	-1,219,181 (787,936)	15,070 (-1,028,609)	-0.59 . (-0.35)	0.95 (-0.67)
Commercial company	-992,670 (746,248)	232,213 (-949,731)	-0.45 (-0.33)	1.12 (0.69)

Source: CLCs members' files and Fare file, 2010-2019 years

*. significant at 90%, * significant at 95%, ** significant at 99%, *** significant at 99.9%*

Results by company size

To test whether there are differentiated effects depending on company size, the model was applied to sub-samples created from the company categories provided by the French National Institute for Statistics and Economic Studies (INSEE). These categories are based on the number of employees and their turnover, i.e., microenterprises (companies with fewer than 10 employees), small and medium-sized enterprises or SMEs (companies with more than 10 employees and fewer than 250), mid-cap companies (companies with fewer than 5,000 employees), and large companies (all companies not included in the previous categories).

For each sub-sample, we selected all companies that belonged to the category in at least one of the Fare years. Due to the very small size of these samples, mid-cap and large companies were grouped together.

As hypothesized, there are small but significant effects for microenterprises, with an increase in turnover of approximately €34,000 per year, and larger effects for SMEs, around €200,000 (Table 6). The rates of change are similar to previous finding, with microenterprises experiencing about a 10% increase and SMEs seeing a larger increase. For large and mid-cap firms, the effect is negative and insignificant in both absolute and relative terms, confirming the greater volatility of turnover at the upper levels of distribution and a less discernible effect of CLCs for these types of firms. The absence of significance may also be due to the small number of observations in these categories, particularly among test firms.

These differentiated effects allow for several interpretations of the effect of CLCs on activity. Thus, it is possible that microenterprises and SMEs, with smaller production volumes, benefit more from their inclusion in a territorialized network regarding the internalization of demand. Their production type may be more aligned with the domestic sector and better respond to local demand, which CLCs might more effectively redirect (Lafuente-Sampietro 2023). Similarly, while the effect of CLCs is small in scale, it may represent a larger relative share of the initially smaller turnover of these firms, making it more easily observable and significant. Thus, for mid-cap and large companies, the marginal contribution of CLCs may be less noticeable when their current production volume is very high. Moreover, the variation in business activity for large companies may be subject to important exogenous events which are not causally linked to the use of CLCs but can occur simultaneously and strongly impact the turnover of certain companies.

Table 6 - Results by firm size with matched control group[iv]

	Absolute turnover			Logarithm of turnover		
	Microenterprises	SME	Mid-caps and large companies	Microenterprises	SME	Mid-caps and large companies
Using a CLC	34,064* (13,885)	214,811** (78,312)	-881,553 (712,805)	0.09*** (0.02)	0.12*** (0.03)	0 (0.09)
Number of full-time equivalents	85,382*** (13,635)	81,294*** (12,346)	43,416** (15,343)	0.12*** (0.01)	0.03*** (0.01)	0.01 . (0)
Business category						
Large companies	10,626,743 (NA)		-3,723,211 (4,778,408)	1.39*** (0.36)		-0.1 (0.33)
Microenterprises	-887,696 . (516,415)	-581,147 . (352,874)	-3,820,637 . (2,147,381)	-0.5 (0.36)	-0.25* (0.12)	-1.24*** (0.34)
SME	-744,499 (512,290)	-533,823 (348,191)	134,812 (386,054)	-0.64 . (0.36)	-0.05 (0.1)	0.03 (0.1)
Municipal density						
Intermediate density	8,705 (13,734)	196,294 (139,568)	1,869,277 . (1,102,007)	0.01 (0.06)	-0.03 (0.09)	-0.16 (0.46)
Sparse	-23,948 (17,824)	476,513 (378,527)	505,761 . (292,300)	-0.2** (0.08)	0.34* (0.16)	-0.3*** (0.06)
Very sparse	94,107* (44,447)	-2,849,863*** (316,502)		0.15 (0.11)	-0.23 (0.18)	
Activity sector						
C1		1,537,490*** (103,104)			-0.13* (0.06)	
C5	-161,415 (122,345)	430,870 (515,542)		-0.14 (0.26)	0.2 (0.35)	
FZ	-14,226 (161,492)			0.19 (0.34)		
GZ	-163,070 (125,350)	859,871 . (513,230)		-0.21 . (0.11)	-0.24 (0.15)	
HZ	-191,069* (77,547)			-0.16 (0.14)		
IZ	-223,832* (111,977)	869,641 (626,455)	2,255,543 (NA)	-0.23 . (0.14)	-0.73** (0.28)	2.32*** (0.06)
JZ	-114,324 (173,273)			-0.54 (0.67)		
KZ	-205,945 . (123,031)	509,860 (327,470)		-0.77** (0.27)	-0.89** (0.34)	
LZ	-269,166* (120,656)	352,070 (947,627)	-330,998 (238,514)	-1.32*** (0.25)	-2.84*** (0.36)	-0.11 . (0.06)
MN	-153,045 (134,680)	569,383 (392,819)		-0.25 (0.19)	-0.73** (0.26)	
OQ	-178,197 (122,339)	582,147 (458,171)		-0.39 . (0.22)	-0.77** (0.26)	
RU	-189,369 (125,667)	608,589 (621,557)		-0.48** (0.18)	-0.61 . (0.34)	
Legal status						
Commercial company		-946,158 (611,261)	841,885 (NA)		-0.43 (0.27)	0.23*** (0.04)

Source: CLCs members' files and Fare file, 2010-2019 years

*. significant at 90%, * significant at 95%, ** significant at 99%, *** significant at 99.9%*

Results by CLC size

In addition to these initial results, we estimate a differentiated effect based on the size of the CLCs joined.

Accordingly, we created a variable categorizing CLCs into three groups according to the clusters estimated by Blanc and Lakócai (2020). The first category includes only the Eusko, which alone constitutes the fifth cluster in the categorization due to having at least twice as many business users as other CLCs. The second cluster combines CLCs with between 400 and 500 business users, corresponding to Cluster 4, including the Cairn, the Doume and the Gonette. The third includes the remaining CLCs, with between 150 and 250 business users and corresponding to Cluster 3. The model was run on the entire sample by replacing the CLC membership indicator with a categorical variable that denotes no CLC membership for control and test firms prior to joining, membership in a very large CLC, i.e., Eusko, membership in a large CLC, and membership in a medium CLC for test firms at the time of joining. The coefficients thus represent the effect of membership in a CLC of a certain size compared to the baseline situation of non-membership in a CLC.

With this design, the observed absolute effects are insignificant, except for the result of medium CLCs, which is significantly positive at 10% level (Table 7). The lack of significance is likely due to the smaller sample sizes for each modality of the variable of interest and the high variability in firm profiles within each CLC category. The effects in relative variation are again highly significant and of a similar magnitude to those found previously, ranging between 10% to 15% increase in annual turnover, with a significantly larger effect observed for medium-sized CLCs.

Table 7 - Results by CLCs size, matched control group[v]

	Absolute turnover	Logarithm of turnover
CLCs size		
Very large	14,811 (30,231)	0.1*** (0.02)
Large	12,292 (27,373)	0.11*** (0.03)
Medium	133,249 . (68,565)	0.14*** (0.03)
Number of full-time equivalents	73,229*** (14,223)	0.03*** (0.01)
Business category		
Large companies	-2,809,411 (5,425,925)	0.12 (0.43)
Microenterprises	-1,606,767* (766,412)	-0.52*** (0.15)
SME	-1,366,224 . (712,670)	-0.3* (0.13)
Municipal density		
Intermediate density	52,534 (41,057)	0.01 (0.06)
Sparse	29,505 (67,071)	-0.17* (0.08)
Very sparse	148,092** (52,902)	0.22* (0.09)
Activity sector		
C1 Food manufacturing	1,634,904*** (210,086)	-0.07 (0.09)
C5 Other industrial product manufacturing	1,291,580*** (250,270)	-0.08 (0.16)
FZ Construction	1,538,723*** (391,428)	0.1 (0.35)
GZ Trade	1,469,035*** (318,280)	-0.29*** (0.09)
HZ Transport and storage	1,459,199*** (303,429)	-0.24 (0.18)
IZ Accommodation and food services	1,408,277*** (327,295)	-0.26 . (0.16)
JZ Information and communication	1,395,298*** (139,670)	-0.74 (0.54)
KZ Financial and insurance activities	1,302,415*** (159,430)	-0.89*** (0.2)
LZ Real estate activities	1,313,663*** (360,602)	-1.43*** (0.14)
MN Administrative and technical services	1,281,275*** (260,577)	-0.53*** (0.14)
OQ Administration. education. health	1,313,229*** (234,744)	-0.55** (0.17)
RU Other service activities	1,365,578*** (250,414)	-0.6*** (0.14)
Legal status		
Public right organization with commercial status	-1,272,117 (787,462)	-0.6 . (0.35)
Commercial company	-1,002,067 (749,469)	-0.45 (0.33)

Source: CLCs members' files and Fare file, 2010-2019 years
*. significant at 90%, * significant at 95%, ** significant at 99%, *** significant at 99.9%*

The observation of larger effects in absolute terms and relative variation for members of average size CLCs is interesting. Although the low significance of the results in absolute terms prevent us from drawing strong conclusions, we do provide a cautious interpretation of these differences in magnitude.

Large CLCs potentially reduce the number of additional customers by integrating many providers into each business user. In a large network, consumers and firms have more options available for spending their CLCs units, and member companies therefore compete more to meet that demand. In contrast, a smaller network may have a stronger constraining effect of CLCs.

Another interpretation to be considered is that some currencies are strongly based on organized proximities already active within the territory (Fois Duclerc and Lafuente-Sampietro, 2023; Torre and Rallet, 2005). However, the existence of pre-existing interpersonal networks may both facilitate the implementation of the CLC and limit its own effect. For example, the Eusko, the largest CLC in our sample, recruits a significant proportion of its corporate members by tracing back production chains of existing members. This approach facilitates deployment but limits its intermediation effect. If the CLC merely overlays a network of prior transactions, its contribution to redirecting demand is weaker. It can thus be assumed that, in the context of a medium-sized CLC, the challenges associated with expanding the CLC may arise from less developed pre-existing social and market networks. Moreover, the CLC is more engaged in generating new proximities and creating of an ad hoc exchange community, thereby having a greater effect on redirecting demand for the members of this new community.

7. CONCLUSION

In this paper, we measured the effect of CLC membership on member firms. To this end, we utilized the natural experiment of firms' self-selection to join a CLC, allowing us to observe changes in their activity before and after this event.

We first proposed a theoretical analysis supporting our hypothesis that using a CLC positively impacts firms' turnover. Accordingly, we identified a constraint and signal effect that may result in an increase in demand for firms upon joining a CLC, thereby boosting their sales.

Empirically, we measured a relatively widespread and significant effect for micro, small and medium-sized enterprises, though it was lacking high precision. The measured effect amounts to approximately €30,000 for microenterprises and €200,000 for SMEs, which is significant given that the average turnover of firms is around €400,000 in their first year of observation (Table 4). Consequently, the effects in relative variation are rather substantial, ranging from 8% to 16% increase in turnover between the years a CLC is used and the years prior, these effects being statistically far more precise

The study, nevertheless, has some limitations that should be considered rigorously to interpret its results.

First and foremost, the scope of the Fare files, which excludes associations without commercial activities and agricultural firms, limit the generalizability of our results to the non-agricultural commercial sector. The decision to investigate turnover as activity indicators prevents analysis of the effects on non-market activities which cannot be measured in terms of turnover. However, non-market activities are mainly conducted by non-profit organizations, which constitute a significant proportion of CLC member organizations and are therefore outside the study's scope.

The CLCs used in this study are also among the most developed French CLCs, which limits the generalizability of the effects observed to relatively large and robust CLCs. Moreover, although the greater effect for the smallest CLCs is less precise, it prompts several questions that warrant further investigation, thus replicating this type of study with smaller CLCs could provide valuable insights.

From a methodological standpoint, we solely rely on firms' tax information. While the two-way fixed effects model best controls for firms' static characteristics and aggregate business cycle effects, it is possible that CLCs membership correlates with dynamic characteristics such as changes in management or production methods, adjustment to poor business performance, or additional commitments during growth period.

The absence of this information potentially constitutes a missing variable bias which the two-way fixed effects model alone may not adequately address.

We also excluded bankruptcies by retaining only firms that were still active in 2019, potentially ensuring a more robust performance among the study population.While this decision significantly reduced the control population more than the test population, it may have removed firms with declining trajectories from both groups, making it impossible to estimate effects for those firms.

Despite the methodological restrictions, these results are of great importance. This study represents a novel investigation into the impact of CLCs on businesses, a question crucial for CLC community stakeholders, public authorities who may consider supporting such projects, and academic research that now benefits from previously unavailable data on the effectiveness of CLCs. As such, the measurement of a significant positive effect for small businesses raises the question of using CLCs as tools for economic development. Since individual firms have positive effects, it stands to reason that the community using CLCs benefits from those, resulting in increased economic activity within that community. Additionally, as businesses using CLCs may demonstrate a stronger commitment to sustainable production, CLCs could serve as an effective tool for fostering selective economic growth focused on ecological production.

This increase in economic activity does not, however, imply that CLCs foster business activity throughout the entire territorial economy, as non-member companies may not benefit from these mechanisms or could even be negatively affected. However, these conclusions do not suggest CLCs have no territorial impact. In fact, by promoting economic development within their community, CLCs transform the local economy by directing economic growth toward actors who share their values and sustainable practices, thereby enabling them to play a more prominent role in their local economic landscape.

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APPENDIX

Annexe 1 : Descriptive statistics of the samples

Indicator	Test (n=1,268)	PPM Control (n=3,334)	Random Control (n=3,821)
Average turnover in first year	€439,857	€399,169	€361,963
Median turnover in first year	€151,385	€156,295	€97,920
Average number of full-time equivalents	3.8	2.6	2.6
Business category in first year			
Microenterprises	90.1%	90.9%	90.4%
Small and medium-sized companies	9.2%	7.9%	8%
Mid-caps companies	0.7%	1%	1%
Large companies	0%	0.3%	0.7%
Communal density in first year			
1 Dense	49%	52.3%	66.1%
2 Intermediate density	20.3%	24.6%	17.5%
3 Sparse	27.8%	21.7%	15.5%
4 Very sparse	2.9%	1.4%	0.8%
CLCs area in first year			
1 Cairn	9.7%	10.2%	4.5%
2 Doume	8.4%	6.8%	2.7%
3 Eusko	38.1%	30.5%	2.6%
4 Florain	3.9%	3.5%	1.9%
5 Gonette	15.5%	22.1%	10.2%
6 SoNantes - Moneko	8.1%	8.5%	3.5%
7 Pêche	4.6%	11.4%	35.7%
8 Pive	6.7%	6%	3%
Unknown	0.5%	0.9%	35.9%
Sector of activity in the first year			
C1 Food manufacturing	11%	7%	1%
C5 Other industrial product manufacturing	3%	2%	1%
DE Extractive industries, energy, water	0%	0%	1%
FZ Construction	2%	2%	8%
GZ Trade	35%	36%	14%
HZ Transport and storage	1%	1%	4%
IZ Accommodation and food services	21%	19%	8%
JZ Information and communication	3%	3%	5%
KZ Financial and insurance activities	0%	0%	3%
LZ Real estate activities	1%	1%	6%
MN Administrative and technical services	9%	15%	22%
OQ Administration, education, health	7%	10%	18%
RU Other service activities	7%	6%	8%
Type of legal unit in the first year			
Legal person	81%	75%	65%
Private individual	19%	25%	35%
Legal status in the first year			
1 Individual entrepreneur	19%	25%	35%
5 Business corporation	78%	74%	62%
6 Other legal person	1%	1%	2%
9 Private law grouping	1%	0%	0%

Source: Fare files, 2010-2019

Annexe 2 - Turnover decile

	First year of observation			Year before CLCs joining	
Decile	Test	PPM	Random	Test	PPM
Min	690	-850	-28,960	690	-850
10%	33,677	30,332	18,140	37,916	32,012
20%	58,562	55,384	36,570	65,464	57,702
30%	80,361	81,255	52,110	93,190	82,488
40%	111,942	113,968	71,420	135,654	117,952
50%	151,385	156,295	97,920	178,925	160,565
60%	211,128	214,264	138,390	261,652	225,304
70%	298,981	300,976	205,846	381,004	316,465
80%	463,858	449,808	336,240	588,978	503,804
90%	878,066	876,117	738,280	1,170,864	976,484
Max	14,863,570	15,466,770	15,580,730	16,288,630	31,551,810

Source: Fare files, 2010-2019

ENDNOTES

[i] Consumers cannot convert CLC units into national currency. Firms are permitted to do so but may incur high costs, either from conversion fees or simply the costs related to the conversion process carried out by the managing organization.
[ii] The Siren number is the national identification number assigned to companies when they register in the national register of companies.
[iii] We used a control variable for the employment areas that was not displayed in the table for readability reasons.
[iv] We used a control variable for the employment areas that was not displayed in the table for readability reasons.
[v] We used a control variable for the employment areas that was not displayed in the table for readability reasons.