Credit Reallocation and Technological Change

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November 9, 2022

Abstract

This paper studies the impact of the dynamic process of credit reallocation on aggregate innovative activities. To draw out theoretical predictions, we build a model with financial and matching frictions and investigate the consequences of lenders' credit reallocation decisions on borrowers' innovation choices. We show that an intensification of the credit reallocation process improves the matching between lenders and innovative firms but, overall, it disrupts innovation activities. Using a novel data set on bank balance sheets and the number of patents in Italian local markets (provinces) during a period of great economic growth and tighter banking regulation, we construct measures of credit reallocation and examine their effect on innovation. Consistent with the predictions of the model, we find that an increase in credit reallocation depresses innovative activity while aggregate credit growth helps to expand it.

Keywords: Credit Market, Credit Reallocation, Technological Change, Innovation
JEL codes: E44; G21; O30

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1 Introduction

The study of the allocation of resources in an economy often focuses on the distribution of labor and physical capital across firms. There is growing evidence that the reallocation of jobs (Davis and Haltiwanger (1992) and Davis et al. (1996)) and physical capital (Eisfeldt and Rampini (2006) and Eisfeldt and Shi (2018)) play a crucial role in economic growth. In contrast with the rich evidence on the importance of financial aggregates in boosting economic growth, the reallocation of financial resources is so far inadequately examined. Moreover, the interaction between the reallocation of financial resources and aggregate economic activity is under-explored. In particular, we know very little about the relationship between the reallocation of financial resources and innovation activities.

The literature on finance and innovation provides evidence that well-functioning financial markets can boost technological change. In addition, particularly in economies with underdeveloped stock and bond markets, banks have been shown to play a critical role in financing firms' innovation. The allocation of bank credit can thus substantially impact innovative activities due to differences in firms' access to credit. Hence, credit reallocation can be an important channel through which aggregate shocks can affect innovation activities and ultimately, influence real economic activity. In light of these considerations, several questions arise. How does credit reallocation across firms affect firms' innovation activities? Does a more intense credit reallocation foster innovation or, rather hinder innovation due potential financial instability?

This paper takes a step towards addressing these questions. First, we employ a model to investigate the consequences of lenders' credit reallocation decisions on borrowers' innovation choice. In the model economy, borrowing firms choose whether to innovate or retain a mature technology, while lenders decide their allocation of credit. We model the credit market as a decentralized one, characterized by matching frictions between borrowers and lenders. We posit that the innovation process is time consuming (e.g. due to the length of R&D projects) and thus it takes more time to produce with the new technology compared with the readily available (old) technology. Lenders and borrowers sign debt contracts promising a repayment to the lender in the event of production success. The different amount of time needed for production with the new and old technology exposes lenders to a liquidity risk (caused by a financial shock). Therefore, lenders have an incentive to terminate their lending agreements early (if they are lending to an innovating firm) and reenter the credit market to find a more profitable borrower (credit reallocation). Our analysis shows that lenders tend to reallocate credit when they face liquidity risks. We obtain that in a region of parameter space, our economy exhibits multiple equilibria: the amount of innovative firms in the economy affects the credit reallocation decision of lenders, and in turn, lenders' credit reallocation choices influence borrowers' innovation choices. Model calibration reveals that overall an increase in the intensity of credit reallocation (as driven by easing of the credit matching process) disrupts innovative activities.

Second, we test the predictions from the model using granular data from the Italian local markets. To investigate the effect of credit reallocation on innovation, we need an environment in which firms heavily depend on bank financing. We also need a time period during which local markets experience a significant heterogeneity in the intensity of innovation activities. With these goals in mind, we pick Italy (a bank-centered country) and the boom years post Second World War (1950-1963) as the object of our investigation.[1]

We follow Herrera et al. (2011) to measure province-level credit reallocation. Their work on credit flow measures utilizes the methodology for measuring job flows developed by Davis and Haltiwanger (1992) and Davis et al. (1996). The measurement of credit reallocation within provinces relies on detailed bank balance sheets data. We use bank-level balance sheet data from the Historical Archive of Credit in Italy (ASCI) following Natoli et al. (2016). The data cover yearly balance sheets of nearly 600 banks for the time period under our analysis. We measure innovation using the number of patents in each province for each year.[2] We complement our main data with information on province characteristics (such as financial development, education etc.) that might affect innovation activities. This data is manually extracted from historical censuses held in 1951, 1961, and 1971 using scanned census documents. To assuage concerns about the endogeneity of credit reallocation in the provinces, we exploit indicators of the provincial tightness of the 1936 Italian Banking regulation. Guiso et al. (2004a) and Guiso et al. (2004b) demonstrate that the banking regulation put in effect in 1936 created substantial heterogeneity in the degree of dynamism of provincial credit markets. Provincies where the regulation was tighter experience lower flows of entry, exit, and reallocation across banks than provinces with less tighter regulation.

We then estimate a two-stage model that in the first stage projects the rate of credit reallocation in a province onto an indicator of tightness of the banking regulation in the province and in the second stage projects the measure of innovation (the number of patents) onto the value of credit reallocation in the province defined by the tightness of local banking regulation. The results reveal that the number of patents decreases as credit reallocation intensifies while higher credit growth increases the number of patents. Hence, in line with the model credit reallocation turns out to have a negative impact on the number of patents. The effects are sizable. A one percentage point increase in credit reallocation leads to a 9.8 percent decline in the number of patents. On the other hand, a one percentage point increase in credit growth causes a 1 percent increase in the number of patents. Our results are robust across empirical specifications, and carry through when controlling for a broad battery of province characteristics or altering the estimation period.

The rest of the paper is organized as follows. Section 2 summarizes the related literature, Section 3 explains the model to study the effect of credit reallocation on firms' innovation. Section 4 describes the data, the credit reallocation measures, and summary statistics. Section 5 provides

[1] The financial system can be characterized as bank-dependent since the stock market in Italy does not play a crucial role in financing firms' activities. The exact time span is determined by the bank balance sheet data.

[2] Patent data comes from the Italian Patent Office (IPO) and the European Patent Office's (EPO) PATSTAT database which includes the international patents. Please see Bianchi and Giorcelli (2020) for the details of patent data.

details about the estimation process, while Section 6 present our main empirical results. Section 7 concludes. Details on the data, proofs and additional robustness tests are relegated to the Appendix.

2 Related Literature

This paper is related to three strands of literature. The first studies how financial markets affect the allocation and reallocation of physical capital and financial resources. Eisfeldt and Rampini (2006) and Chen and Song (2013) investigate the impact of financial frictions on the allocation and reallocation of physical capital across firms. Galindo et al. (2007) study the effect of financial shocks on the allocation of physical investment. Eisfeldt and Shi (2018)[3] argue that capital flows from less productive firms to more productive ones. Lanteri (2018) provides a microfoundation for the interplay between new and used capital and shows that used capital prices are more volatile and procyclical than prices of new capital.

The reallocation of financial resources remains overlooked in the literature. Theoretical evidence provides results stemming from different frictions. The negative effect of credit reallocation is that having multiple creditors reduces the available funding, but relationship lending increases available funds to a firm due the frictions in the credit market (Petersen and Rajan (1994)). On the contrary, expanding credit relationships to multiple banks decreases the probability of failure for a project due to monitoring effect (Detragiache et al. (2000)). Furthermore, lending competition forces lenders to reallocate credit toward more captured borrowers due to higher expected profit (Dell'Ariccia and Marquez (2004)). Banks can also play a 'Schumpeterian role' in the economy. Credit rellocation can be interpreted as a creative destruction process. Banks reallocate credit from firms with poor prospects to expanding and successful firms (Keuschnigg and Kogler (2020)).

There is growing empirical evidence on the dynamics of credit reallocation. Dell'Ariccia and Garibaldi (2005) provide evidence that inter-bank loan reallocation is intense using data from U.S. Banks' Call Report Files. Chang et al. (2010) find that there is no correlation between credit reallocation and regional economic growth in China from 1991 to 2005. Herrera et al. (2011) lay out stylized facts on credit reallocation across U.S. businesses. Credit reallocation is slightly procyclical, substantially volatile and intense. Additionally, it is mainly across firms in similar industries, geography and size. Hyun and Minetti (2019) reveal that credit reallocation across Korean firms intensifies and become more procyclical after the 1997 crisis. They conclude that intensified credit reallocation enhances firm efficiency. De Jonghe et al. (2020) show that banks reallocate credit toward low-risk firms, to sectors where they have more specialization, or to sectors in which their market share is high after a negative funding shock.

The second strand of literature studies the effect of finance on technological change and innovation. Hall and Lerner (2010), Brown et al. (2012), and Kerr and Nanda (2015)[4] conclude that

[3]See for more details about capital reallocation literature.

[4]See for a very detailed review of literature on financing innovation.

well-functioning financial markets can boost technological innovation. Caballero and Hammour (1994) study how innovative production can replace old technologies during a recession. Caballero and Hammour (2005) find that credit frictions can cause an excess destruction of production units during a recession. Garcia-Macia (2017) investigates the effects of a crisis on the investment decision on tangible and intangible capital by heterogeneous firms. Wang (2017) show that firms with initially high knowledge capital tend to save more to increase their financial assets which they can pledge as collateral. In addition, firms can also increase their investment in pledgeable assets to protect themselves from the negative effects of financial crisis. Araujo et al. (2019) investigate the effect of a credit crunch on a firm's technology choice. Collateral-poor firms loose access to credit due to a contraction in collateral value. On the contrary, collateral-rich firms gain easy access to credit market which fosters innovation. Entry to credit market can play an important role as in Malamud and Zucchi (2019). Costly access to external financing discourages innovative firms' entry disrupting creative destruction.

Lastly, our paper is also related to the literature on how banking regulations impact growth and innovation. Differences in local financial development can substantially impact lending practices and growth (Jayaratne and Strahan (1996), Guiso et al. (2004a), Dehejia and Lleras-Muney (2007)). Additionally, a frequent result in the literature is that banking regulations may hinder innovation due to the long-term nature of the innovation process.

3 The Model

This section describes a general equilibrium model of the credit market where borrowers can retain a mature technology or adopt a new technology. We then explore the impact of lenders' credit reallocation decisions on borrowers' technology choice. Our objective is to analyze how credit reallocation affects the innovation process represented by the operation of a new technology.

3.1 Agents, Goods, and Technology

Consider a three-period economy ($t = 1, 2, 3$). There is a final good and distinct, indivisible assets (machines) that produce the final good. The population consists of a continuum of risk neutral agents who derive utility from their period 3 consumption of final good. There are two groups of agents each of measure one: unskilled (u) and skilled (s) agents with different initial endowments. Unskilled agents start with one machine while skilled agents have no initial endowment.

Besides storage, there are two technologies available for production: new and old technology. The new technology represents the innovation process. We assume that only skilled agents can produce with the new technology. The two groups of agents differ in their productivity. The probability of success for the skilled agents, λ_s, is higher than for the unskilled agents, λ_u ($\lambda_s > \lambda_u$), and these probabilities are independent of the technology.

For simplicity, machines cannot be used again once the production process ends. The new technology takes more time to yield production than the old technology. In particular, production with the old technology takes one period, while production with the new technology takes two periods.

Returns differ between the new and the old technology. Innovation offers a productivity edge, yielding a higher amount of final good: the old technology yields an output y_s of final good while the new technology returns $y_s(1+\gamma)$ final good. Furthermore, if an unskilled agent does not transfer her machine and successfully implements the old technology, the machine yields a lower return y_u. In other words, skilled agents who choose to produce with the new technology obtain the highest amount of output and skilled agents who choose to produce with the old technology obtain a higher amount of output than unskilled agents producing with the old technology ($y_s(1+\gamma) > y_s > y_u$).[5]

3.2 Credit

Skilled and unskilled agents can effectively act as borrowers and lenders in the economy, respectively.

If an unskilled agent lends a machine to a skilled agent but production fails, the machine is returned to the lender. If the machine was used in the old technology, a salvage value of a can be recovered by the lender. The salvage value from a failed new technology production is instead normalized to 0 for simplicity. Intuitively, machines accompanying new technologies are likely to be firm specific and illiquid. This makes it hard for lenders to liquidate them compared to machines used in old technologies.

Given the long-term nature of the new techology, it is more exposed to interim liquidity shocks. In the event of such an unfavorable shock, an unskilled agent who lent to an innovating skilled agent can end the credit relationship and reallocate the machine to avoid a continuation cost σ.

3.3 Market Frictions

We follow Kiyotaki and Wright (1993) to introduce market frictions: the inability to match an agent who wants to transfer her machine to another agent who wants to use it. We capture this friction by introducing an exogenous parameter x that captures the level of specilization in the economy. Particularly, x denotes the proportion of machines that can be used by skilled agents and the proportion of skilled agents who can use a specific machine. In addition, unskilled and skilled agents meet in pairs under a uniform random matching technology.

There are two markets where agents meet. The first one opens in period 1. Unskilled agents (the lenders) lend their machines to skilled agents (the borrowers). We call this market *the credit market*. The second market opens in period 2 after the lenders observe borrowers' technology choice

[5] This assumption will make the trade of machines meaningful. It also follows the typical assumption from the search literature that an agent is not satisfied with her endowment, which motivates trade; see. e.g., Kiyotaki and Wright (1993).

and any unfavorable shocks. The specification of the production technology provides a rationale for credit reallocation in period 2. We call this market *the reallocation market.* If a borrower chooses the new technology and an interim negative shock occurs, the lender have the opportunity either to break the credit relationship and reallocate their machines or to continue with the innovation process facing the continuation cost σ. If the lenders reallocate their machines, the borrowers can only produce with old technology which takes one period to complete. In particular, the lenders are informed about the features of the innovation process and can realize a liquidity shock or an exogenous shock which hinders the innovation process in period 2. Therefore, a positive measure of lenders have the incentive to reallocate their machines in order to make themselves prone to these shocks. The existence of the reallocation market is ensured with this rationale. If no shock is realized in period 2, the reallocation market is not formed and innovation process continues without any interruption.

3.4 Contractual Structure

Suppose that an unskilled agent (the lender) transfer her machine to a skilled agent (the borrower) in period 1 when they meet in a pair in the credit market. The two agents sign a contract to formalize transactions between the lenders and the borrowers.

We only consider debt contracts to focus on credit reallocation. A debt contract specifies the upfront payment to the lender, property rights of the machine in case of failure, and the repayment in case of successful production. The debt contract requires no upfront payment to the unskilled agent, gives full property rights to the unskilled agent in the event of failure, and promises a repayment to the unskilled agent in the event of success. In other words, the unskilled agent lends her machine to the skilled one in exchange for future payments. This agreement can be interpreted as a debt contract. In addition, we describe the repayments in terms of final goods. The repayment of new technology ($y_d(1+\gamma)$) is higher than the old technology (y_d) if the production is successful. The amount of repayment is lower than the return of successful production ($y_s(1+\gamma) > y_d(1+\gamma)$ and $y_s > y_d$).

The unskilled agent (lender) has the option to break the credit relationship if the skilled agent (borrower) innovates (produces with new technology). The costly action that the unskilled agent needs to perform provides a rationale for credit reallocation. Contractually, a lender cannot be enforced to commit to continue the credit relationship that facilitates the innovation because the state of nature (or an unexpected unfavorable shock) cannot be contracted on as in Aghion and Bolton (1992) and Diamond and Rajan (2001).

3.5 Summary

The timing and mechanisms of the model can be summarized in the following way. Figure 1 illustrates the timing of events.

Period 1. In the credit market, unskilled (lenders) and skilled (borrowers) agents meet in pairs under a uniform random matching technology. An unskilled agent can transfer the machine when she meets a skilled agent whose specialization matches with the type of her machine. In this case, they sign a debt contract. Then, the skilled agents choose whether to innovate (new technology) or not (old technology).

Period 2. Skilled and unskilled agents producing with old technology are either successful or failed. Skilled agents incur a maintenance cost to prevent further depreciation of the machine before it is returned to the unskilled agents in the event of failure. Skilled and unskilled agents who successfully produce with old technology have access to a storage technology that is used to preserve the payoffs for one period until the end (period 3). Machines that fail cannot be reused. The unskilled agents get a salvage value for the failed machines and use the storage technology to preserve the salvage value for one period until the end (period 3).

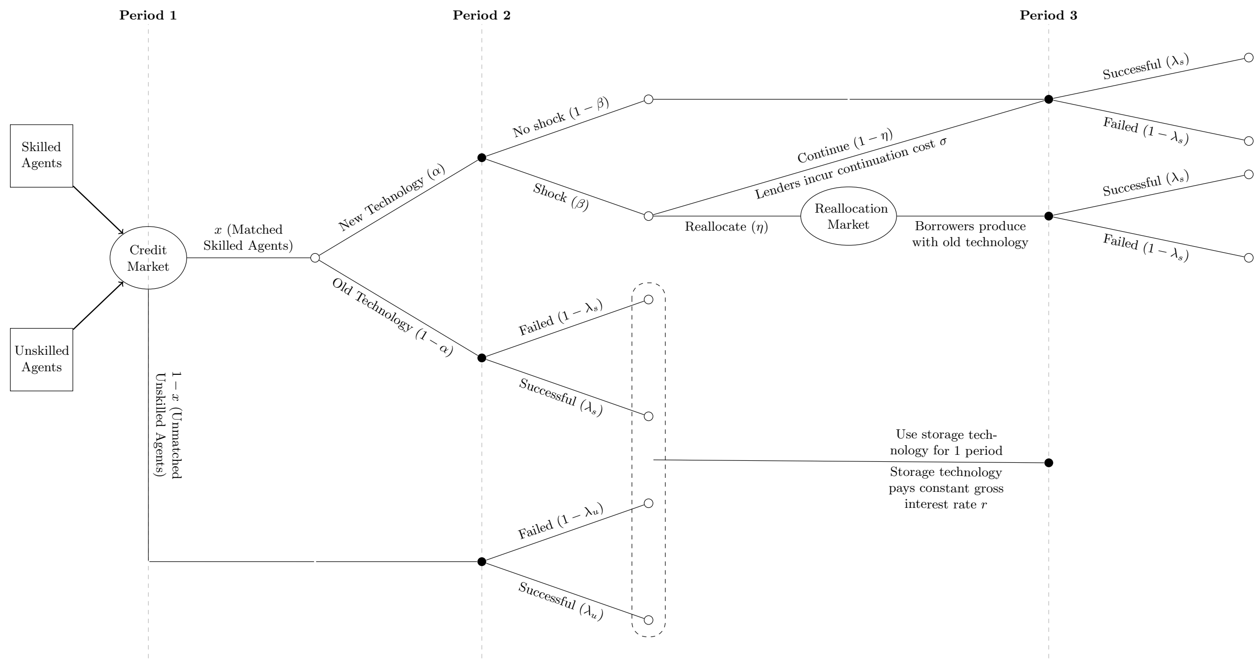
The unskilled agents who lend their machines to innovating skilled agents observe the skilled agents' technology choice. In addition, they realize if there is an unfavorable shock (a liquidity shock etc.) that can hinder the innovation process. If no shock hits the economy, innovation process continues without interruption and the outcome is observed in period 3. If an unfavorable shock is realized, the unskilled agents can either continue with the innovation process facing an effort (continuation) cost or reallocate their machines to another skilled agent who can only produce with old technology. After the unskilled agents' decision is observed the reallocation market is formed in period 2. The participants in this market are the unskilled agents who take back their machines and skilled agents whose production process with new technology is interrupted. The machines recalled early or before production process ends can be used by other agents. Agents meet in pairs under a uniform random matching technology in the reallocation market. All skilled agents are matched with an unskilled agent in the reallocation market because the amount of skilled and unskilled agents are equal and all machines can be used by a skilled agent. Agents can only produce with old technology after the reallocation market since there is only one period remaining. The outcome is realized in period 3.

Period 3. Agents producing with old technology after the reallocation market and new technology are either successful or failed. In the event of failure, the unskilled agents do not get the salvage value as the machines fully depreciate in this period. Agents consume.

3.6 Equilibrium

To solve for the equilibrium we proceed in steps. First, we start with the reallocation market in period 2. Second, we analyze the credit market and then, finally, we characterize the equilibrium.

Figure 1: Flow of Agents



3.6.1 Reallocation Market

Credit is reallocated in this market in period 2. Unskilled agents who reallocate their machines become sellers in this market. Skilled agents seek to obtain a machine to produce with old technology for the last period.

The amount of credit reallocation is equal to

$$\Omega = x\alpha\beta\eta \tag{1}$$

since we assume a unit continuum of both types of agents. It is the amount of machines that are reallocated by the unskilled agents (η) if an unfavorable shock is realized (β) after observing the skilled agents' technology choice (α) among all matched skilled agents (x).

The matching technology in the credit market (x) represents economy-wide matching technology. There are equal measure of agents in the credit market and, consequently, the measure of skilled and unskilled agents are the same in the reallocation market due to symmetry assumption. Additionally, all machines can be used by a skilled agent. Thus, x captures the matching in the reallocation market.

Now, we can derive the value functions of the skilled and unskilled agents in the credit reallocation market as follows

$$V_s^{n,R} = x\lambda_s(y_s - y_d) \tag{2}$$

$$V_u^{n,R} = x\lambda_s y_d + (1-x)\lambda_u y_u \tag{3}$$

where $V_s^{n,R}$ is the value function of a skilled agent and $V_u^{n,R}$ is the value function of an unskilled agent in the credit reallocation market.

3.6.2 Credit Market

We now analyze the credit market, the choice between reallocation and continuation for the unskilled agents (lenders), and the technology choice of skilled agents (borrowers) at period 1. Denote by W_s the value function of a skilled agent and W_u the value function of an unskilled agent at the beginning of period 1 net endowments of final good. The value functions are

$$W_u = V_o + x(1-\alpha)V_u^o + x\alpha(1-\beta)V_u^{n,C} + x\alpha\beta \max\left\{V_u^{n,C} - \sigma, V_u^{n,R}\right\} \tag{4}$$

$$W_s = x \max\left\{V_s^n, V_s^o\right\} \tag{5}$$

where for the unskilled agents, V_o is the value of the outside option (being unmatched), V_u^o is the value of lending their machine to a skilled agent producing with old technology, $V_u^{n,C}$ represents the continuation value of producing with new technology, $V_u^{n,R}$ displays the value when they reallocate their machines. For the skilled agents, V_s^n is the value of producing with new technology and V_s^o is the value of producing with old technology.

The expected payoff of an unskilled agent, W_u, is the sum of the expected payoffs from the outside option (unmatched and producing on their own), lending to a skilled agent producing with old technology, lending to a skilled agent producing with new technology without an unfavorable shock to the economy, and the decision between continuation and reallocation in the event of an unfavorable shock is realized. Similarly, the expected payoff of a skilled agent depends on the choice between new and old technology.

Next, we define the value functions mentioned above. Firstly, consider the value functions of the unskilled agent

$$V_o = (1+r)\Big[\lambda_u y_u + (1-\lambda_u)a\Big] \tag{6}$$

$$V_u^o = (1+r)\Big[\lambda_s y_d + (1-\lambda_s)a\Big] \tag{7}$$

$$V_u^{n,C} = \lambda_s(1+\gamma)y_d \tag{8}$$

and, secondly, consider the value functions of the skilled agent

$$V_s^o = (1+r)\lambda_s(y_s - y_d) \tag{9}$$

$$V_s^n = (1-\beta)V_s^{n,C} + \beta\Big[\eta V_s^{n,R} + (1-\eta)V_s^{n,C}\Big] \tag{10}$$

$$V_s^{n,C} = \lambda_s(1+\gamma)(y_s - y_d) \tag{11}$$

where $V_s^{n,R}$ and $V_u^{n,R}$ are as defined in the previous section.

The next lemma formalizes the conditions for a credit relationship. Under the following conditions the unskilled agents prefer meeting skilled agents in the credit market.

***Lemma* 1** *In period 1, an unskilled agent will always prefer lending her machine to a skilled agent than producing on her own if*

(i) $y_u < a < y_d$ *and*

(ii) $\sigma < (1-x)\lambda_u y_u \dfrac{\eta}{1-\eta} - \dfrac{1+r}{\beta(1-\eta)}$.

Proof. See the Appendix A.

3.6.3 Unskilled Agents' Choice

The expected payoff from continuation is higher than the expected payoff from reallocation as long as $V_u^{n,C} - \sigma > V_u^{n,R}$. Lemma 2 outlines the unskilled agents' decision.

***Lemma* 2** *Suppose that an unskilled and a skilled agent meet at period 1. Then, at period 2, conditional on skilled agents' technology choice, the unskilled agent will continue with the innovation process if and only if*

$$\gamma > \frac{\sigma - (1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} \tag{12}$$

and, they believe that a positive measure of the unskilled agents continues with the innovation process. Otherwise, the unskilled agents will reallocate their machines (disrupting the innovation process).

Proof. See the Appendix A.

3.6.4 Skilled Agents' Choice

The expected payoff of new technology is higher than the expected payoff from old technology as long as $V_s^n > V_s^o - \mu$. Lemma 3 characterizes the skilled agents' technology choice.

***Lemma* 3** *Suppose that an unskilled and a skilled agent meet at period 1. Then, the skilled agents will innovate if and only if*

$$\gamma > \frac{r + (1-x)\beta\eta}{1-\beta\eta} \tag{13}$$

and, they believe that a positive measure of the skilled agents choose to innovate. Otherwise, the skilled agents will choose to produce with old technology.

Substituting for the unskilled agents' decision, η, one of the following cases is realized:

(i) If $\gamma < r$, all of the skilled agents will only choose to produce with old technology.

(ii) If $r \leq \gamma \leq \frac{r+(1-x)\beta}{1-\beta}$, all of the skilled agents will choose either old technology or new technology, and there exists a γ' where the skilled agents will be indifferent between old and new technology.

(iii) If $\gamma > \frac{r+(1-x)\beta}{1-\beta}$, all of the skilled agents will only choose to produce with new technology.

Proof. See the Appendix A.

3.6.5 Disruptive Credit Reallocation

Credit reallocation negatively impacts innovation process. Combining the conditions from Lemmas 1-3, Lemma 4 characterizes the the conditions that facilitate the hindering effect of credit reallocation.

***Lemma* 4** *Credit reallocation disrupts the innovation process if*

$$\frac{r+(1-x)\beta\eta}{1-\beta\eta} < \gamma \leq \frac{\sigma}{\lambda_s y_d} - \frac{(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} \tag{14}$$

Proof. See the Appendix A.

3.6.6 Equilibrium Characterization

Now, we can present the equilibrium. There are two choices in the model: the technology choice of skilled agents and the unskilled agents' decision between reallocation and continuation.

Let M denote the set of period 1 meetings between skilled and unskilled agents in the credit market at period 1. Define S_s as the choice of the skilled agent and S_u as the choice of the unskilled agent. Consider a generic point i in this set and let $S_s \times S_u$ be the profile of actions. We have $S_s = \{N, O\}$ and $S_u = \{C, R\}$ where N and O represent the choice of new and old technology, respectively, for the skilled agent and C and R represent the choice of continuation and reallocation, respectively, for the unskilled agent. Now, define $C(i, s_s, s_u, v)$ as the outcome of ith meeting, where the skilled agent chooses s_s, the unskilled agent chooses s_u and $v = (\alpha, \eta)$ is the distribution of skilled agents between two technologies and the distribution of unskilled agents between continuation and reallocation.

***Definition* 1** *A Nash equlibrium is a pair (C, v) such that:*

(i) In any meeting $i \in M$, agents' choice $c(i, s_s, s_u, v)$ maximizes surplus.

(ii) The aggregation of agents' choices across meetings generates a distribution of skilled agents between two technologies and a distribution of unskilled agents between continuation and reallocation.

Proposition 1 combines the results of Lemmas 1-4. It characterizes the distribution of skilled agents between two technologies, and, the distribution of unskilled agents between the choice of continuation and reallocation if the borrower chooses to produce with new technology in the event of an unfavorable shock to the economy.

Proposition* 1** ***(Distribution of Agents) *Suppose that an unskilled agent (lender) and a skilled agent (borrower) meet at period 1. Regardless of the unskilled agents decision, (i) (no innovation) the skilled agents will not innovate if $\gamma < r$, and (ii) (innovation) the skilled agents will innovate if $\gamma > \frac{r+(1-x)\beta}{1-\beta}$. If $\gamma < \gamma'$ in the interval $r \leq \gamma \leq \frac{r+(1-x)\beta}{1-\beta}$, the skilled agents will not innovate regardless of the unskilled agents decision. Assuming $\gamma > \gamma'$, (i) (no disruption to innovation process) the skilled agents will innovate and the unskilled agents will continue if $r \leq \frac{\sigma-(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} < \gamma \leq \frac{r+(1-x)\beta}{1-\beta}$, and (ii) (disruption to innovation process) the skilled agents will innovate but the unskilled agents will reallocate their machines if $r \leq \gamma \leq \frac{\sigma-(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} \leq \frac{r+(1-x)\beta}{1-\beta}$.*

Proof. See the Appendix A.

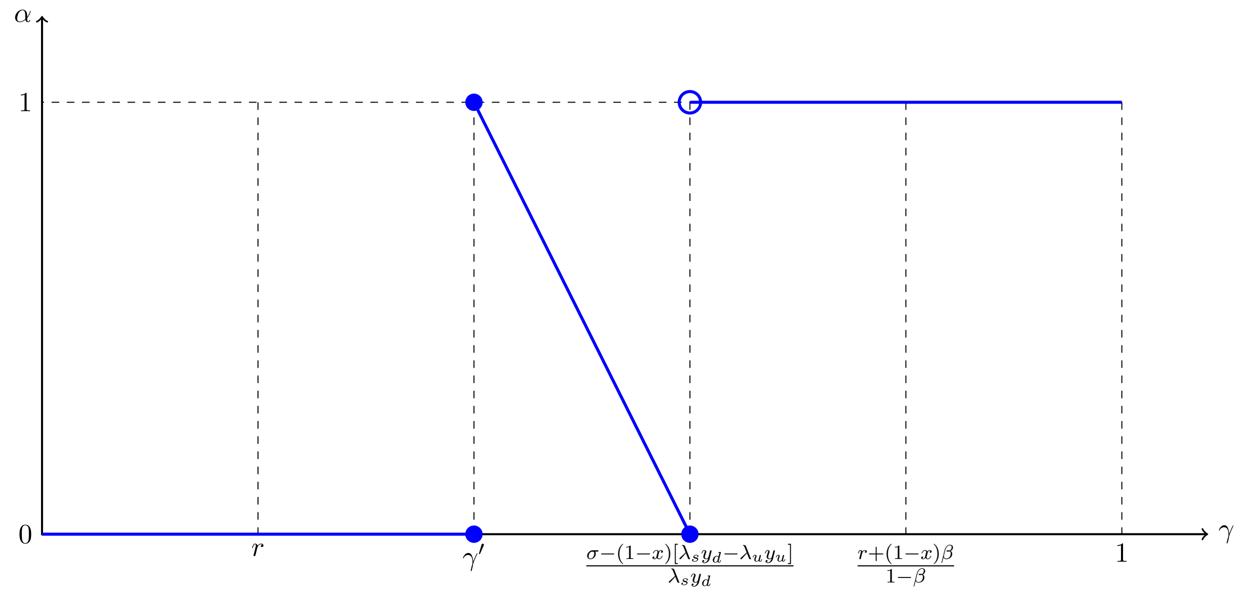
Figure 2 displays the proposition. The intervals from the proposition presented on the figure. To summarize, the skilled agents will not innovate if $\gamma < r$ and $\gamma < \gamma'$ regardless of the unskilled agents' choice. Hence, we get $\alpha = 0$. The skilled agent will innovate if $\gamma > \gamma'$. The intervals matter for this case. If $\gamma > \frac{r+(1-x)\beta}{1-\beta}$ the skilled agents will innovate regardless of the unskilled agents' choice. We get $\alpha = 1$. The disruptive effect of credit reallocation appears in the interval $r \leq \gamma \leq \frac{r+(1-x)\beta}{1-\beta}$. The innovation process will not be interrupted, if $\gamma' \leq \frac{\sigma-(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} < \gamma \leq \frac{r+(1-x)\beta}{1-\beta}$ or $\frac{\sigma-(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} \leq \gamma' < \gamma \leq \frac{r+(1-x)\beta}{1-\beta}$. Again, we have $\alpha = 1$. On the other hand, the unskilled agents' decision will interrupt the innovation process if $\gamma' < \gamma \leq \frac{\sigma-(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} \leq \frac{r+(1-x)\beta}{1-\beta}$. Thus, we start with $\alpha = 1$, but end up with $\alpha = 0$. The choice of reallocating credit harms the innovation process as depicted in Figure 2.

In conclusion, the analysis predicts that, as long as the productivity edge provided by innovation is not too small, agents will innovate. However, if the productivity edge is not big enough, the lenders will reallocate credit and disrupt the innovation process.

3.7 A Numerical Example

In this section, we develop some numerical experiments that help further grasp the intuition behind the results of the model. Table 1 outlines the exercise. We will consider two cases in two

Figure 2: Relationship between reallocation and innovation



different scenarios: high and low local financial development in an economic boom period or an economic downturn period. An economic boom period represents lower interest rate for the storage technology, the effort cost of lenders to continue will be lower, and the probability of a shock is lower. An economic downturn period indicates that the storage technology pays a higher interest rate, the continuation cost of lenders will be higher, and a shock is more likely to occur. We define local financial development depending on x which shows matching efficiency in the credit market. We fix technology parameters. The probability of success for the skilled agents is $\lambda_s = 0.8$. The probability of success for the unskilled agents is $\lambda_u = 0.6$. The return amount production yields is $y_s = 1.8$ for the skilled agents and $y_u = 1.3$ for the unskilled agents. The repayment in the event of successful production is $y_d = 1.5$. The unskilled agents receives the salvage value $a = 1.4$ in period 2 if noninnovating skilled agents fail to produce.

We calculate the thresholds for the productivity edge given the parameters. Column 4 of Table 1 presents the thresholds for the productivity edge. Given in Proposition 1, $\underline{\gamma}$ represent the lower bound of the interval below which the skilled agent will never innovate, $\overline{\gamma}$ is the upper bound after which the skilled agents will innovate regardless of the unskilled agents decision. $\hat{\gamma}$ shows the cutoff point for the unskilled agents. Below $\hat{\gamma}$ the unskilled agents will reallocate credit and above they will continue with the innovation process. Column 5 displays the intervals for the skilled agents to innovate and the threshold for the unskilled agents' decision.

In an economic boom scenario, it is more likely to have higher productivity edge provided by innovation and better economic conditions. The lower bound of unconditional innovation choice

Table 1: Value of Parameters

Parameters (Technology)	Parameters (Economy)	Parameters (Credit Market)	Thresholds	Cases	Result
			Panel A: Economic boom		
$\lambda_s = 0.8$	$r = 0.1$		High Local Financial Development		
$\lambda_u = 0.6$	$\beta = 0.1$	$x = 0.8$	$\underline{\gamma} = 0.1$	$(i)\underline{\gamma} < \gamma < \hat{\gamma}$	Disruptive credit reallocation
$y_s = 1.8$	$\sigma = 0.5$		$\overline{\gamma} = 0.13$	$(ii)\hat{\gamma} < \gamma$	No interruption to innovation process
$y_u = 1.3$			$\hat{\gamma} = 0.35$		
$y_d = 1.5$			Low Local Financial Development		
$a = 1.4$		$x = 0.2$	$\underline{\gamma} = 0.1$	$(i)\underline{\gamma} < \gamma < \hat{\gamma}$	Disruptive credit reallocation
			$\overline{\gamma} = 0.2$	$(ii)\hat{\gamma} < \gamma < \overline{\gamma}$	No interruption to innovation process
			$\hat{\gamma} = 0.14$		
			Panel B: Economic downturn		
	$r = 0.3$		High Local Financial Development		
	$\beta = 0.6$	$x = 0.8$	$\underline{\gamma} = 0.3$	$(i)\underline{\gamma} < \gamma < \hat{\gamma}$	Disruptive credit reallocation
	$\sigma = 1$		$\overline{\gamma} = 1.05$	$(ii)\underline{\gamma} < \hat{\gamma} < \gamma$	No interruption to innovation process
			$\hat{\gamma} = 0.76$		
			Low Local Financial Development		
		$x = 0.2$	$\underline{\gamma} = 0.3$	$(i)\underline{\gamma} < \gamma < \hat{\gamma}$	Disruptive credit reallocation
			$\overline{\gamma} = 1.95$	$(ii)\underline{\gamma} < \hat{\gamma} < \gamma$	No interruption to innovation process
			$\hat{\gamma} = 0.55$		

of the skilled agents $\overline{\gamma}$ and the continuation threshold for the unskilled agents $\hat{\gamma}$ are lower in the economic boom environment. The lenders will be more likely to continue with the innovation process. On the contrary, the productivity edge will be lower in an economic downturn and the lenders will be more likely to reallocate credit in the economic downturn environment. Furthermore, local financial development matters for the decisions of agents. In highly developed local financial markets, the lenders are more likely to reallocate and interrupt the innovation process.

4 Data

In this section, we describe the data and the methodology for credit reallocation measures. We collect patent counts, bank-level credit flows, and province characteristics from census data. The bank loan data covers the period between 1890 and 1973 and the patent data is from 1950 to 2010 with a gap between 1963 and 1968. Thus, the final data set comprises the period between 1950 and 1963. However, including data from 1968 to 1973 does not change the results.[6]

We perform our investigation at the province level. A province is a unit of analysis very similar to a county in the US. In Italy, the relevant local market in banking is the province according to the Italian Antitrust authority. Additionally, the Bank of Italy used the same rule to define a local market concerning opening new branches and extending credit outside of a bank's location. Therefore, we collect data at the province level.

[6]The inclusion of extra data and results from this exercise is discussed in Appendix D.

4.1 Institutional Background

In this paper, we study the effect of credit reallocation on innovation and technological change. To achieve that we require an environment in which firms heavily depend on bank financing and a time during which a great expansion in innovative activities was experienced. Picking Italy as the subject of the investigation provides abundant advantages in focusing on bank financing. The financial system can be characterized as bank-dependent since the stock market in Italy does not play a crucial role in financing firms' activities. Hence, Italy provides a very useful environment to isolate the role of banks, in particular credit reallocation, in fostering innovation.

Overall, Italy traditionally has a financial system dominated by credit institutions (De Bonis et al. (2012)). The ratio of loans to deposits rose above one during the economic boom from 1958 to 1963. Bank loans and deposits reached 75% of GDP, and the total factor productivity growth was particularly exceptional from the 1950s to the mid-1970s, the so-called "Italian economic miracle" period.[7] Thus, focusing on Italy during this period is very informative in terms of investigating the role of credit reallocation in boosting innovation.

4.2 Patent Data

In the literature, R&D spending and patent counts are commonly used as two main measures of innovation. Even though each has advantages and disadvantages, we choose to use patent counts because R&D spending cannot tell us whether the innovation process is successful.[8]

We start with European Patent Office's (EPO) PATSTAT database. However, the missing information (i.e. location) on patent applications seriously affected the data collecting process. We use a matched patent count data set to overcome the issue. The data set matches the names on patents with individuals and location. Then, to refine and improve the matching the data set uses work histories provided by Italy's Social Security Administration. In addition, observations are manually checked and confirmed for the matched names on patents to increase precision.[9] As a result, the data set has more accurate information and more complete picture at the province level. It includes patent data using the Italian Patent Office (IPO) between 1950 and 2010, and the international patents included in the European Patent Office's (EPO) PATSTAT database. The data set provides number of patents at each province in Italy during the given time period.

The patent data is able to distinguish between the assignees and the inventors of a patent. An assignee can be a firm or an individual who holds the intellectual property rights over the patented invention. Hence, patent counts only for assignees can disrupt the geographical variety. For example, a large firm headquartered in province A may be the patent's assignee, while the inventor of this patent works in a plant of the large firm in province B. In this example, the patent

[7]See Malanima and Zamagni (2010), De Bonis et al. (2012) and Nuvolari and Vasta (2015) for more details.
[8]See Hall (2011) for a more detailed discussion.
[9]Please see Bianchi and Giorcelli (2020) for a detailed discussion of patent count data set.

would be counted in province A if we use patent assignee and province B if we use the patent's inventor. The separation between the assignees and the inventors provides a better way to capture the effect of credit reallocation on innovation.

4.3 Banking Data

Following Herrera et al. (2011), we use bank-level loan data to measure credit flows. For the same time period it is almost impossible to find firm-level debt structures in Italy. The banking data clearly represents the banking system with detailed balance sheet items. This feature makes it very well suited for analyzing credit flows.

We use bank-level balance sheet data from Historical Archive of Credit in Italy (ASCI) following Natoli et al. (2016). ASCI provides data for nearly 2,600 banks for the time between 1890 and 1973. The data includes yearly balance sheet of banks and there are more than 41,000 balance sheets in the data set. Bank balance sheet data collection is built on Bank of Italy's earlier work. Due to confidentiality of bank supervision statistics, the data ends in 1973. Under our analysis, we use the yearly balance sheets of nearly 600 banks for the time period. There are 14 types of assets and 9 types of liabilities included in the data set. The important feature of the data set is that the main balance sheet items are comparable over time since the construction is done with a uniform balance sheet structure.[10]

The data set has information on each bank's province and region. Thus, we can create aggregate measures at province level. We obtain total loans summing short-term and long-term loans from balance sheet. We use total loans to calculate credit reallocation measures.

4.4 Province Characteristics

We use province characteristics as controls in our analysis. We collect data from historical censuses held in 1951, 1961, and 1971. The main problem is that the data is not digitally available. Only scanned census documents are accessible at the Italian National Institute of Statistics' (ISTAT) website.[11] We manually extracted data for province characteristics using scanned census documents. Particularly, we use general population censuses (*"Censimento Generale Della Popolazione"*) and industry and commerce censuses (*"Censimento Generale Dell'Industria E Del Commercio"*) to obtain province characteristics. Using general summary data (*"Dati Generali Riassuntivi"*) from censuses, we can extract a good amount of useful data at province level.

We acquire population and education related characteristics from general population censuses. We use *share of active population* as an indicator of labor force participation and *share of higher education degrees* as an indicator for level of education at a province.

[10] More details about the data set can be found in Natoli et al. (2016).
[11] ISTAT catalog can be accessed at ebiblio.istat.it.

We obtain economic province characteristics from industry and commerce censuses. We use *share of individual firms* as an indicator for economic development[12]. We also get number of firms, workers, and bank branches from industry and commerce censuses. We add *number of workers per firm* and *number of bank branches per firm* to control for economic and financial characteristics of provinces.

We calculate *credit market concentration* as a simple Herfindahl–Hirschman Index (HHI) using the bank level loan data for each province. Lastly, we measure *productivity* as total value added for each firm. Although, the results are robust to different definitions of productivity.

4.5 Measurement Issues

The measurement of credit flows using bank loans has an important caveat. Bank loans do not account for inflation making it hard to measure the real exposure of patenting activities to banks. We deflate the original bank loan data using an implicit GDP deflator to overcome this issue. Additionally, we deflate province characteristics if necessary, in particular we deflate total value added. We acknowledge that using non-deflated (nominal) credit flows might have important insights. However, the results are all in real terms.

4.6 Credit Reallocation Measures

To obtain credit reallocation measures we closely follow Herrera et al. (2011). Their work on credit flow measures utilizes the methodology for measuring job flows developed by Davis and Haltiwanger (1992) and Davis et al. (1996). We use credit and loan interchangeably.

Let us define c_{bt} as the average of the loans of a bank b at time $t-1$ and at time t. Then, we define C_{st} as the average of loans for a set s of banks where the set is a province. We define time t loan growth rate of a bank, g_{bt}, taking the first difference of its loans divided by c_{bt}.

Now, given a set s of banks, we can define credit creation and credit destruction to establish credit reallocation measures. We calculate credit creation at time t, POS_{st}, as the weighted sum of the loan growth rates of banks with rising loans or newborn banks. Similarly, we calculate credit destruction at time t, NEG_{st}, as the weighted sum of the absolute values of the loan growth rates of banks with shrinking loans or dying banks. Then, for both measures, we weight the loan growth rate of a bank b with the ratio c_{bt}/C_{st}. We obtain the following measures

$$POS_{st} = \sum_{\substack{b \in s_t \\ g_{bt} > 0}} g_{bt} \left(\frac{c_{bt}}{C_{st}} \right) \tag{15}$$

[12] Guiso et al. (2004a) show that individuals are more likely to start a business in more developed regions in Italy.

$$NEG_{st} = \sum_{\substack{b \in s_t \\ g_{bt} < 0}} |g_{bt}| \left(\frac{c_{bt}}{C_{st}} \right) \tag{16}$$

where s_t is the set of banks at time t. Finally, we can define credit reallocation, SUM_{st}, as the sum of credit creation and credit destruction, $SUM_{st} = POS_{st} + NEG_{st}$. In addition, we can define the net credit growth as $NET_{st} = POS_{st} - NEG_{st}$, and the excess credit reallocation as the reallocation in excess of the minimum required to accommodate the net credit change, $EXC_{st} = SUM_{st} - |NET_{st}|$.

4.7 Choosing a Credit Reallocation Measure

The intensity of credit reallocation is important in its own right and its movement alongside the economic activity. However, our goal is to understand whether credit reallocation influences economic activity, in our case innovation. Therefore, an important task is to decide which credit reallocation measure provides better information on credit markets. To deal with this task, we discuss some features and properties of each credit reallocation measure in this section.

Davis (1998) argues that using gross job reallocation, the sum of job creation and job destruction, as the main indicator of reallocation intensity is harmless enough in many contexts. However, he concludes that gross job reallocation becomes a questionable measure of reallocation in a time-series context. Instead, he offers excess job reallocation as a robust measure of reallocation.

We adopt the same approach and disregard gross credit reallocation in our analysis. We explain the main problem of gross credit reallocation using its definitions. We define gross credit reallocation in two different ways. First, gross credit reallocation increases with simultaneous credit creation and destruction, $SUM_{st} = POS_{st} + NEG_{st}$. Second, gross credit reallocation also rises with a change in the absolute value of the net credit growth, $SUM_{st} = EXC_{st} + |NET_{st}|$ where $NET_{st} = POS_{st} - NEG_{st}$. Thus, using gross credit reallocation makes it hard to compare two provinces in our case. A simple example given for gross job reallocation helps to better understand. An economy with a 5% credit creation rate and 0% credit destruction rate has 5% gross credit reallocation rate, while an economy with 0% credit creation and destruction rates has 0% gross credit reallocation rate. However, we cannot say that the first economy has more reallocation activity than the second economy. Because both economies have 0% excess credit reallocation and we define excess credit reallocation as the part of gross credit reallocation over and above the amount required to accommodate the net credit growth. Hence, it is a better measure of simultaneous credit creation and destruction.

Overall, we choose excess credit reallocation as our main measure of credit reallocation and use net credit growth as an indicator of development in credit markets.

4.8 Properties of Credit Reallocation

The intensity of credit reallocation can help shed light on the impact of reallocation on innovation. In particular, examining the dynamic behavior of credit reallocation and differences at the province level can be informative about how credit reallocation affects innovation and what factors can play a key role. This section investigates properties of credit reallocation across provinces from 1950 to 1963.[13]

Figure 3 and Section 2 displays how credit reallocation measures change from 1950 to 1963 compared to real GDP growth. We take the average of credit reallocation measures for each province in a given year. In the early 1950s, gross credit reallocation and real GDP growth move in the opposite directions. On the other hand, credit destruction, consequently excess credit reallocation, moves hand in hand with the real GDP growth in the early 1950s. Gross credit reallocation and net credit growth declined in the early 1950s and then increased towards the mid-1950s. However, they gradually decreased until late 1950s. Until this point, we can say that gross credit reallocation and net credit growth demonstrate an opposite movement compared to real GDP growth. This negative relationship reverses after 1958. Starting in the 1960s, gross credit reallocation and net credit growth started to follow a more similar pattern with real GDP growth. Lastly, credit destruction and excess credit reallocation stay relatively low during sample period. Overall, credit creation, gross credit reallocation, and net credit growth closely follow each other over time, while credit destruction and excess credit reallocation display a similar movement. These results are not unexpected considering that the time coincides with the greatest development of the Italian economy. Also, we work with bank loans instead of firm debts and we expect banks to increase the amount of loans during an economic expansion period.

Figure 4 presents the relationship between innovation and credit reallocation from 1950 to 1963. Again we take the average of credit reallocation measures and number of patents for each province for a given year. Patents increase towards the end of 1950s after a slight decline in the early 1950s. This period coincides with the Italian economic boom. However, after this prosperous period, there is a large decline in the number of patents in the early 1960s. Nuvolari and Vasta (2015) argue that scientific activities prevail patenting during this period.

Next, we try to explore more how innovation and credit reallocation are related at the province level. We examine how provinces are distributed using number of patents and credit reallocation measures. We present the results of this exercise in Figure 5, Figure 6, Figure 7, Figure 8, and Figure 9. We take the average of number of patents and credit reallocation measures for the whole sample period to draw the scatter plots. First thing to notice is that Milan, Rome, Turin, Florence, Bologna, and Genoa are the provinces with the highest average number of patents. This result is expected, particularly for Milan. Bianchi and Giorcelli (2020) show that 12.7% of patents granted between 1968 and 2010 were assigned to an individual or a firm located in Milan. However, credit

[13] Please see Data Appendix (Appendix C) for inclusion of additional data.

reallocation is not amongst the highest for these five provinces. Smaller provinces have higher credit reallocation compared to larger provinces. We see a similar picture for credit creation and credit destruction. Hence, this exercise suggest a negative relationship between innovation and credit reallocation.

4.9 Summary Statistics for Province Characteristics

The relationship between credit reallocation and macroeconomic variables can offer important insights about what possible factors can play a key role between the credit market and the aggregate economy. This section studies province characteristics that can offer some insights on the impact of reallocation on innovation.

We present Section 3 to examine province characteristics considered in our analysis. We take the average of all considered variables for all provinces at a given year. Data collected from censuses are presented only at the year the census held. First, the number of patents follows a path similar to an inverted-U shape between 1950 and 1963.[14]

We measure productivity as the total value added per firm in a province. Productivity gradually decreases until 1961 and starts to increase after. The evidence suggests that innovation and productivity follow a similar path over time. The number of banks is stable over time moving around 4 banks on average in each province, while number of bank branches on average increases substantially over time. There are 96 branches on average in each province in 1951, while the number of bank branches reaches 118 on average in 1961. Additionally, credit market in Italy is highly concentrated between 1950 and 1963.

Average number of workers for each firm increases from 3.64 in 1951 to 3.99 in 1961, while the share of active population decreases from 46.2% in 1951 to 40.4% in 1961. Italy's great economic development period pays out as share of higher education degrees increases from 3.8% in 1951 to 4.95% in 1961.

5 The Empirical Model

In this section, we describe the empirical strategy in detail. Our goal is to identify the effect of credit reallocation on innovation. However, we suspect that credit reallocation can be endogenous to financial development. For instance, highly developed regions in terms of economic and financial output may also have the most financially developed banking systems. We present Figure 10 to display the regional differences. We take the average number of patents, net credit growth, and excess credit reallocation for each region for the entire period. Panel (a) shows that the average number of patents is higher in highly developed regions. Net credit growth is higher in less developed (mostly southern) regions (Panel (b)). Finally, excess credit reallocation, our main

[14]Please see Data Appendix (Appendix C) for inclusion of additional data.

credit reallocation measure, is higher in highly developed regions but two less developed regions have the highest credit reallocation rates (Panel (c)).

Moreover, unobserved factors that affect economic and financial activity may be correlated with credit reallocation. This relationship may cause a bias in our results. Therefore, we must use exogenous factors of financial development to instrument our credit reallocation measures. Considering these endogeneity issues, our empirical strategy is estimating a two-stage model that in the first stage projects the rate of credit reallocation in a province onto an indicator of local financial development and in the second stage projects a the measure of innovation (number of patents) onto value of credit reallocation in the province defined by local financial development.

We first discuss our instruments and their validity. Then, we lay out the empirical model employed for estimation.

5.1 Instruments

Banking regulations play an important role in shaping the financial system in Italy. There is considerable diversity in the banking development due to regulatory reforms in the banking system. Particularly, the banking regulation in effect from 1936 to the end of the 1980s is the source of a large fraction of diversity observed in Italian banking development. Guiso et al. (2004a) and Guiso et al. (2004b) discuss in great detail that the banking regulation put in effect in 1936 creates a partly exogenous geographical diversity in banking development, which might be informative in isolating the effect of bank financing on real outcomes. Therefore, it might help identify the effect of credit reallocation on innovation. Additionally, the banking sector structure allows us to safely rely on the geographical diversity in the banking sector to examine the impact of credit reallocation on innovation.

The Italian Government enacted the banking legislation of 1936 in response to the 1930–1931 banking crisis. The government introduced strict market entry regulations to preserve the banking system from instability. Four categories for credit institutions were established: national, cooperative, local commercial, and savings banks. The regulation required all banks to shut down branches located outside its geographical boundaries determined by the legislation. Furthermore, national banks were allowed to open new branches in the main cities. Cooperative and local commercial banks were allowed to open new branches within the boundaries of the province where they were located in 1936. On the other hand, savings banks were allowed to expand within the boundaries of the region where they were located in 1936. Finally, the Bank of Italy was designated as the sole authority enabling banks to extend credit outside their geographical boundaries determined by the legislation. The banking regulation passed in 1936 remained in effect until 1985.

Guiso et al. (2004a) argue that this regulation significantly hampered the growth of the financial system. Furthermore, they document that banks in these four categories experience substantially different growth paths. Considering this fact, they show that these differences in growth can explain the regional variation in credit supply after 60 years. They select the number of total branches (per million inhabitants) in a region in 1936, the fraction of branches owned by local versus national banks, the number of savings banks (per million inhabitants), and the number of cooperative banks (per million inhabitants) to instrument financial development. They find that these candidate variables can explain 72% of the cross-sectional variation in the supply of credit in the 1990s.

We also perform a similar exercise to find our instruments. We choose *the number of savings banks in 1936 (per 100,000 inhabitants)* to instrument credit reallocation. The main reason for selecting the number of savings banks is that they are the only category of banks allowed to extend credit outside of the province where they were located. In addition, we choose *the inverse of credit market concentration in 1936* to instrument net credit growth. We measure credit market concentration with a Herfindahl–Hirschman Index (HHI) of bank loans. The inverse of credit market concentration provides the effective number of banks in the credit market making it a good candidate instrument for net credit growth. Additionally, the first-stage regression results (See Table D.1 and Table D.2) confirm that these two variables are correlated with the variables of interest, namely excess credit reallocation and net credit growth. Finally, Guiso et al. (2004a) discuss in great detail how and why these instruments are uncorrelated with the error term. They extensively argue that the structure of local credit markets in 1936 was not the outcome of characteristics of the region or forced by the legislation. On the contrary, the structure of the credit markets was random and mostly the outcome of politics.

5.2 Fixed Effects Model

The empirical fixed effects model can be expressed as follows

$$Patent_{it} = \alpha_t + \beta_i + \gamma Credit_{it} + \varepsilon_{it} \qquad \text{(the second stage)} \tag{17}$$

$$Credit_{it} = \kappa_t + \eta_i + FinDev_{it} + \nu_{it} \qquad \text{(the first stage)} \tag{18}$$

where $Patent_{it}$ is the average number of patents (per 1,000 firms) in province i in year t, α_t is a time fixed effect that captures nation-wide shocks to economic activity in year t, β_i is a regional fixed effect[15] that measures the component of economic activity specific to the region of province i (reflecting time-invariant unexplained factors that differ across regions), $Credit_{it}$ is the rate of credit reallocation or credit growth in province i in year t, and ε_{it} is the residual. In addition to time and regional fixed effects, Equation 17 (the first stage) includes $FinDev_{it}$, local financial development indicators as instrumental variables to account for different development levels. We expect that local financial development indicators are correlated with credit reallocation but they

[15] Since we instrument credit reallocation with 1936 local financial development indicators, we can only exploit cross sectional variation at province level. Hence, we need to drop province fixed effects and add regional fixed effects.

affect economic activity only through the credit market. We use $Savings_i$, the number of savings banks in province i in 1936 (per 100,000 inhabitants), to instrument credit reallocation. Then, we use $IHHI_i$ the inverse of credit market concentration in province i in 1936, to instrument net credit growth.

6 Main Estimation Results

In this section we present our main results. Empirical evidence suggests a negative relationship between credit reallocation and innovation (See Figure 6). Thus, our primary goal is to further investigate whether credit reallocation negatively impacts innovation. In addition, we examine the relationship between net credit growth and innovation. Because the time coincides with Italy's great economic boom, the economic growth would reflect on net credit growth. Thus, we try to see the impact of economic advancement on innovation.

We use excess credit reallocation, which nets out the minimum reallocation needed to accommodate net credit growth, as our main indicator of reallocation intensity to examine the impact of credit reallocation on innovation. We also use net credit growth to reestimate the model to shed light on the economic growth and innovation mechanisms. Section 4 and Section 5 reports coefficient estimates from estimation and associated heteroskedasticity-robust standard errors in parentheses.

We start by discussing the baseline estimates (Column 1 in Section 4 and Section 5). The estimates reveal that the number of patents decreases as credit reallocation increases, while, expanding credit helps increase the number of patents. Hence, unsurprisingly, we confirm that credit reallocation harms innovation measured by the number of patents. A one percentage point increase in excess credit reallocation leads to a 9.8 percent decline in the number of patents. On the other hand, a one percentage point increase in net credit growth causes a 1 percent increase in the number of patents. We support the fact that great economic development boosts innovation.

First-stage regression results reveal that an increase in the number of savings banks rises excess credit reallocation. This result is expected because savings banks were the only category of banks allowed to expand within the boundaries of the region where they were located in 1936. Moreover, a rise in the effective number of banks (inverse of credit market concentration) causes an increase in net credit growth.

Next, we investigate whether credit reallocation and net credit growth in previous periods impact innovation. We present the results of this exercise in Columns 3 and 4 in Section 4 and Section 5. With the inclusion of lags of excess credit reallocation, the coefficient on contemporary credit reallocation does not substantially change. However, the sign of lags of credit reallocation is the opposite of current credit reallocation, although the coefficients are not statistically significant. Net credit growth experiences a similar sign reversal with the only difference that the first lag of net credit growth is statistically significant. The sign reversal for lags is not entirely surprising.

Italy experienced a miraculous economic development during the 1950s, followed by a slowdown in economic growth and innovative activities. Nuvolari and Vasta (2015) claim that scientific activities prevail patenting between 1960 and 1970. Hence, this fact explains the sign reversal for net credit growth and its significance. We show that an increase in net credit growth in the previous period leads to a decrease in the number of patents in the current period.

Furthermore, we control for province characteristics in addition to the baseline estimates. Columns 2, 5 and 6 in Section 4 and Section 5 present the results of our experiments with different specifications. We pick province characteristics to account for various aspects of development in a province. First, we start by controlling for the share of the active population, the number of bank branches per firm, the share of individual firms, the share of higher education degrees, and productivity measured as total value added per firm in the estimation for excess credit reallocation (Column 2). We do not use the number of banks instead of the number of bank branches. We think that bank branches may better capture unobserved effects of credit reallocation considering savings banks can expand outside of the province but within the region where they are located. The results reveal that controlling for province characteristics decreases the magnitude of coefficient estimates for excess credit reallocation compared to the baseline estimates. Still, the direction of impact remains the same. The same exercise results differently for net credit growth. The magnitude and sign of coefficient estimates for net credit growth do not substantially change compared to the baseline estimates with the inclusion of province characteristics as control variables.

Additionally, human capital (share of higher education degrees) and approximate labor participation (share of the active population) have a positive and statistically significant effect on innovation. This result is expected considering the evidence provided in the literature. These results are the same in both estimations. On the other hand, the share of individual firms, an indicator of economic development, negatively impacts the number of patents in both estimations. The number of bank branches negatively affects innovation in the estimation with excess credit reallocation, while it positively impacts innovation in the estimation with net credit growth, but the coefficient estimate is statistically insignificant.

Lastly, we combine province characteristics with the lags of excess credit reallocation and net credit growth. Columns 5 and 6 present the results in Section 4 and Section 5. The direction of the effect stays the same for both excess credit reallocation and net credit growth. However, the magnitude of coefficient estimates for excess credit reallocation compared to the baseline estimates decreases in this case. At the same time, they stay around the same for coefficient estimates for net credit growth.

Additionally, we perform robustness checks to examine the strength of our instruments. We leave the robustness of results to the north-south divide, an alternative specification and inclusion of additional data from 1968 to 1973 to Appendix D.

7 Conclusion

In this paper, we study the impact of credit reallocation on innovation. We combine a theoretical and an empirical approach to achieve this goal. We employ a model to investigate the consequences of lenders' credit reallocation decisions on borrowers' innovation choice. We show that lenders tend to reallocate credit when they face liquidity risks. The amount of innovative firms in the economy affects the credit reallocation decision of lenders, and in turn, lenders' credit reallocation choices influence borrowers' innovation choices. Model calibration reveals that overall, an increase in the intensity of credit reallocation (as driven by easing of the credit matching process) disrupts innovative activities. Then, we test the predictions from the model using granular data from the Italian local markets.

We use bank-level loan data to calculate credit reallocation and patent count data to measure innovation. Focusing on Italy provides a very informative environment to isolate the effect of banks, in particular credit reallocation, on innovation. We also use the fact that the sample time period coincides with the so-called "Italian economic miracle" period and tighter banking regulations. In addition, we suspect that highly developed regions in terms of economic output may also have the most financially developed banking systems. Hence, we estimate a two-stage model using instruments from the banking regulations. We exploit the banking legislation in 1936 to pick our instruments. The banking legislation in 1936 creates a partly exogenous geographical diversity in banking system that lasts without substantial changes until 1985.

Our results reveal a negative relationship between credit reallocation and innovation. We find that an intensification in credit reallocation disrupts firms' innovation through a decline in the number of patents. On the other hand, a rise in net credit growth boosts innovation by increasing the number of patents. Our results carry through when we control for various province characteristics. We find that human capital and labor force participation indicators positively affect innovation, while financial and economic development indicators depress innovation. We further show that our results are robust to weak instruments, across alternative empirical specifications, and altering the estimation period via inclusion of additional data.

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A Proofs

Proof of Lemma 1. An unskilled agent will always prefer to transfer her machine to a skilled agent if $V_u > V_o$. We can define the expected payoff of lending a machine V_u as the sum of the expected payoffs from lending to a skilled agent producing with old technology V_u^o and new technology V_u^n. Next, we plug in the value functions. We obtain

$$
\begin{aligned}
&V_u > V_o \\
&(1-\alpha)V_u^o + \alpha V_u^n > V_o \\
&(1-\alpha)V_u^o + \alpha\Big\{(1-\beta)V_u^{n,C} + \beta\Big[\eta V_u^{n,R} + (1-\eta)(V_u^{n,C} - \sigma)\Big]\Big\} > V_o \\
&(1-\alpha)V_u^o + \alpha\Big\{(1-\beta\eta)V_u^{n,C} + \beta\eta V_u^{n,R} - \beta(1-\eta)\sigma\Big\} > V_o \\
&\alpha\Big\{(1-\beta\eta)(1+\gamma)\lambda_s y_d + \beta\eta x\lambda_s y_d + \beta\eta(1-x)\lambda_u y_u - \beta(1-\eta)\sigma\Big\} + \\
&\qquad (1-\alpha)\Big\{(1+r)\Big[\lambda_s y_d + (1-\lambda_s)a\Big]\Big\} - (1+r)\Big[\lambda_u y_u + (1-\lambda_u)a\Big] > 0 \\
&\vdots \\
&\alpha\Big\{\underbrace{\Big[(1-\beta\eta)(1+\gamma) + \beta\eta x\Big]\lambda_s y_d}_{>0} + \underbrace{\beta\eta(1-x)\lambda_u y_u - \beta(1-\eta)\sigma - (1+r)}_{(ii)}\Big\} + \\
&\qquad (1+r)\Big\{\underbrace{(1-\alpha)\lambda_s(y_d - a) + \lambda_u(a - y_u)}_{(i)}\Big\} > 0
\end{aligned}
$$

We derive two conditions and get

(i) $y_u < a < y_d$

(ii) $\sigma < (1-x)\lambda_u y_u \frac{\eta}{1-\eta} - \frac{1+r}{\beta(1-\eta)}$

Proof of Lemma 2. The expected payoff from continuation is higher than the expected payoff from reallocation as long as $V_u^{n,C} - \sigma > V_u^{n,R}$. We substitute for the necessary value functions. Then, we obtain

$$
\begin{aligned}
V_u^{n,C} - \sigma &> V_u^{n,R} \\
\lambda_s(1+\gamma)y_d - \sigma &> x\lambda_s y_d + (1-x)\lambda_u y_u
\end{aligned}
$$

solving for γ, we get the condition needed for the unskilled agents to continue as following

$$
\gamma > \frac{\sigma - (1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d}
$$

Proof of Lemma 3. The expected payoff from new technology is higher than the expected payoff from old technology as long as $V_s^n > V_s^o$. We get the following

$$
\begin{aligned}
&(1-\beta)V_s^{n,C} + \beta\Big[\eta V_s^{n,R} + (1-\eta)V_s^{n,C}\Big] > V_s^o \\
&(1-\beta\eta)V_s^{n,C} + \beta\eta V_s^{n,R} > V_s^o \\
&(1-\beta\eta)\lambda_s(1+\gamma)(y_s - y_d) + \beta\eta x\lambda_s(y_s - y_d) > (1+r)\lambda_s(y_s - y_d) \\
&\vdots \\
&\gamma > \frac{r + (1-x)\beta\eta}{1-\beta\eta}
\end{aligned}
$$

After substituting for the necessary value functions, we find inequality (13) as the condition. Then, we substitute for the unskilled agents choice η to define intervals for the skilled agents decision. First, we set $\eta = 0$ so that all of the unskilled agents continues and the expected payoff from new technology is maximized. Inequality (13) becomes

$$\gamma \geq r$$

In this region of the parameter space, the skilled agents will choose to produce only with either new technology or old technology. However, if we have

$$\gamma < r$$

choosing new technology is never the best reply, and thus, choosing old technology is the unique choice (case (i)).

Second, we set $\eta = 1$ so that all of the unskilled agents reallocates and the expected payoff from new technology is minimized. Inequality (13) becomes

$$\gamma > \frac{r + (1-x)\beta}{1-\beta}$$

In this region of the parameter space, the expected payoff of producing with new technology is higher than the expected payoff of producing with old technology. Therefore, choosing new technology dominates choosing old technology for the skilled agents (case (iii)).

Finally, we can consider the case

$$r \leq \gamma \leq \frac{r + (1-x)\beta}{1-\beta}$$

In this region of the parameter space, there is a value γ' such that the skilled agents are indifferent choosing between new and old technology. For this value of γ, there exists a case in which some of the skilled agents will choose new technology and others will choose old technology.

Proof of Lemma 4. We combine the conditions from Lemmas 1-3. First, we consider the condition for the skilled agents' new technology decision. A skilled agent will innovate if

$$\gamma > \frac{r + (1-x)\beta\eta}{1-\beta\eta}$$

Next, the unskilled agents lend their machines if

$$\sigma < (1-x)\lambda_u y_u \frac{\eta}{1-\eta} - \frac{1+r}{\beta(1-\eta)} \quad \Longrightarrow \quad \frac{\sigma}{\lambda_s y_d} < (1-x)\frac{\lambda_u y_u}{\lambda_s y_d}\frac{\eta}{1-\eta} - \frac{1+r}{\lambda_s y_d \beta(1-\eta)}$$

and they will reallocate their machines if

$$\gamma \leq \frac{\sigma}{\lambda_s y_d} - \frac{(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d}$$

Thus, we can derive an interval in which the skilled agents choose new technology and innovate in period 1, while, the unskilled agents will reallocate their machines in period 2. If γ is in the following interval

$$\frac{r + (1-x)\beta\eta}{1-\beta\eta} < \gamma \leq \frac{\sigma}{\lambda_s y_d} - \frac{(1-x)[\lambda_s y_d - \lambda_u y_u]}{\lambda_s y_d} < (1-x)\frac{\lambda_u y_u}{\lambda_s y_d}\frac{\eta}{1-\eta} - \frac{1+r}{\lambda_s y_d \beta(1-\eta)}$$

the reallocation decision of the unskilled agents hinders the innovation process.

Proof of Propsition 1. Using Lemmas 1-4, the proof of the proposition is immediate. Considering parts (i) and (iii) of Lemma 3, we show *innovation* and *no innovation* cases regardless of the unskilled agents' decision. Then, using part (ii), we show that the skilled agents will not innovate if $\gamma < \gamma'$. Next, we combine part (ii) of Lemma 3 and and Lemma 2. The skilled agents will innovate if $\gamma > \gamma'$. Within the interval from part (ii) of Lemma 3, we plug in the cutoff point from Lemma 2. Hence, we get the results.

B Tables and Figures

This section includes the tables and figures mentioned in the main body of text.

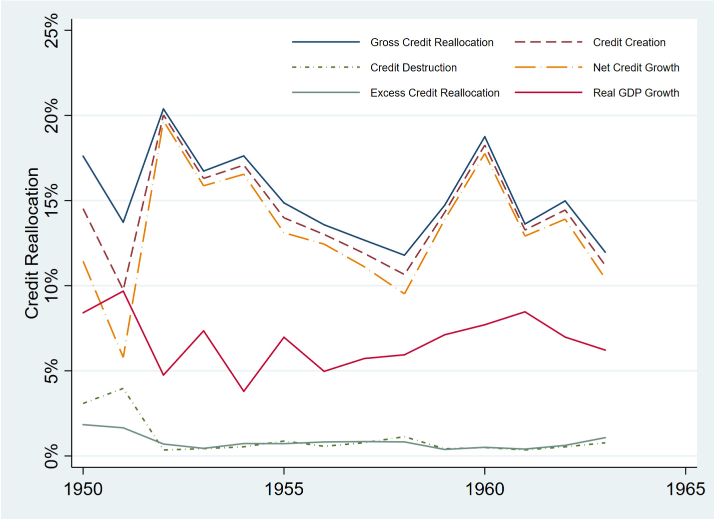


Figure 3: This figure plots the measures of credit allocation alongside with the real GDP growth. The credit reallocation measures are defined in Section 4.6 of the main text.

Figure 4: This figure plots the three main measures of credit allocation alongside with the average number of patents per firm.

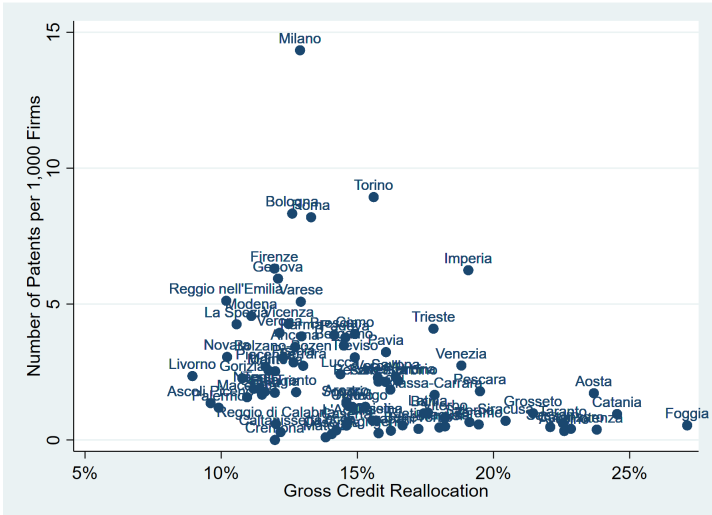


Figure 5: This figure plots the distribution of provinces using gross credit reallocation and the number of patents per 1,000 firms.

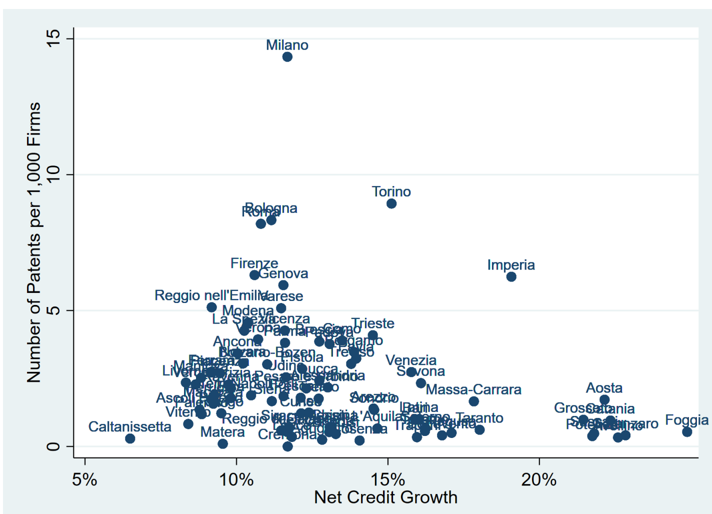


Figure 6: This figure plots the distribution of provinces using net credit growth and the number of patents per 1,000 firms.

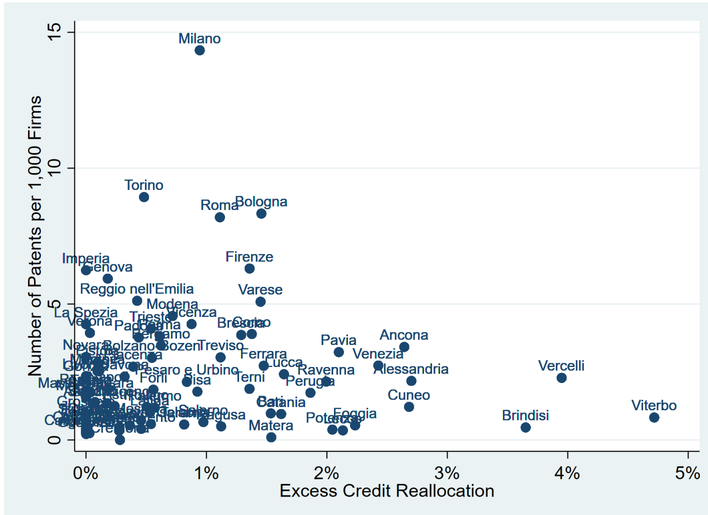


Figure 7: This figure plots the distribution of provinces using excess credit reallocation and the number of patents per 1,000 firms.

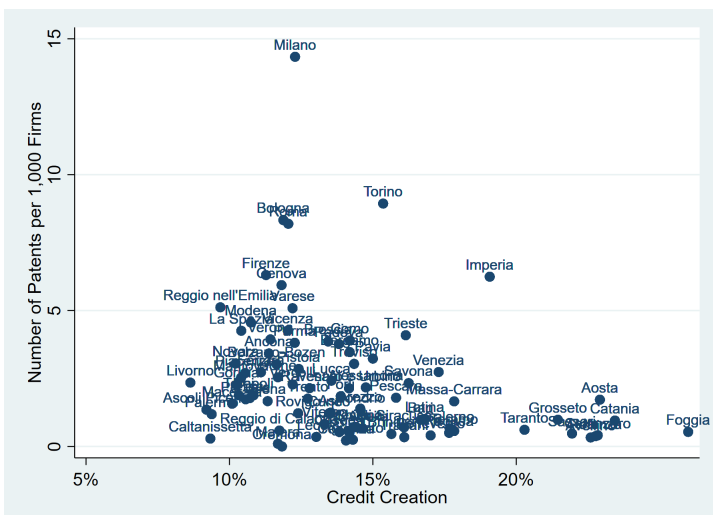


Figure 8: This figure plots the distribution of provinces using credit creation and the number of patents per 1,000 firms.

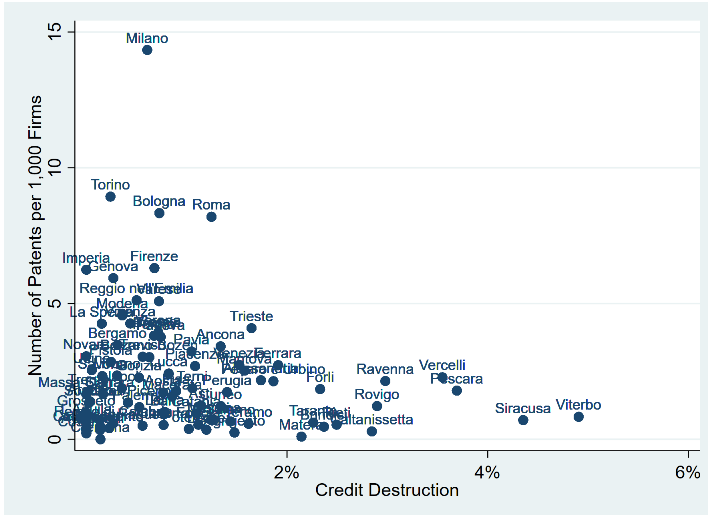


Figure 9: This figure plots the distribution of provinces using credit destruction and the number of patents per 1,000 firms.

(a) Number of Patents

(b) Net Credit Growth

(c) Excess Credit Reallocation

Figure 10: This figure plots the regional overview of three main variables of interest. Panel (a) displays the average number of patents for each region. The Northern regions have higher number of patents. Panel (b) presents the regional distribution of net credit growth. The Southern regions have higher net credit growth as expected. Panel (c) shows the regional differences in the excess credit reallocation measure. Overall, the Northern regions have higher levels of excess credit reallocation, but two of the Southern regions have the highest levels.

Table 2: Summary statistics for credit reallocation measures

The table reports the yearly averages of credit reallocation measures for each year over the sample period. The summary statistics refer to the 1950-1963 period. Credit flows are computed from the bank-level loan changes using the methodology described in the paper. Real GDP growth is added at the last column to make comparisons.

Year	Gross Credit Reallocation	Net Credit Growth	Excess Credit Reallocation	Credit Creation	Credit Destruction	Real GDP Growth
1950	17.61%	11.44%	1.84%	14.53%	3.09%	8.41%
1951	13.73%	5.79%	1.65%	9.76%	3.97%	9.68%
1952	20.38%	19.68%	0.70%	20.03%	0.35%	4.75%
1953	16.73%	15.87%	0.45%	16.30%	0.43%	7.35%
1954	17.62%	16.55%	0.73%	17.08%	0.54%	3.80%
1955	14.86%	13.11%	0.72%	13.99%	0.88%	6.97%
1956	13.58%	12.44%	0.82%	13.01%	0.57%	4.97%
1957	12.68%	11.11%	0.84%	11.89%	0.78%	5.72%
1958	11.79%	9.52%	0.82%	10.65%	1.13%	5.94%
1959	14.72%	13.88%	0.38%	14.30%	0.42%	7.12%
1960	18.75%	17.77%	0.51%	18.26%	0.49%	7.71%
1961	13.62%	12.91%	0.41%	13.27%	0.36%	8.47%
1962	14.98%	13.91%	0.62%	14.45%	0.54%	6.98%
1963	11.96%	10.41%	1.08%	11.19%	0.77%	6.22%

Table 3: Summary statistics for province characteristics

The table reports the yearly averages of province characteristics over the sample period. The statistics are computed averaging across all of the provinces for each year in the sample period which refers to the 1950-1963 period. The number of patents are the total number of patents divided by the total number of firms. Productivity is measured as the total value added per firm. The number of banks is the total banks divided by number of provinces. Credit market concentration is measured by a Herfindahl Index of number of banks. Share of individual firms is the average of share of sole proprietary firms across all provinces. Share of higher education degrees represents the average share of population obtained higher education degrees and an indicator of human capital. Share of active population is the fraction of population actively working or searching for a job, an approximation for labor force participation.

Year	Number of Patents	Productivity (000 lire)	Number of Banks	Credit Market Concentration	Number of Workers per Firm	Number of Bank Branches	Share of Individual Firms	Share of Higher Education Degrees	Share of Active Population
1950	73.43	269.43	3.45	0.68					
1951	68.53	248.85	4.26	0.62	3.64	96.33	91.37%	3.79%	46.24%
1952	71.49	240.87	4.50	0.61					
1953	79.02	232.74	4.50	0.61					
1954	82.72	225.95	4.51	0.61					
1955	84.83	218.88	4.52	0.61					
1956	82.10	210.35	4.50	0.61					
1957	76.31	206.52	4.37	0.62					
1958	72.88	202.40	3.34	0.68					
1959	79.30	203.61	4.45	0.61					
1960	71.60	200.43	4.45	0.61					
1961	61.73	349.22	4.44	0.61	3.99	118.60	91.45%	4.94%	40.44%
1962	60.93	331.51	4.43	0.61					
1963	31.15	305.50	4.43	0.61					

Table 4: Credit reallocation and innovation

The table reports regression coefficients for the impact of credit reallocation on innovation within provinces. The regressions are estimated by two-stage least squares to control for the endogeneity of credit flows. The dependent variable is the number of patents per firm in each province. Heteroskedasticity-robust standard errors are in parentheses. All regressions include region and year fixed effects. *, **, and *** denote statistical significance at the 10, 5 and 1% level, respectively. We use *the number of savings banks in 1936 (per 100,000 inhabitants)* to instrument excess credit reallocation. The main reason for selecting the number of savings banks is that they are the only category of banks allowed to extend credit outside of the province where they were located. Last row of the table reports the F-statistic for an F-test of joint significance of the instrument.

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Excess Credit Reallocation	-0.098***	-0.027**	-0.102***	-0.111***	-0.026**	-0.027**
	(0.028)	(0.012)	(0.030)	(0.033)	(0.012)	(0.013)
Share of Active Population		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.136***			-0.136***	-0.135***
		(0.040)			(0.040)	(0.040)
Share of Individual Firms		-0.035***			-0.035***	-0.035***
		(0.004)			(0.004)	(0.004)
Share of Higher Education Degrees		0.049***			0.049***	0.049***
		(0.006)			(0.006)	(0.006)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Excess Credit Reallocation (First lag)			0.004	0.004	-0.000	-0.000
			(0.004)	(0.004)	(0.002)	(0.002)
Excess Credit Reallocation (Second lag)				0.011		0.001
				(0.007)		(0.002)
Observations	1,204	1,204	1,204	1,204	1,204	1,204
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
F-Stat	17.43	19.02	15.74	14.27	17.36	15.95

Table 5: Credit growth and innovation

The table reports regression coefficients for the impact of credit growth on innovation within provinces. The regressions are estimated by two-stage least squares to control for the endogeneity of credit flows. The dependent variable is the number of patents per firm in each province. Heteroskedasticity-robust standard errors are in parentheses. All regressions include region and year fixed effects. *, **, and *** denote statistical significance at the 10, 5 and 1% level, respectively. We use *the inverse of credit market concentration in 1936* to instrument net credit growth. We measure credit market concentration with a Herfindahl–Hirschman Index (HHI) of bank loans. The inverse of credit market concentration provides the effective number of banks in the credit market making it a good candidate instrument for net credit growth. Last row of the table reports the F-statistic for an F-test of joint significance of the instrument.

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Net Credit Growth	0.010**	0.014**	0.012*	0.012*	0.017**	0.017**
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Share of Active Population		-0.001			-0.001	-0.001
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.067			-0.070	-0.069
		(0.068)			(0.074)	(0.074)
Share of Individual Firms		-0.037***			-0.036***	-0.036***
		(0.005)			(0.005)	(0.005)
Share of Higher Education Degrees		0.046***			0.045***	0.045***
		(0.008)			(0.009)	(0.009)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Net Credit Growth (First lag)			-0.003**	-0.003**	-0.003**	-0.003**
			(0.001)	(0.001)	(0.001)	(0.001)
Net Credit Growth (Second lag)				-0.000		0.000
				(0.001)		(0.001)
Observations	1,162	1,162	1,162	1,162	1,162	1,162
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
F-Stat	7.631	9.369	5.853	5.898	7.182	7.345

C Data Appendix

In this section, we further describe the data sources and provide additional information and summary statistics.

C.1 Banking Data

Following Herrera et al. (2011), we use bank-level loan data to measure credit flows. For the same time period it is almost impossible to find firm-level debt structures in Italy. The banking data clearly represents the banking system with detailed balance sheet items. This feature makes it very well suited for analyzing credit flows.

We use bank-level balance sheet data from Historical Archive of Credit in Italy (ASCI) following Natoli et al. (2016). ASCI provides data for nearly 2,600 banks for the time between 1890 and 1973. The data includes yearly balance sheet of banks and there are more than 41,000 balance sheets in the data set. Bank balance sheet data collection is built on Bank of Italy's earlier work. Due to confidentiality of bank supervision statistics, the data ends in 1973. There are 14 types of assets (liquid assets, bonds, mortgages, etc.) and 9 types of liabilities (capital, reserves, deposits, etc.) included in the data set. Additionally, total costs and total revenues are included from the income statements. The important feature of the data set is that the main balance sheet items are comparable over time since the construction is done with a uniform balance sheet structure.

The main categories of banks operating between 1890 and 1973 are banks of national interest (*banche di interesse nazionale*), cooperative banks (*banche popolari*), savings banks (*casse di risparmio ordinarie*), banking houses (*ditte bancarie*), central institutes (*istituti di credito di categoria*), public law banks (*istituti di credito di diritto pubblico*), first class pledge banks (*monti di pieta di prima categoria*), and joint-stock or ordinary credit banks (*società ordinarie di credito*). In addition, other banks are a class of important credit institutions which are not initially but subsequently included in one of the categories above. Table C.1 illustrates the number of credit institutions for each category over the sample period.

The data set has information on the location of the headquarters of each bank. Considering this fact with the restrictive banking legislation of 1936, we can see the provincial and the regional distributions.

The representation of banks are low before 1950 but increases from 1951 to 1969. For example, the number of cooperative banks appears in the ASCI sample is low before 1950, especially in the Center and in the South. It is higher than fifty percent in the North. However, visibility of cooperative banks increases above fifty percent from 1951 to 1969. The northern regions have higher coverage rates compared to the southern regions. The main reason is that larger banks are more likely to be included in the ASCI sample due to reporting and recording practices. Typically, the southern banks are smaller on average and less likely to be included in the sample.

Table C.1: Composition of ASCI sample

Year	Other banks	Banks of national interest	Cooperative banks	Savings banks	Banking houses	Central institutes	Public law banks	First class pledge banks	Joint-stock banks and branches of foreign banks	Total
1950	1	3	64	78	13	3	5	8	116	291
1951	1	3	121	78	28	2	5	9	119	366
1952	1	3	136	78	31	3	5	7	123	387
1953	1	3	135	78	31	2	5	8	124	387
1954	1	3	135	78	31	3	5	8	124	388
1955		3	136	78	31	3	6	8	124	389
1956		3	137	77	30	3	6	8	123	387
1957		3	131	77	29	3	6	7	120	376
1958		3	61	78	10	2	6	7	111	278
1959		3	133	78	29	3	6	8	123	383
1960		3	132	78	29	3	6	8	124	383
1961		3	133	78	29	3	6	8	121	381
1962		3	132	78	23	3	6	8	127	380
1963		3	132	78	23	3	6	8	127	380
1964		3	132	78	21	3	6	8	126	377
1965		3	130	78	21	4	6	8	123	373
1966		3	129	78	21	3	6	7	121	368
1967		3	125	78	18	3	6	7	113	353
1968		3	122	78	16	3	6	7	108	343
1969		3	122	78	15	3	6	7	107	341
1970		3	196	80	29	5	6	7	137	463
1971		3	188	80	24	5	6	7	138	451
1972		3	185	80	21	5	6	7	135	442
1973		3	182	80	18	5	6	7	140	441

The main source of the data set from 1937 to 1973 is the Bank of Italy's supervisory documents. The Banking Act of 1936 requires all banks in a legally defined category to submit interim and annual reports. During this period, the precision of data is higher than previous periods. Official reporting schemes and clear accounting rules since 1948 enable the Bank of Italy to create a more precise and homogenous balance sheet data set. Official guidelines lead to higher quality data with fewer errors and at least 80% of the balance sheets are verified during this period.

C.1.1 Credit Reallocation Measures

In this section, we further provide additional summary statistics for credit reallocation measures at the province level. Following Herrera et al. (2011), we use bank-level loan data to measure credit flows. Table C.2 and Table C.3 present *Net Credit Growth* and *Excess Credit Reallocation* at the province level.

C.2 Province Characteristics

We collect data from historical censuses held in 1951, 1961, and 1971. The main problem is that the data is not digitally available. Only scanned census documents are accessible at the Italian National Institute of Statistics' (ISTAT) website.[16] We manually extracted data for province characteristics using scanned census documents. Particularly, we use general population censuses (*"Censimento Generale Della Popolazione"*) and industry and commerce censuses (*"Censimento Generale Dell'Industria E Del Commercio"*) to obtain province characteristics. Using general

[16] ISTAT catalog can be accessed at ebiblio.istat.it.

Table C.2: Net Credit Growth

Provincia	1950	1951	1952	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970	1971	1972	1973
Agrigento	2.32%	-13.77%	7.07%	57.80%	23.14%	23.26%	20.24%	-6.71%	3.85%	4.49%	16.51%	8.13%	21.46%	11.78%	0.45%	7.43%	7.55%	11.38%	3.47%	16.94%	9.28%	10.89%	20.50%	11.87%
Alessandria	13.31%	18.68%	15.57%	21.99%	27.55%	8.70%	6.87%	7.79%	5.02%	4.72%	37.91%	5.85%	-5.46%	13.71%	7.64%	7.51%	4.42%	5.99%	13.92%	16.14%	4.42%	-1.64%	8.09%	17.35%
Ancona	-0.22%	-0.02%	22.77%	14.08%	3.78%	18.28%	3.77%	13.03%	9.09%	8.00%	16.94%	12.17%	11.36%	7.51%	-1.10%	1.40%	14.45%	25.57%	17.93%	17.87%	3.38%	8.84%	9.51%	23.70%
Aosta	57.11%	57.11%	57.11%	8.92%	34.03%	10.01%	21.77%	13.36%	13.83%	14.30%	14.30%	9.92%	9.06%	-10.73%	-6.54%	9.94%	11.83%	1.08%	14.36%	0.00%	-0.64%	-20.11%	-9.72%	-0.34%
Arezzo	3.35%	10.27%	24.03%	22.03%	11.32%	13.85%	6.40%	17.52%	10.54%	15.98%	24.81%	15.71%	17.14%	10.36%	5.17%	13.01%	13.82%	6.34%	9.99%	12.14%	4.97%	-0.07%	17.10%	6.53%
Ascoli Piceno	1.96%	-4.61%	10.69%	14.58%	7.78%	12.65%	6.54%	5.52%	4.97%	9.98%	26.99%	10.30%	10.39%	5.19%	15.53%	-0.10%	15.40%	13.06%	16.83%	16.34%	-0.19%	10.19%	12.45%	6.15%
Asti	-14.33%	16.98%	19.04%	8.20%	19.49%	9.82%	15.61%	15.00%	4.36%	10.57%	21.47%	21.85%	13.33%	12.04%	0.03%	5.73%	5.49%	4.59%	9.13%	11.00%	12.80%	14.74%	1.34%	3.42%
Avellino	18.18%	18.18%	18.18%	13.30%	37.81%	17.59%	6.25%	9.26%	26.40%	43.55%	43.55%	32.76%	25.49%	5.83%	-4.80%	-46.54%	31.51%	18.68%	43.90%	20.61%	4.40%	2.53%	23.39%	-1.52%
Bari	24.70%	23.40%	12.21%	10.41%	24.98%	5.19%	14.98%	14.90%	10.83%	20.94%	13.17%	10.88%	17.15%	18.86%	-0.01%	16.32%	9.83%	32.06%	14.10%	17.99%	3.41%	-1.87%	20.04%	13.74%
Belluno																					0.00%	7.84%	-10.10%	19.02%
Benevento	0.54%	11.68%	32.56%	30.24%	7.72%	28.28%	30.70%	9.89%	23.82%	11.42%	8.97%	7.38%	11.07%	20.72%	-2.73%	7.87%	0.73%	11.13%	8.98%	21.64%	12.03%	8.43%	7.27%	1.06%
Bergamo	0.91%	3.14%	23.15%	16.29%	20.81%	20.28%	10.90%	9.81%	9.93%	16.31%	27.37%	14.38%	17.02%	4.05%	-2.05%	1.03%	6.76%	14.55%	10.47%	21.29%	1.01%	4.89%	13.28%	8.25%
Bologna	1.45%	3.06%	16.76%	7.68%	12.23%	9.40%	12.80%	8.18%	7.56%	12.71%	15.89%	12.35%	19.91%	16.12%	-2.94%	9.52%	11.94%	17.83%	12.55%	11.45%	9.60%	-1.37%	8.77%	18.14%
Bolzano-Bozen	40.66%	-4.97%	0.79%	15.57%	7.28%	2.83%	16.64%	15.35%	9.82%	11.83%	10.15%	10.08%	7.40%	10.77%	-16.48%	-8.20%	12.17%	19.99%	20.30%	13.35%	4.45%	1.82%	11.66%	16.85%
Brescia	7.08%	-0.88%	17.61%	16.30%	9.36%	9.58%	18.93%	17.05%	20.23%	16.81%	10.15%	11.42%	15.03%	9.62%	-6.07%	1.03%	6.88%	15.11%	13.22%	21.78%	4.91%	15.37%	20.08%	4.51%
Brindisi	30.73%	5.68%	22.88%	11.79%	19.74%	3.21%	22.83%	-6.24%	21.53%	20.92%	-1.36%	3.26%	18.95%	11.97%	5.37%	7.23%	8.87%	20.37%	9.09%	-1.78%	-2.59%	-5.57%	-2.63%	14.48%
Caltanissetta	5.98%	-10.77%	9.52%	2.91%	26.52%	-17.12%	32.81%	16.77%	9.95%	26.25%	-2.99%	-2.99%	-2.99%	-2.99%							12.11%	12.11%	-0.31%	6.38%
Campobasso																					0.00%	17.01%	22.78%	24.64%
Caserta	19.42%	19.42%	19.42%	4.69%	13.86%	13.34%	13.71%	12.61%	16.06%	19.51%	19.51%	18.23%	-10.78%	3.90%	42.70%	8.15%	14.53%	-5.82%	5.87%	9.60%	-7.69%	8.67%	21.20%	27.40%
Catania	46.79%	46.79%	46.79%	-4.00%	23.80%	5.87%	14.60%	18.13%	20.01%	21.89%	21.89%	14.71%	16.88%	18.67%	-2.61%	8.19%	10.80%	12.02%	28.83%	16.81%	11.68%	14.45%	11.23%	12.62%
Catanzaro	34.26%	34.26%	34.26%	40.23%	27.30%	33.42%	9.50%	11.34%	12.36%	13.38%	13.38%	26.75%	27.02%	2.33%	13.92%	3.79%	6.90%	16.28%	29.49%	9.45%	-0.36%	-5.72%	3.78%	3.80%
Chieti	5.19%	-17.43%	28.41%	3.56%	27.58%	1.08%	13.94%	14.54%	10.15%	27.33%	23.51%	9.19%	21.83%	14.17%	2.61%	18.79%	15.98%	9.12%	10.83%	14.05%	6.60%	6.32%	1.10%	9.72%
Como	12.55%	4.06%	15.82%	19.02%	16.48%	17.96%	15.30%	4.45%	10.55%	24.09%	14.16%	14.76%	19.97%	-0.37%	0.64%	5.40%	8.43%	8.17%	10.87%	7.10%	0.64%	7.80%	14.28%	3.70%
Cosenza	16.01%	30.34%	22.82%	24.19%	18.29%	8.20%	17.32%	11.68%	12.82%	12.34%	9.39%	2.86%	4.43%	6.20%	12.78%	6.79%	13.67%	17.90%	18.43%	13.64%	4.47%	2.56%	5.26%	6.57%
Cremona	12.81%	2.51%	19.91%	3.49%	10.57%	20.16%	12.80%	6.22%	7.95%	13.34%	20.85%	15.18%	16.70%	1.17%	2.50%	2.48%	3.27%	12.26%	6.84%	7.47%	8.21%	6.98%	2.73%	-8.12%
Cuneo	7.90%	11.94%	8.57%	18.30%	12.62%	15.55%	6.28%	12.54%	2.39%	17.52%	16.00%	10.22%	16.16%	13.89%	9.23%	4.30%	4.49%	8.37%	9.64%	18.85%	14.25%	8.77%	-3.47%	6.07%
Ferrara	-14.80%	5.37%	16.77%	23.17%	-1.55%	21.58%	9.71%	6.54%	5.61%	6.89%	25.34%	15.86%	-0.08%	8.23%	-1.17%	4.09%	10.83%	7.10%	10.98%	10.05%	-1.69%	-3.69%	1.50%	7.22%
Firenze	0.17%	2.59%	14.01%	6.41%	10.18%	13.75%	10.46%	11.97%	2.21%	6.03%	17.91%	15.68%	19.51%	17.49%	0.64%	3.18%	7.03%	18.46%	10.41%	14.96%	4.65%	3.60%	10.76%	10.05%
Foggia	43.01%	30.56%	15.95%	39.94%	36.85%	23.55%	4.59%	4.32%	21.50%	26.10%	25.36%	33.46%	14.62%	28.48%	7.91%	10.10%	24.61%	15.39%	25.73%	11.25%	6.50%	0.95%	2.75%	22.22%
Forli	-13.04%	-15.66%	17.58%	21.78%	14.14%	19.90%	18.11%	12.58%	8.44%	13.54%	12.97%	20.31%	17.82%	13.25%	-8.28%	0.30%	7.84%	16.44%	18.17%	15.64%	1.71%	2.16%	1.60%	7.51%
Frosinone																					0.00%	6.34%	7.19%	20.31%
Genova	4.44%	4.37%	24.37%	19.31%	9.84%	12.28%	4.09%	5.07%	-2.51%	11.92%	26.47%	13.03%	18.37%	10.62%	4.59%	-8.55%	14.21%	7.44%	11.84%	6.91%	15.39%	-3.51%	17.65%	3.46%
Gorizia	15.36%	1.31%	4.01%	-4.38%	22.32%	16.11%	13.87%	20.00%	-2.98%	7.21%	22.33%	6.42%	6.33%	8.22%	-13.87%	-4.34%	15.99%	13.61%	57.47%	30.74%	23.90%	-5.45%	2.99%	6.12%
Grosseto	27.42%	12.71%	20.75%	22.36%	14.60%	6.32%	5.84%	23.07%	9.35%	44.65%	70.38%	6.79%	28.97%	7.09%	-4.69%	12.82%	40.79%	24.26%	15.99%	11.86%	7.73%	7.73%	1.65%	10.67%
Imperia	21.61%	12.92%	2.74%	25.12%	18.24%	31.34%	14.12%	27.71%	19.31%	28.94%	21.54%	19.03%	12.75%	11.68%	4.78%	-24.86%	-5.89%	29.76%	4.42%	11.17%	-10.50%	-10.10%	1.61%	5.42%
La Spezia	25.17%	-2.16%	11.31%	13.57%	12.68%	7.92%	10.63%	3.78%	6.20%	11.78%	14.45%	6.86%	10.35%	11.05%	4.35%	5.07%	7.89%	15.59%	12.66%	14.04%	4.17%	3.31%	6.90%	11.57%
L'Aquila	14.11%	19.30%	12.86%	25.43%	10.59%	11.51%	4.38%	10.96%	14.71%	11.13%	14.85%	11.50%	25.61%	18.16%	-0.79%	9.55%	9.01%	6.53%	12.98%	16.30%	11.28%	11.64%	11.44%	4.13%
Latina	39.49%	13.68%	17.03%	33.74%	41.86%	39.16%	0.75%	10.53%	-3.33%	0.00%	12.18%	-3.91%	16.79%	6.42%	11.01%	12.43%	11.66%	8.62%	8.66%	23.91%	6.66%	9.52%	3.76%	2.22%
Lecce	10.61%	-1.83%	13.72%	23.48%	26.69%	0.66%	14.91%	4.78%	0.98%	3.93%	14.01%	21.38%	21.37%	10.94%	8.07%	10.53%	13.61%	10.50%	15.07%	19.54%	10.28%	12.99%	9.24%	12.33%
Livorno	8.62%	18.05%	12.51%	12.78%	10.68%	0.82%	6.92%	1.94%	-4.30%	3.22%	7.27%	11.74%	12.33%	14.03%	1.47%	2.10%	4.96%	12.30%	22.57%	14.81%	12.95%	13.64%	18.57%	-0.98%
Lucca	20.33%	1.69%	18.65%	5.30%	22.78%	14.53%	12.50%	14.19%	18.59%	11.17%	11.08%	3.25%	5.01%	19.19%	-6.97%	7.99%	6.67%	12.32%	6.02%	-0.04%	3.82%	-13.45%	2.20%	14.33%
Macerata	-2.47%	-9.17%	4.23%	17.54%	6.44%	8.08%	24.51%	-0.35%	19.70%	5.07%	15.50%	16.92%	15.31%	8.02%	9.32%	27.59%	17.81%	22.21%	13.44%	7.38%	5.46%	3.06%	11.92%	7.97%
Mantova	-11.64%	0.03%	24.50%	9.43%	-3.56%	22.56%	15.82%	11.78%	10.92%	11.42%	15.04%	-6.21%	12.42%	11.09%	-7.66%	8.21%	6.48%	12.63%	12.46%	18.42%	0.89%	1.79%	3.02%	16.04%
Massa-Carrara	31.14%	10.19%	21.43%	34.80%	24.35%	26.05%	12.30%	15.71%	7.67%	15.31%	15.54%	6.87%	11.38%	16.96%	6.30%	9.88%	9.34%	18.06%	9.08%	9.58%	19.59%	8.34%	13.11%	9.97%
Matera	11.93%	-2.25%	20.67%	1.68%	24.07%	13.01%	6.64%	2.13%	-13.70%	-3.30%	31.26%	10.63%	11.24%	19.67%	14.42%	17.50%	16.48%	17.02%	15.90%	10.51%	5.03%	2.28%	2.93%	24.15%
Messina	34.12%	6.95%	25.58%	0.54%	0.60%	9.76%	12.11%	22.13%	-14.64%	14.94%	15.89%	37.51%	16.69%	1.74%	-8.85%	3.26%	3.59%	9.61%	16.07%	4.01%	16.98%	5.55%	-2.78%	19.94%
Milano	17.29%	11.05%	23.26%	15.03%	6.09%	12.09%	9.89%	9.15%	-1.89%	11.72%	17.42%	16.57%	11.59%	4.27%	-2.27%	2.62%	9.97%	6.91%	7.45%	4.36%	12.80%	7.67%	19.63%	2.86%
Modena	2.86%	0.81%	17.27%	9.79%	9.30%	9.23%	11.10%	12.22%	12.22%	20.64%	11.80%	10.25%	10.24%	7.71%	-2.50%	2.11%	11.04%	14.41%	9.25%	16.03%	6.53%	0.55%	12.17%	22.35%
Napoli	5.38%	10.38%	22.46%	13.26%	11.08%	7.80%	-0.82%	7.12%	11.52%	13.48%	23.80%	8.15%	15.99%	-2.84%	-1.57%	13.05%	10.76%	3.10%	8.70%	6.68%	11.86%	1.93%	20.81%	-1.85%
Novara	8.71%	10.08%	24.95%	10.73%	9.96%	7.19%	16.52%	2.60%	6.41%	14.53%	14.15%	4.08%	12.19%	0.97%	-0.77%	-0.11%	8.50%	9.08%	1.36%	14.12%	7.16%	3.82%	13.76%	-10.71%
Padova	18.75%	-7.33%	18.76%	22.41%	11.08%	16.88%	16.75%	6.41%	11.11%	15.40%	22.10%	12.95%	13.31%	4.47%	-7.06%	4.66%	7.80%	16.29%	21.49%	9.92%	3.14%	4.52%	3.91%	19.06%
Palermo	19.44%	5.46%	18.97%	9.32%	5.35%	6.69%	9.73%	13.34%	0.27%	5.56%	10.88%	13.88%	8.45%	-3.40%	-0.76%	0.14%	8.53%	6.61%	14.63%	6.91%	13.73%	5.24%	3.71%	14.35%
Parma	-4.73%	-0.42%	27.95%	17.89%	11.79%	17.86%	7.74%	4.27%	16.68%	11.49%	15.83%	9.97%	15.72%	10.36%	-6.13%	6.58%	7.92%	10.38%	11.15%	10.11%	8.96%	9.59%	7.61%	20.07%
Pavia	20.84%	1.61%	21.26%	20.95%	19.60%	10.28%	15.88%	7.28%	12.17%	16.58%	9.49%	16.05%	11.41%	11.93%	2.06%	-3.35%	4.78%	6.05%	6.35%	14.06%	10.38%	7.36%	8.54%	21.33%
Perugia	3.05%	-6.60%	8.14%	14.70%	14.53%	9.95%	11.96%	5.50%	20.26%	4.48%	15.85%	10.68%	12.40%	3.37%	7.63%	7.64%	12.75%	18.21%	15.10%	10.92%	4.11%	8.98%	11.93%	14.75%
Pesaro e Urbino	21.38%	-20.24%	28.87%	5.03%	10.54%	3.85%	15.91%	11.94%	15.91%	20.58%	17.36%	13.01%	23.17%	4.94%	-12.82%	-1.61%	12.04%	20.10%	21.60%	20.37%	6.38%	7.05%	6.72%	7.14%
Pescara	26.93%	-34.88%	5.43%	12.78%	38.86%	-16.81%	2.43%	30.23%	17.10%	25.34%	14.41%	12.41%	26.32%	9.09%	-10.97%	7.52%	16.67%	16.77%	14.09%	13.63%	15.82%	6.18%	11.97%	1.50%
Piacenza	6.84%	-12.43%	14.70%	16.04%	4.22%	19.18%	7.56%	5.39%	22.61%	3.00%	3.16%	12.77%	3.65%	25.74%	-6.93%	-7.58%	1.74%	23.46%	8.39%	15.46%	7.16%	1.95%	2.53%	12.39%
Pisa	-2.04%	-4.03%	9.48%	17.62%	22.47%	17.34%	6.56%	3.62%	8.52%	6.89%	10.79%	12.65%	10.35%	17.15%	-4.51%	10.01%	10.75%	16.20%	16.69%	16.78%	11.07%	-1.68%	14.54%	13.43%
Pistoia	34.32%	-2.77%	14.04%	7.60%	7.16%	5.89%	11.84%	24.02%	3.08%	1.88%	14.76%	11.61%	9.73%	27.20%	-3.63%	-0.66%	11.14%	12.35%	12.90%	10.23%	10.40%	1.25%	12.58%	11.73%
Pordenone																			1.74%	14.10%	7.97%	7.43%	3.22%	23.69%
Potenza	21.31%	22.78%	29.56%	28.80%	33.19%	27.01%	8.60%	23.32%	25.92%	22.23%	38.46%	16.97%	4.00%	2.29%	5.31%	6.36%	0.70%	11.20%	17.38%	3.66%	-7.46%	-3.48%	7.67%	28.07%
Ragusa	10.47%	22.83%	22.48%	19.77%	19.54%	25.66%	25.62%	15.43%	16.68%	11.81%	10.40%	14.55%	14.25%	9.89%	3.66%	-0.03%	10.29%	12.41%	16.70%	9.18%	3.95%	0.40%	1.99%	7.43%
Ravenna	4.16%	-27.75%	5.62%	22.46%	8.40%	24.45%	5.37%	13.80%	3.92%	6.05%	24.11%	15.94%	13.98%	16.83%	-2.20%	6.21%	2.48%	15.75%	14.77%	10.99%	4.39%	-3.48%	-4.40%	3.51%
Reggio di Calabria	1.11%	7.14%	25.23%	14.81%	21.81%	19.25%	11.53%	5.06%	10.22%	4.27%	8.63%	10.20%	8.66%	12.69%	16.99%	15.44%	19.10%	12.06%	13.89%	8.68%	4.91%	2.07%	4.08%	-1.83%
Reggio nell'Emilia	-1.15%	-2.91%	18.47%	10.91%	9.87%	1.08%	7.79%	13.86%	10.27%	17.64%	21.31%	7.09%	8.67%	5.64%	0.46%	4.58%	14.39%	14.15%	4.25%	8.70%	5.31%	1.89%	3.22%	20.38%
Rieti	-10.80%	-20.18%	25.13%	17.02%	25.68%	23.49%	11.39%	4.98%	-1.40%	9.82%	19.02%	23.63%	17.73%	17.88%	0.55%	1.74%	15.85%	10.42%	15.82%	16.68%	9.99%	1.57%	3.44%	11.87%
Roma	16.69%	12.81%	17.98%	16.80%	7.84%	13.27%	9.65%	-2.10%	-7.59%	9.68%	16.91%	15.97%	11.00%	12.36%	0.39%	1.82%	9.52%	11.76%	10.43%	12.28%	13.16%	8.96%	18.19%	-0.33%
Rovigo	-2.25%	-4.47%	46.40%	-3.07%	28.60%	3.19%	6.57%	-14.07%	33.24%	5.68%	-13.18%	7.79%	19.47%	19.08%	-2.52%	-8.17%	10.31%	-1.66%	27.88%	0.05%	4.79%	-1.43%	-2.30%	23.77%
Salerno	-13.29%	14.11%	30.27%	23.09%	22.49%	17.65%	13.58%	6.40%	11.07%	21.79%	30.79%	22.81%	12.61%	14.03%	12.73%	6.92%	12.07%	22.80%	12.25%	14.75%	7.20%	20.43%	8.37%	21.34%
Sassari	5.53%	37.04%	24.24%	30.76%	24.90%	12.87%	11.23%	5.76%	7.17%	25.57%	28.82%	27.78%	28.87%	34.74%	7.23%	8.02%	25.24%	7.96%	16.17%	15.84%	1.22%	5.45%	0.85%	-4.81%
Savona	15.64%	26.17%	18.40%	30.30%	4.27%	19.26%	9.28%	24.77%	10.90%	11.20%	23.11%	13.16%	11.38%	7.42%	4.18%	0.19%	5.25%	7.71%	5.15%	20.44%	2.24%	-2.86%	5.46%	11.54%
Siena	-2.34%	5.77%	20.03%	19.11%	20.79%	14.30%	7.32%	6.86%	5.66%	18.79%	13.38%	10.67%	3.51%	12.45%	5.18%	8.49%	18.24%	16.20%	19.83%	4.89%	1.32%	-4.25%	22.85%	-9.34%
Siracusa	-60.95%	1.39%	27.32%	18.84%	29.42%	23.91%	6.77%	12.41%	18.60%	24.80%	24.80%	18.88%	14.32%	3.80%	7.62%	11.79%	10.06%	16.21%	19.47%	2.11%	18.07%	6.72%	17.68%	10.31%
Sondrio	23.66%	2.39%	27.04%	21.25%	14.67%	18.69%	17.53%	12.78%	13.70%	12.03%	16.53%	10.44%	8.89%	4.01%	-3.07%	6.04%	7.59%	11.59%	13.88%	8.67%	5.58%	2.75%	5.11%	11.47%
Taranto	29.07%	31.71%	42.60%	7.55%	43.00%	-5.28%	21.89%	33.97%	-9.78%	-16.60%	40.11%	12.45%	9.50%	12.17%	19.81%	26.27%	38.45%	10.45%	20.72%	15.19%	6.50%	-2.24%	14.83%	12.80%
Teramo	-3.24%	-13.69%	22.20%	2.00%	25.86%	43.50%	22.42%	24.66%	9.28%	12.34%	19.03%	21.94%	36.71%	4.08%	-1.66%	13.49%	15.77%	15.07%	7.21%	9.93%	14.00%	22.27%	12.40%	16.11%
Terni	7.56%	-5.29%	7.77%	17.80%	23.07%	11.98%	3.76%	10.53%	3.82%	5.66%	12.67%	7.59%	15.50%	7.39%	4.90%	1.10%	6.04%	13.17%	22.40%	11.50%	9.44%	4.99%	9.27%	9.33%
Torino	13.36%	6.28%	18.49%	11.50%	21.13%	11.46%	16.66%	18.67%	13.97%	14.41%	21.41%	18.70%	15.08%	10.54%	-4.32%	1.83%	9.75%	11.16%	15.61%	5.79%	7.72%	-2.59%	12.70%	8.13%
Trapani	14.35%	9.63%	25.43%	17.72%	21.95%	16.68%	8.82%	8.36%	9.93%	22.45%	19.40%	18.10%	22.14%	8.46%	-2.02%	4.88%	18.63%	15.74%	8.40%	15.77%	10.42%	7.84%	6.50%	14.83%
Trento	23.84%	13.73%	12.40%	10.94%	10.04%	13.64%	11.64%	13.83%	7.11%	16.05%	15.50%	9.74%	12.88%	6.64%	-7.88%	1.85%	12.92%	12.91%	17.22%	5.80%	3.22%	4.55%	12.01%	14.33%
Treviso	38.38%	12.52%	13.15%	14.10%	5.33%	12.86%	-0.04%	25.96%	6.76%	14.89%	26.71%	13.50%	1.41%	7.45%	-2.53%	5.15%	9.94%	14.96%	10.99%	24.26%	0.30%	3.77%	9.06%	19.26%
Trieste	35.37%	28.63%	5.62%	-6.43%	-9.89%	9.40%	20.34%	19.43%	8.44%	21.70%	-2.96%	13.67%	15.99%	43.71%	-3.07%	7.96%	19.24%	20.19%	34.32%	29.03%	3.34%	10.11%	-11.68%	23.29%
Udine	11.90%	2.97%	23.96%	15.45%	11.32%	2.38%	12.27%	17.73%	9.93%	12.61%	13.56%	14.22%	9.20%	5.38%	0.66%	5.68%	8.63%	17.82%	14.13%	18.92%	7.70%	-0.74%	2.85%	8.22%
Varese	8.21%	8.14%	14.42%	3.09%	18.05%	5.96%	11.99%	5.89%	17.45%	16.90%	19.64%	11.30%	14.78%	4.85%	-1.04%	0.04%	9.26%	0.16%	5.08%	14.53%	5.69%	12.19%	20.04%	9.63%
Venezia	25.86%	-4.35%	5.92%	17.43%	10.09%	8.92%	71.23%	7.22%	8.58%	23.46%	16.19%	3.13%	22.25%	4.87%	-21.52%	7.56%	20.61%	11.67%	10.17%	15.60%	-8.60%	-11.98%	2.06%	12.36%
Vercelli	-7.61%	-9.37%	34.55%	20.94%	18.13%	-5.05%	5.06%	11.76%	2.37%	9.75%	10.95%	4.18%	9.00%	16.54%	12.67%	-0.93%	3.48%	5.38%	5.84%	17.80%	15.88%	8.83%	11.42%	16.82%
Verona	3.40%	-9.81%	14.23%	13.49%	10.11%	9.81%	15.10%	14.74%	8.21%	14.44%	12.52%	14.65%	16.32%	12.77%	-6.18%	4.05%	7.21%	14.65%	23.93%	11.53%	7.82%	5.15%	6.18%	19.51%
Vicenza	3.73%	5.29%	25.82%	11.36%	10.00%	8.81%	12.53%	11.22%	9.79%	20.21%	14.30%	7.40%	12.58%	9.32%	-2.59%	4.71%	7.53%	17.66%	15.49%	11.63%	-3.33%	1.17%	11.32%	21.34%
Viterbo	-21.30%	-0.25%	27.84%	30.10%	5.35%	20.63%	-12.68%	-1.43%	10.78%	3.98%	12.04%	16.63%	25.73%	0.31%	11.58%	14.66%	17.10%	18.79%	7.53%	-1.45%	13.39%	23.47%	14.12%	14.85%

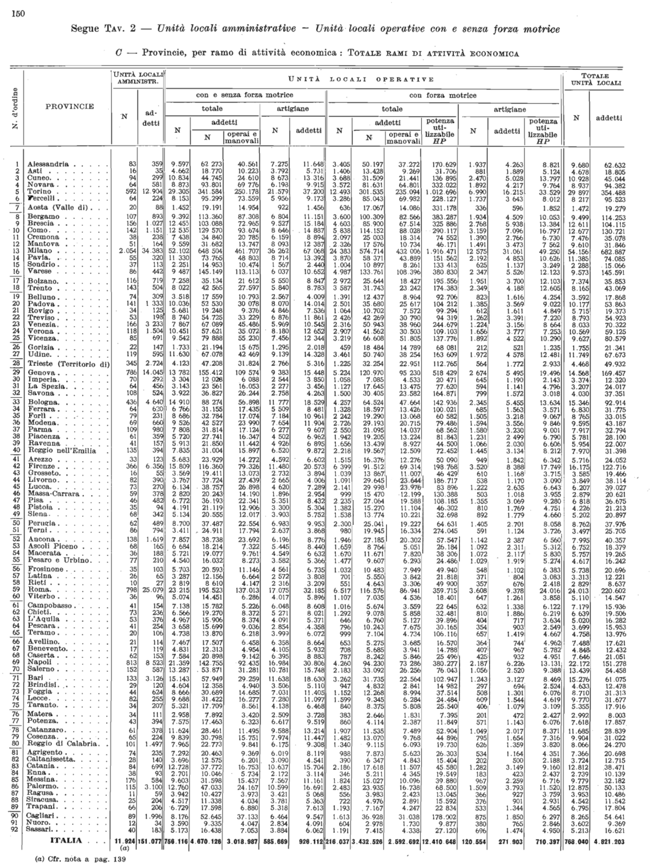
Table C.3: Excess Credit Reallocation

Provincia	1950	1951	1952	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970	1971	1972	1973
Agrigento	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.40%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.97%	0.00%	0.00%	0.00%	0.86%	0.00%	0.00%	0.00%	0.00%	0.00%
Alessandria	0.00%	0.66%	0.00%	0.00%	0.00%	0.00%	0.13%	3.97%	11.47%	8.08%	0.00%	4.19%	4.56%	4.75%	14.99%	2.60%	2.79%	0.79%	0.00%	0.00%	1.01%	2.66%	2.32%	0.28%
Ancona	13.55%	4.09%	0.00%	1.01%	3.67%	0.00%	1.45%	0.00%	0.00%	3.21%	0.00%	0.00%	0.00%	10.02%	6.47%	2.84%	0.00%	0.00%	0.00%	0.00%	1.40%	0.32%	0.00%	0.00%
Aosta	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Arezzo	0.00%	0.38%	0.00%	0.00%	0.00%	0.00%	0.00%	0.57%	0.00%	0.00%	0.00%	0.00%	0.09%	0.00%	0.00%	0.00%	0.00%	0.00%	5.10%	3.43%	0.00%	0.00%	0.38%	0.40%
Ascoli Piceno	1.61%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.81%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.81%	0.00%	0.00%	0.00%	0.00%	4.33%	0.00%	0.00%	0.00%
Asti	2.05%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.27%	0.00%	0.00%	0.00%	0.00%	0.00%	1.47%	0.22%	0.19%	0.00%	0.00%	0.00%	3.90%	0.33%	0.48%	0.00%
Avellino	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Bari	0.49%	4.10%	2.46%	4.08%	0.00%	0.72%	2.33%	4.89%	0.40%	1.07%	0.00%	0.51%	0.00%	0.42%	4.20%	0.45%	0.00%	0.00%	0.31%	0.00%	0.00%	4.28%	0.00%	0.02%
Belluno																					0.00%	0.00%	0.00%	0.00%
Benevento	4.15%	2.25%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.95%
Bergamo	7.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.69%	0.00%	0.00%	0.00%	0.00%	0.03%	0.52%	2.56%	0.05%	0.00%	0.02%	0.00%	3.48%	2.06%	0.06%	0.03%
Bologna	10.41%	5.04%	0.00%	0.00%	2.96%	1.18%	0.01%	0.00%	0.06%	0.00%	0.00%	0.00%	0.00%	0.72%	1.07%	1.34%	1.53%	0.25%	0.08%	0.36%	0.85%	0.85%	1.84%	0.08%
Bolzano-Bozen	0.00%	0.00%	5.20%	0.00%	0.63%	1.83%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.00%	0.00%	0.00%	0.00%	0.00%	0.36%	0.55%	0.90%	0.00%
Brescia	0.00%	16.09%	0.11%	0.35%	0.00%	0.00%	0.00%	0.24%	0.00%	0.00%	0.55%	0.24%	0.00%	0.46%	0.07%	2.33%	0.16%	0.05%	0.00%	0.00%	3.80%	0.11%	0.17%	0.00%
Brindisi	0.00%	15.35%	0.00%	0.00%	0.00%	10.96%	0.00%	10.25%	0.00%	0.00%	9.77%	4.78%	0.00%	0.00%	3.71%	6.34%	0.00%	0.00%	0.00%	6.24%	3.88%	13.21%	2.60%	1.38%
Caltanissetta	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%							0.00%	0.00%	5.16%	1.38%
Campobasso																					0.00%	0.00%	1.08%	0.00%
Caserta	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.09%	1.29%	0.00%
Catania	4.08%	4.08%	4.08%	0.79%	0.00%	0.27%	0.00%	0.00%	0.00%	0.00%	0.00%	1.46%	0.00%	7.93%	4.04%	2.64%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.11%	1.12%
Catanzaro	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.05%	2.68%	27.36%
Chieti	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Como	0.00%	6.95%	0.00%	0.00%	0.00%	0.00%	0.00%	2.56%	0.00%	0.00%	0.00%	0.00%	0.00%	9.76%	1.72%	1.88%	0.25%	0.00%	0.00%	0.00%	0.68%	1.06%	0.26%	1.00%
Cosenza	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.12%	0.13%
Cremona	0.00%	0.51%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.62%	0.00%	0.09%	0.00%	0.00%	1.72%	0.86%	0.00%	0.00%	0.00%	0.11%	0.00%	0.00%	0.05%	0.00%	3.80%
Cuneo	1.80%	2.53%	11.01%	0.00%	5.26%	2.37%	6.57%	1.12%	4.73%	0.00%	0.00%	0.56%	1.61%	0.00%	1.93%	2.31%	0.62%	0.15%	0.36%	0.00%	0.02%	1.37%	3.99%	1.20%
Ferrara	0.29%	3.44%	0.00%	0.00%	3.26%	0.00%	0.16%	4.64%	3.57%	0.93%	0.00%	0.00%	4.38%	0.00%	2.98%	3.27%	0.00%	0.00%	0.00%	0.00%	3.50%	0.70%	0.80%	7.94%
Firenze	2.83%	4.46%	0.00%	0.22%	0.03%	0.00%	1.32%	0.66%	8.10%	1.20%	0.17%	0.00%	0.00%	0.05%	3.13%	4.61%	0.01%	0.00%	0.00%	0.00%	0.30%	0.08%	0.00%	0.03%
Foggia	0.00%	8.78%	0.00%	0.00%	0.71%	1.98%	14.03%	5.78%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	5.05%	0.00%	0.00%	0.00%	0.00%	0.27%	5.12%	4.11%	0.00%
Forli	5.64%	0.25%	0.00%	0.00%	0.00%	0.00%	0.00%	1.56%	0.00%	0.38%	0.00%	0.00%	0.00%	0.00%	2.54%	4.17%	0.37%	0.00%	0.00%	0.00%	2.58%	3.37%	2.51%	0.00%
Frosinone																					0.00%	0.00%	5.37%	0.00%
Genova	0.01%	0.00%	0.04%	0.01%	0.66%	0.10%	0.13%	0.06%	1.39%	0.07%	0.00%	0.00%	0.01%	0.06%	0.55%	0.29%	0.01%	0.00%	0.44%	0.00%	0.00%	0.09%	0.00%	0.00%
Gorizia	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.31%	0.00%	0.00%
Grosseto	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Imperia	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
La Spezia	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.18%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
L'Aquila	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.13%	0.00%	0.00%	0.12%	0.00%	0.85%	0.00%	0.00%	1.09%	0.00%
Latina	0.00%	1.26%	0.00%	0.00%	0.00%	0.00%	1.87%	4.30%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.32%	14.04%
Lecce	0.00%	0.00%	5.35%	1.69%	0.57%	11.93%	1.19%	1.86%	0.00%	0.00%	0.86%	0.00%	6.40%	0.00%	3.06%	2.28%	0.00%	0.97%	0.00%	0.00%	1.30%	2.48%	3.77%	0.35%
Livorno	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Lucca	0.00%	7.87%	0.00%	1.51%	0.51%	8.82%	0.00%	0.00%	0.00%	0.00%	0.00%	4.30%	0.00%	0.00%	0.33%	0.09%	0.00%	0.00%	0.98%	12.94%	0.00%	1.10%	0.00%	0.00%
Macerata	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.46%	0.34%
Mantova	0.00%	0.00%	0.00%	0.00%	0.38%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.53%	0.00%	0.43%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.08%	0.40%	0.30%	0.00%
Massa-Carrara	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Matera	0.00%	0.00%	0.00%	2.72%	8.90%	0.00%	9.91%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Messina	0.00%	1.41%	0.00%	0.78%	3.08%	0.00%	0.34%	0.00%	0.53%	0.00%	0.00%	0.00%	0.00%	0.25%	0.61%	0.00%	0.00%	0.12%	0.00%	0.00%	0.00%	0.00%	3.75%	0.00%
Milano	0.06%	0.79%	0.09%	1.02%	0.44%	0.59%	0.15%	1.24%	5.12%	0.04%	0.16%	0.40%	1.83%	1.29%	3.59%	0.75%	0.48%	0.74%	0.63%	1.62%	0.53%	4.93%	0.27%	4.88%
Modena	2.59%	4.33%	0.46%	1.41%	0.07%	0.17%	0.00%	0.40%	0.06%	0.00%	0.07%	0.29%	0.23%	0.00%	0.90%	3.59%	0.25%	0.00%	0.00%	0.00%	0.89%	1.38%	0.44%	0.00%
Napoli	0.03%	0.01%	0.00%	0.16%	0.00%	0.00%	0.82%	0.07%	0.00%	0.00%	0.00%	0.00%	0.02%	1.48%	0.88%	0.84%	0.20%	0.21%	0.00%	0.17%	0.45%	0.48%	0.44%	3.08%
Novara	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.65%	0.79%	0.00%	0.00%	0.00%	0.00%	0.00%	0.13%	0.90%
Padova	2.22%	2.47%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.44%	3.94%	0.00%	0.00%	0.00%	0.00%	0.00%	0.46%	0.00%	0.41%	0.00%
Palermo	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.75%	0.00%	0.00%	0.00%	0.00%	7.25%	2.63%	3.66%	0.00%	0.00%	0.00%	0.00%	0.00%	0.78%	0.00%	0.00%
Parma	6.34%	1.19%	0.00%	0.00%	1.04%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	2.86%	0.00%	0.00%	0.01%	0.00%	0.00%	0.62%	2.78%	0.19%	0.09%
Pavia	0.00%	9.26%	0.00%	0.00%	0.00%	0.00%	1.53%	0.07%	0.00%	0.00%	15.12%	0.00%	3.41%	0.00%	10.64%	0.86%	1.90%	0.00%	0.73%	0.00%	0.61%	3.92%	0.90%	0.00%
Perugia	4.93%	3.72%	6.59%	0.00%	0.00%	1.71%	0.00%	0.78%	0.00%	3.50%	0.00%	0.00%	0.00%	4.86%	0.85%	1.36%	0.00%	0.00%	0.00%	0.00%	2.37%	1.27%	0.00%	1.70%
Pesaro e Urbino	0.00%	0.79%	0.00%	6.79%	0.00%	0.26%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.89%	0.00%	10.25%	0.00%	0.00%	0.00%	0.00%	1.87%	0.09%	2.88%	0.00%
Pescara	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Piacenza	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.49%	0.00%	0.00%	0.00%	0.00%	0.00%	3.88%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Pisa	6.17%	1.90%	0.00%	0.00%	0.00%	0.00%	2.20%	0.71%	0.00%	0.00%	0.00%	0.98%	0.86%	0.13%	0.00%	0.00%	0.00%	0.32%	0.00%	1.80%	0.00%	0.00%	0.02%	0.00%
Pistoia	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.23%	1.09%	0.00%	1.68%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Pordenone																			0.00%	0.00%	0.00%	0.51%	8.51%	2.06%
Potenza	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.79%	0.00%	0.00%	0.00%	0.00%	7.70%	9.15%	0.00%	0.00%	1.87%	0.00%	0.00%	14.20%	10.43%	8.26%	0.42%	0.00%
Ragusa	7.20%	0.84%	0.00%	2.80%	0.00%	0.00%	0.98%	0.00%	0.00%	2.88%	0.68%	0.06%	0.00%	0.25%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.71%	0.00%	0.00%
Ravenna	4.88%	0.36%	6.19%	0.00%	2.49%	0.00%	7.21%	1.49%	2.85%	0.00%	0.00%	2.45%	0.00%	0.00%	5.43%	3.21%	1.37%	0.00%	0.00%	0.53%	3.70%	0.57%	4.08%	2.17%
Reggio di Calabria	0.00%	0.00%	0.00%	0.05%	0.00%	0.00%	4.37%	2.43%	0.00%	0.00%	0.43%	0.00%	0.27%	0.00%	2.34%	0.00%	0.00%	0.00%	0.00%	0.00%	3.47%	8.74%	0.82%	5.30%
Reggio nell'Emilia	0.78%	0.00%	0.00%	0.09%	0.16%	4.03%	0.00%	0.00%	0.00%	0.00%	0.35%	0.02%	0.00%	0.51%	4.46%	0.15%	0.00%	0.26%	0.00%	0.16%	0.00%	7.91%	3.89%	0.00%
Rieti	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.09%	0.00%	1.03%	8.16%	0.00%	0.00%	0.00%	0.00%	1.71%	5.02%	1.65%	0.00%
Roma	0.08%	1.13%	0.33%	0.35%	0.00%	0.02%	0.00%	5.46%	2.93%	0.00%	2.48%	0.23%	2.07%	0.49%	4.40%	3.10%	0.21%	0.00%	1.45%	0.29%	0.24%	0.07%	0.23%	6.36%
Rovigo	0.00%	0.00%	0.00%	0.00%	0.00%	2.34%	1.33%	0.00%	0.00%	0.00%	3.37%	0.00%	0.00%	0.00%	0.00%	6.43%	2.78%	1.80%	0.00%	6.97%	0.00%	2.27%	9.39%	0.00%
Salerno	9.45%	1.36%	0.00%	0.00%	0.00%	1.42%	0.00%	0.13%	0.00%	0.00%	0.00%	0.00%	1.28%	0.00%	0.77%	1.46%	0.00%	0.00%	0.00%	0.00%	0.00%	3.33%	1.75%	0.38%
Sassari	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.08%	0.00%	0.00%	0.00%	0.00%	0.81%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.85%	0.00%	1.82%	1.54%
Savona	0.00%	0.00%	0.00%	0.00%	1.56%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.92%	9.10%	2.12%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.15%
Siena	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.40%	0.00%	0.00%	0.00%
Siracusa	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.26%	0.64%	0.00%	7.15%
Sondrio	0.00%	0.76%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Taranto	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.87%	0.00%	0.00%
Teramo	0.00%	0.00%	0.00%	7.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.27%	10.22%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Terni	3.82%	2.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	10.59%	0.20%	0.00%	0.00%	0.00%	2.25%	0.00%	4.37%	1.04%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.51%
Torino	0.40%	0.40%	0.11%	0.94%	0.16%	0.41%	0.91%	0.00%	0.69%	0.00%	0.00%	0.17%	0.81%	1.75%	0.51%	1.63%	0.00%	1.67%	0.00%	1.13%	0.73%	0.80%	0.67%	0.47%
Trapani	0.00%	0.00%	0.00%	1.63%	0.00%	0.00%	0.74%	0.54%	0.92%	0.00%	0.00%	0.00%	0.00%	0.00%	4.44%	0.11%	0.00%	0.00%	2.48%	0.00%	0.00%	2.25%	0.91%	0.00%
Trento	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%	0.50%	0.00%	1.41%	0.00%	0.00%	0.00%	0.00%	0.00%	1.01%	0.85%	0.60%
Treviso	0.00%	0.14%	0.00%	0.00%	0.09%	0.05%	4.89%	0.00%	0.00%	0.00%	0.00%	0.00%	10.20%	0.27%	0.84%	2.86%	1.20%	0.00%	0.00%	0.00%	3.91%	0.61%	2.33%	0.00%
Trieste	0.53%	0.00%	0.00%	0.00%	1.57%	0.00%	0.57%	0.00%	0.00%	0.00%	4.03%	0.00%	0.00%	0.84%	0.65%	0.00%	0.00%	0.00%	0.00%	0.54%	0.00%	0.00%	0.27%	0.00%
Udine	0.00%	0.00%	0.00%	0.31%	0.03%	0.68%	0.14%	0.22%	0.00%	0.00%	0.00%	0.06%	0.00%	0.10%	4.57%	1.06%	0.99%	0.00%	0.02%	0.00%	2.29%	3.60%	2.91%	5.40%
Varese	0.00%	1.08%	7.43%	2.69%	0.00%	3.94%	0.00%	1.70%	0.40%	0.00%	0.00%	2.23%	0.83%	0.00%	2.16%	2.84%	0.00%	1.93%	0.00%	0.65%	0.00%	0.00%	0.00%	0.00%
Venezia	0.00%	7.42%	10.94%	0.02%	4.46%	0.00%	0.25%	0.00%	0.00%	2.37%	0.00%	8.33%	0.00%	0.18%	0.00%	4.57%	0.00%	0.00%	0.00%	0.91%	1.22%	0.18%	16.12%	7.59%
Vercelli	35.80%	3.66%	0.00%	0.00%	1.02%	6.06%	0.00%	0.00%	3.88%	0.00%	0.00%	2.80%	0.00%	2.06%	2.54%	3.42%	0.75%	0.00%	4.52%	0.00%	0.00%	0.98%	0.00%	0.00%
Verona	0.00%	0.00%	0.00%	0.00%	0.00%	0.43%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.00%	0.00%
Vicenza	1.89%	0.03%	0.00%	0.00%	0.76%	0.00%	0.65%	0.00%	7.04%	0.00%	0.22%	0.02%	0.01%	1.64%	0.83%	0.17%	0.58%	0.14%	0.00%	0.00%	0.59%	0.54%	0.51%	0.00%
Viterbo	17.22%	8.96%	0.00%	0.00%	18.27%	0.00%	4.10%	0.00%	0.00%	9.05%	0.00%	0.00%	0.00%	8.46%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.63%	0.00%	0.00%

summary data (*"Dati Generali Riassuntivi"*) from censuses, we can extract a good amount of useful data at province level.

We obtain economic province characteristics from industry and commerce censuses. We use *share of individual firms* as an indicator for economic development[17]. We also get number of firms, workers, and bank branches from industry and commerce censuses. We add *number of workers per firm* and *number of bank branches per firm* to control for economic and financial characteristics of provinces. Figure C.1 presents an example from the 1951 census of industry and commerce.

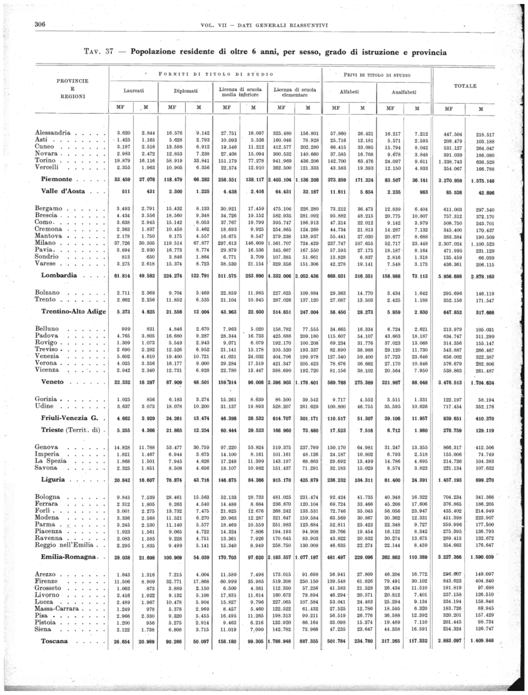
Figure C.1: An example from the 1951 census of industry and commerce

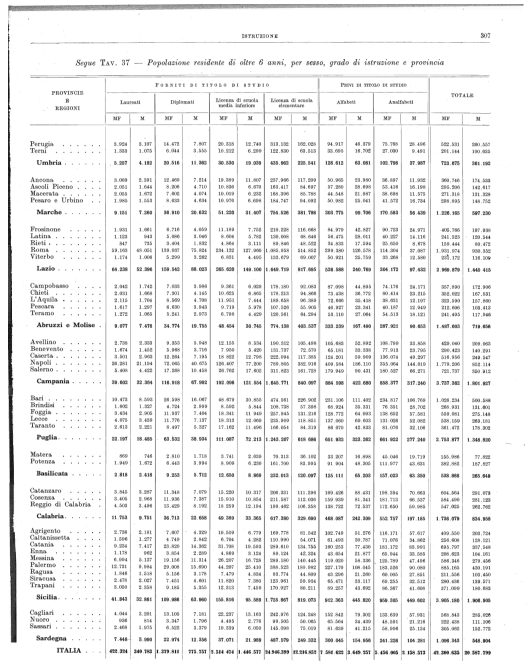


We acquire population and education related characteristics from general population censuses. We use *share of active population* as an indicator of labor force participation and *share of higher education degrees* as an indicator for level of education at a province. Figure C.2 presents an example from the 1951 census of population related with education.

[17] Guiso et al. (2004a) show that individuals are more likely to start a business in more developed regions in Italy.

Figure C.2: An example from the 1951 census of population related with education





C.3 Patent Data

The purpose of this section is to clarify the data collecting process for patents. We will compare two patent data sets collected for this study and explain the reason why we end up using the patent data set provided by Bianchi and Giorcelli (2020) in the final version. First, they are able to match the names on patents with individuals and location. They start with matching the names of high school graduates to the inventors of patents. Then, to refine and improve the matching they use work histories provided by Italy's Social Security Administration. In addition, they manually check and confirm the matched names on patents to increase precision. As a result, the data set has more accurate information and more complete picture at the province level. They collect patent data using the Italian Patent Office (IPO) between 1950 and 2010, and the international patents included in the European Patent Office's (EPO) PATSTAT database. The data set provides number of patents at each province in Italy during the given time period. Table C.4 presents the distributions of patents per province.

Second, we collect raw patent data using EPO's portal PATSTAT for Italy for the period between 1950 and 1982 in the earlier versions of this study. We exclude utility models and designs as it is a common practice in the literature. Using a matching algorithm, we were able to create a data set based on the name on the patent applications. The raw data has some information available including an application and person identifier, name of the applicant, year of application

Table C.4: The number of patents per province from Bianchi and Giorcelli (2020)

Provincia	1950	1951	1952	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980
Agrigento	4	1	2	0	3	3	8	5	2	7	6	6	3	0	2	1	0	1	1	0	2	0	1	0	3	4	1
Alessandria	38	50	44	64	60	43	52	63	46	47	48	42	37	31	23	22	19	52	60	29	32	42	50	47	38	33	38
Ancona	32	41	49	59	64	70	75	46	57	72	57	44	41	16	15	16	11	41	35	25	31	25	41	53	49	38	35
Aosta	12	12	13	12	2	6	10	7	2	5	2	6	3	0	3	2	4	5	6	6	3	2	5	7	3	1	5
Arezzo	7	10	15	16	10	17	37	17	16	21	21	9	17	5	12	8	6	10	32	16	20	19	31	46	65	44	29
Ascoli Piceno	5	16	17	25	16	18	22	22	19	21	16	10	15	1	24	14	13	36	42	28	27	30	33	49	54	23	35
Asti	9	18	11	21	8	15	16	14	6	16	14	11	9	8	5	10	7	22	28	26	13	10	19	20	41	17	33
Avellino	1	2	2	5	7	11	3	5	6	7	6	4	4	1	3	2	0	2	5	6	4	2	2	3	7	4	4
Bari	33	25	27	34	38	38	49	37	37	41	29	35	23	12	6	12	9	28	22	20	10	21	15	22	22	33	18
Belluno	14	12	9	11	23	20	25	14	17	18	12	8	9	3	4	4	4	17	19	17	9	13	4	13	25	14	10
Benevento	6	6	1	4	5	5	8	2	8	1	2	3	2	0	3	3	2	6	7	7	8	8	6	4	9	3	12
Bergamo	71	89	76	91	86	84	98	75	88	100	79	76	77	40	49	52	28	108	110	64	79	77	99	84	122	112	112
Bologna	296	225	251	275	298	331	304	299	261	294	294	247	262	126	119	89	76	261	300	196	218	253	269	302	249	222	201
Bolzano-Bozen	30	43	37	55	59	56	70	39	49	42	43	33	28	19	17	16	17	54	71	43	39	30	30	49	62	38	63
Brescia	134	119	111	108	148	129	128	105	114	164	166	133	107	59	49	41	40	150	167	114	106	137	119	185	196	127	159
Brindisi	5	1	1	4	7	9	6	7	5	3	3	4	5	0	4	1	1	3	2	6	4	0	1	8	3	1	3
Cagliari	5	16	10	12	19	14	13	12	17	28	17	8	9	3	4	5	4	16	10	4	8	8	12	10	21	15	11
Caltanissetta	2	3	3	1	0	3	8	3	2	0	2	1	4	0	1	1	1	1	2	1	2	1	2	3	2	2	1
Campobasso	1	9	4	3	4	5	5	5	7	6	7	0	1	2	4	2	1	1	6	1	1	1	4	7	3	3	2
Caserta	10	5	9	10	13	14	11	12	7	10	10	6	7	2	9	3	1	14	13	10	12	7	8	10	15	12	5
Catania	27	14	20	30	31	39	32	35	31	28	21	21	19	11	10	6	4	29	19	28	15	21	15	21	34	26	12
Catanzaro	9	3	1	9	6	14	15	8	12	15	12	7	7	1	2	2	1	12	7	7	5	2	2	11	7	7	5
Chieti	13	9	8	12	11	8	8	12	9	3	11	9	7	2	6	1	0	4	5	7	12	14	7	17	16	12	9
Como	118	119	93	120	132	116	94	99	92	115	96	83	85	54	44	27	29	107	133	74	93	108	77	79	88	86	96
Cosenza	4	1	1	3	4	7	8	6	3	4	3	6	7	2	5	3	4	8	11	6	4	6	6	13	10	5	5
Cremona	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	10	9	17	35	16	16	42	20	19	30	21	30
Cuneo	30	37	26	31	39	32	32	41	35	38	30	34	25	10	14	10	3	41	35	28	26	30	34	47	46	38	30
Enna	0	3	2	3	1	4	3	2	1	1	2	0	3	1	1	0	0	0	1	1	0	1	0	0	1	0	2
Ferrara	54	28	26	40	65	44	40	35	51	39	44	34	44	17	0	0	0	0	0	0	0	0	0	0	0	0	0
Firenze	244	238	239	278	285	286	264	292	208	237	256	195	204	89	85	67	41	201	225	155	129	140	145	182	179	158	173
Foggia	11	6	7	9	11	19	20	6	9	11	10	6	9	2	1	0	2	10	10	3	3	4	4	9	6	2	3
Forli	31	25	37	40	32	49	47	30	42	53	51	26	28	11	8	14	4	30	33	21	29	18	19	31	43	19	32
Frosinone	6	5	6	2	6	15	11	11	5	7	4	7	4	4	9	9	4	19	13	10	7	6	5	11	18	14	7
Genova	334	284	332	303	310	295	275	220	233	259	192	175	165	80	94	56	39	136	150	99	106	126	99	105	123	101	87
Gorizia	21	8	15	18	12	10	12	17	7	15	9	2	7	2	3	4	4	12	13	12	9	7	11	8	8	11	6
Grosseto	4	12	12	6	5	10	17	15	3	6	6	9	8	0	2	4	2	17	3	10	6	9	7	7	15	9	4
Imperia	60	45	55	51	64	43	60	62	82	92	69	53	63	28	7	7	2	20	24	20	11	12	7	10	6	8	5
La Spezia	46	42	35	52	51	48	40	43	36	33	37	22	22	7	14	10	7	28	16	12	10	16	13	30	12	13	13
L'Aquila	4	4	4	13	13	10	16	7	7	5	2	4	9	1	5	3	1	3	7	11	5	6	3	6	14	8	13
Latina	5	8	6	8	8	14	9	13	7	5	6	10	9	4	5	4	9	23	17	22	7	14	10	13	13	16	8
Lecce	4	7	6	6	16	9	13	9	4	9	1	4	4	1	6	6	3	6	5	10	6	1	11	10	13	11	2
Livorno	28	27	24	29	28	33	35	26	19	35	24	19	12	14	9	5	8	19	19	17	13	11	11	30	24	21	16
Lucca	32	32	38	40	28	37	40	54	40	53	31	34	33	12	12	12	11	26	29	13	18	23	17	14	25	21	15
Macerata	11	9	17	11	18	32	21	29	18	20	21	12	10	8	13	7	5	16	16	16	11	14	9	21	20	30	29
Mantova	51	43	52	75	62	58	48	39	49	28	47	35	44	23	24	7	7	23	26	16	21	17	33	21	41	44	33
Massa-Carrara	13	11	12	14	14	28	13	12	9	10	17	4	11	7	6	7	6	16	16	10	11	9	4	14	17	13	13
Matera	0	1	0	0	1	1	1	1	0	2	0	0	0	0	0	1	0	0	2	1	2	0	3	2	3	0	2
Messina	19	25	17	16	16	15	9	24	19	24	14	12	9	4	6	6	2	13	14	8	5	6	5	10	20	13	7
Milano	1622	1581	1667	1833	1869	1941	1878	1813	1751	1938	1818	1579	1551	870	753	594	426	1590	1619	1082	1270	1203	1099	1267	1265	1051	996
Modena	54	63	56	64	85	92	98	105	117	122	121	104	134	66	83	63	29	180	173	111	101	148	134	113	139	117	72
Napoli	117	117	108	140	124	149	117	121	108	116	106	95	73	35	48	21	30	84	67	47	60	56	43	71	82	37	42
Novara	89	55	67	69	71	60	79	65	54	68	60	61	39	22	25	27	17	58	86	22	31	45	45	40	37	46	41
Nuoro	5	3	1	0	3	4	6	0	3	3	6	2	1	1	1	1	0	0	0	0	1	0	0	2	3	0	0
Padova	65	92	89	90	102	91	113	78	115	78	53	85	80	31	35	31	28	149	122	98	87	76	94	100	104	53	60
Palermo	41	33	25	43	41	40	39	37	38	40	32	25	37	11	13	14	7	36	32	26	15	22	28	14	26	32	30
Parma	68	77	72	62	87	91	64	56	73	54	50	51	50	23	34	27	15	70	84	46	49	59	58	52	69	67	51
Pavia	72	64	82	88	90	137	97	75	73	90	73	80	77	36	23	26	18	68	62	41	31	61	39	52	53	44	68
Perugia	31	25	30	28	32	36	43	32	34	36	36	24	13	16	11	16	14	40	39	24	32	26	14	39	34	22	21
Pesaro e Urbino	17	17	21	22	23	29	23	22	33	26	23	17	20	11	12	8	7	39	52	26	36	23	23	25	18	27	15
Pescara	8	5	11	18	22	14	16	21	17	13	17	11	17	4	3	7	6	23	16	9	16	7	8	20	12	6	8
Piacenza	34	20	38	29	37	50	39	31	37	35	36	28	21	20	16	7	6	26	37	27	18	23	24	39	40	17	24
Pisa	22	22	17	26	31	28	27	32	22	32	29	26	35	15	10	7	7	36	47	23	24	28	24	21	32	41	20
Pistoia	17	15	15	25	26	35	32	48	29	51	28	23	27	20	16	10	6	34	29	23	28	35	32	25	32	21	23
Potenza	12	2	9	8	2	7	10	4	5	2	1	3	4	1	5	1	2	3	4	0	1	1	4	4	12	3	5
Ragusa	6	2	3	0	13	2	10	3	3	5	3	4	0	2	1	2	4	9	6	4	2	5	3	16	5	3	3
Ravenna	19	20	21	25	34	25	25	23	30	32	45	18	26	17	13	16	16	50	35	19	23	21	28	31	55	30	33
Reggio di Calabria	11	10	9	16	6	7	14	13	11	13	16	7	8	2	8	7	1	10	8	9	7	6	4	9	9	9	2
Reggio nell'Emilia	52	56	55	97	63	110	83	86	109	89	87	109	98	41	57	45	20	101	125	63	47	83	83	82	68	71	77
Rieti	2	7	5	2	1	4	6	3	6	0	1	2	2	2	0	0	0	4	3	2	2	3	3	6	8	13	4
Roma	603	529	552	599	702	656	651	598	483	638	440	410	355	176	183	148	123	474	444	295	311	343	274	396	439	346	290
Rovigo	12	5	8	21	16	10	14	13	15	20	21	12	17	4	5	5	4	11	13	7	10	8	7	11	8	6	12
Salerno	11	20	21	20	15	27	24	24	18	16	19	10	21	9	12	12	10	36	24	17	14	18	11	27	25	8	11
Sassari	7	2	7	3	7	8	5	6	1	6	16	8	1	1	3	2	3	3	10	4	2	5	24	32	22	22	13
Savona	39	33	23	33	21	31	30	27	29	35	24	18	15	11	6	6	3	19	20	18	19	13	12	21	21	14	17
Siena	23	18	21	19	16	21	18	21	13	13	18	21	13	10	8	5	4	23	31	19	19	18	19	17	21	15	12
Siracusa	8	6	3	6	17	10	3	4	11	8	4	5	11	1	4	2	3	5	10	5	1	2	3	5	9	3	1
Sondrio	5	2	3	5	8	8	6	9	7	15	8	11	5	6	1	6	2	0	3	2	3	5	8	5	5	4	3
Taranto	11	6	7	6	12	9	9	3	5	7	8	2	9	3	5	8	1	13	5	4	8	3	3	8	13	12	5
Teramo	5	8	2	6	8	2	3	10	4	8	2	6	3	2	0	1	0	7	9	4	2	1	2	6	1	3	2
Terni	10	17	16	18	16	25	23	15	13	15	5	6	8	7	6	2	7	9	12	6	7	6	5	8	9	4	9
Torino	766	692	708	691	692	722	699	630	650	570	513	439	496	213	200	186	143	613	588	471	481	478	530	530	511	414	425
Trapani	5	1	2	4	5	2	5	5	4	8	11	6	8	1	4	4	3	6	4	4	1	6	3	0	10	6	3
Trento	28	28	31	36	36	36	30	31	40	24	32	25	20	9	16	21	14	40	43	40	34	25	28	44	50	42	46
Treviso	50	57	51	62	83	68	55	50	48	55	62	45	63	41	33	29	29	97	100	76	79	88	70	103	98	71	85
Trieste	62	46	77	88	84	55	56	43	34	43	52	25	30	16	21	4	8	35	23	29	23	17	8	16	31	26	15
Udine	61	54	42	49	79	86	87	87	72	77	59	56	36	27	65	27	22	158	160	144	125	126	114	167	119	121	110
Varese	107	108	135	122	142	112	127	94	97	101	107	107	89	48	62	39	42	176	166	128	101	129	111	106	120	94	95
Venezia	59	45	45	57	58	70	53	68	58	76	70	53	54	29	25	27	14	69	62	38	49	37	36	47	46	46	61
Vercelli	66	56	59	53	51	38	50	46	25	44	35	25	33	16	20	14	18	53	50	26	22	30	25	34	34	30	27
Verona	67	98	93	123	97	122	115	120	101	93	96	78	72	37	48	40	18	99	92	87	63	59	59	94	67	63	57
Vicenza	78	74	78	83	90	110	97	87	122	109	107	95	76	52	60	62	28	139	133	111	109	138	106	155	159	95	122
Viterbo	5	2	12	9	14	10	14	11	3	9	6	8	8	5	6	1	0	12	6	1	3	3	4	13	11	9	3

and location information. The first problem we face is that not all applications have location information available. To deal with this problem, we use a simple matching algorithm. Matching non-standardized names on patent applications with firms available in a standardized database is a widely studied topic. Thoma et al. (2010) set a list of rules and discuss different methods on how to combine patent data sets with each other and other sources of data. Lotti and Marin (2013) follow their methodology and study how to match Italian patents from PATSTAT database with a commercial database on Italian firms.

Our approach to match patent applications with a location is much simpler compared to those. We only need location information for a patent application since we aggregate the number of patent applications at province level. The main problem is that almost all patent applications before 1977 do not have available location information. This is because EPO was established in 1977. The data before this year is gathered from national patent offices and there are blanks in the applications. However, most of these firms filed for a patent before 1977 also applied for a patent after 1977. Thus, we can match these firms with a location since firm or individual specific identifiers are available. We create a list of firms and individuals with their locations. Then, using the person identifier (person can be a firm or individual) we are able to match and create a database with location information.

Furthermore, we benefit from de Rassenfosse et al. (2019) to expand our patent database. They provide geographic coordinates for inventor and applicant locations. The database starts at 1980 and spans over more than 30 years. The application number is available in their publicly available data. We use patent applications from 1980 since it is the only year overlapping with our time period. Doing so, we are able to add almost 5,000 more patent applications to our database (Table C.5). We should note that most of the unmatched patent applications belongs to individuals rather than firms.

After this simple matching, we end up with 66,520 patent applications corresponding to 2,927 unique person identifiers (almost all of them are firms). The right panel of Table C.5 shows that around 90% of matched applications made by firms that have a patent application both before and after 1977. Hence, our sample consists of firms keep innovating over the time period selected.

However, the missing information (i.e. location) on patent applications seriously affected the data collecting process. Table C.6 presents the distributions of patent applications for the earlier data set. Milan has the most patent applications and around 15 provinces comprises almost 85% of all patent applications between 1950 and 1980. Furthermore, these top 15 provinces have almost complete data during the period. The rest of provinces has a lot of gaps in the data.

Overall, the reason why we do not use the earlier patent data set becomes more clear comparing Table C.4 and Table C.6. The completeness of the data set from Bianchi and Giorcelli (2020) provides a balanced panel to conduct our analysis.

Table C.5: The number of patent applications matched

	Using only raw patent data			**Using raw patent data and de Rassenfosse et al. (2019)**		
Type	Unmatched	Matched	Total	Unmatched	Matched	Total
before77	72,081	993	73,074	72,081	993	73,074
both	32,659	56,788	89,447	29,995	59,452	89,447
after77	35,122	3,948	39,070	32,995	6,075	39,070
Total	139,862	61,729	201,591	135,071	66,520	201,591

Note: *before77* represents firms or individuals only filed a patent application before 1977. *after77* represents firms or individuals only filed a patent application after 1977. *both* represents firms or individuals filed a patent application before and after 1977.

Table C.6: Patent applications per province from old data set

Province	1950	1951	1952	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980
Agrigento																															1
Alessandria				1			8	4	14	2	2	14	13	7	21	5	29	15	10	12	34	14	8	188	397	518	578	661	756	713	684
Ancona																					1			1	2	1	4	3	6	8	27
Aosta																												4		2	20
Arezzo																												13	2	4	9
Ascoli Piceno									1	1		3	3	8	7	14	14	15	25	34	23	46	52	34	57	79	48	38	37	49	83
Asti																							1		2	2	11	25	36	38	62
Avellino																															3
Bari																													3	11	20
Barletta-Andria-Trani																												1	6	1	7
Belluno																		1						2					2	12	2
Benevento																															2
Bergamo								1	2				2			1	6	1	1	1	3	8	15	4	21	11	37	30	68	74	99
Biella																									5	5	5		3	12	6
Bologna	1	4		1		1	3	2	2	1	6	2	3	2	4	5	8	38	17	41	21	87	78	130	389	286	307	456	288	430	617
Brescia										2	5	9	11	1			2	16	7	11	45	75	86	92	139	113	222	266	275	287	379
Brindisi																															2
Cagliari																															2
Caltanissetta																					3	38	18	54	71	264	535	279	313	187	284
Campobasso																															7
Caserta																			2	1	2			16	15	90	71	58	50	50	25
Catania																	2						3	2	5	4	3	4	2	4	4
Catanzaro																											1				4
Chieti																								2	20	36	46	9	1	12	71
Como									3	4	2	7	10	1	6	1		14	26	18	10	15	49	37	40	47	74	41	105	121	190
Cosenza																											1		1	1	4
Cremona									1						2		2	2						8	27	32	46	25	5	36	47
Crotone																														1	
Cuneo				13		4	4	8	11	32	10	4	13	12	16	46	50	59	121	57	38	31	16	73	65	57	66	101	97	50	120
Fermo																													1	3	8
Ferrara																	1	3	1		1			1	2	10	6	20	18	36	31
Florence	3	5	1	1	3	1			2	2	3	3	2	4		2	53	18	12	75	8	13	59	95	240	120	306	113	162	191	297
Foggia																															3
Forlì-Cesena																									1	3		4	10	12	13
Frosinone																										1			3	21	17
Genoa	2	1		1	1		2		1	2	1	1		4	2		10	3		2	10	13	42	39	37	33	69	77	72	60	118
Gorizia										1			2	2		1			1	6		6	24	18	30	24	10	1	10	34	48
Imperia																															2
La Spezia																1			5	2	1							2	3	2	7
L'Aquila																				3		2	4	3	2	1	4	6	10	1	5
Latina																													1	2	9
Lecce																									1	1	5	10	5	7	12
Lecco	1															1	2	2			1	2	1	6	16	16	52	32	66	129	200
Livorno																						1			1	2	20	35	54	51	63
Lodi																						9	12	76	204	168	123	81	49	160	231
Lucca																								1	2	15	1	2			4
Macerata																							1	1		3	2	1	1	2	6
Mantua																								1			3		6	25	22
Massa and Carrara																									2	4	6	21	45	30	57
Matera																															1
Messina																													5		7
Milan	12	35	34	44	34	58	81	68	77	128	242	278	220	182	142	183	309	676	676	596	798	988	1342	1410	1886	2768	2741	2358	2367	2638	3029
Modena							2											1	1		4		2	5	16	18	29	6	32	65	83
Monza and Brianza														2		7				2	8	10	29	51	37	60	49	66	71	116	117
Naples																	1						1	3	4	5	35	8	14	33	54
Novara																2	2		2	1	2	7	6	2	4	11	13	21	20	36	54
Padua			2													1				1		2	15	14	30	18	22	21	48	42	83
Palermo																														1	3
Parma																			3				3	2	3	2	9	5	4	15	65
Pavia					3	2	2			4	73	63	32	32	18	62	56	110	171	226	305	83	439	412	370	391	269	171	238	306	469
Perugia																				1				2		1	2	9	11	9	26
Pesaro and Urbino																							2	1	19	11	17	5	4	11	8
Pescara																				1									1		5
Piacenza																					2	3	1	2	5	6	16	11	10	14	46
Pisa								4		5	2	14	1		1	2		8	13			1	2	10	4	1	9	16	11	19	30
Pistoia																												1		15	45
Pordenone			1												3	1	6	14	64	39	25	9	11	20	19	23	43	47	68	43	96
Potenza																														3	7
Prato																													2	1	
Ragusa																											1	3	2	3	7
Ravenna																						4	6	4	5	1	3	5	21	13	30
Reggio Calabria																														4	4
Reggio Emilia																										8	4	16	9	14	41
Rieti																															1
Rimini																								3	1	3	8	3	7	10	32
Rome							2	2	1		6	9	21	10	11	11	14	30	34	34	28	40	74	140	177	199	260	426	561	818	915
Rovigo													2					4		1			1	1	2	2	3	2	2	1	9
Salerno																	1					1	2	2	1	1					35
Sassari																														1	3
Savona																1						1			2	7	9	4	7	13	26
Siena																	1						8		4	3	13	7	7	3	13
Sondrio																						2	1			1		2	1	9	1
South Sardinia																													1	6	
South Tyrol										1													2		4	7	24	20	21	39	34
Syracuse																															11
Taranto																												4	1		8
Teramo																								1				2	1	2	2
Terni																										1		2		9	6
Trapani																															1
Trento																							2	5	31	4	40	24	7	29	20
Treviso												1							1	1	2	3	2	10	10	19	15	14	48	36	57
Trieste																		1					4	8	14	3	1	9	17	19	6
Turin	33	19	10	21	21	15	12	20	13	21	21	16	10	14	16	26	47	50	63	99	88	139	201	186	308	267	464	529	718	492	836
Udine											3	2		1		1							3	6	5	44	32	26	50	47	54
Varese					1	1		2	2	14				1	1			1	3	2	2	7	17	21	28	34	44	45	60	88	176
Venice																						2	1	2	1		4	11	10	33	55
Verbano-Cusio-Ossola				1	2	2	2	3	10		3	3	3						1				1	2		1					3
Vercelli								1															1				3		1		13
Verona															3	1	1		2		3	2	4	3	2	5	18	11	7	57	30
Vicenza		2				2	1	5	7	2	1	24		21	2	6	3		4	35	18	73	8	29	41	60	73	28	74	143	115
Viterbo																													1	2	2

C.4 Additional Patent Data from 1968 to 1973

The bank loan data covers the period between 1890 and 1973 and the patent data is from 1950 to 2010 with a gap between 1963 and 1968. Thus, the final data set comprises the period between 1950 and 1963. However, to shed more light we include patent data from 1968 to 1973 to the sample. We try to provide better summary statistics.

Figure C.3 and Table C.7 displays how credit reallocation measures changes over time compared to real GDP growth since there is no gap in bank loan data. We take the average of credit reallocation measures for each province in a given year. In the early 1950s, gross credit reallocation and real GDP growth move in the opposite directions. On the other hand, credit destruction, consequently excess credit reallocation, moves hand in hand with the real GDP growth in the early 1950s. Gross credit reallocation and net credit growth declined in the early 1950s and then increased towards the mid-1950s. However, they gradually decreased until late 1950s. Starting in the 1960s, gross credit reallocation and net credit growth started to follow a more similar pattern with real GDP growth. Lastly, credit destruction and excess credit reallocation stay relatively low during sample period. Overall, credit creation, gross credit reallocation, and net credit growth closely follow each other over time, while credit destruction and excess credit reallocation display a similar movement. These results are not unexpected considering that the time coincides with the greatest development of the Italian economy. Also, we work with bank loans instead of firm debts and we expect banks to increase the amount of loans during an economic expansion period.

Figure C.4 presents the relationship between innovation and credit reallocation over time. Again we take the average of credit reallocation measures and number of patents for each province for a given year. Patents increase towards the end of 1950s after a slight decline in the early 1950s. This period coincides with the Italian economic boom. However, after this prosperous period, there is a large decline in the number of patents in the early 1960s. Nuvolari and Vasta (2015) argue that scientific activities prevail patenting during this period.

Next, we try to explore more how innovation and credit reallocation are related at the province level. We examine how provinces are distributed using number of patents and credit reallocation measures. We take the average of number of patents and credit reallocation measures for the whole sample period to draw the scatter plots. The inclusion of data between 1968 and 1973 does not substantially affect the distribution of provinces (See Figure C.5, Figure C.6, Figure C.7, Figure C.8, and Figure C.9). Hence, the plots suggest a negative relationship between innovation and credit reallocation as earlier data.

Furthermore, we present Table C.8 with the inclusion of data between 1968 and 1973 to examine province characteristics considered in our analysis. We take the average of all considered variables for all provinces at a given year. Data collected from censuses are presented only at the year the census held. First, the number of patents follows a path similar to an inverted-U shape between 1950 and 1963. Table C.8 reveals that the number of patents significantly decreases until 1971 and after a substantial increase in 1971. This result is not surprising because Nuvolari and Vasta (2015) claims that scientific activities prevail patenting between 1960 and 1970. Thus, the sudden increase in the number of patents in 1971 can be the fruit of scientific activities performed during this period.

We measure productivity as the total value added per firm in a province. Productivity gradually decreases until 1961 and starts to increase after. However, Table C.8 shows that it declines again until 1971 and a very large increase in 1971 happened in productivity. The evidence suggests that innovation and productivity follow a similar path over time. The number of banks is stable over time moving around 4 banks on average in each province, while number of bank branches on average increases substantially over time. There are 96 branches on average in each province in 1951, while the number of bank branches reaches 146 on average in 1971. Additionally, credit market in Italy is highly concentrated between 1950 and 1963, but the concentration starts to decrease after 1970.

Average number of workers for each firm increases from 3.64 in 1951 to 4.02 in 1971, while the share of active population decreases from 46.2% in 1951 to 36.9% in 1971. Italy's great economic development period pays out as share of higher education degrees increases from 3.8% in 1951 to 8% in 1971.

Figure C.3: Credit reallocation measures over time with real GDP growth rate

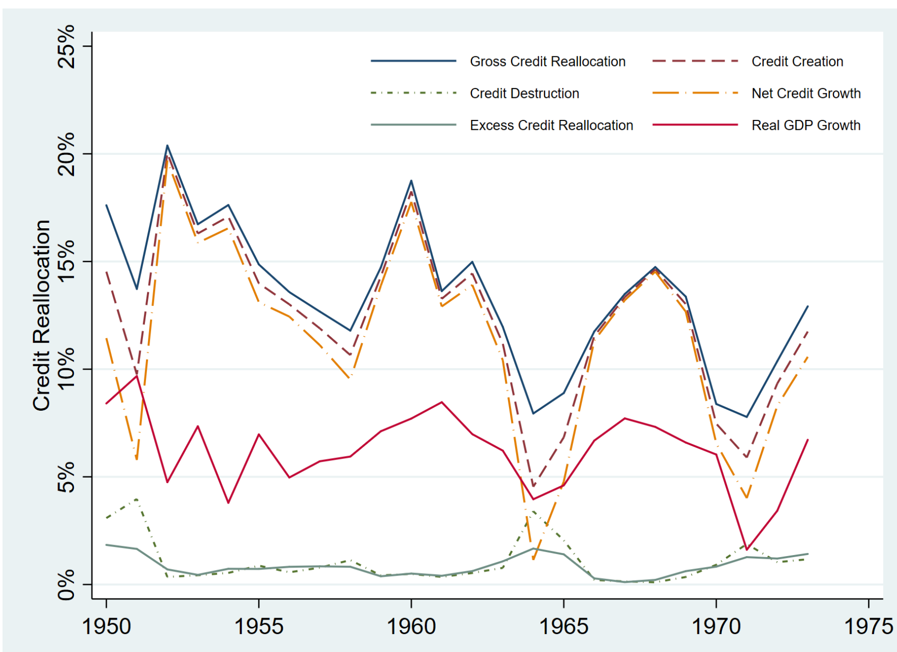


Figure C.4: Credit reallocation measures over time with number of patents

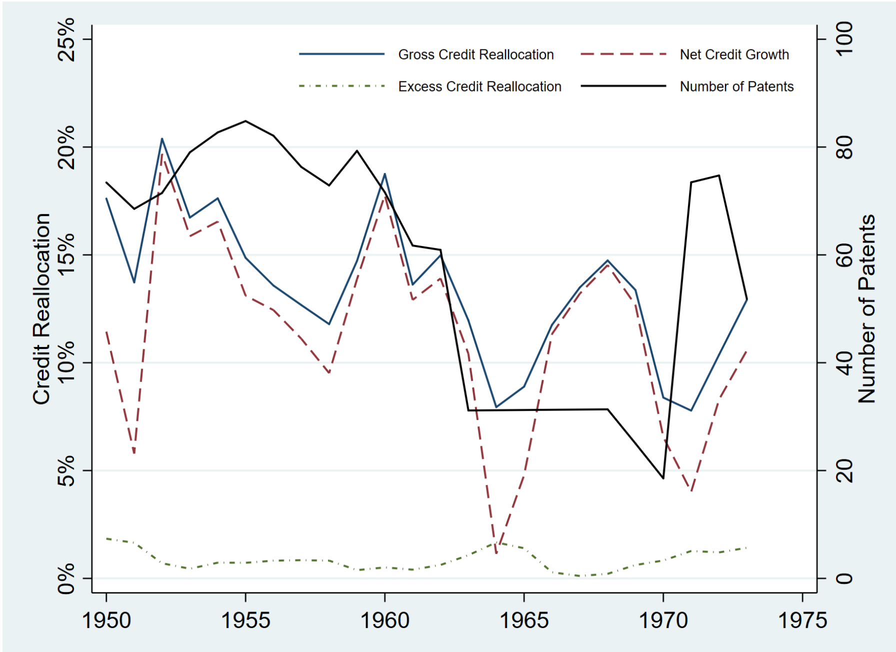


Figure C.5: Distribution of provinces with reallocation measures

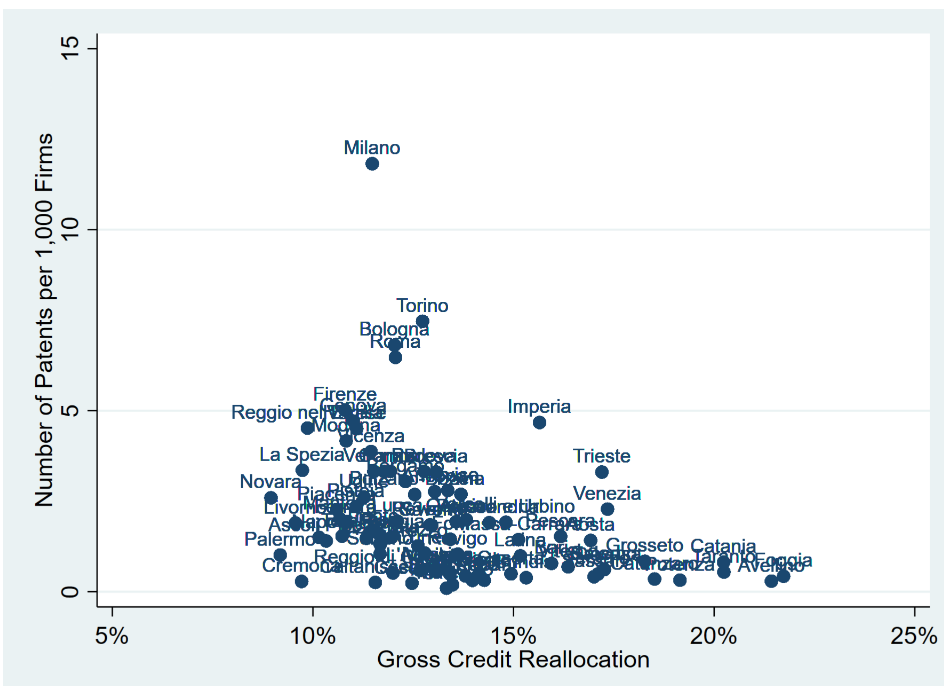


Figure C.6: Distribution of provinces with reallocation measures

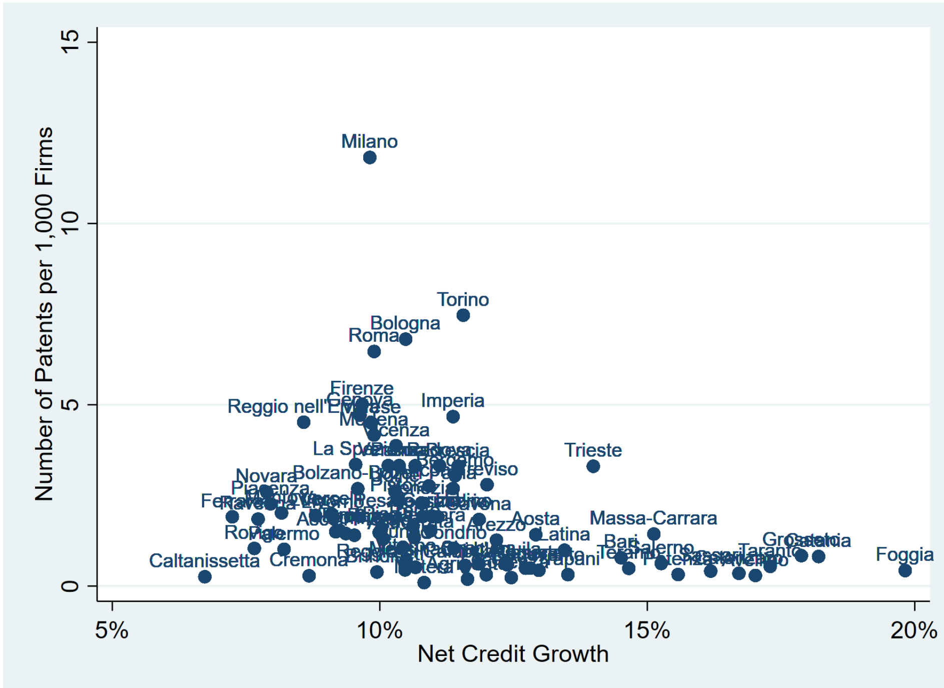


Figure C.7: Distribution of provinces with reallocation measures

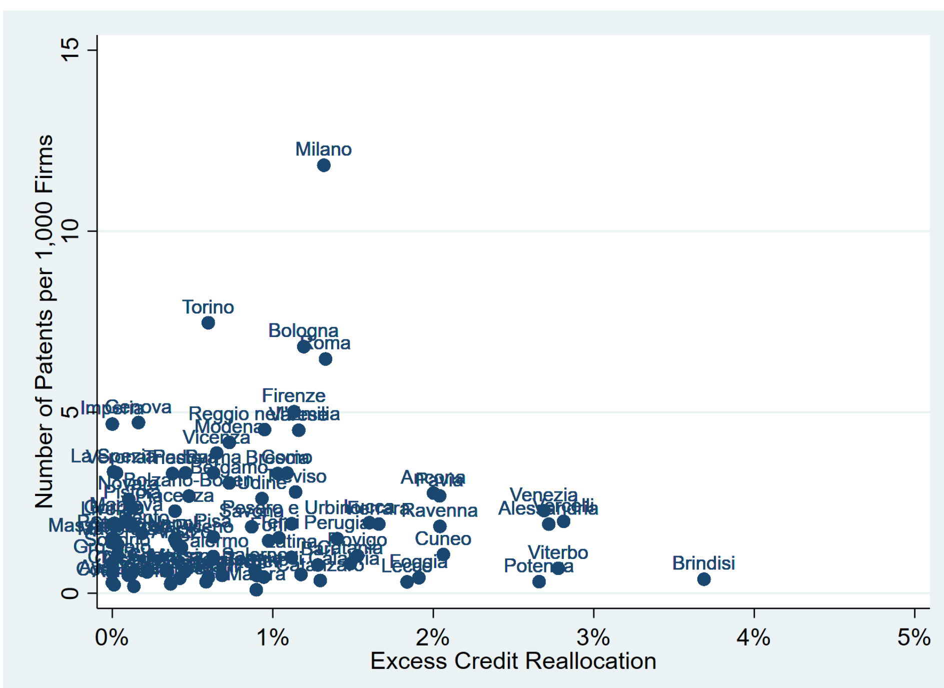


Figure C.8: Distribution of provinces with reallocation measures

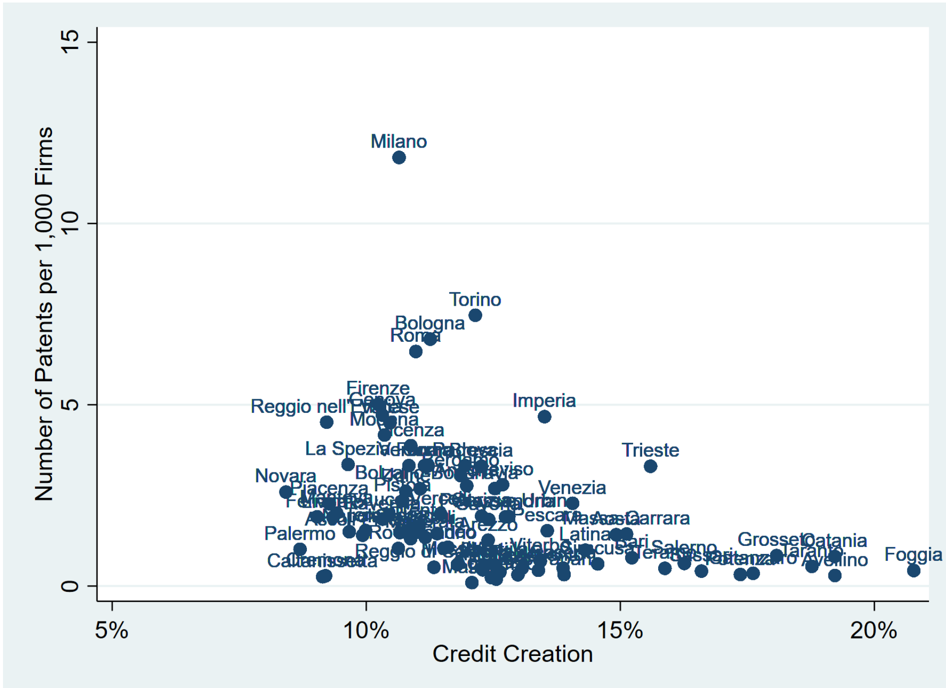


Figure C.9: Distribution of provinces with reallocation measures

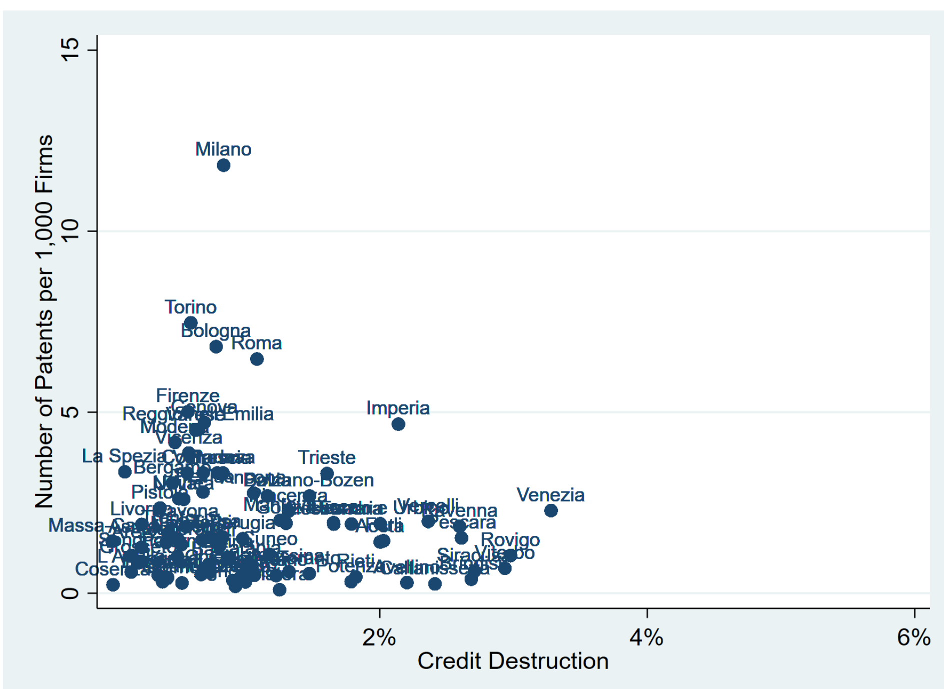
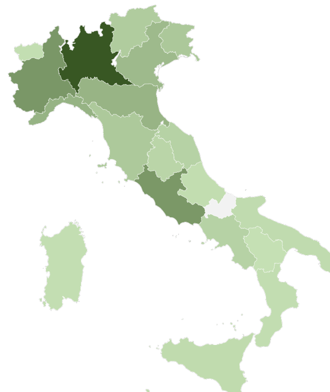
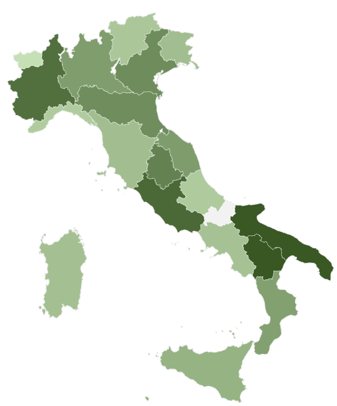


Figure C.10: Regional overview



(a) Number of Patents

(b) Net Credit Growth



(c) Excess Credit Reallocation

Table C.7: Summary statistics for credit reallocation measures

Year	Gross Credit Reallocation	Net Credit Growth	Excess Credit Reallocation	Credit Creation	Credit Destruction	Real GDP Growth
1950	17.61%	11.44%	1.84%	14.53%	3.09%	8.41%
1951	13.73%	5.79%	1.65%	9.76%	3.97%	9.68%
1952	20.38%	19.68%	0.70%	20.03%	0.35%	4.75%
1953	16.73%	15.87%	0.45%	16.30%	0.43%	7.35%
1954	17.62%	16.55%	0.73%	17.08%	0.54%	3.80%
1955	14.86%	13.11%	0.72%	13.99%	0.88%	6.97%
1956	13.58%	12.44%	0.82%	13.01%	0.57%	4.97%
1957	12.68%	11.11%	0.84%	11.89%	0.78%	5.72%
1958	11.79%	9.52%	0.82%	10.65%	1.13%	5.94%
1959	14.72%	13.88%	0.38%	14.30%	0.42%	7.12%
1960	18.75%	17.77%	0.51%	18.26%	0.49%	7.71%
1961	13.62%	12.91%	0.41%	13.27%	0.36%	8.47%
1962	14.98%	13.91%	0.62%	14.45%	0.54%	6.98%
1963	11.96%	10.41%	1.08%	11.19%	0.77%	6.22%
1964	7.94%	1.14%	1.67%	4.54%	3.40%	3.96%
1965	8.89%	4.78%	1.40%	6.84%	2.05%	4.60%
1966	11.75%	11.33%	0.29%	11.54%	0.21%	6.68%
1967	13.49%	13.20%	0.11%	13.35%	0.14%	7.71%
1968	14.74%	14.53%	0.21%	14.64%	0.11%	7.32%
1969	13.37%	12.67%	0.62%	13.02%	0.35%	6.59%
1970	8.38%	6.55%	0.83%	7.47%	0.92%	6.04%
1971	7.78%	4.02%	1.27%	5.90%	1.88%	1.61%
1972	10.37%	8.30%	1.21%	9.33%	1.04%	3.43%
1973	12.92%	10.57%	1.42%	11.75%	1.17%	6.72%

Table C.8: Summary statistics for province characteristics

Year	Number of Patents	Productivity (000 lire)	Number of Banks	Credit Market Concentration	Number of Workers per Firm	Number of Bank Branches	Share of Individual Firms	Share of Higher Education Degrees	Share of Active Population
1950	73.43	269.43	3.45	0.68					
1951	68.53	248.85	4.26	0.62	3.64	96.33	91.37%	3.79%	46.24%
1952	71.49	240.87	4.50	0.61					
1953	79.02	232.74	4.50	0.61					
1954	82.72	225.95	4.51	0.61					
1955	84.83	218.88	4.52	0.61					
1956	82.10	210.35	4.50	0.61					
1957	76.31	206.52	4.37	0.62					
1958	72.88	202.40	3.34	0.68					
1959	79.30	203.61	4.45	0.61					
1960	71.60	200.43	4.45	0.61					
1961	61.73	349.22	4.44	0.61	3.99	118.60	91.45%	4.94%	40.44%
1962	60.93	331.51	4.43	0.61					
1963	31.15	305.50	4.43	0.61					
1964	-	287.96	4.44	0.61					
1965	-	278.67	4.39	0.61					
1966	-	272.11	4.33	0.61					
1967	-	263.97	4.16	0.61					
1968	31.36	260.61	4.02	0.62					
1969	25.02	251.20	4.00	0.62					
1970	18.56	235.84	5.28	0.56					
1971	73.47	498.07	5.14	0.56	4.02	146.42	90.22%	7.98%	36.85%
1972	74.73	469.82	5.03	0.57					
1973	51.83	415.81	5.02	0.57					

D Robustness

This section includes the robustness tests.

D.1 Weak Instruments

First-stage regression results suggest that we may suffer from weak instruments. If our instruments are weakly correlated with the endogenous regressors, IV estimators can be biased due to the poor properties of two-stage least squares when instruments are weak. Hence, further investigation is required. We need to perform a weak instrument test to detect weak correlation with the endogenous regressor. Then, we need to make weak-instrument robust inference in case our instruments fail to pass the test.[18]

A widely accepted common rule for testing the strength of an instrument is an F-statistic greater than 10 from the first-stage regression (Staiger and Stock (1997)). On a cursory look, we can say that our instruments perform well, especially for excess credit reallocation. But there are some model specifications in which the instrument fails to pass a weak instrument test, particularly for net credit growth. Therefore, we need to investigate further.

Andrews et al. (2019) survey the literature on detecting weak instruments and making weak-instrument robust inference. They conclude that the efficient F-statistic from Olea and Pflueger (2013) should be used for detecting weak instruments. In a just-identified setting, the efficient F-statistics coincide with the usual F-statistic from the first-stage regression. Furthermore, they indicate that the efficient F-statistic should be compared to Stock and Yogo (2005) critical values in just-identified settings, and to Olea and Pflueger (2013) critical values in over-identified settings. In addition, Keane and Neal (2021) draw the same conclusion about detecting weak instruments.

On a cursory look at the lower panels of Table D.1 and Table D.2, we can say that our instruments perform well, especially for excess credit reallocation. The F-statistic from the first-stage regression is above the rule thumb of 10. But there are some model specifications in which the instrument fails to pass the threshold of 10, particularly for net credit growth. Thus, we perform a weak instrument test to ensure that our instruments do well. We compare the F-statistic from the first-stage regression to the critical values of Stock and Yogo (2005).

Furthermore, we need to make weak-instrument robust inference in case the instrument fails to pass weak instrument test. Keane and Neal (2021) claim that in a just-identified setting with one endogenous regressor, the F-statistic for weak instrument test from Anderson and Rubin (1949) is uniformly the most powerful test. We present the relevant Anderson-Rubin (AR) F-statistic in Table D.1 and Table D.2. However, the instrument for excess credit reallocation does well and can be regarded as a "strong" instrument. Thus, we check the AR F-statistics for our instrument for net credit growth. AR test confirms that we can make weak-instrument robust inference.

[18] Please see Andrews et al. (2019) and Keane and Neal (2021) for a detailed discussion of detecting and treating weak instruments.

Table D.1: Credit reallocation and innovation

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Excess Credit Reallocation	-0.098***	-0.027**	-0.102***	-0.111***	-0.026**	-0.027**
	(0.028)	(0.012)	(0.030)	(0.033)	(0.012)	(0.013)
Share of Active Population		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.136***			-0.136***	-0.135***
		(0.040)			(0.040)	(0.040)
Share of Individual Firms		-0.035***			-0.035***	-0.035***
		(0.004)			(0.004)	(0.004)
Share of Higher Education Degrees		0.049***			0.049***	0.049***
		(0.006)			(0.006)	(0.006)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Excess Credit Reallocation (First lag)			0.004	0.004	-0.000	-0.000
			(0.004)	(0.004)	(0.002)	(0.002)
Excess Credit Reallocation (Second lag)				0.011		0.001
				(0.007)		(0.002)
Observations	1,204	1,204	1,204	1,204	1,204	1,204
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	17.43	19.02	15.74	14.27	17.36	15.95
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	17.43	19.02	15.74	14.27	17.36	15.95
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	32.04	6.196	33.17	34.34	5.705	5.272
First Stage Regression						
VARIABLES	EXC	EXC	EXC	EXC	EXC	EXC
No. of Savings Banks in 1936 (per 100,000 inhabitants)	0.015***	0.015***	0.015***	0.014***	0.015***	0.014***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.2: Credit growth and innovation

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Net Credit Growth	0.010**	0.014**	0.012*	0.012*	0.017**	0.017**
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Share of Active Population		-0.001			-0.001	-0.001
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.067			-0.070	-0.069
		(0.068)			(0.074)	(0.074)
Share of Individual Firms		-0.037***			-0.036***	-0.036***
		(0.005)			(0.005)	(0.005)
Share of Higher Education Degrees		0.046***			0.045***	0.045***
		(0.008)			(0.009)	(0.009)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Net Credit Growth (First lag)			-0.003**	-0.003**	-0.003**	-0.003**
			(0.001)	(0.001)	(0.001)	(0.001)
Net Credit Growth (Second lag)				-0.000		0.000
				(0.001)		(0.001)
Observations	1,162	1,162	1,162	1,162	1,162	1,162
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	7.631	9.369	5.853	5.898	7.182	7.345
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	7.631	9.369	5.853	5.898	7.182	7.345
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	9.519	19.79	10.39	10.60	21.14	21.33
First Stage Regression						
VARIABLES	NET	NET	NET	NET	NET	NET
Inverse Credit Market Concentration in 1936	0.008***	0.009***	0.007**	0.007**	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.2 Robustness to the North-South Divide

In this section, we show that our results are not driven by the North-South divide. Historically, the Southern regions and provinces tend to be financially underdeveloped in Italy. In addition, the structure of the banking industry in 1936 was a result of the Banking legislation of 1936. The structure in the Northern regions was more likely to be the outcome of historical events and forced consolidation regardless of the level of economic development in 1930s. Therefore, excluding the Southern regions provides more exogeneity for our instruments.

We drop the provinces in the Southern regions from the sample. The results hold even more strongly for excess credit reallocation. However, the significance of net credit growth seems to disappear. Table D.3 and Table D.4 present the results.

Table D.3: Credit reallocation and innovation in the Northern provinces

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Excess Credit Reallocation	-0.188***	-0.060**	-0.198***	-0.218***	-0.059**	-0.061**
	(0.057)	(0.025)	(0.064)	(0.066)	(0.026)	(0.027)
Share of Active Population		-0.000*			-0.000*	-0.000*
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.223***			-0.223***	-0.223***
		(0.071)			(0.071)	(0.072)
Share of Individual Firms		-0.028***			-0.028***	-0.028***
		(0.005)			(0.005)	(0.005)
Share of Higher Education Degrees		0.036***			0.036***	0.036***
		(0.011)			(0.011)	(0.011)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Excess Credit Reallocation (First lag)			0.010	0.010	-0.001	-0.001
			(0.009)	(0.010)	(0.003)	(0.003)
Excess Credit Reallocation (Second lag)				0.023		0.002
				(0.020)		(0.006)
Observations	546	546	546	546	546	546
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	11.53	12.21	9.978	10.95	10.60	12.76
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	11.53	12.21	9.978	10.95	10.60	12.76
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	44	8.863	44.91	45.16	7.884	6.857
First Stage Regression						
VARIABLES	EXC	EXC	EXC	EXC	EXC	EXC
No. of Savings Banks in 1936 (per 100,000 inhabitants)	0.017***	0.020***	0.017***	0.015***	0.019***	0.018***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.4: Credit growth and innovation in the Northern provinces

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Net Credit Growth	0.039*	0.029	0.050	0.048	0.036	0.034
	(0.022)	(0.018)	(0.035)	(0.032)	(0.026)	(0.023)
Share of Active Population		-0.002			-0.002	-0.002
		(0.001)			(0.001)	(0.001)
No. of Bank Branches per Firms		-0.247**			-0.255**	-0.257**
		(0.107)			(0.126)	(0.120)
Share of Individual Firms		-0.039***			-0.041***	-0.041***
		(0.009)			(0.011)	(0.011)
Share of Higher Education Degrees		0.020			0.017	0.019
		(0.019)			(0.024)	(0.022)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Net Credit Growth (First lag)			-0.008	-0.008	-0.005	-0.005
			(0.006)	(0.006)	(0.004)	(0.004)
Net Credit Growth (Second lag)				0.003		0.003
				(0.003)		(0.003)
Observations	518	518	518	518	518	518
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	3.645	3.403	2.188	2.442	2.239	2.550
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	3.645	3.403	2.188	2.442	2.239	2.550
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	13.32	8.407	13.81	13.76	8.789	8.832
First Stage Regression						
VARIABLES	NET	NET	NET	NET	NET	NET
Inverse Credit Market Concentration in 1936	0.009*	0.008*	0.007	0.007	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.3 Robustness to an Alternative Specification

We test the robustness of baseline results by controlling for province characteristics and adding lags of the variable of interest. We further perform more tests to assess the robustness of the baseline results. Table D.5 and Table D.6 present the results. We change the definition of the dependent variable to "Patents per 100,000 people," as widely used in the literature, and repeat the same exercises with the new definition. The results are robust to a change in the definition of the dependent variable. The signs of excess credit reallocation and net credit growth remain the same as all province characteristics. However, the magnitudes of the coefficient estimates change drastically with new definition, which is expected due to change in the denominator of the dependent variable.

Table D.5: Credit reallocation and innovation (Alternative specification)

VARIABLES	(1) Patents per 100,000 people	(2) Patents per 100,000 people	(3) Patents per 100,000 people	(4) Patents per 100,000 people	(5) Patents per 100,000 people	(6) Patents per 100,000 people
Excess Credit Reallocation	-393.191***	-141.073***	-409.612***	-447.789***	-140.352**	-144.709**
	(112.978)	(53.241)	(121.219)	(136.262)	(54.996)	(58.856)
Share of Active Population		1.870***			1.870***	1.871***
		(0.580)			(0.580)	(0.580)
No. of Bank Branches per 100,000 People		-0.037			-0.037	-0.038
		(0.051)			(0.051)	(0.051)
Share of Individual Firms		-119.726***			-119.725***	-119.567***
		(18.139)			(18.130)	(18.204)
Share of Higher Education Degrees		132.263***			132.253***	132.511***
		(24.512)			(24.497)	(24.622)
Productivity (Total Value Added per capita)		1.522***			1.522***	1.520***
		(0.156)			(0.156)	(0.156)
Excess Credit Reallocation (First lag)			18.617	18.434	-0.824	-0.826
			(16.636)	(17.752)	(7.680)	(7.776)
Excess Credit Reallocation (Second lag)				48.030		5.268
				(29.938)		(10.993)
Observations	1,204	1,204	1,204	1,204	1,204	1,204
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	17.43	20.65	15.74	14.27	18.86	17.14
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	17.43	20.65	15.74	14.27	18.86	17.14
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	31.50	9.654	32.81	34.21	9.012	8.300
First Stage Regression						
VARIABLES	EXC	EXC	EXC	EXC	EXC	EXC
No. of Savings Banks in 1936 (per 100,000 inhabitants)	0.015***	0.015***	0.015***	0.014***	0.015***	0.014***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.6: Credit growth and innovation (Alternative specification)

VARIABLES	(1) Patents per 100,000 people	(2) Patents per 100,000 people	(3) Patents per 100,000 people	(4) Patents per 100,000 people	(5) Patents per 100,000 people	(6) Patents per 100,000 people
Net Credit Growth	39.293**	51.718**	47.595*	47.975*	60.679**	60.184**
	(18.963)	(21.676)	(24.427)	(24.506)	(27.106)	(26.762)
Share of Active Population		-1.014			-0.983	-1.004
		(1.463)			(1.605)	(1.601)
No. of Bank Branches per 100,000 People		-0.102*			-0.110*	-0.109*
		(0.059)			(0.062)	(0.062)
Share of Individual Firms		-147.844***			-148.395***	-148.325***
		(21.718)			(22.722)	(22.649)
Share of Higher Education Degrees		144.856***			141.821***	142.138***
		(29.499)			(30.941)	(30.892)
Productivity (Total Value Added per capita)		1.259***			1.261***	1.262***
		(0.187)			(0.195)	(0.195)
Net Credit Growth (First lag)			-10.720**	-10.652**	-11.495**	-11.575**
			(4.938)	(4.981)	(5.109)	(5.093)
Net Credit Growth (Second lag)				-0.797		1.026
				(2.258)		(2.355)
Observations	1,162	1,162	1,162	1,162	1,162	1,162
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	7.631	9.185	5.853	5.898	7.182	7.318
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	7.631	9.185	5.853	5.898	7.182	7.318
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	9.705	16.32	10.67	10.92	17.56	17.73
First Stage Regression						
VARIABLES	NET	NET	NET	NET	NET	NET
Inverse Credit Market Concentration in 1936	0.008***	0.009***	0.007**	0.007**	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.4 Robustness to Inclusion of Additional Data

Second, we use the patent data from 1950 to 1963 in the main estimations because there is a gap between 1963 and 1968 in the patent data. To check whether the data from 1968 to 1973 change the results, we include this data in our sample and reestimate all the models. The results are robust to the inclusion of further data. The coefficient estimates for excess credit reallocation slightly increase, while the coefficient estimates for net credit growth remain virtually unaltered.

Table D.7: Credit reallocation and innovation (Full sample from 1950 to 1973)

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Excess Credit Reallocation	-0.132***	-0.039**	-0.146***	-0.161***	-0.043**	-0.048**
	(0.043)	(0.018)	(0.052)	(0.061)	(0.021)	(0.023)
Share of Active Population		0.000*			0.000*	0.000*
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.053			-0.056	-0.055
		(0.035)			(0.036)	(0.037)
Share of Individual Firms		-0.030***			-0.030***	-0.030***
		(0.003)			(0.003)	(0.003)
Share of Higher Education Degrees		0.037***			0.038***	0.037***
		(0.005)			(0.005)	(0.005)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Excess Credit Reallocation (First lag)			0.015*	0.015*	0.005	0.005
			(0.008)	(0.008)	(0.003)	(0.003)
Excess Credit Reallocation (Second lag)				0.016		0.005
				(0.010)		(0.003)
Observations	1,718	1,718	1,717	1,716	1,717	1,716
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	11.18	11.58	8.940	7.856	9.324	8.207
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	11.18	11.58	8.940	7.856	9.324	8.207
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	41.08	7.333	42.27	43.30	7.663	7.785
First Stage Regression						
VARIABLES	EXC	EXC	EXC	EXC	EXC	EXC
No. of Savings Banks in 1936 (per 100,000 inhabitants)	0.009***	0.009***	0.008***	0.008***	0.009***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.8: Credit growth and innovation (Full sample from 1950 to 1973)

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Net Credit Growth	0.011**	0.016***	0.013**	0.014**	0.020**	0.020**
	(0.005)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Share of Active Population		-0.001**			-0.001*	-0.001*
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		0.020			0.019	0.020
		(0.063)			(0.071)	(0.072)
Share of Individual Firms		-0.030***			-0.030***	-0.030***
		(0.004)			(0.004)	(0.004)
Share of Higher Education Degrees		0.036***			0.036***	0.036***
		(0.006)			(0.007)	(0.007)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Net Credit Growth (First lag)			-0.003**	-0.003**	-0.004**	-0.004**
			(0.001)	(0.001)	(0.002)	(0.002)
Net Credit Growth (Second lag)				-0.000		-0.000
				(0.001)		(0.001)
Observations	1,658	1,658	1,657	1,656	1,657	1,656
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	8.668	10.50	6.505	6.365	7.990	7.930
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	8.668	10.50	6.505	6.365	7.990	7.930
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	11.59	23.59	12.52	12.67	25.47	25.61
First Stage Regression						
VARIABLES	NET	NET	NET	NET	NET	NET
Inverse Credit Market Concentration in 1936	0.006***	0.007***	0.005**	0.005**	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.4.1 The North-South Divide

The results are not driven by the North-South divide, since they hold (even more strongly) when we drop Southern regions from the sample with the inclusion of additional data. Financially underdeveloped regions tend to be in the South. In sum, the 1936 law froze the Italian banking system at a very peculiar time. If we exclude the South, the structure of the banking industry in 1936 was the result of historical accidents and forced consolidation, with no connection to the level of economic development at that time. Table D.9 and Table D.10 present the results.

Table D.9: Credit reallocation and innovation in the Northern provinces (Full sample from 1950 to 1973)

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Excess Credit Reallocation	-0.202***	-0.049**	-0.217***	-0.237***	-0.051**	-0.054*
	(0.060)	(0.024)	(0.070)	(0.074)	(0.026)	(0.028)
Share of Active Population		-0.000**			-0.000**	-0.000**
		(0.000)			(0.000)	(0.000)
No. of Bank Branches per Firms		-0.186***			-0.187***	-0.186***
		(0.057)			(0.058)	(0.059)
Share of Individual Firms		-0.032***			-0.032***	-0.031***
		(0.004)			(0.004)	(0.004)
Share of Higher Education Degrees		0.023***			0.023***	0.023***
		(0.008)			(0.008)	(0.008)
Productivity (Total Value Added per Firm)		0.000***			0.000***	0.000***
		(0.000)			(0.000)	(0.000)
Excess Credit Reallocation (First lag)			0.017	0.017	0.002	0.003
			(0.011)	(0.012)	(0.003)	(0.003)
Excess Credit Reallocation (Second lag)				0.026		0.003
				(0.020)		(0.005)
Observations	780	780	780	780	780	780
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	11.76	13.18	9.893	10.45	11.07	12.60
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	11.76	13.18	9.893	10.45	11.07	12.60
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	51.75	5.440	52.70	52.87	5.161	4.687
First Stage Regression						
VARIABLES	EXC	EXC	EXC	EXC	EXC	EXC
No. of Savings Banks in 1936 (per 100,000 inhabitants)	0.013***	0.016***	0.012***	0.012***	0.015***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.10: Credit growth and innovation in the Northern provinces (Full sample from 1950 to 1973)

VARIABLES	(1) Patents per firms	(2) Patents per firms	(3) Patents per firms	(4) Patents per firms	(5) Patents per firms	(6) Patents per firms
Net Credit Growth	0.058	0.054	0.078	0.077	0.066	0.065
	(0.041)	(0.041)	(0.073)	(0.073)	(0.059)	(0.057)
Share of Active Population		-0.004			-0.004	-0.004
		(0.003)			(0.003)	(0.003)
No. of Bank Branches per Firms		-0.166			-0.164	-0.166
		(0.156)			(0.186)	(0.182)
Share of Individual Firms		-0.039***			-0.040***	-0.041***
		(0.011)			(0.013)	(0.013)
Share of Higher Education Degrees		0.008			0.004	0.005
		(0.024)			(0.030)	(0.029)
Productivity (Total Value Added per Firm)		0.000***			0.000**	0.000**
		(0.000)			(0.000)	(0.000)
Net Credit Growth (First lag)			-0.015	-0.015	-0.009	-0.009
			(0.015)	(0.015)	(0.009)	(0.009)
Net Credit Growth (Second lag)				0.001		0.004
				(0.004)		(0.004)
Observations	740	740	740	740	740	740
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	2.018	1.855	1.098	1.108	1.248	1.304
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	2.018	1.855	1.098	1.108	1.248	1.304
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	18.94	18.17	19.06	19.02	18.17	18.14
First Stage Regression						
VARIABLES	NET	NET	NET	NET	NET	NET
Inverse Credit Market Concentration in 1936	0.005	0.005	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.4.2 An Alternative Specification

We perform the estimation with the dependent variable of "Patents per 100,000 people", including additional data. Table D.11 and Table D.12 present the results. The results are robust to a change in the definition of the dependent variable. The signs of excess credit reallocation and net credit growth remain the same as all province characteristics. However, the magnitudes of the coefficient estimates change drastically with new definition, which is expected due to change in the denominator of the dependent variable.

Table D.11: Credit reallocation and innovation (Alternative specification - Full sample from 1950 to 1973)

VARIABLES	(1) Patents per 100,000 people	(2) Patents per 100,000 people	(3) Patents per 100,000 people	(4) Patents per 100,000 people	(5) Patents per 100,000 people	(6) Patents per 100,000 people
Excess Credit Reallocation	-533.406***	-202.366**	-594.176***	-655.353***	-226.240**	-247.446**
	(176.771)	(84.992)	(215.094)	(249.404)	(98.357)	(110.530)
Share of Active Population		1.372***			1.378***	1.395***
		(0.434)			(0.442)	(0.452)
No. of Bank Branches per 100,000 People		-0.012			-0.015	-0.017
		(0.042)			(0.044)	(0.045)
Share of Individual Firms		-127.659***			-127.584***	-127.129***
		(15.661)			(15.982)	(16.305)
Share of Higher Education Degrees		128.329***			129.252***	129.534***
		(20.664)			(21.468)	(22.233)
Productivity (Total Value Added per capita)		0.840***			0.837***	0.832***
		(0.143)			(0.148)	(0.153)
Excess Credit Reallocation (First lag)			62.751**	63.925*	26.028*	26.521*
			(32.007)	(34.884)	(14.196)	(14.994)
Excess Credit Reallocation (Second lag)				66.671*		23.029
				(40.470)		(16.944)
Observations	1,718	1,718	1,717	1,716	1,717	1,716
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	11.18	13.10	8.940	7.856	10.66	9.382
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	11.18	13.10	8.940	7.856	10.66	9.382
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	37.68	9.749	38.95	40.10	10.24	10.32
First Stage Regression						
VARIABLES	EXC	EXC	EXC	EXC	EXC	EXC
No. of Savings Banks in 1936 (per 100,000 inhabitants)	0.009***	0.010***	0.008***	0.008***	0.009***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.12: Credit growth and innovation (Alternative specification - Full sample from 1950 to 1973)

VARIABLES	(1) Patents per 100,000 people	(2) Patents per 100,000 people	(3) Patents per 100,000 people	(4) Patents per 100,000 people	(5) Patents per 100,000 people	(6) Patents per 100,000 people
Net Credit Growth	50.058**	60.528**	60.328**	60.981**	71.974**	72.238**
	(21.672)	(23.861)	(28.357)	(28.885)	(30.290)	(30.453)
Share of Active Population		-2.525			-2.325	-2.321
		(1.605)			(1.725)	(1.720)
No. of Bank Branches per 100,000 People		-0.042			-0.047	-0.047
		(0.049)			(0.052)	(0.053)
Share of Individual Firms		-139.148***			-138.657***	-138.699***
		(16.628)			(17.358)	(17.359)
Share of Higher Education Degrees		134.859***			134.192***	134.152***
		(23.095)			(24.408)	(24.480)
Productivity (Total Value Added per capita)		0.720***			0.725***	0.725***
		(0.147)			(0.156)	(0.156)
Net Credit Growth (First lag)			-13.492**	-13.262**	-14.586**	-14.584**
			(6.019)	(5.999)	(5.848)	(5.825)
Net Credit Growth (Second lag)				-1.695		-0.315
				(2.457)		(2.504)
Observations	1,658	1,658	1,657	1,656	1,657	1,656
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Instruments						
Weak Instrument Test by Stock and Yogo (2005)						
F-Stat	8.668	10.64	6.505	6.365	8.241	8.223
Stock-Yogo Critical Values						
10% of Maximal IV Size	16.38	16.38	16.38	16.38	16.38	16.38
15% of Maximal IV Size	8.96	8.96	8.96	8.96	8.96	8.96
20% of Maximal IV Size	6.66	6.66	6.66	6.66	6.66	6.66
25% of Maximal IV Size	5.53	5.53	5.53	5.53	5.53	5.53
Weak Instrument Test by Olea and Pflueger (2013)						
Efficient F-Stat	8.668	10.64	6.505	6.365	8.241	8.223
Critical Values						
5% of Worst Case Bias	37.42	37.42	37.42	37.42	37.42	37.42
10% of Worst Case Bias	23.11	23.11	23.11	23.11	23.11	23.11
20% of Worst Case Bias	15.06	15.06	15.06	15.06	15.06	15.06
30% of Worst Case Bias	12.04	12.04	12.04	12.04	12.04	12.04
Weak Instrument Robust Inference - AR Test (Anderson and Rubin (1949))						
AR F-Stat	14.44	19.26	15.39	15.50	20.87	21.09
First Stage Regression						
VARIABLES	NET	NET	NET	NET	NET	NET
Inverse Credit Market Concentration in 1936	0.006***	0.007***	0.005**	0.005**	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1