Inferences from Financial Statements of Legally Registered Mafia Firms in Italy

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Doctoral thesis submitted to the Doctorate Program in Business of the Universitat de Barcelona

Barcelona, December of 2014

To Maika and my parents

“Intellectual growth should commence at birth and cease only at death”

Albert Einstein

Acknowledgments

I wish to express my gratitude to those people who allowed me to attain something that at the beginning seemed almost unattainable. In particular, I thank my thesis director Prof. Josep Maria Argilès for his constant, timely, patient and valuable support. Many thanks also go to Prof. Jaume Valls, director of the UB Business PhD, who gave me the opportunity to undertake and win this challenge. I am extremely grateful to my friend Dr. Michele Giuranno from Università del Salento that provided me with the precious access to AIDA database. Furthermore, I thank Libera (Associations, names and numbers against mafias) that provided me relevant information for the development of this thesis. Since 1995 Libera has been engaged in the fight against mafias and in the promotion of legality and justice. Least, but not last, I thank my wife Dr. Maika Valencia who supported me both professionally and personally.

Diego Ravenda, Barcelona, December 2014

Abstract

In this dissertation we examine labor tax avoidance, expenses manipulation and accrual management within a sample of 224 Italian firms defined as legally registered Mafia firms (LMFs), due to having been confiscated by judicial authorities in relation to alleged connections of their owners with Italian organized crime. Based on the insights gained, we further develop a predictive model that can contribute to the detection of LMFs.

Overall, our results reveal that, before being confiscated, LMFs engage more in labor tax avoidance and accrual management relative to lawful firms (LWFs). Furthermore, LMFs upward manage material expenses and downward manage personnel and service expenses with a cumulative negative effect on reported cash flow relative to sales. On the other hand, following their confiscation and consequent assignment to legal administrators, practices of LMFs mostly become insignificantly different from those of LWFs, although LMFs continue exhibiting a higher degree of accrual management. Finally, our detection model correctly classifies 76.41% of firms within a matched sample of 852 firm-years including LMFs before confiscation and LWFs.

Unlisted LMFs are socially irresponsible by nature because of their illicit purposes. In addition, their incentives, *modus operandi* and financial statement formats differ from those of listed companies. Hence, our study allows inferring conclusions on the relations of corporate social responsibility with earnings management and labor tax avoidance. Furthermore, it adopts new earnings management and labor tax avoidance measures that, as well as providing additional insights, may enhance further research on their effectiveness in other cultural, legal and institutional contexts and for other types of firm.

Finally, but no less important, our findings can aid practitioners and regulators in identifying accounting signals that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices, especially in countries with a strong criminal presence.

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Chapter 1: General Introduction

1.1 Framework, Objectives and Contributions

The Mafias, which are considered to be the most sophisticated form of criminal organization, also run businesses in the lawful economic sphere in which they usually invest proceeds from illicit trafficking (money laundering). Legally registered Mafia firms (LMFs), according to criminologists' terminology, can be defined as firms that are legally registered and apparently engage in lawful activities but are owned by a Mafia family (Champeyrache, 2004). Specifically, LMFs differ from lawful firms (LWFs) in three main ways (Gambetta, 1993; Fantò, 1999): the owners are members of a criminal organization; total or partial funding comes from illegal activities; and criminal methods involving violence, intimidation or corruption may be used while doing business. Legal and illegal activities are therefore closely intertwined within LMFs as the legal activities mostly serve to launder profits stemming from illegal ones (Fantò, 1999).

A reliable estimate of the presence of LMFs in Italy is hardly achievable. Nonetheless, the relevance of the phenomenon can be inferred from a recent study, performed by Transcrime (2013) on behalf of Italian Ministry of Interior, which quantifies the annual illegal revenues of Mafias in Italy between 8.3 and 13 billion Euros. Furthermore, 8.7% of the total investment of Mafias in legal economy between 1983 and 2011 is represented by companies and stocks.

In this regard, our study is based on a sample of 224 Italian firms defined as LMFs, due to having been confiscated at some point by judicial authorities in relation to alleged connections of their owners with Italian organized crime. In particular, we perform some inferences from their financial statements which may contribute to advances in several topics mostly studied in business and accounting areas. We identify two main time periods: the pre-confiscation period and the post-confiscation period within a time frame of 10 years from 2003 to 2012 for which financial statements are available on AIDA database. In this way, we aim to assess whether the confiscation of LMFs and their consequent assignment to legal administrators have a significant impact on their practices.

In general, we aim to understand whether Accounting can contribute to understanding the mechanisms of the criminal economy and terrorist funding. In this regard, Compin (2008) suggests that one of the role of Accounting in a criminal business is to mask the crime by ensuring that the accounting information, although deceptive, contains all the necessary virtues and in turn maintains an impression of rationality and economic credibility.

For this purpose, we examine earnings management and labor tax avoidance in LMFs and finally build a predictive model that can contribute to the detection of LMFs. Within earnings management we consider both accrual management and expenses manipulation. Indeed, the large amount of research carried out thus far indicates that managers exercise discretion and manage earnings for different purposes using a wide variety of methods, ranging from carrying out special transactions (e.g., Roychowdhury, 2006; Cohen et al., 2008; Zang, 2012) that usually affect firm's operating activities, expenses and cash flow (CFO) to the discretionary manipulation of accruals with no CFO impact (Dechow and Dichev, 2002; Dechow et al., 2010). In addition, we adopt some unexplored or not fully explored earnings management proxies based on specific accruals and expenses classified by nature. Indeed, previous studies mostly examine aggregate accruals and expenses classified by function such as production, R&D and selling, general and administrative (SG&A).

Overall, we mainly find that LMFs manage revenue, expense and aggregate accruals both before and after confiscation. On the other hand, before confiscation LMFs upward manage material expenses and downward manage personnel and service expenses with a cumulative negative effect on reported cash flow relative to sales. In contrast, following the confiscation and the intervention of legal administrators, personnel and service expenses manipulation becomes insignificant, whereas material expenses manipulation significantly decreases relative to before confiscation.

As regards labor tax avoidance, we develop two new measures, based on social contribution expenses reported in financial statements, and test them and their determinants within our sample of LMFs. We report that before confiscation LMFs engage more in labor tax avoidance than LWFs do, whereas after confiscation there is no significant difference between both types of firm. Furthermore, we find that several factors have a significant influence on the probability of engaging in such a practice.

Finally, based on the insights gained from our aforementioned studies, we develop a detection model of LMFs which correctly classifies 76.41% of firms within a matched sample of 852 firm-years including LMFs before confiscation and LWFs.

Our studies contribute to the business and accounting literature in several ways. First of all, to the best of our knowledge, there are no previous studies that examine earnings management and labor tax avoidance in LMFs. These unlisted firms may particularly interest the scientific community given that they are socially irresponsible by nature, because of their illicit purposes. In addition, their incentives, *modus operandi* and financial statement formats differ from those of listed companies. Hence, our study allows inferring conclusions on the relations of corporate social responsibility (CSR) with earnings management and labor tax avoidance. Furthermore, it adopts new earnings management and labor tax avoidance measures that provide additional insights and may enhance further research on their effectiveness in other cultural, legal and institutional contexts and for other types of firm.

Finally, but no less important, our findings can aid practitioners and regulators in identifying accounting signals in firm management that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices, especially in those countries where organized crime is deeply rooted.

The aforementioned studies are organized in 4 chapters and each chapter has a structure of a standalone paper. However, all chapters are closely related because of the main object of study, represented by LMFs, on which we apply our constructs and test our hypotheses. Specifically, chapter 2 deals with labor tax avoidance, chapter 3 examines expenses manipulation, chapter 4 analyses accrual management, chapter 5 develops the detection model and chapter 6 includes concluding remarks.

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Chapter 2: Labor Tax Avoidance and Its Determinants: The Case of Mafia Firms in Italy

2.1 Abstract

This paper develops two new measures of labor tax avoidance (LTAV) based on social contribution expenses reported in financial statements and tests them and their determinants within a sample of 224 Italian firms defined as legally registered Mafia firms (LMFs) due to having been confiscated at some point by judicial authorities, in relation to alleged connections with Italian organized crime. Overall, our results reveal that before confiscation LMFs engage more in LTAV than lawful firms do, whereas after confiscation there is no significant difference between both types of firm. Furthermore, we find that several factors have a significant influence on the probability of engaging in such a practice.

This study can enhance further research on the effectiveness of our measures and on the determinants of LTAV in other contexts and for other types of firm. Moreover, these measures can be added to the other direct and indirect methods commonly employed to measure and detect undeclared work representing a primary means of LTAV. Finally, our study allows inferring conclusions on the relation between corporate social responsibility and tax avoidance, suggesting that socially irresponsible firms, such as LMFs, are more likely to adopt this practice.

2.2 Introduction

Previous studies on tax avoidance (TAV) have concentrated mostly on income tax avoidance (ITAV). In this study we focus our attention on labor tax and develop two new measures of labor tax avoidance (LTAV) based on social contribution expenses (SOCs) reported in financial statements. Subsequently, we test them and their determinants on a sample of 224 Italian firms defined as legally registered Mafia firms (LMFs) due to having been confiscated at some point by judicial authorities, in relation to alleged connections with Italian organized crime. We additionally examine the effect that the confiscation of the firms and their assignment to legal administrators may have on LTAV. Hence, we identify two main time periods: the pre-confiscation period and the post-confiscation period within a time frame of 10 years from 2003 to 2012 for which financial statements are available on AIDA database.

Indeed, the Mafias, which are considered to be the most sophisticated form of criminal organization, also run businesses in the lawful economic sphere in which they usually invest proceeds from illicit trafficking (money laundering). LMFs, according to criminologists' terminology, can be defined as firms that are legally registered and apparently engage in lawful activities but are owned by a Mafia family (Champeyrache, 2004). LMFs differ from lawful firms (LWFs) in three main ways (Gambetta, 1993; Fantò, 1999): the owners are members of a criminal organization; funding partially or totally comes from illegal activities; and criminal methods involving violence, intimidation or corruption might be used while doing business. Legal and illegal activities are therefore closely intertwined within LMFs as the legal activities mostly serve to launder profits stemming from illegal ones (Fantò, 1999).

On the other hand, labor tax consists of social security contributions and other insurances computed on gross wages of all employees that the employers are legally required to withhold and pay to tax authorities. However, if employers underreport the real size of their labor force or the hours actually worked or the position covered to the social security authorities, they may then be able to avoid payment of the legally due social security contributions. In addition, we expect underreporting of labor force and related expenses to be consistently reflected in the financial statements. Although the base of calculation of labor tax is different from that of income tax, their avoidance has similar negative effects on society by reducing tax revenue which is needed to finance public goods and services (Freedman, 2003; Slemrod, 2004; Landolf, 2006; Lanis and Richardson, 2012). Following Hanlon and Heitzman (2010) and Dyreng et al. (2008) we define TAV broadly as the reduction of firm's explicit income and labor tax liability through specific transactions. We do not distinguish between technically legal TAV and illegal evasion as in several cases the legality of a transaction, usually linked to its "economic substance" or a "business purpose", cannot be clearly determined. For example, LTAV may be legal if carried out through rearrangement of wages for hired employees with other forms of pay or compensation in order to avoid a portion of taxes (e.g., employee discount, fringe benefits, income from property leasing) (Feld and Schneider, 2010; Krumplyte and Samulevicius, 2010). Although our measures of LTAV can reflect both legal and illegal tax reductions we consider that, because of our research design, the illegal tax evasion related to the employment of undeclared work (UDW) may be the primary explanation of the results conveyed by our measures. Indeed, UDW is the primary illegal means commonly used to avoid labor tax payment (Feld and Larsen, 2005; Feld and Schneider 2010). Hence, our measures of LTAV can also be categorized as a new direct method to measure UDW based on financial statement information.

Overall, our results reveal that before confiscation LMFs engage more in LTAV by exhibiting lower abnormal social contribution expenses (ABSOCs) than LWFs, whereas after confiscation there is no significant difference between these two types of firm or this difference significantly decreases. These results may indicate a larger resort to UDW of LMFs before confiscation which is mitigated after confiscation due to the reinstatement of legality and the consequent regularization of all employees carried out by legal administrators. Furthermore, we find that before confiscation LMFs which are larger and exhibit abnormally higher material expenses are less likely to engage in LTAV, whereas LMFs with higher return on assets and a greater proportion of inventory are more likely to engage in such a practice and vice versa.

Prior research has focused on the examination of ITAV in varying types of firms in diverse contexts. For example, Rego (2003) finds that multinational corporations with more extensive foreign operations engage more in ITAV measured by effective tax rates (ETRs) than firms with less extensive foreign operations which have fewer opportunities to adopt such a practice. More recently, Wilson (2009) and Lisowsky (2010) document similar results in terms of likelihood of corporate tax shelter utilization. Other studies find that private companies are more tax aggressive than public companies especially in a few selected industries, such as banks and insurers (e.g., Cloyd et al., 1996; Beatty and Harris, 1999; Mills and Newberry, 2001). Moreover, although public family firms are similar to private firms in the concentration of ownership of selected individuals, Chen et al. (2010) find that the former are less tax aggressive than their non-family counterparts.

Some traits of LMFs can be identified in some studies on ITAV aforementioned. Nonetheless, to the best of our knowledge there are no previous studies in the literature that examine TAV in LMFs and more specifically LTAV using financial statement information and the factors that may influence its practice at firm level. In this paper we aim to bridge this gap. In addition, our study contributes to the business literature given that it adopts new LTAV measures that may enhance further research on their effectiveness and on the determinants of LTAV in other cultural, legal and institutional contexts and for other types of firm. Moreover, these measures can be added to the other direct and indirect methods commonly employed by practitioners and researchers for the difficult task of measuring UDW. Most important, their ability to infer the presence of UDW can contribute to protecting employees against illegal exploitation and to avoiding tax revenue loss and related issues of equity in the social security system. Furthermore, these measures can supplement current compliance risk-assessment models used by tax authorities. On the other hand, our study examines LMFs that may particularly interest the scientific community due to their singularities. Indeed, they are socially irresponsible by nature because of their illicit purposes. Moreover, they are private firms with incentives, *modus operandi* and legal financial statement formats (i.e. income statement by nature) that differ from those of public listed companies. Finally, it allows inferring conclusions on the relation between corporate social responsibility (CSR) and LTAV, suggesting that socially irresponsible firms, such as LMFs, tend to engage more in such a practice.

The remainder of the paper proceeds as follows: "Legally Registered Mafia Firms" section introduces LMFs; "Related Research and Hypothesis Development" section reviews the literature and develops the hypotheses; "Research Design" section describes the research design and sample data; "Results and Discussions" section presents empirical results and their discussion; "Conclusions" section includes concluding remarks.

2.3 Legally Registered Mafia Firms

For the purpose of this study, we define "organized crime" according to the Italian legal provision of "associazione a delinquere di tipo mafioso" (article 416-bis of the Italian criminal code). In particular, art. 416-bis states that:

“A mafia-type association consists of three or more individuals and those who belong to it make use of the power of intimidation afforded by the associative bond and the state of subjugation and criminal silence (omertà) which derives from it to commit crimes, to acquire directly or indirectly the management or control of economic activities, concessions, authorizations or public contracts and services, either to gain unjust profits or advantages for themselves or for others, or to prevent or obstruct the free exercise of the vote, or to procure votes for themselves or to others at a time or electoral consultation”.

Ever since their appearance in the middle of the 19th century, Italian criminal organizations have infiltrated the social and economic life of many regions only in Southern Italy. The Sicilian Mafia, the most notorious of these organizations, would later expand into other foreign countries including the United States. There are several known mafia-like organizations in Italy: Cosa Nostra of Sicily and Ndrangheta of Calabria are considered among the biggest cocaine smugglers in Europe and, together with Camorra of Naples, began to develop between 1500 and 1800. More recently in the 1980s, two new organizations, Stidda and Sacra Corona Unita of Apulia, also appeared.

One of the main reasons for criminal organizations to take on new businesses is so as to be able to invest and launder significant financial resources coming from illegal activities, such as usury, extortion, drug, waste and arms trafficking and so on. This form of investment of illicit capital is a way to break into legal markets in order to obtain high profits and launder so-called "dirty" money. Another very important aspect is the need to achieve social consensus through activities that ensure employment and income for the population in the areas in which the criminal organization exercises control of the territory.

Several authors in Sociology have analyzed characteristics of LMFs. Fantò (1999) suggests that the main trait of LMFs is not the type of business run but the nature of the capital accumulation process that led to their formation as well as the strength of intimidation on which they are hinged. This force of intimidation, according to the same author, in addition to being the precondition that allows LMFs to take a dominant position in a territory, it is also a kind of surplus value that is added to what normally yields the legal capital invested in the same area and under the same conditions. The mafia-style intimidation is the point of greatest strength, the source of the competitive advantages of firms and economies of the Mafias over firms and the legal economy.

Arlacchi (1983) identifies the following competitive advantages of the LMFs over the LWFs: discouragement of competition (securing goods and raw materials at favorable prices, as well as orders, contracts and commercial outlets using criminal intimidation); wage compression (evasion of social security contributions and insurance, non-payment of overtime, denial of trade union rights); availability of financial resources (investment of huge proceeds coming from illegal activities (money laundering) without bearing the cost of credit).

In this study a firm is classified as LMF if, at some point during its existence, it has been confiscated by Italian authorities because of alleged connections to one of the Italian criminal organizations. After the first instance of court confiscation the LMF is entrusted to one or more legal administrators. The Legal Administration (LA) is an institution designed to protect and manage confiscated assets and firms and to avoid their progressive impoverishment. The LA is based on strong principles of corporate social responsibility and public interest. The main objectives of legal administrators are: the reinstatement of legality in the management of the firm, the reorganization and turnaround of the firm according to sound management principles. However the administration of these firms in not always sufficiently dynamic and market-oriented and conservatism may prevail. Furthermore, it ought to be noted that the confiscation of first instance is a temporary measure that can be followed, even after several years, by the definitive confiscation as the last phase of the trial.

The body in charge of the administration and assignment of assets (including firms) definitively confiscated to organized crime is the Italian agency Agenzia Nazionale Beni Sequestrati e Confiscati (ANBSC) which was created through Decree Law on February 4th 2010. The main concern of ANBSC is to ensure the continuation of firms after confiscation, as most of them risk bankruptcy with the consequent loss of employment resulting in a hugely negative impact on their workforce and subsequently social stability. According to the most recent available data on the ANBSC official website

(http://www.benisequestraticonfiscati.it) the number of confiscated firms on January 7th 2013 was 1,708. After confiscation firms can be sold, leased or liquidated and although the efforts of ANBSC to ensure the continuation of the business, the most of the firms end up being liquidated or going bankrupt as they are unable to face the market competition after losing the support of organized crime and banks.

LMFs are mainly created as limited-liability companies (Società a responsabilità limitata (SRL)) with a reduced number of owners that exercise a close control on operations directly or indirectly through trusted managers that are often affiliates of the same criminal organization. One might then assume that the potential misalignment of interests and goals between them is reduced, with no significant agency problems. The minimum required starting equity for a SRL is € 10,000. Its capital is divided into shares which can be bought or sold just by notarial act. SRLs can issue corporate bonds but are subject to many limitations. Organized crime may prefer this corporate structure because the initial investment is lower than alternative legal forms, audit committee is not required, and even from a fiscal point of view there are fewer charges.

2.4 Related Research and Hypothesis Development

There are two lines of research that are highly relevant for this paper. The first consists of studies on UDW typical of public economics or labor relations areas and the second consists of studies on ITAV mostly concentrated in the business and accounting areas.

2.4.1 UDW and Its Measure

The phenomenon of UDW is known under a broad variety of different names. Terms such as "cash-in-hand", "black work", "informal economy", "shadow economy", "underground economy" and many others have been used to describe the phenomenon or parts of it. Indeed, there is no single comprehension on the concept of UDW in the scientific and applied literature. The choice of the research object definition is determined by research objectives and specifics of used research methods. The analysis of UDW in the light of tax non-compliance spotlights phenomena attributable to tax evasion and avoidance. In this regard, Feld and Larsen (2005) defines UDW as income from productive economic activities which are legal and taxable, but on which income tax, social security contributions, VAT, etc., are not paid, because they are not reported to the tax, social security or customs authorities. These activities are not only deliberately concealed from public authorities in order to save taxes, but also to avoid certain legal labor market standards, such as minimum wages, maximum working hours, safety standards, etc., and to avoid certain administrative obligations, such as completing statistical questionnaires or other administrative forms (Feld and Schneider, 2010). These are the only differences between undeclared and declared work. If there are other differences, then it is not defined as UDW. If the goods and/or services are illegal (e.g. drug-trafficking), for example, then this is "criminal" activity. If the activity is not remunerated, similarly, it is part of the unpaid informal economy (Williams, 2010). Thus, UDW is the part of the shadow economy which only involves labor as a production factor and the related evasion of tax and social security contributions (Schneider and Enste, 2002). In addition, the term UDW does not describe a uniform type of employment. Indeed, it rather covers a variety of forms of work that constitute distinctly different types involving different degrees of social integration, as they are based on different motives of employees and strategies of employers or contractors, and their interplay (Pfau-Effinger, 2009). Pfau-Effinger (2009) distinguishes three main types of undeclared workers form a workers' motivational perspective. The poverty escape type, in which, from a supply side perspective, UDW avoids extreme poverty and provides the main source of income. This type is common within populations that are restricted from entering regular employment. From a demand side perspective this type of UDW is linked to a cost-saving strategy of firms for tasks that require relatively low skills in private households (Pfau-Effinger, 2009). The second type of UDW is the moonlight type which covers mainly qualified craftsmen who are unregistered self-employed. Last but not least, the solidarity-orientated type is UDW in which the main motive is the mutual support within social networks, more than the monetary gain. With regard to LMFs the first type may be prevalent considering the traditionally high unemployment rate of regions in South of Italy where LMFs in our sample are more abundant. Recent studies find that UDW is still large and growing relative to declared work in nearly all-global regions (Schneider, 2008; Schneider and Bajada, 2005; Williams, 2009a; Williams, 2010). UDW creates considerable costs on several levels: tax authorities receive less revenue in the form of income tax or value added taxes; social security institutions do not get contributions and undeclared activities partly inhibit the creation of regular employment with full social protection. UDW in firms is found mostly in sectors characterized by high work intensity but with low levels of organizational rationalization and of production (Pfau-Effinger, 2009). This is linked to the character of UDW: there is relatively little commitment to the employing enterprise, and thus also relatively little enterprise-specific worker qualification and relatively high worker fluctuation (turnover) levels. These features are not compatible with jobs in primary labor market sectors and high-production enterprises that use highly developed technologies (Williams and Windebank, 1998). In this regard, LMFs in our sample are particularly concentrated in sectors traditionally associated with higher UDW. For the development of adequate policy measures which deal with UDW, it is important to have sufficient and comparable information not only about the extent, but also about the structure of UDW (Schneider and Enste, 2000). Unfortunately, it is very difficult to get accurate information about shadow economy activities on the goods and labor market, because all individuals engaged in these activities do not wish to be identified (Schneider et al., 2010). Nonetheless, previous studies use several direct and indirect methods in order to approximately measure UDW. Indirect methods try to determine the size of the hidden economy (UDW) by measuring the "traces" it leaves in the official statistics. They are often called indicator approaches and use mainly macroeconomic data such as such national accounts, electricity consumption, cash transactions, employment figures, etc. (Schneider and Enste, 2000; Dell'Anno et al., 2007; Schneider et al., 2010). Such methods can be divided into six categories: (1) the discrepancy between national expenditure and income statistics; (2) the discrepancy between the official and real labor force statistics; (3) the transaction approach; (4) the currency demand (or cash deposit ratio) approach; (5) the physical input (e.g. electricity) method; and (6) the model approach or MIMIC method. The model or MIMIC approach understands the dimension of the hidden economy to be a "latent variable", and therefore applies statistical modeling, namely structural equation modeling (SEM), commonly employed in social research (psychology, sociology, marketing, etc.) to explore unobservable variables such as attitudes, personality, beliefs, satisfaction, etc. Using this approach Schneider (2004) finds that Greece has the largest shadow economy in Europe, followed by Italy and Spain. Dell'Anno et al. (2007) also use the MIMIC method to estimate the size and the evolution of the shadow economy in three Mediterranean countries, namely France, Spain and Greece. They find that in the French case the shadow economy is declining whereas the submerged economy in Spain and Greece is on increase. Moreover, their results confirm that unemployment, the fiscal burden and self-employment are the main causes of the shadow economy in these countries, and confirm that an inverse relationship exists between the official GDP growth rate and that of the unofficial economy. Finally, applying the same MIMIC method to the Spanish case, Alañón and Gómez-Antonio (2005) find a considerable shadow economy, measuring between 8 and 18.8% of GDP in the period 1976–2002, and demonstrate that the shadow economy is significantly influenced by the tax burden, the degree of regulation and unit labor costs. Some indirect methods have been criticized because of the questionable basic assumptions and the unreliable macroeconomic estimates on which they rely (Schneider and Enste, 2000; Ahumada et al., 2007; Feige and Urban, 2008).

On the other hand, direct methods to measure UDW are microeconomic approaches based on contacts with or observations of persons and/or firms to gather direct information about UDW (Dell’Anno et al., 2007). They employ either surveys based on voluntary replies or tax auditing and other compliance methods (Schneider and Enste, 2000; Feld and Larsen, 2005; Williams, 2006). The main advantage of the direct method of voluntary sample surveys lies in the detailed information that can be gained about the structure of the UDW although the results depend greatly on the respondents’ willingness to cooperate (Schneider and Enste, 2000). In this regard, Williams (2006) analyses the results of a cross-national survey conducted across 27 EU member states in 2007 involving 26,659 face-to-face interviews. He unravels the heterogeneous nature of UDW across the European Union and the marked geographical variations in its configuration. Furthermore, he finds that most countries currently use only a relatively limited range of the potential policy measures at their disposal to tackle UDW. Using information on characteristics of artisan firms in Piedmont (Italy) in 2000 to 2005 and tax evasion observed directly from the audit exercise, Di Porto (2011) estimates UDW and finds that tax inspections could actually be counterproductive, decreasing both tax compliance and tax revenues. Williams (2009b) shows how the formal economy can be permeated by informal practice. He reports a 2007 survey in the 27 EU member states finding that some 5 percent of all formal employees receive from their formal employer two wages, one declared and the other an undeclared and cash-in-hand "envelope" wage. Nevertheless, such a practice is not evenly distributed across all population groups, sectors and geographical areas. The economic sector where formal employees most commonly receive undeclared earnings, meanwhile, is construction. Construction is exactly the sector in which LMFs in our sample are more abundant.

Finally, it is worth mentioning that UDW in Italy is a substantial problem. Every year the Italian Statistical Institute (ISTAT) estimates the percentage of Italian undeclared employees, to provide an aggregate level of full-time employed (FTE) irregular workers per region and per year for the four main productive sectors (industry, constructions, agriculture, and services). For most of the years taken in our study, 2003-2009, the percentage of undeclared workers estimated by ISTAT is about 12 percent of the total amount FTE in the labor market, of which 19 percent is in the southern Italian regions (i.e., Calabria, Apulia, Sicily and Campania) where most of LMFs in our sample are located.

2.4.2 ITAV and Hypothesis Development

Turning to the other line of research relevant for our paper, previous studies on ITAV can guide us to develop our hypotheses since we assume that the motivations and the incentives to engage in ITAV are similar to those to engage in LTAV. That said, some previous studies support our expectation on the higher probability of LMFs engaging in LTAV than LWFs.

In this regard, when managers perceive that government enforcement of tax rules is stronger, the higher expected probability of detection and potential for imposition of penalties may discourage TAV. That is, managers may decrease TAV when they believe tax authorities are more likely to detect the avoidance and impose additional taxes plus penalties (Crocker and Slemrod, 2005; Desai et al., 2007; Hoopes et al., 2012; Atwood et al., 2012). LMFs benefit from a lower level of scrutiny from outsiders since they can count on the protection granted by the criminal organization through bribery, intimidation and political infiltrations. Thus, for this first reason we expect LMFs to be more likely to engage in LTAV than LWFs.

On the other hand, Dyreng et al. (2010) track the movement of 908 CEOs, CFOs, and other executives across firms during the period 1992 to 2006 in order to examine whether individual executives have an effect on their firms' ITAV. By examining executives who switch firms, they attempt to control for firm fixed effects and identify executive-specific effects. Results indicate that individual executives play a significant role in determining the level of ITAV that firms undertake, incremental to characteristics of the firm. Moreover, Bertrand and Schoar (2003) investigate whether and how individual managers affect corporate behavior and performance. They find, among others, that the realizations of all investment, financing, and other organizational practices of firms appear to systematically depend on the specific executives in charge and some of the managerial differences in corporate practices are systematically related to differences in corporate performance. Although the two studies above are based on publicly traded U. S. firms, we consider that their results are even more so applicable to LMFs. Indeed, in LMFs mafia-member owners exercise a close control on operations directly or indirectly through trusted managers that are often affiliates or surrogates of the same criminal organization. We then expect a significant influence of mafia-member owners on possible illicit practices of their firms including TAV.

Considering LMFs as firms clearly socially irresponsible, we can also refer to some previous studies on the relation between CSR and ITAV in order to get some additional insight for the development of our hypotheses. In this regard, based on a sample of 408 publicly listed Australian corporations for the 2008/2009 financial year, Lanis and Richardson (2012) find that the higher the level of CSR disclosure of a corporation, the lower is the level of aggressive ITAV considered as a socially irresponsible and illegitimate activity. Furthermore, Huseynov and Klamm (2012) examine the effect of three measures of CSR (corporate governance, community and diversity) and tax management fees on ITAV measured by ETRs in firms that use auditor-provided tax services. They find that tax fees are associated with lower GAAP ETR regardless of a firm's strengths or concerns for corporate governance or diversity, but are associated with lower Cash ETR when a firm has corporate governance strengths or diversity concerns. However, tax fees are associated with higher GAAP ETR in a firm with a high number of community concerns and with higher Cash ETR in a firm with any community concerns. Finally, other studies show how some firms that claim to be socially responsible are also engaged in TAV and evasion. Focusing on tax evasions, Preuss (2010, 2012)) finds that firms with headquarters in tax havens tend to make stronger claims of social responsibility than U.S. headquartered firms, and thus conclude that there is a conflict between claiming social responsibility and engaging in off-shore financial centers to reduce their tax liabilities. Similarly, Sikka (2010) provides examples to show how companies, including major accountancy firms, make promises of responsible conduct, but indulge in TAV and evasion. However, Sikka's conclusions are based on case examples, which provide anecdotal evidence, but the analysis lacks rigor (Huseynov and Klamm, 2012).

LMFs benefit from significant competitive advantages (Arlacchi, 1983) and do not need to claim to be socially responsible. Indeed, they mostly derive their gains from coercive market transactions through intimidation, illegal political connections ensured by their infiltrators in the public institutions and privileges granted by illegality and bribery.

Based on previous considerations our study thus empirically tests the following research hypotheses:

> ***H1****: Ceteris paribus, before confiscation LMFs engage more in LTAV than LWFs do.*

As already discussed, after confiscation one of the tasks of legal administrators is the reinstatement of legality within the firm which may for example include the regularization of existing undeclared workers. Hence, the second hypothesis of our study is:

> ***H2****: Ceteris paribus, there is no significant difference in level of LTAV between LMFs after confiscation and LWFs or this difference, although significant, is significantly lower than that between LMFs before confiscation and LWFs.*

2.5 Research Design

2.5.1 LTAV Measures (Dependent Variables)

The dependent variables of our empirical tests are two new measures of LTAV represented by abnormal social contribution expenses (ABSOCs). Importantly, lower ABSOCs suggest higher probability of firm engagement in LTAV and vice versa. It is noteworthy that our analysis is allowed by legal structure of income statement in Italy that classifies costs by nature rather than by function. In order to compute our first measure, we estimate the normal level of SOCs (NSOCs) using the model adopted by prior studies (e.g., Roychowdhury, 2006; Cohen et al., 2008; Kim et al., 2012) for calculation of abnormal production costs:

$$\frac{SOC_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \beta_4 \frac{\Delta S_{t-1}}{TA_{t-1}} + \varepsilon_t \qquad (1)$$

Where SOC_t is the social contribution expenses in year t that we assume mostly related to production; TA_{t-1} is the total assets in year t-1; S_t is the net sales in year t; and ΔS_t is the change in net sales from year t-1 to t (S_t - S_{t-1}). The firm subscript is suppressed for simplicity.

Parameters of Eq. (1) are estimated cross-sectionally for each industry-year with at least 15 observations in order to control for industry-wide changes under different economic conditions (Jeter and Shivakumar, 1999) that affect SOCs while allowing the coefficients to vary across time (e.g., Kasznik, 1999; DeFond and Jiambalvo, 1994). We use all active firms in AIDA (excluding LMFs) which are not listed on the stock exchange and with financial statements available for 10 years from 2003 to 2012. The total number of these firms at the moment of its retrieval from AIDA is 78,340. The level of ABSOCs (*ABSOC1*) is measured as the estimated residual from Eq. (1).

UDW by reducing personnel expenses has the effect of increasing taxable income and income tax burden. LMFs may compensate this through a fraudulent understatement of sale revenues in order to reduce income tax as well as value added tax (VAT) payable. Hence, the ability of measure *ABSOC1* to reflect UDW and LTAV greatly depends on the doubtful reliability of reported sales.

Differently from sales, consumption of raw materials and trading goods is less likely to be under-reported for ITAV purposes although it may be over-reported. Indeed, raw material and trading goods expenses reduce taxable income and increase VAT receivable. We then compute a second measure of ABSOCs (*ABSOC2*) by replacing in Eq. (1) sales with material consumption (*CONSUM*) computed by adding raw materials and trading goods expenses to change in related inventories:

$$\frac{SOC_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{CONSUM_t}{TA_{t-1}} + \beta_3 \frac{\Delta CONSUM_t}{TA_{t-1}} + \beta_4 \frac{\Delta CONSUM_{t-1}}{TA_{t-1}} + \varepsilon_t \quad (2)$$

ABSOC2 is measured as the estimated residual from Eq. (2).

Additionally, in order to test the robustness of our results we perform our analysis both on the full sample and on the two subsamples including respectively firm-year observations with positive and negative values of each of the two measures of LTAV.

2.5.2 Control Variables and Base Regression Model

We explain LTAV measures expressing ABSOCs as depending on firm type (LMF or LWF), period (pre-confiscation and post-confiscation) and other control variables mostly used in previous research on ITAV. Indeed, we assume that engagement in LTAV is associated with the opportunities to engage in ITAV given that UDW increases taxable income through personnel expenses underreporting as well as reducing SOCs. As already mentioned, we assume that lower ABSOCs imply higher probability of engaging in LTAV and vice versa.

As independent variables strictly related to our hypotheses we use binary variables *CRIME1* taking value of 1 for LMFs before confiscation, *CRIME2* taking value of 1 for LMFs after confiscation and *CRIME3* taking value of 1 for LWFs and excluded as a base variable from the final regression model.

Turning to control variables, previous studies on the association between ITAV and firm size (*SIZE*) produce conflicting results. Zimmerman (1983) finds a negative association between ITAV measured by ETRs and *SIZE* and justifies it under the political cost theory claiming that taxes are one part of the higher political costs borne by larger firms. Lower ITAV for larger firms is furthermore found by Rego (2003) and Atwood et al. (2012). On the other hand, Stickney and McGee (1982), Porcano (1986) and Richardson and Lanis (2007) document a positive association between ITAV and *SIZE*. Interestingly, based on empirical evidence, Gupta and Newberry (1997, p. 28) assert that the inconsistent results suggest that firm-size effects could be sample-specific and not likely to exist over time in firms with longer histories. Finally, a further indication on the likely effect of *SIZE* on LTAV may come from Perrini et al. (2007) that, within a sample of 3,680 Italian firms, find that large firms are more likely than small and medium ones to engage in formal CSR strategies also aiming to improve their employee conditions. Hence, we measure *SIZE* as natural logarithm of total assets and given the inconsistent evidence from previous research we do not make any prediction on its relation with LTAV.

Previous research finds a positive association between ITAV, proxied by ETRs, and long–term leverage (*LEVLONG*) given that, among other reasons, interest expenditure is tax deductible while dividends are not (Gupta and Newberry, 1997; Stickney and McGee, 1982; Richardson and Lanis, 2007; Dyreng et al. 2008; Lisowsky, 2010; Atwood et al., 2012). Nonetheless, other studies document a negative association between ITAV related to tax shelter transactions and long-term leverage consistent with the belief of tax shelters being a non-debt tax shield that substitutes for the use of interest tax deductions (Graham and Tucker, 2006; Lisowsky, 2010). We include long-term leverage (*LEVLONG*) in our model and we expect a negative association between this variable and ABSOCs since firms in financial distress and possibly bearing high interest expenses may engage in an aggressive personnel and related SOCs reduction with an associated higher probability of resorting to LTAV.

Previous studies show that firms with larger capital intensity (*CAPINT*), measured as the proportion of fixed assets both tangible and intangible, engage more in ITAV due to tax incentives that permit taxpayers to write-off the cost of depreciable assets over periods shorter than their economic lives (Stickney and McGee, 1982; Gupta and Newberry, 1997; Richardson and Lanis, 2007). On the other hand, firms with a greater proportion of inventory (*INVTA*), substitute for capital intensity, engage less in ITAV (Stickney and McGee, 1982; Gupta and Newberry, 1997; Richardson and Lanis, 2007; Lanis and Richardson, 2012). In contrast, we expect ABSOCs to be positively associated with *CAPINT* and thus negatively with *INVTA*. Indeed, the fact that firms with larger *CAPINT* usually require less but more qualified labor force may discourage the resort to LTAV. In this regard, Pfau-Effinger (2009) finds a higher presence of UDW especially in sectors with high work intensity and low technology.

To the extent that tax incentives (e.g., depreciation), causing book income to differ from taxable income, are not proportionately related to book income, ETRs can change simply due to changes in book income (Richardson and Lanis, 2007). Hence, we expect *ROA* (income before tax divided by total assets) to be positively associated with LTAV consistent with previous studies indicating that more profitable firms, which have the greatest incentive to reduce taxes, engage in more ITAV (Gupta and Newberry, 1997; Richardson and Lanis, 2007; Atwood et al., 2012; Wilson, 2009; Rego, 2003).

An additional control variable used in previous research on ITAV is sales growth (Atwood et al., 2012; Badertscher et al., 2010). We replace it with assets growth (*GROWTH*) that we consider more reliable and less likely to be significantly manipulated relative to sales growth in LMFs. We expect a positive association between *GROWTH* and ABSOCs contrasting with previous studies finding a positive association between ITAV and growth (Atwood et al., 2012; Chen et al., 2010; Badertscher et al., 2010). Indeed, with regard to ITAV growing firms may make more investments in tax-favored assets that generate timing differences in the recognition of expenses (Chen et al., 2010). On the other hand, growing firms have available significant financial resources that may discourage the reduction of personnel costs through LTAV.

Similar to previous studies on ITAV (Desai and Dharmapala, 2006; Wilson 2009; Lisowsky 2010; Atwood et al., 2012) we furthermore examine the relation between LTAV and two specific accrual measures such as change in receivables (*CH_REC*) and change in inventory (*CH_INV*) both deflated by lagged total assets. We expect a positive relation between ABSOCs and these accruals given that firms may try to offset lower ABSOCs having an income-increasing effect with lower inventory and receivables change accruals having an income-decreasing effect. Previous studies find a positive relation between aggressive ITAV and discretionary or unadjusted accruals (Wilson 2009; Frank et al., 2009; Lisowsky 2010; Atwood et al., 2012) in public listed companies suggesting that some ITAV is achieved through accruals management. Nonetheless, we base our opposed expectation on particularities of firms in our study which are private with different incentives from public listed companies.

Besides accrual management we consider the possibility of a manipulation of real activities though transactions affecting the cash flow (e.g., Roychowdhury, 2006). In particular, we focus on material expenses including both raw materials and trading goods that may be increased even fraudulently through fictitious transactions in order to reduce taxable income. Hence, we estimate the abnormal level of material expenses (*ABMAT*) using the model adopted by prior studies (e.g., Roychowdhury, 2006; Cohen et al., 2008; Kim et al., 2012) for abnormal production costs and consisting of the residuals of the following regression:

$$\frac{MAT_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \beta_4 \frac{\Delta S_{t-1}}{TA_{t-1}} + \varepsilon_t \tag{3}$$

Where MAT_t are material expenses in year t. Parameters of Eq. (3) are estimated in the same way as those of Eq. (1). We expect a negative relation between ABSOCs and *ABMAT* since firms engaging more in LTAV may also over-report material expenses and/or under-report sales revenue in order to avoid income tax. This may result in higher *ABMAT*.

In order to test our assumption that LTAV and ITAV may be performed simultaneously, we additionally include in our model a measure of ITAV expecting a positive association with our measures of LTAV. Hanlon and Heitzman (2010) list 12 measures of ITAV commonly used in the literature including different ETRs measures, the most frequently used (Lanis and Richardson, 2012), and book-tax difference measures (Manzon and Plesko, 2002; Desai and Dharmapala, 2006). Among the different measures we adopt the current *ETR* (current tax expense divided by pre-tax book income) (Richardson, and Lanis, 2007; Hanlon and Heitzman, 2010; Lanis and Richardson, 2012). This measure is affected by tax deferral strategies but is not affected by changes in the tax accounting accruals (Hanlon and Heitzman, 2010).

Previous studies find that the level of economic development in a country is negatively associated with the level of tax evasion and corruption (Treisman, 2000; Tsakumis et al., 2007; Richardson, 2008). Furthermore, regional development inequalities in Italy especially between North and South of the country may influence the level of salaries, although in Italy collective agreements define employee salaries by category at national level rather than at regional level. Hence, we include the level of economic development, measured as the natural logarithm of regional GDP (Gross Domestic Product) per capita (*LNGDP*) of the firm location, as a control variable in our base regression model. We expect a positive relation between *LNGDP* and ABSOCs across regions.

Moreover, similar to previous studies on ITAV (Lisowsky, 2010; Dyreng et al., 2010; Lanis and Richardson, 2012) we consider the particular situation of firms bearing losses. Thus, we add a control dummy variable *LOSS* that takes a value of 1 if the firm reports two or more consecutive years of negative income including the current and 0 otherwise. On the one hand, loss firms may engage more in LTAV in order to improve the profitability even though, on the other hand, the income tax saving coming from losses may reduce the incentive to avoid labor tax. Hence, do not make any prediction on the sign of the variable *LOSS*.

Industry-sector dummy variables (*INDSEC*) defined at the two-digit SIC code level are also included as control variables in our study, given that it is possible for TAV intensity to fluctuate across different industry sectors (e.g. Omer et al., 1993; Derashid and Zhang, 2003; Richardson and Lanis, 2007; Lanis and Richardson, 2012). In particular for LTAV, firms in sectors with high work intensity and low levels of organizational rationalization and of production are expected to resort more to UDW (Pfau-Effinger, 2009). Nonetheless, we do not make any specific sign prediction for the *INDSEC* dummies.

Finally, year dummy variables (*YEAR*) are included in our regression model to control for differences in ABSOCs that could possibly exist over the sample period. Again, no sign predictions are made for the *YEAR* dummies.

In summary, to test our hypotheses we estimate the following base regression model for our LTAV measures:

$$LTAV\_PROXY_t = \beta_0 + \beta_1 CRIME1_t + \beta_2 CRIME2_t + \beta_3 SIZE_t + \beta_4 LEVLONG_t + \beta_5 CAPINT_t + \beta_6 INVTA_t + \beta_7 ROA_t + \beta_8 GROWTH_t + \beta_9 CH\_REC_t + \beta_{10} CH\_INV_t + \beta_{11} ABMAT_t + \beta_{12} LNGDP_t + \beta_{13} LOSS_t + \beta_{14} ETR_t + \sum \emptyset_i INDSEC_{it} + \sum \alpha_i YEAR_i + \varepsilon_t \quad (4)$$

The variables, whose firm subscript is suppressed for simplicity, are defined in the Appendix.

2.5.3 Data and Sample Selection

LMFs sample consists of 224 firms confiscated to organized crime during the 1994 to 2013 period, some of them provided by ANBSC and others found in online newspapers and AIDA database. The financial statements for all firms are obtained from AIDA, the Italian Bureau Van Dijk database. It contains comprehensive information on 1 million companies with a turnover above € 500,000 in Italy, including the indication for some of them of the confiscation status and date of confiscation. Firms provided by ANBSC have all been confiscated by final judgment but their small size or their liquidation means that only 54 out of 1663 have financial statements available on AIDA in 2013. In addition, we include firms confiscated in first instance and found on AIDA database (118) and online newspapers (52) until reaching a total of 224. For the 224 LMFs we obtain from AIDA available financial statement data for the year of confiscation and for the years prior to and following the confiscation within the period of 2003 to 2012. Hence, for some LMFs we only have available either financial data prior to confiscation or financial data after confiscation. We then estimate our base regression model of Eq. (4) including LMFs firm-years and AIDA population of active unlisted firm-years from 2003 to 2012 in LMFs industries. We initially avoid the matched sample procedure although in our base regression model we control for year, size and two-digit industry SIC code. Table 2.1 summarizes the sample selection procedure that yields the 224 LMFs and the 78,340 LWFs.

Table 2.1. Sample selection

	Number of firms
LMFs sample	
LMFs definitively confiscated at November 5th 2012 provided by ANBSC	1,663
Less: LMFs provided by ANBSC with data unavailable on AIDA database	-1,609
Add: LMFs found on AIDA database with status confiscated	118
Add: confiscated LMFs found in online newspapers with data available in AIDA	52
Final LMFs sample	**224**
LMFs year observations in base regression model (*ABSOC1*)	**1,046**
LWFs control sample	
Aida population of active and unlisted firms with available financial data from 2003 to 2012 in the same two-digit SIC industries as LMFs	**78,340**
LWFs year observations in base regression model (*ABSOC1*)	**587,555**

Source: ANBSC and AIDA database, 2013.

Table 2.2 presents the industry distribution by two-digit SIC groups of LMFs in our sample and AIDA population of active unlisted firms with available financial data from 2003 to 2012 in the same industries as the LMFs.

Table 2.2. Industry distribution of LMFs and AIDA population of active unlisted firms with available financial data from 2003 to 2012 restricted to LMFs industries (LWFs)

Sic code	Industry description	AIDA population		LMFs	
		Freq.	**Percent**	**Freq.**	**Percent**
01	Agricultural production-crops	644	0.82%	4	1.79%
14	Mining and quarrying of nonmetallic minerals, except fuels	463	0.59%	9	4.02%
15	Building construction-general contractors and operative builders	5,486	7.00%	41	18.30%
16	Heavy construction other than building construction-contractors	524	0.67%	3	1.34%
17	Construction-special trade contractors	4,032	5.15%	8	3.57%
20	Food and kindred products	3,224	4.12%	6	2.68%
					(Continued on the next page)

Sic code	Industry description	AIDA population		LMFs	
		Freq.	**Percent**	**Freq.**	**Percent**
25	Furniture and fixtures manufacturing	829	1.06%	3	1.34%
28	Chemicals and allied products manufacturing	1,598	2.04%	1	0.45%
29	Petroleum refining and related industries	158	0.20%	2	0.89%
32	Stone, clay, glass and concrete products manufacturing	1,960	2.50%	13	5.80%
34	Fabricated metal products, except machinery and transportation equipment	7,038	8.98%	2	0.89%
42	Motor freight transportation and warehousing	2,894	3.69%	18	8.04%
44	Water transportation	586	0.75%	1	0.45%
45	Transportation by air	95	0.12%	1	0.45%
47	Transportation services	1,884	2.40%	3	1.34%
49	Electric, gas and sanitary services	1,419	1.81%	7	3.13%
50	Wholesale trade, durable goods	14,064	17.95%	23	10.27%
51	Wholesale trade, nondurable goods wholesale dealing in	7,821	9.98%	19	8.48%
52	Building materials, hardware, garden supply, and mobile home dealers wholesale dealing in	1,018	1.30%	1	0.45%
53	General merchandise stores	324	0.41%	1	0.45%
54	Food stores	1,737	2.22%	16	7.14%
55	Automotive dealers and gasoline service stations	536	0.68%	4	1.79%
56	Apparel and accessory stores	1,920	2.45%	3	1.34%
57	Home furniture, furnishings, and equipment stores	872	1.11%	1	0.45%
58	Eating and drinking places	1,007	1.29%	2	0.89%
59	Miscellaneous retail	1,475	1.88%	1	0.45%
65	Real estate	2,239	2.86%	7	3.13%
70	Hotels, rooming houses, camps, and other lodging places	1,600	2.04%	3	1.34%
72	Personal services	327	0.42%	1	0.45%
73	Business services	5,001	6.38%	2	0.89%
75	Automotive repair, services, and parking	882	1.13%	1	0.45%
79	Amusement and recreation services	744	0.95%	5	2.23%
(Continued on the next page)					

Sic code	Industry description	AIDA population		LMFs	
		Freq.	**Percent**	**Freq.**	**Percent**
80	Health services	1,165	1.49%	9	4.02%
81	Legal services	19	0.02%	1	0.45%
87	Engineering, accounting, research, management, and related services	2,755	3.52%	2	0.89%
Total		**78,340**	**100.00**%	**224**	**100.00**%

Source: AIDA database, 2013.

Compared to the population of active and unlisted firms on AIDA with available financial data from 2003 to 2012, the sample LMFs are especially more abundant in industry groups: building construction-general contractors and operative builders (18.30% of LMFs sample versus 7.00% of population), food stores (7.14% versus 2.22%) and Motor freight transportation and warehousing (8.04% versus 3.69%). On the other hand, there is a lower proportion of LMFs mostly in wholesale trade, durable goods (10.27% versus 17.95%), business services (0.89% versus 6.38%) and fabricated metal products, except machinery and transportation equipment (0.89 versus 8.98%). It is noteworthy that Building construction-general contractors and operative builders is the sector with the higher percentage (18.30%) of LMFs in our sample. This sector presents most of the characteristics of sectors in which previous research finds a higher presence of UDW (Pfau-Effinger, 2009) such as high work intensity and low technology.

Table 2.3 shows the distribution of LMFs by Italian region where they are legally registered and indicates the Mafia organization with major presence in that region based on a recent study of Transcrime (2013). Because of their different locations we can reasonably assume that LMFs in our sample represent a variety of Mafia organizations, although we do not have the information on the Mafia organization each LMF is exactly connected to. Therefore, the probability of a selection bias is mostly reduced and a possible concern may only be related to the predominance of Cosa Nostra. Indeed, 50.89% of LMFs are located in Sicily where Cosa

Nostra is largely dominant. Moreover, each confiscation is individually and independently carried out by judicial authorities, being LMFs part of the assets belonging to any person accused of connections with any Mafia organization.

Table 2.3. LMFs by Italian region and Mafia organization

Italian Region	Number of LMFs	Percentage of LMFs	Mafia organization with major presence in the region*
Sicily	114	50.89%	Cosa Nostra
Calabria	61	27.23%	Ndrangheta
Campania	20	8.93%	Camorra
Lazio	13	5.80%	Camorra
Apulia	6	2.68%	Sacra Corona Unita
Lombardy	4	1.79%	Ndrangheta
Abruzzo	3	1.34%	Camorra
Piedmont	2	0.89%	Ndrangheta
Emilia-Romagna	1	0.45%	Ndrangheta
Total	**224**	**100.00%**	

**Source: Transcrime (2013)*

Some features of our sample selection may affect our results and generate biases limiting the generalization to other settings. We just consider LMFs that have been confiscated and with available financial data on AIDA. This database only includes companies with a turnover above € 500,000. For some firms confiscation year is not available and we find it out through a Google search for articles in local online newspapers including details on confiscation and whose correctness is reasonable but cannot be corroborated. Several preventive confiscations may have been carried out for the same firm and subsequently cancelled by the court. Criminal connection is in these cases uncertain.

Finally, Table 2.4 includes number of LMFs by confiscation year. It can be seen that 2012 is the year with largest number of confiscated LMFs and more than 50% of LMFs have been confiscated from 2010 to 2013.

Table 2.4. LMFs by confiscation year

Confiscation year	Number of confiscated LMFs	Percentage
1994	3	1.33%
1995	1	0.44%
1996	1	0.44%
1997	1	0.44%
1998	2	0.89%
1999	1	0.44%
2000	2	0.89%
2001	3	1.33%
2002	2	0.89%
2004	10	4.45%
2005	1	0.45%
2006	9	4.01%
2007	18	8.03%
2008	24	10.71%
2009	19	8.48%
2010	24	10.72%
2011	35	15.64%
2012	37	16.54%
2013	31	13.87%
Total	**224**	**100.00%**

Source: ANBSC and AIDA database, 2013.

2.6 Results and Discussions

2.6.1 Estimation of Normal SOCs

Tables 2.5 and 2.6 respectively report the estimation results by two-digit SIC code of Eq. (1) and Eq. (2) used to determine NSOCs. Results are presented following the Fama and MacBeth (1973) procedure. More specifically, the reported coefficients and R^2 are mean values by two-digit SIC code of cross-sectional estimations across 280 industry-years.

Significance levels of coefficients are calculated using the standard errors of the coefficients across industry-years.

Table 2.5. Estimation of NSOCs based on net sales (Eq. (1))

SIC code	$1/TA_{t-1}$		S_t/TA_{t-1}		$\Delta S_t /TA_{t-1}$		$\Delta S_{t-1}/TA_{t-1}$		Intercept		Mean obs.	Mean R^2	F	
01	8.418	***	0.005	***	0.000		0.001		0.011	***	607	0.148	85.98	***
14	25.943	***	0.046	***	-0.020	***	-0.008	**	0.001		433	0.411	6,633.16	***
15	19.421	***	0.042	***	-0.020	***	-0.008	***	0.000		5,126	0.514	515.56	***
16	26.731	***	0.036	***	-0.018	***	-0.009	***	0.013	***	493	0.407	205.29	***
17	20.167	***	0.031	***	-0.015	***	-0.006	***	0.016	***	3,831	0.309	857.85	***
20	17.820	***	0.014	***	-0.008	**	-0.004		0.008	***	3,044	0.252	698.80	***
25	18.197	***	0.023	***	-0.013	***	-0.003		0.016	***	792	0.266	264.00	***
28	13.535	***	0.019	***	-0.006	**	-0.008	**	0.013	***	1,530	0.208	504.91	***
29	10.271	***	0.002	*	-0.002		-0.005		0.024	***	146	0.110	62.23	***
32	19.707	***	0.033	***	-0.019	***	-0.009	***	0.007	***	1,854	0.327	289.15	***
34	25.501	***	0.033	***	-0.017	***	-0.011	***	0.013	***	6,764	0.320	1,725.95	***
42	20.410	***	0.010	***	0.006	*	0.005		0.037	***	2,521	0.133	307.93	***
44	17.561	***	0.055	***	-0.032	**	0.012		0.039	***	547	0.362	192.15	***
45	-10.381		0.029	***	-0.011		-0.027		0.043	***	87	0.194	25.38	***
47	9.587	***	0.004	***	0.002	***	-0.001		0.036	***	1,788	0.091	445.47	***
49	29.173	***	0.011	***	-0.005		-0.007		0.023	***	1,335	0.166	74.50	***
50	9.816	***	0.003	***	0.000		-0.003	***	0.020	***	13,326	0.070	78.37	***
51	6.568	***	0.005	***	-0.002	*	-0.002	**	0.014	***	7,380	0.101	454.47	***
52	0.585		0.016	***	-0.008	***	-0.007	***	0.007	***	958	0.219	454.13	***
53	5.399	***	0.011	***	0.004	**	0.002		0.014	***	304	0.250	219.45	***
54	3.473	***	0.018	***	-0.001		-0.006	**	0.008	***	1,627	0.414	1,020.19	***

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SIC code	$1/TA_{t-1}$		S_t/TA_{t-1}		$\Delta S_t /TA_{t-1}$		$\Delta S_{t-1}/TA_{t-1}$		Intercept		Mean obs.	Mean R^2	F	
55	2.863	***	0.008	***	-0.002		-0.003	***	0.005	***	493	0.292	909.01	***
56	-1.758	**	0.026	***	-0.010	***	-0.012	***	0.002	**	1,493	0.458	967.60	***
57	-1.305	***	0.015	***	-0.007	**	-0.005	**	0.013	***	825	0.239	500.01	***
58	13.618	***	0.038	***	-0.011	**	-0.002		0.027	***	951	0.540	2,183.82	***
59	2.721	***	0.013	***	-0.003		-0.004	**	0.019	***	1,389	0.175	489.44	***
65	1.483	***	0.027	***	-0.011	***	-0.003	*	0.001	***	2,100	0.358	308.92	***
70	7.743	***	0.051	***	-0.023	***	-0.016	***	0.007	***	1,510	0.747	885.82	***
72	4.468	*	0.049	***	-0.012		0.007		0.021	***	307	0.383	351.60	***
73	6.547	***	0.032	***	-0.005	**	0.006		0.043	***	4,721	0.145	764.51	***
75	28.460	***	0.003	***	0.004	*	0.002		0.029	***	835	0.236	103.60	***
79	21.286	***	0.011	***	0.004		0.000		0.034	***	702	0.175	99.62	***
80	-11.218	***	0.048	***	-0.016	**	-0.014	**	0.020	***	1,084	0.357	2,397.74	***
81	26.109	***	0.030	***	0.006		-0.003		0.009	*	18	0.654	174.87	***
87	15.451	***	0.017	***	-0.003		0.000		0.039	***	2,598	0.122	89.81	***

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. The coefficients and R^2, reported by two-digit SIC code, are the mean values of coefficients and R2 of cross-sectional estimations across 280 industry-years.*

Table 2.6. Estimation of NSOCs based on material consumption (Eq. (2))

SIC code	$1/TA_{t-1}$		$CONSUM_t/TA_{t-1}$		$\Delta CONSUM_t/TA_{t-1}$		$\Delta CONSUM_{t-1}/TA_{t-1}$		Intercept		Mean obs.	Mean R^2	F	
01	14.932	***	-0.002	**	0.002		0.001		0.014	***	608	0.123	182.74	***
14	53.923	***	0.011	***	0.003		0.003		0.023	***	433	0.232	330.67	***
15	45.565	***	0.023	***	-0.012	***	-0.002		0.016	***	5,124	0.327	350.79	***
16	44.324	***	0.018	***	0.007		-0.001		0.035	***	493	0.264	88.11	***
17	38.200	***	-0.009	***	0.021	***	0.005	*	0.047	***	3,831	0.214	155.48	***
20	26.727	***	0.001	*	0.001		0.001		0.021	***	3,043	0.165	86.21	***
25	29.625	***	0.000		0.006		0.002		0.039	***	792	0.178	137.19	***
28	20.501	***	-0.001		0.011	***	-0.003		0.033	***	1,530	0.100	219.33	***
29	11.299	***	-0.002	**	0.002		-0.002		0.027	***	146	0.103	19.76	***
32	39.203	***	-0.007	***	0.011	**	0.001		0.035	***	1,854	0.196	147.16	***
34	40.858	***	-0.017	***	0.026	***	0.004		0.051	***	6,764	0.233	229.02	***
42	27.222	***	-0.005	***	0.030	***	0.019	***	0.050	***	2,521	0.108	465.43	***
44	63.382	***	-0.042	***	0.020		0.043	**	0.101	***	547	0.191	146.65	***
45	8.922		-0.002		0.032		-0.002		0.068	***	87	0.063	2.06	
47	13.334	***	-0.003	***	0.006	*	0.002		0.043	***	1,787	0.080	306.63	***
49	36.262	***	-0.009	***	0.013	***	0.004	*	0.036	***	1,334	0.145	423.82	***
50	11.609	***	-0.002	***	0.003	***	-0.002	**	0.027	***	13,325	0.067	147.22	***
51	9.717	***	0.000	***	0.000		-0.003	*	0.021	***	7,379	0.075	347.29	***
52	5.749	***	0.008	***	-0.004	*	-0.006	***	0.018	***	957	0.086	74.21	***
53	8.534	***	0.007	***	0.008	**	0.003		0.022	***	304	0.151	356.49	***
54	6.703	***	0.018	***	-0.001		-0.006	*	0.016	***	1,628	0.325	373.81	***

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SIC code	**$1/TA_{t-1}$**		**$CONSUM_t/TA_{t-1}$**		**$\Delta CONSUM_t/TA_{t-1}$**		**$\Delta CONSUM_{t-1}/TA_{t-1}$**		**Intercept**		**Mean obs.**	**Mean R^2**	**F**	
55	5.053	***	0.007	***	-0.001		-0.003	***	0.008	***	493	0.241	330.06	***
56	3.781	**	0.024	***	-0.010	***	-0.012	***	0.013	***	1,493	0.258	246.01	***
57	2.561	***	0.011	***	-0.006	*	-0.006	*	0.022	***	825	0.104	68.02	***
58	37.917	***	0.012	***	0.007		0.008		0.062	***	951	0.326	700.32	***
59	10.826	***	0.002	**	0.003		-0.003		0.032	***	1,388	0.074	81.81	***
65	23.431	***	0.012	***	-0.009	**	0.002		0.007	***	2,099	0.175	142.26	***
70	51.250	***	0.047	***	-0.017		-0.006		0.020	***	1,510	0.541	216.69	***
72	39.838	***	-0.019	***	0.027	**	0.009		0.068	***	307	0.208	74.26	***
73	26.983	***	-0.029	***	0.032	***	0.015	***	0.082	***	4,719	0.076	1,877.84	***
75	30.539	***	-0.005	***	0.007	***	0.002		0.038	***	835	0.243	152.77	***
79	32.457	***	-0.010	**	0.028	***	0.022	**	0.042	***	702	0.153	412.59	***
80	22.959	***	0.026	***	0.020		0.001		0.050	***	1,085	0.139	120.60	***
81	25.773	***	1.841	***	-0.632		-0.012		0.045	***	18	0.487	92.84	***
87	28.266	***	-0.022	***	0.024	***	0.005		0.057	***	2,596	0.107	339.34	***

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. The coefficients and R2, reported by two-digit SIC code, are the mean values of coefficients and R2 of cross-sectional estimations across 280 industry-years.*

Initially, it should be noted that all the estimated regressions are significant at the 0.01 level according to the F tests, except for the singular case of SIC code 45 (Transportation by air) in Eq. (2) estimations. Significance of coefficients, their sign and R^2 vary across the various two-digit SIC codes although in different degrees. Hence, the industry sector is a relevant aspect to consider in the interpretation of LTAV measures calculated based on the residuals of the estimations. Overall, the average R^2 across the 280 industry-years is 0.29 for Eq. (1) and 0.19 for Eq. (2). For comparison, previous studies aiming to detect accrual-based earnings management through abnormal accruals find values of R^2 even below 0.19 in regressions estimating normal accruals (Dechow et al., 2010).

2.6.2 Descriptive Statistics and Univariate Analysis

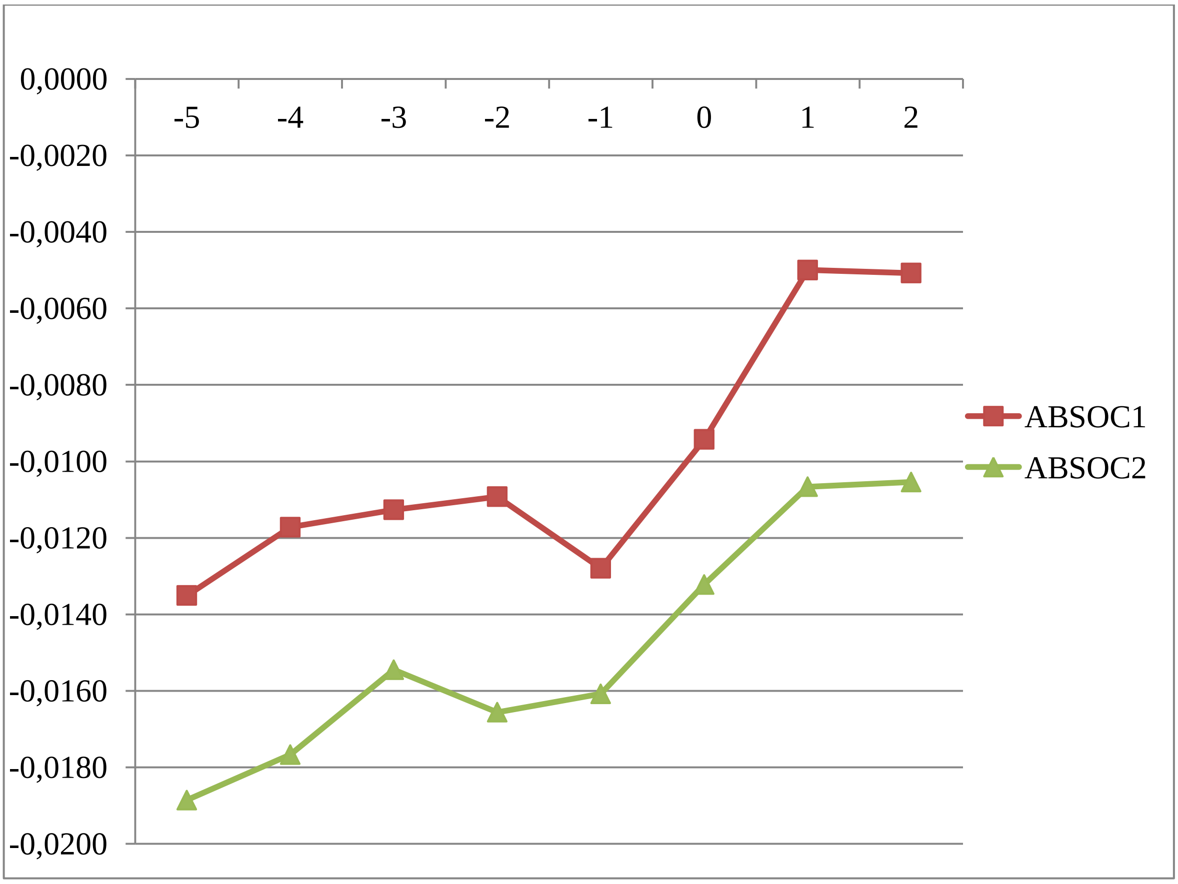
Table 2.7 and Figure 2.1 present median *ABSOC1* and *ABSOC2* for LMFs and for years -5 to +2 relative to the year 0 of confiscation. We report medians because they are less likely than means to be influenced by extreme observations. We find significantly negative *ABSOC1* and *ABSOC2* in all the years except in year +2 for *ABSOC1*. These results provide a first indication of LTAV which before confiscation and according to both measures does not exhibit a clear trend. Hence, we infer that LMFs before confiscation may engage in LTAV consistently so as not to show significant fluctuations to the authorities and raise any red flags. On the other hand, after confiscation and in particular in years 0 and 1 LTAV sharply decreases (*ABSOC1* and *ABSOC2* increase) as a consequence of the intervention of legal administrators. In confirmation of this, an untabulated two-tailed Mann–Whitney–Wilcoxon test indicates that median *ABSOC1* and *ABSOC2* for LMFs are significantly ($p<0.01$) higher after confiscation (-0.0052 and -0.0105, respectively) relative to before confiscation (-0.0117 and -0.0161, respectively). Finally, it is worth noting that *ABSOC1* shows higher percentage variations than *ABSOC2* in years -1, 0 and 1 most likely due to the higher fluctuations of net sales compared to material consumption around confiscation.

Table 2.7. Time series of LTAV measures in LMFs around confiscation year = 0

	ABSOC1			***ABSOC2***		
Year	**Median**	**Test**	**Δ%Median**	**Median**	**Test**	**Δ%Median**
-5	-0,0135	**		-0,0189	***	
-4	-0,0117	***	13,21%	-0,0177	***	6,31%
-3	-0,0113	***	3,90%	-0,0154	***	12,56%
-2	-0,0109	***	3,04%	-0,0166	***	-7,19%
-1	-0,0128	***	-17,15%	-0,0161	***	2,89%
0	-0,0094	***	26,35%	-0,0132	***	17,78%
1	-0,0050	***	46,97%	-0,0107	***	19,35%
2	-0,0051		-1,55%	-0,0105	***	1,14%

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed Wilcoxon signed-rank test for the difference of median from zero. Δ%Median represents the percentage change of median relative to previous period.*

Figure 2.1. Time series of LTAV measures in LMFs around confiscation year = 0



The following Table 2.8 presents descriptive statistics for each variable considered in our base regression model comparing the LMFs firm-years before and after confiscation to the LWFs firm-years. Again, we report medians because they are less likely than means to be influenced by extreme observations. All continuous variables, except *LNGDP*, are winsorized at the top and bottom 1 percent of their distributions to avoid the influence of outliers.

Table 2.8. Descriptive statistics and variable comparison between LMFs and LWFs

	LMFs before confisc.		LMFs after confisc.		LWFs		LMFs before confisc. - LWFs		LMFs after confisc. - LWFs	
Variable	**N**	**Median**	**N**	**Median**	**N**	**Median**	**Difference**	**Test**	**Difference**	**Test**
ABSOC1	616	-0.0117	490	-0.0052	659,094	-0.0047	-0.0070	***	-0.0005	
P_ABSOC1	172	0.0196	182	0.0130	267,636	0.0182	0.0014		-0.0052	**
N_ABSOC1	444	-0.0180	308	-0.0141	391,458	-0.0155	-0.0025	***	0.0015	**
ABSOC2	616	-0.0161	490	-0.0105	659,016	-0.0067	-0.0094	***	-0.0038	***
P_ABSOC2	153	0.0205	160	0.0165	259,845	0.0206	-0.0002		-0.0041	
N_ABSOC2	463	-0.0231	330	-0.0178	399,171	-0.0176	-0.0055	***	-0.0003	
SIZE	967	7.9444	553	8.2300	753,484	7.8023	0.1421		0.4277	***
LEVLONG	967	0.0238	553	0.0643	753,480	0.0296	-0.0058		0.0347	***
CAPINT	967	0.1621	553	0.1874	753,400	0.1514	0.0107		0.0360	*
INVTA	967	0.0540	553	0.0885	753,457	0.1157	-0.0617	***	-0.0272	
ROA	967	0.0220	553	0.0113	753,371	0.0276	-0.0055	***	-0.0163	***
GROWTH	750	0.1089	517	0.0043	671,352	0.0371	0.0718	***	-0.0328	***
CH_REC	698	0.0261	490	0.0048	599,106	0.0028	0.0233	***	0.0019	
CH_INV	750	0.0002	517	0.0000	671,298	0.0000	0.0002	***	0.0000	
ABMAT	622	0.0599	490	0.0529	661,717	-0.0037	0.0636	***	0.0567	***
LNGDP	1436	9.7159	804	9.7307	777,380	10.2886	-0.5728	***	-0.5580	***
ETR	966	0.4229	553	0.3340	751,630	0.5153	-0.0924	***	-0.1813	***
%LOSS	3.90%		15.05%		6.34%		-2.44%	***	8.71%	***

*Notes: The sample full period spans 2003–2012. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed Mann–Whitney–Wilcoxon test for the differences in medians of continuous variables. Pearson chi-squared test of independence for categorical variable %LOSS = % of firms with two or more consecutive years of negative income. See Appendix for variable definition.*

Medians of our variables of interest *ABSOC1* and *ABSOC2* are both negative and significantly ($p<0.01$) lower for LMFs before confiscation relative to LWFs, providing a first indication in support of our hypothesis H1 on the higher LTAV in LMFs. Consistently, the same results are found for variables *N_ABSOC1* and *N_ABSOC2*, whereas there is no significant difference at conventional levels in variables *P_ABSOC1* and *P_ABSOC2*.

On the other hand, consistent with our hypothesis H2 there is no significant difference at conventional levels in variable *ABSOC1* between LMFs after confiscation and LWFs, whereas variable *ABSOC2* remains significantly ($p<0.01$) lower for LMFs even though the difference in medians decreases from -0.0094 to -0.0038. In addition, in LMFs unsigned values of variables *P_ABSOC1* and *N_ABSOC1* becomes significantly ($p<0.05$) lower than those of LWFs confirming the change of behavior relative to before confiscation as a consequence of the actions of legal administrators. In contrast, no significant difference at conventional levels is found in variables *P_ABSOC2* and *N_ABSOC2* between both types of firm. It is noteworthy that in LMFs before confiscation *N_ABSOC1* observations represent 72.08% of total *ABSOC1* observations and *N_ABSOC2* observations represent 75.16% of total *ABSOC2* observations. Furthermore, after confiscation the percentage decreases to 62.86% for *N_ABSOC1* and to 67.35% for *N_ABSOC2*. Overall, these percentages provide further evidence in support of our hypotheses H1 and H2.

As regards the rest of variables, before confiscation variable *LEVLONG* is not significantly different at conventional levels between the two types of firm. However, after confiscation LMFs appear significantly ($p<0.01$) more long term indebted than LWFs because of the likely loss of the criminal organization financial support. A consequent LMFs wider resort to bank financing may additionally explain the significant increase in their long term indebtedness after confiscation.

Furthermore, LMFs are significantly ($p<0.01$) less profitable (*ROA*) than LWFs both before and after confiscation. An overinvestment of financial resources stemming from illegal activities (money laundering) and a downward earnings manipulation for ITAV purposes may explain this lower profitability of LMFs before confiscation. On the other hand, after confiscation the explanation may lie in the loss of business opportunities and competitive advantages (Arlacchi, 1983; Fantò, 1999) and in the cost of the reinstatement of legality including the regularization of UDW. A further consistent indication is the significantly ($p<0.01$) higher total assets growth rate (*GROWTH*) of LMFs before confiscation relative to LWFs, presumably financed with dirty money, which becomes significantly ($p<0.01$) lower after confiscation because of the likely suspension of any money laundering activity. Moreover, significantly ($p<0.01$) higher variables *CH_REC* and *CH_INV* for LMFs before confiscation relative to LWFs may suggest a wider engagement in accrual-based earnings management of the former firms. A higher real activities manipulation of LMFs through material expenses can also be inferred by significantly ($p<0.01$) higher variable *ABMAT* both before and after confiscation. Variable *LNGDP* is significantly ($p<0.01$) lower for LMFs relative to LWFs given that LMFs in our sample are mostly concentrated in southern Italian regions with a traditional lower economic development. Interestingly, significantly ($p<0.01$) lower variable *ETR* for LMFs both before and after confiscation provides evidence of a higher ITAV in these firms. This result supports our assumption on LTAV and ITAV being performed in parallel because of the similar underlying motivations and incentives. It is noteworthy that the percentage of firms with two or more consecutive years of negative income (*%LOSS*) is significantly ($p<0.01$) lower for LMFs before confiscation relative to LWFs. Nonetheless, after confiscation the situation is completely reversed consistently with the average decline of economic performance of LMFs.

Finally, an untabulated analysis shows that correlations among independent variables of our base regression model in Eq. (4) are low (below 0.43), thus providing a first indication that collinearity is unlikely to affect estimations.

2.6.3 Base Regression Results

We estimate our model in Eq. (4) through a linear regression with panel-corrected standard errors in order to consider heteroskedasticity and contemporaneous correlation across panels. Table 2.9 presents the results for our LTAV measures.

Table 2.9. Heteroskedastic panels corrected standard errors linear regression of LTAV measures

		ABSOC1		*P_ABSOC1*		*N_ABSOC1*		*ABSOC2*		*P_ABSOC2*		*N_ABSOC2*	
Variable	**Exp. Sign**	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
CRIME1 (H1)	–	-0.0045	0.0040	0.0009	0.7440	-0.0043	0.0000	-0.0081	0.0000	-0.0024	0.4060	-0.0074	0.0000
CRIME2 (H2)	?	0.0010	0.5490	0.0070	0.0030	-0.0017	0.0850	0.0011	0.5790	0.0079	0.0110	-0.0036	0.0000
SIZE	?	-0.0012	0.0000	-0.0054	0.0000	0.0036	0.0000	-0.0007	0.0000	-0.0050	0.0000	0.0037	0.0000
LEVLONG	–	-0.0138	0.0000	-0.0150	0.0000	0.0027	0.0000	-0.0264	0.0000	-0.0201	0.0000	-0.0046	0.0000
CAPINT	+	0.0076	0.0000	-0.0131	0.0000	0.0154	0.0000	-0.0077	0.0000	-0.0151	0.0000	0.0043	0.0000
INVTA	–	0.0018	0.0000	-0.0139	0.0000	0.0123	0.0000	-0.0067	0.0000	-0.0141	0.0000	0.0050	0.0000
ROA	–	-0.0236	0.0000	-0.0247	0.0000	-0.0046	0.0000	-0.0082	0.0000	-0.0172	0.0000	0.0013	0.0070
GROWTH	+	0.0010	0.0000	0.0142	0.0000	-0.0100	0.0000	0.0087	0.0000	0.0180	0.0000	-0.0067	0.0000
CH_REC	+	0.0028	0.0000	0.0029	0.0000	-0.0004	0.0550	0.0043	0.0000	0.0030	0.0000	0.0009	0.0000
CH_INV	+	0.0439	0.0000	0.0382	0.0000	0.0112	0.0000	0.0309	0.0000	0.0358	0.0000	0.0015	0.0000
ABMAT	–	-0.0494	0.0000	-0.0498	0.0000	-0.0105	0.0000	-0.0457	0.0000	-0.0453	0.0000	-0.0051	0.0000
LNGDP	+	-0.0007	0.0010	-0.0013	0.0000	-0.0017	0.0000	0.0046	0.0000	-0.0007	0.0730	0.0011	0.0000
LOSS	?	0.0047	0.0000	0.0036	0.0000	0.0004	0.0000	0.0037	0.0000	0.0045	0.0000	-0.0008	0.0000
ETR	+	0.0012	0.0000	0.0006	0.0000	0.0002	0.0000	0.0014	0.0000	0.0008	0.0000	0.0004	0.0000
INDSEC	?	Yes		Yes		Yes		Yes		Yes		Yes	
YEAR	?	Yes		Yes		Yes		Yes		Yes		Yes	
Intercept	?	0.0146	0.0000	0.0907	0.0000	-0.0411	0.0000	-0.0361	0.0000	0.0880	0.0000	-0.0693	0.0000
Number of obs.		588,601		238,731		349,870		588,547		232,429		356,118	
R^2		0.1397		0.3601		0.3880		0.1283		0.3388		0.3882	
Wald $\chi 2$		53,736	0.0000	74,381	0.0000	133,577	0.0000	50,992	0.0000	70,125	0.0000	137,146	0.0000

Notes: The p-values are two-tailed. See Appendix for variable definition.

Initially, it is noteworthy that all the estimated regressions are significant at the 0.01 level according to the chi-square tests. On the other hand, consistent with our hypothesis H1 coefficient on variable *CRIME1* is negative and significant at the 0.01 level in *ABSOC1, ABSOC2, N_ABSOC1* and *N_ABSOC2* regressions whereas in *P_ABSOC1* and *P_ABSOC2* regressions it is not significant a conventional levels. Overall, these results suggest that before confiscations LMFs engage more in LTAV than LWFs do. Indeed, the consistent results showed by both variables *ABSOC1* and *ABSOC2* in support of our hypothesis H1 provide the first insight into the ability of these measures to correctly reflect LTAV in the examined firms. In particular, computation of *ABSOC1* is based on reported sales whereas computation of *ABSOC2* is based on reported material consumption. Hence, the consistency of the results between both measures provides evidence of robustness in front of possible manipulations that may affect both material consumption and sales reported figures.

In addition, coefficient on *CRIME2* is not significant at conventional levels both in *ABSOC1 and* in *ABSOC2* regression providing support for our hypothesis H2. In contrast, in *N_ABSOC2* regression coefficient on *CRIME2* is negative and significant ($p<0.01$) and in *N_ABSOC1* regression it is negative and only marginally significant ($p<0.10$). However, an untabulated test shows that in both regressions it is significantly ($p<0.01$ and $p<0.05$, respectively) higher and then closer to zero than coefficient on *CRIME1*. This suggests that the difference in level of LTAV significantly decreases after confiscation consistent with hypothesis H2. Finally, in *P_ABSOC1* and *P_ABSOC2* regressions coefficient on *CRIME2* is positive and significant ($p<0.01$ and $p<0.05$, respectively). Overall, these results provide further evidence on the ability of our measures to actually reflect LTAV given that an action commonly taken by legal administrators after confiscation is the regularization of UDW which causes an increase in SOCs.

As regards the other variables, coefficient on *SIZE* is negative and significant ($p<0.01$) in *ABSOC1, P_ABSOC1, ABSOC2* and *P_ABSOC2* regressions, whereas it is positive and significant ($p<0.01$) in *N_ABSOC1* and *N_ABSOC2* regressions. These results indicate that within the subsample with negative *ABSOCs* smaller firms are more likely to engage in LTAV in contrast to the opposed indication that can be inferred from the results on the full sample. The coefficients on the rest of variables are significant ($p<0.01$) and have the expected sign with some exceptions. For example, coefficient on *INVTA* is significant ($p<0.01$) and negative, as expected, in *ABSOC2, P_ABSOC1 and P_ABSOC2* regressions, whereas in *ABSOC1, N_ABSOC1* and *N_ABSOC2* regressions it is positive. Some conflicting results are also found for coefficient on *CAPINT* which is positive and significant ($p<0.01$), as expected, in *ABSOC1*, *N_ABSOC1* and *N_ABSOC2* regressions whereas it is negative and significant in *ABSOC2, P_ABSOC1 and P_ABSOC2* regressions. Finally, coefficient on *LOSS* is significant ($p<0.01$) and positive in all regressions except in *N_ABSOC2* regression.

In summary, the multiple regression analysis provides evidence that, consistent with hypothesis H1, before confiscation LMFs engage more in LTAV than LWFs do by exhibiting lower ABSOCs. Furthermore, consistent with hypothesis H2, there is no significant difference in level of ABSOCs and thus in LTAV between LMFs after confiscation and LWFs or this difference significantly decreases relative to before confiscation.

2.6.4 Additional Analyses

2.6.4.1 Regression Analysis with Interactions

In order to empirically determine the effect of each control variable on LTAV in LMFs before confiscation we estimate additional regressions including the interactions of control variables with the binary variable *CRIME1*. Interestingly, there are mainly four variables that have a significant effect on LTAV in LMFs before confiscation. Specifically, coefficients on the interaction variables *SIZE*CRIME1 and ABMAT*CRIME1* are positive and significant ($p<0.05$) indicating respectively that larger LMFs and with higher abnormal material expenses are less likely to engage in LTAV and vice versa. On the other hand, coefficients on interaction variables *ROA*CRIME1* and *INVTA*CRIME1* are negative and significant ($p<0.05$) suggesting respectively that LMFs with higher profitability and a greater proportion of inventory are more likely to engage in LTAV and vice versa.

2.6.4.2 Alternative Model Using Unadjusted SOCs

We estimate an alternative regression model by replacing in Eq. (4) dependent variables on ABSOCs with the unadjusted SOCs variable SOC_t/TA_{t-1} as well as adding the independent variables of Eq. (1). We omit variable *SIZE* whose effect is already reflected by highly correlated variable $1/TA_{t-1}$ ($r = -0.76$, $p<0.01$). Our purpose is to assess whether our results are confirmed through a more direct measure of paid SOCs such as SOC_t/TA_{t-1} which can be considered a low cost alternative to ABSOCs in terms of calculation efforts. Table 2.10 shows the results of our estimation. Because the residuals can be correlated across firm and/or over time, test statistics and reported significance levels are based on the standard errors adjusted by a two dimensional cluster at the firm and year levels (Gow et al., 2010; Colin et al., 2011).

Table 2.10. Two dimensional cluster corrected standard errors regression of unadjusted SOCs

Variable	Exp. Sign	Coef.	p-value
CRIME1 (Hypothesis H1)	–	-0.0061	0.0340
CRIME2 (Hypothesis H2)	?	-0.0004	0.9050
$1/TA_{t-1}$	?	13.9642	0.0000
S_t/TA_{t-1}	+	0.0111	0.0000
$\Delta S_t /TA_{t-1}$	?	-0.0029	0.0130
$\Delta S_{t-1}/TA_{t-1}$	?	-0.0011	0.2880
LEVLONG	–	-0.0239	0.0000
CAPINT	+	-0.0023	0.0840
INVTA	–	-0.0085	0.0000
ROA	–	-0.0149	0.0100
GROWTH	+	0.0042	0.0000
CH_REC	+	0.0025	0.0000
CH_INV	+	0.0389	0.0000
ABMAT	–	-0.0516	0.0000
LNGDP	+	0.0023	0.0010
LOSS	?	0.0043	0.0000
ETR	+	0.0015	0.0000
INDSEC	?	Yes	
YEAR	?	Yes	
Intercept	?	0.0082	0.2400
Number of obs.		535,820	
R^2		0.4131	
Wald $\chi 2$		13,925	0.0000

Notes: The p-values are two-tailed. See Appendix for variable definition.

The unadjusted SOCs regression is significant at the 0.01 level according to the chi-square test. Its results mostly confirm previous findings based on ABSOCs regressions. Indeed, coefficient on variable *CRIME1* is negative and significant ($p<0.05$), supporting hypothesis H1, and coefficient on variable *CRIME2* is not significant at conventional levels, supporting hypothesis H2. Furthermore, the magnitude of coefficient on *CRIME1* (-0.0061) represents about 12% of the average SOC_t/TA_{t-1} (0.0508) for the full population of LWFs, providing a rough indication of the intensity of LTAV.

As regards the rest of control variables, results are similar to those of Eq. (1) and Eq. (4) in terms of sign and significance of variables.

In summary, the usage of unadjusted SOCs provides additional support to our results by spotting a different SOCs payment pattern between LMFs and LWFs as well as confirming significant associations with other variables that may influence LTAV. Nonetheless, the related variable SOC_t/TA_{t-1}, individually considered, says little about the LTAV pattern of a firm. Indeed, a basis for comparison and assessment is not immediately available as the official tax rate can be for those studies that try to measure ITAV through ETRs. Additionally, differences in industry sectors and annual economic conditions are not reflected in unadjusted SOCs. On the other hand, ABSOCs are calculated as the residuals of cross-sectional regressions for each industry-year and their sign (positive or negative) provides a first immediate indication of the likelihood of a firm engaging in LTAV practices.

2.6.4.3 Matching Procedure

We perform a further robustness test of our results by estimating our base regression model within a matched sample. So as to define a control sample, researchers choose from a wide range of firm characteristics on which to match such as: cash flows, year, industry, net income, size proxied by sales or total assets, ROA, etc. (Defond and Jiambalvo, 1994; Perry and Williams, 1994; Defond and Subramanyam, 1998; Teoh et al., 1998; Kothari et al., 2005). We match each LMF with three LWFs on year, industry, sign of profitability (ROA) and asset quintile. Indeed, we believe that matching on actual profitability or actual assets is problematic (e.g., by using propensity scores) because the profitability or assets of LMFs are likely to be far more manipulated and unreliable than those of LWFs. Hence, using something more generic, like sign of profitability or an asset group considers that there might be some marginal manipulation of income or assets by LMFs, but that the manipulation is not so massive as to cause an LMF to report a profit instead of a loss, or jump into another asset quintile. Matching is performed for both LMF pre-confiscation firm-year observations and for LMF post-confiscation firm-year observations. We add to the dummy variables *CRIME1* and *CRIME2* the new dummy variables *LAW1* and *LAW2*. *LAW1* takes value of 1 for LWF observations matched to LMF pre-confiscation firm-years and 0 otherwise, whereas *LAW2* takes value of 1 for LWF observations matched to LMF post-confiscation firm-years. For each LTAV measure, we estimate two regressions excluding as base dummy variable *LAW1* or *LAW2*, alternatively. However, we present a result column for each dependent variable and only report values for variables *CRIME1* (vs. base *LAW1)* and *CRIME2* (vs. base *LAW2).* Indeed, switching base from *LAW1* to *LAW2* does not affect value and significance of the other independent variables except for the intercept whose values and significances are separately reported for each base. Table 2.11 shows the results of our estimations.

Table 2.11. Heteroskedastic panels corrected standard errors linear regression of LTAV measures within a matched sample

		ABSOC1		*ABSOC2*	
Variable	**Exp. Sign**	**Coef.**	**p-value**	**Coef.**	**p-value**
CRIME1 (Hypothesis H1) (base LAW1)	–	-0.0054	0.0070	-0.0074	0.0010
CRIME2 (Hypothesis H2) (base LAW2)	?	0.0013	0.5390	0.0021	0.3800
SIZE	?	-0.0015	0.0050	-0.0017	0.0020
LEVLONG	–	-0.0091	0.0020	-0.0184	0.0000
CAPINT	+	0.0044	0.1160	-0.0080	0.0070
INVTA	–	0.0007	0.8090	-0.0128	0.0000
ROA	–	-0.0412	0.0000	-0.0176	0.1030
GROWTH	+	0.0009	0.7840	0.0051	0.1280
CH_REC	+	0.0068	0.0990	0.0090	0.0410
CH_INV	+	0.0394	0.0000	0.0269	0.0010
ABMAT	–	-0.0388	0.0000	-0.0387	0.0000
LNGDP	+	0.0002	0.9260	0.0072	0.0090
LOSS	?	0.0019	0.2740	0.0014	0.4740
ETR	+	0.0004	0.4990	0.0009	0.0970
INDSEC	?	Yes		Yes	
YEAR	?	Yes		Yes	
Intercept (base LAW1)	?	0.0086	0.7520	-0.0539	0.0660
Intercept (base LAW2)	?	0.0101	0.7130	-0.0522	0.0770
Number of obs.		4,044		4,044	
R^2		0.1382		0.1448	
Wald $\chi 2$		364.61	0.0000	416.92	0.0000

Notes: The p-values are two-tailed. LAW1: dummy variable taking value of 1 for LWF observations matched to LMF pre-confiscation firm-years and 0 otherwise; LAW2: dummy variable taking value of 1 for LWF observations matched to LMF post-confiscation firm-years and 0 otherwise. See Appendix for the other variable definition.

Again, all the estimated regressions are significant at the 0.01 level according to the chi-square tests. Results of matched sample estimations are mostly consistent with those of the unmatched sample. Indeed, both in *ABSOC1* and *ABSOC2* regressions coefficient on variable *CRIME1* is negative and significant ($p<0.01$), providing further support for hypothesis H1, and coefficient on variable *CRIME2* is not significant at conventional levels, providing further support for hypothesis H2. As regards the rest of control variables, results are similar to those of the unmatched sample estimations in terms of sign and significance of variables.

In summary, the documented robustness of our results to different estimation methods can relieve concerns that our findings are driven by uncontrolled factors.

2.7 Conclusions

In this study, we analyze LTAV and its determinants within a sample of 224 Italian firms, defined as LMFs due to having been confiscated at some point by Italian judicial authorities, in relation to alleged connections with Italian organized crime. We build two new measures of LTAV based on SOCs reported by firms in their financial statements. Overall, our results reveal that before confiscation LMFs engage more in LTAV than LWFs do as suggested by their lower ABSOCs. After confiscation, following the reinstatement of legality performed by legal administrators, there is no significant difference in level of LTAV between both types of firm or this difference significantly decreases as indicated by results on difference in ABSOCs. Moreover, a further analysis shows that before confiscation LMFs which are larger and exhibit abnormally higher material expenses are less likely to engage in LTAV, whereas LMFs with higher return on assets and with a greater proportion of inventory are more likely to engage in such a practice and vice versa. Our results are robust to a variety of estimation methodologies.

Our study contributes to the academic literature in several ways. First of all, it is the first to examine LTAV based on financial statement information and the factors that may influence its practice at firm level. In particular, it adopts two new LTAV measures that may enhance further research on its effectiveness in other contexts and for other types of firm. Moreover, these measures can be added to the other direct and indirect methods commonly employed to measure UDW. More importantly, their ability to infer the presence of UDW can contribute to protecting employees against illegal exploitation and to avoiding tax revenue loss and related issues of equity in the social security system. Furthermore, these measures can supplement current compliance risk-assessment models used by tax authorities. On the other hand, our study examines LMFs that may particularly interest the scientific community due to their singularities. Indeed, they are socially irresponsible by nature and are private firms with incentives, *modus operandi* and legal financial statement formats that differ from those of public listed companies. Finally, our research allows inferring conclusions on the relation between CSR and LTAV, suggesting that socially irresponsible firms, such as LMFs, tend to engage more in such a practice.

These findings, however, are subject to several limitations. We cannot reject the possibility of a bias in the selection of our sample of LMFs considering that undetected LMFs are unobservable and smaller LMFs, unavailable on AIDA, are excluded. Furthermore, there could be selection biases in LMFs pursued and confiscated by Italian authorities. Our measures of LTAV, based on ABSOCs, greatly depend on the reliability of reported sales revenue and material consumption figures. The likely manipulation of these figures and the consequent endogenity in the calculation models may affect the correct interpretation of our measures, although the consistent results of estimations within a matched sample may partially relieve this concern.

We propose several opportunities for future research. Our measures could be applied to other types of firm that are expected to engage in LTAV in order to gain further insight into their measurement ability. Furthermore, alternative models could be tested in order to improve the predictive power of normal SOC regressions and produce more accurate LTAV measures. Finally, this study could be replicated in other countries, where organized crime is deeply rooted or UDW is a widespread practice, in order to determine whether its results are confirmed in a different cultural, legal and institutional context.

2.8 Appendix

2.8.1 Definition of Variables of the Base Regression Model (Eq. (4)):

LTAV_PROXY = ABSOC1, P_ ABSOC1, N_ ABSOC1, ABSOC2, P_ ABSOC2 or *N_ ABSOC2:*

ABSOC1 = Abnormal SOCs equal to estimated residual from Eq. (1)

P_ ABSOC1 = Positive *ABSOC1*

N_ ABSOC1 = Negative *ABSOC1*

ABSOC2 = Abnormal SOCs equal to estimated residual from Eq. (2)

P_ ABSOC2 = Positive *ABSOC2*

N_ ABSOC2 = Negative *ABSOC2*

CRIME1 = Dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise

CRIME2 = Dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise

SIZE = Natural logarithm of total assets in thousands

LEVLONG = Long-term debts divided by total assets

CAPINT = Net property, plant and equipment and net intangible fixed assets divided by total assets

INVTA = Inventory divided by total assets

ROA = Income before tax divided by total assets

GROWTH = (Total assets − lagged total assets)/ lagged total assets

CH_REC = (Receivables - lagged receivables)/ lagged total assets

CH_INV = (Inventory - lagged inventory)/lagged total assets

ABMAT = Abnormal material expenses equal to residuals from Eq. (3)

LNGDP = Natural logarithm of regional GDP per capita (source ISTAT)

LOSS = Dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise

ETR = Current tax expense divided by income before tax

INDSEC = Dummy variables representing industry defined by the two-digit SIC code

YEAR = Dummy variables representing the fiscal year

2.8.2 Abbreviations

ABSOCs: abnormal social contribution expenses

ANBSC: Agenzia Nazionale Beni Sequestrati e Confiscati

CFO: cash flow from operations

CSR: corporate social responsibility

ETR: effective tax rate

FTE: full-time employed

ISTAT: Italian Statistical Institute

ITAV: income tax avoidance

LA: legal administration

LMF: legally registered Mafia firm

LTAV: labor tax avoidance

LWF: lawful firm

NSOCs: normal social contribution expenses

SRL: Società a responsabilità limitata

SOCs: social contribution expenses

TAV: tax avoidance

UDW: undeclared work

VAT: value added tax

2.9 References

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Chapter 3: Expenses Manipulation within Legally Registered Mafia Firms in Italy

3.1 Abstract

This study aims to determine whether accounting information can contribute to understanding the mechanisms of the criminal economy and funding. For this purpose, it examines expenses manipulation within a sample of 224 Italian firms defined as legally registered Mafia firms (LMFs), due to having been confiscated by judicial authorities in relation to alleged connections of their owners with Italian organized crime.

Empirical results reveal that before being confiscated LMFs upward manage material expenses and downward manage personnel and service expenses with a cumulative negative effect on reported cash flow relative to sales. In contrast, following the confiscation and the intervention of legal administrators, personnel and service expenses manipulation becomes insignificant, whereas material expenses manipulation significantly decreases relative to before confiscation.

This study develops expenses manipulation proxies that provide information on which expense by nature is manipulated without precluding most of the conclusions allowed by proxies classifying expenses by function and mostly applied in prior studies. Furthermore, it allows inferring conclusions on the relation between corporate social responsibility and earnings management through expenses manipulation, given that LMFs are socially

irresponsible by nature. Finally, it can help practitioners and regulators to identify accounting signals that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices, especially in countries with a strong criminal presence.

3.2 Introduction

The Mafias, which are considered to be the most sophisticated form of criminal organization, also run businesses in the lawful economic sphere in which they usually invest proceeds from illicit trafficking (money laundering). Legally registered Mafia firms (LMFs), according to criminologists' terminology, can be defined as firms that are legally registered and apparently engage in lawful activities but are owned by a Mafia family (Champeyrache, 2004). LMFs differ from lawful firms (LWFs) in three main ways (Fantò, 1999; Gambetta, 1993): the owners are members of a criminal organization; funding partially or totally comes from illegal activities; and criminal methods involving violence, intimidation or corruption might be used while doing business. Legal and illegal activities are therefore closely intertwined within LMFs as the legal activities mostly serve to launder profits stemming from illegal ones (Fantò, 1999).

A reliable estimate of the presence of LMFs in Italy is hardly achievable. Nonetheless, the relevance of the phenomenon can be inferred from a recent study, performed by Transcrime (2013) on behalf of Italian Ministry of Interior, which quantifies the annual illegal revenues of Mafias in Italy between 8.3 and 13 billion Euros. Furthermore, 8.7% of the total investment of Mafias in legal economy between 1983 and 2011 is represented by companies and stocks.

The general objective of this paper is to understand whether Accounting can contribute to understanding the mechanisms of the criminal economy and funding. In this regard, Compin

(2008) suggests that one of the role of Accounting in a criminal business is to mask the crime by ensuring that the accounting information, although deceptive, contains all the necessary virtues and in turn maintains an impression of rationality and economic credibility. Specifically, we examine expenses manipulation (EXM) within a sample of 224 Italian firms defined as LMFs, due to having been confiscated at some point by judicial authorities in relation to alleged connections of their owners with Italian organized crime. In particular, LMFs are compared with a sample of unlisted LWFs for which there is no evidence of criminal connection. We carry out the comparison for LMFs both before and after their confiscation and assignment to legal administrators. Therefore, we identify two main time periods: the pre-confiscation period and the post-confiscation period within a time frame of 10 years from 2003 to 2012 for which financial statements are available on AIDA database. In this way, we also aim to assess whether the confiscation of LMFs has a significant impact on their EXM practices.

EXM can be situated within the academic literature on earnings management (EM) through real activities manipulation. In this setting, previous studies mostly apply proxies classifying expenses by function such as production, R&D and selling, general and administrative (SG&A) (e.g., Cohen and Zarowin, 2010; Kim et al., 2012; Roychowdhury, 2006; Zang, 2012). In contrast, we develop EXM proxies by classifying expenses by nature in accordance with the legal structure of the income statement in Italy. Specifically, we estimate the abnormal material expenses including both raw materials and trading goods, the abnormal service expenses and the abnormal personnel expenses. We use the term EXM, rather than EM through real activities manipulation, for several reasons. First, it is more difficult for LMFs to infer the direction of the related impact on earnings. Indeed, due to their illicit purposes, we assume for LMFs a higher probability of fraudulent manipulations which may be reflected in abnormal and inconsistent expense patterns as well as in a lower efficiency in resource consumption showed in the financial statements (i.e., underreporting of inventory, record of fictitious transactions, etc.). Second, the reference to “real activities” may be misleading for LMFs given that abnormal expenses may be due to fictitious transactions. Finally, we mostly examine expenses rather than revenues.

Overall, our results reveal that, relative to LWFs, before confiscation LMFs upward manage material expenses and downward manage personnel and service expenses with a cumulative negative effect on reported cash flow from operations (CFO) relative to sales. On the other hand, after confiscation personnel and service EXM becomes insignificant, whereas material EXM significantly decreases relative to before confiscation. These latter results provide evidence of the relevant impact of legal administrators’ takeover on the accounting practices of LMFs. Furthermore, we find a significantly negative association between accrual management (AM), proxied by discretionary revenue accruals, and EXM, proxied by abnormal material expenses, consistent with previous studies showing a simultaneous or substitutive use of different EM methods (Badertscher, 2011; Cohen et al., 2008; Cohen and Zarowin, 2010; Zang, 2012). Hence, we infer that discretionary revenue accruals may be a better AM proxy than discretionary aggregate accruals whether the objective is to clearly distinguish effects on earnings of EXM strategies from those of AM strategies. Indeed, discretionary revenue accruals are less likely to be affected by overproduction EXM strategy which necessarily leads to an increase in inventory accruals included in aggregate accruals. Moreover, an additional analysis indicates that LMFs which are smaller and exhibit higher discretionary revenue accruals are more likely to upward manage material expenses. This also suggests a simultaneity in revenue and expense manipulations that makes the directional effect on earnings hardly predictable. Finally, estimations within a matched sample support the robustness of our results.

Prior research examines EM in varying types of firms and in diverse contexts. In particular, different studies find a significant relation between EM and firms committing financial statement fraud (Beneish, 1997; Jones et al., 2008; Lee et al., 1999; Perols and Lougee, 2011). Chaney et al. (2011) find that EM is more intensive within firms with political connections relative to firms lacking such connections. Other studies examine the EM behavior pattern of socially responsible firms with inconsistent results (Chih et al., 2008; Gargouri et al., 2010; Kim et al., 2012). Prencipe (2012) shows that US multinational firms manage earnings less than domestic firms do. Wang and Yung (2011) find lower levels of EM among state-owned enterprises than privately-owned firms in China. Lara et al. (2009) provide evidence that failed firms upward manage earnings in the years prior to failure. Coppens and Peek (2005) find the tax incentives reduce the benefits of engaging in income-increasing EM in countries with strong tax alignment. Finally, Prencipe et al. (2008) provide empirical evidence on the motivations for EM in listed family companies relative to listed nonfamily firms in Italy.

Although some traits of LMFs can be identified in the aforementioned studies on EM, our study contributes to the accounting literature given that, to the best of our knowledge, it is the first that specifically examines EM and in particular EXM in LMFs. These unlisted firms may particularly interest the scientific community given that they are socially irresponsible by nature because of their illicit purposes. In addition, their incentives, *modus operandi* and financial statement formats differ from those of listed companies. Hence, our study allows inferring conclusions on the relation between corporate social responsibility (CSR) and EM. Moreover, it develops alternative EXM proxies that provide information on which expense by nature is manipulated without precluding most of the conclusions allowed by proxies adopted in prior studies. Finally, our paper can aid practitioners and regulators in identifying accounting signals in firm management that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices, especially in countries with a strong criminal presence.

The remainder of the paper proceeds as follows: the next section introduces LMFs; "Related Research and Hypothesis Development" section reviews the literature and develops the hypotheses; "Methodology" section describes the methodology; "Results and Discussions" section presents the results and their discussion; "Conclusions" section includes concluding remarks.

3.3 Legally Registered Mafia Firms

For the purpose of this study, we define "organized crime" according to the Italian legal provision of "associazione a delinquere di tipo mafioso" (article 416-bis of the Italian criminal code). Furthermore, art. 416-bis states that:

"*A mafia-type association consists of three or more individuals and those who belong to it make use of the power of intimidation afforded by the associative bond and the state of subjugation and criminal silence (omertà) which derives from it to commit crimes, to acquire directly or indirectly the management or control of economic activities, concessions, authorizations or public contracts and services, either to gain unjust profits or advantages for themselves or for others, or to prevent or obstruct the free exercise of the vote, or to procure votes for themselves or to others at a time or electoral consultation*".

One of the main reasons for criminal organizations to take on new businesses is so as to be able to invest and launder significant financial resources coming from illegal activities. In this way, criminal organizations achieve high profits and social consensus by ensuring employment and income for the population in the areas where they exercise control of the territory. Several authors in Sociology examine characteristics of LMFs. Fantò (1999) suggests that the main trait of LMFs is not the type of business run but the nature of the capital accumulation process that led to their formation as well as the strength of intimidation on which they are hinged. This mafia-style intimidation is a source of surplus value and competitive advantages of LMFs over LWFs. Arlacchi (1983) identifies the following competitive advantages of the LMFs: discouragement of competition (securing goods and raw materials at favorable prices, as well as orders, contracts and commercial outlets using criminal intimidation); wage compression (evasion of social security contributions and insurance, non-payment of overtime, denial of trade union rights); availability of financial resources (investment of huge proceeds coming from illegal activities (money laundering) without bearing the cost of credit).

After the first instance of court confiscation LMFs are entrusted to one or more legal administrators. The legal administration is an institution designed to reinstate the legality, protect and manage confiscated LMFs and avoid their progressive impoverishment. However, the confiscation of first instance is a temporary measure that can be followed, even after several years, by the definitive confiscation as the last phase of the trial.

The body currently in charge of the administration and assignment of assets (including firms) definitively confiscated due to organized crime is the Italian agency Agenzia Nazionale Beni Sequestrati e Confiscati (ANBSC). According to the most recent available data on the ANBSC official website (http://www.benisequestraticonfiscati.it) the number of confiscated firms on January 7th 2013 was 1,708. After definitive confiscation firms can be sold, leased or liquidated and although the efforts of ANBSC to ensure the continuation of the business, most of the firms end up being liquidated or going bankrupt as they are unable to face the market competition after losing the support of organized crime and banks.

LMFs are mainly created as limited-liability companies (Società a responsabilità limitata (Srl)) with a reduced number of owners that exercise a close control on operations directly or indirectly through trusted managers that are often affiliates of the same criminal organization. One might then assume that the potential misalignment of interests and goals between them is reduced, with no significant agency problems. Organized crime may prefer this corporate structure because the minimum required starting equity (€ 10,000) is lower than alternative legal forms, audit committee is not required, and even from a fiscal point of view there are fewer charges.

3.4 Related Research and Hypothesis Development

3.4.1 Expenses Manipulation in Prior Research

Previous research finds that managers discretionally manage earnings for different purposes using a wide variety of methods, ranging from carrying out special transactions (e.g., Cohen et al., 2008; Roychowdhury, 2006; Zang, 2012) that usually affect firm's operating activities, expenses and CFO to the opportunistic manipulation of accruals with no CFO impact. In this paper we mainly focus on EXM proxies that we expect to exhibit significant differences for LMFs because of their specific purposes and characteristics. Previous studies define EXM in the context of real activities manipulation as departures from normal operational practices, without a sound economic justification, in order to meet certain earnings thresholds (Cohen and Zarowin, 2010; Roychowdhury, 2006). In addition, Gunny (2010) and Badertscher (2011) define these departures as actions that change the timing or structuring of an operation, investment, and/or financing transaction in an effort to influence the output of the accounting system. Specifically, prior research documents that managers of listed companies provide price discounts or more lenient credit terms to temporarily boost sales. Furthermore, they overproduce to lower the cost of goods sold, and reduce discretionary expenditures in order to improve reported margins (Cohen and Zarowin, 2010; Gunny, 2010; Roychowdhury, 2006; Zang, 2012). Hence, sales manipulation and overproduction cause abnormally high production costs relative to sales, and reduction of discretionary expenditures causes abnormally low discretionary expenditures relative to sales. As Roychowdhury (2006) suggests, the effect of these manipulation methods on CFO is multidirectional and consequently ambiguous. Additionally, other studies provide evidence of EXM performed through the opportunistic reduction of R&D expenditures to increase reported income (Baber et al., 1991; Bens et al., 2002; Bushee, 1998; Gunny, 2010; Osma and Young, 2009). Finally, timing the sale of fixed assets to report gains is another case empirically tested in previous studies (Bartov, 1993; Gunny, 2010; Herrmann et al., 2003).

3.4.2 Motivations for Expenses Manipulation within LMFs

Prior studies (e.g., Badertscher, 2011; Cohen et al., 2008; Cohen and Zarowin, 2010; Kim et al., 2012; Roychowdhury, 2006; Zang, 2012) assume that EXM is mostly performed to boost earnings rather than reducing them, mainly because they analyze listed companies. On the other hand, we examine unlisted firms whose incentives and EXM patterns may differ from those of listed companies. Specifically, previous studies identify tax avoidance as a primary incentive for EM in unlisted firms, especially in countries with strong tax alignment (Ball and Shivakumar, 2005; Burgstahler et al., 2006; Van Tendeloo and Vanstraelen, 2008). In this regard, Alford et al. (1993) and Hung (2000) indicate Italy as a country with high alignment of financial and tax accounting. On the other hand, the use of financial statements in contracting with stakeholders reduces incentives to engage in EM for tax avoidance purposes

(Beatty and Harris, 1998; Coppens and Peek, 2005; Klassen, 1997). Indeed, this practice may result in negative consequences at the firm level such as larger costs of debt and equity or higher likelihood of a lawsuit (Francis et al., 2005).

However, LMFs can usually count on financial resources coming from illegal activities which reduce the need for bank financing and the related incentive to report a positive financial performance or an acceptable earnings quality. Hence, LMFs do not have to face trade-offs in their financial and tax reporting decisions. Moreover, we expect a higher level of EXM for LMFs due to the low level of scrutiny from outsiders of these firms, in connection with the protection ensured by their criminal ties and infiltrators in all spheres of political and institutional life of the country. In this aspect, some analogy might be found with the case of politically connected firms studied by Chaney et al. (2011) which exhibit higher EM than firms lacking such connections. Additionally, previous studies find that a low external monitoring intensity is associated with a higher level of EM including EXM (e.g., Duellman et al., 2013; Wongsunwai, 2013).

On the other hand, previous studies find that EXM, as a departure from optimal operational decisions, is negatively associated with firms' future performance (Cohen and Zarowin, 2010; Roychowdhury, 2006; Zhao et al., 2012). Hence, some managers might find EXM particularly costly because their firms face intense competition in the industry (Zang, 2012). Nonetheless, in the surveys conducted by Bruns and Merchant (1990) and Graham et al. (2005), financial executives express a preference for EXM through real activities over AM. Indeed, AM is more likely to draw auditor or regulatory scrutiny and, due to the reversing nature of accruals, may only provide a limited leeway at year end to meet the desired earnings benchmarks (Badertscher, 2011; Cohen and Zarowin, 2010; Roychowdhury, 2006).

In particular, LMFs may mostly resort to EXM rather than AM for several additional reasons. First, EXM can be used to permanently reduce current period taxable income more effectively than AM by fraudulently removing certain cash flows from the balance sheets. Second, money laundering may require recording fictitious transactions that may lead to EXM patterns detected in our proxies. Finally, LMFs face a very low competition due to the competitive advantages aforementioned (Arlacchi, 1983; Fantò, 1999) which outweigh the costs of suboptimal operational decisions arising from EXM.

3.4.3 Relation between Expenses Manipulation and CSR

A further indication on the EXM patterns of LMFs may come from some prior research on the relation between CSR and EM. Indeed, LMFs can be assumed to be socially irresponsible whether we refer to the widely accepted Carroll's (1979) definition of CSR implying that CSR firms work to make a profit, obey the law, behave ethically, and be a good corporate citizen by financially supporting worthy social causes (Carroll, 1991).

In practice, previous studies use a variety of methods to measure CSR. Some of these methods are: reputation indices or databases such as The Kinder, Lydenberg, and Domini (KLD) database (Hong and Andersen, 2011; Kim et al., 2012) which rates US listed companies based on several social dimensions; corporate crime (Baucus and Baucus, 1997; Davidson and Worrell, 1990) and tax avoidance (Dowling, 2013; Lanis and Richardson, 2012) indicators; content analysis of corporate publications on practices regarding environmental, community, employee, and consumer issues (Gray et al., 1995; Turker, 2009); scales measuring the CSR perceptions and values of managers (Quazi and O'Brien, 2000; Ruf et al., 1998); scales considering the extent to which businesses meet the economic, legal, ethical, and discretionary responsibilities imposed on them by their stakeholders (Maignan and Ferrell, 2000; Turker, 2009).

We do not directly measure CSR in LMFs. However, based on the CSR measures applied in previous research, we can reasonably assume LMFs to be socially irresponsible considering their aforementioned common practices, the nature of their owners and their questionable values. Based on this assumption, previous findings on the relation between CSR and EM may provide additional insights into EXM behavior of LMFs. In this regard, previous studies find that more socially responsible U.S. public firms, based on KLD database, are less likely to engage in EM and to be the subject of SEC investigations (Hong and Andersen, 2011; Kim et al., 2012). Previously Chih et al. (2008) examine the relationships between CSR and EM across 1,653 companies in 46 countries and find inconsistent results across different EM proxies. On the other hand, Prior et al. (2008) find that firm managers who engage in EM practices use CSR strategically to gain support from stakeholders and reduce their activism and vigilance. More recently, based on a sample of 109 Canadian companies, Gargouri et al. (2010) find a positive association between firm's corporate social performance ratings related to environment and employees and EM activities. Finally, based on a survey of professional accountants within private industry in Hong Kong, Shafer (2013) finds a significant association between perceptions of the organizational ethical climate and belief in the importance of CSR and between the latter and accountants' ethical judgments and behavioral intentions regarding accounting and operating earnings manipulation.

In summary, given the inconsistent evidence from prior research with mixed implications on the relation between CSR and EM, in this study we also aim to provide additional insight into this relation.

3.4.4 Definition of Expenses Manipulation Proxies and Hypothesis Formulation

We expect LMFs to manipulate expenses differently and for different purposes from listed firms mostly considered in previous studies on EXM. Therefore, EXM proxies used in previous research (Badertscher, 2011; Cohen et al., 2008; Cohen and Zarowin, 2010; Duellman et al., 2013; Kim et al., 2012; Roychowdhury, 2006; Zang, 2012) such as abnormal CFO, abnormal production costs and abnormal discretionary expenses may not be able to accurately portrait the EXM patterns of LMFs. In particular, we do not expect LMFs to usually resort to overproduction as a tool to increase earnings as assumed by Roychowdhury (2006). Indeed, overproduction may have undesirable effects for LMFs such as: increasing reported earnings and taxable income and reducing current CFO. Furthermore, LMFs benefit from competitive advantages granted by criminal methods and do not need to provide price discounts to temporarily boost sales. Finally, because of the particularities of LMFs and the sectors in which they mostly operate, we expect discretionary expenses related to R&D and SG&A to represent a relative small percentage of total reported operating expenses.

Hence, in our study we adopt as proxies for EXM: abnormal personnel expenses, abnormal material expenses including both raw materials and trading goods, abnormal service expenses as well as the previously used abnormal CFO. These alternative EXM proxies, relative to those used in prior research, have the advantage of providing information on the nature of expenses firms manipulate although they do not specify the related function. Nonetheless, we can reasonably assume that material expenses are variable, mostly related to production and thus directly affected by overproduction EM strategy. On the other hand, service expenses may also partially fall under the category of discretionary expenses (R&D and SG&A). However, the part related to production is most likely to be fixed (e.g., maintenance, rents, etc.) and, consequently, unaffected by overproduction EM strategy. Similarly, personnel expenses cannot clearly be assigned to a specific function and, especially in the short term, they are most likely to be fixed and unaffected by overproduction EM strategy. Therefore, we expect EM through overproduction to be mainly reflected in higher abnormal material expenses as well as an increase in year-end inventory.

Regarding our expectations for LMFs, these firms may fraudulently reduce personnel expenses by exploiting their employees and even resorting to undeclared work in order to avoid payment of social security contributions (Arlacchi, 1983). Therefore, we formulate the following first hypothesis:

> ***Hypothesis 1a***. *Ceteris paribus, before confiscation LMFs exhibit lower abnormal personnel expenses than LWFs do.*

Furthermore, LMFs may increase material expenses exhibiting a lower efficiency in the consumption of resources in order to reduce taxable income or to disguise money laundering. Specifically, they may underreport inventory in the balance sheet or record fictitious transactions with related parties, without an economic substance or at prices out of the market. In this regard, previous studies identify false invoicing as a technique commonly used for the so-called trade-based money laundering (Ferwerda et al., 2013; Zdanowicz, 2009). Hence, our second hypothesis is:

> ***Hypothesis 2a***. *Ceteris paribus, before confiscation LMFs exhibit higher abnormal material expenses than LWFs do.*

On the other hand, services expenses may also be manipulated similarly to material expenses. Nonetheless, they may appear abnormally lower relative to LWFs given that LMFs may be less prone to contract external services (advertising, consultancy, maintenance, etc.) because of their competitive advantages. This leads to our third hypothesis:

> ***Hypothesis 3a***. *Ceteris paribus, before confiscation LMFs exhibit lower abnormal service expenses than LWFs do.*

The cumulative effect of these manipulation methods on CFO and earnings is multidirectional and ambiguous. Therefore, we formulate the following null hypothesis by addressing this issue empirically:

> ***Hypothesis 4a***. *Ceteris paribus, before confiscation there is no significant difference in level of abnormal CFO between LMFs and LWFs.*

According to ANBSC statistics, after confiscation most of the LMFs fall into financial distress and often end up in liquidation. The main reasons for that may be: the loss of privileged and illegal business opportunities, the increase of operating expenses (e.g., regularization of undeclared workers and increase in service expenses for external support) and the shortage of funding as the dirty money flow is interrupted and the banks are more reluctant to grant credit. Previous studies (Charitou et al., 2007; Lara et al., 2009; Rosner, 2003) find that distressed firms prior to bankruptcy engage in income-increasing EM in order to conceal the deteriorating financial conditions. Furthermore, after the confiscation one of the tasks of legal administrators is the reinstatement of legality within LMFs. Hence, we expect them to engage less in EXM than their predecessors because the incentives of confiscated LMFs may be more aligned with those of LWFs. Therefore, the further hypotheses of our study are:

> ***Hypothesis 1b***. *Ceteris paribus, there is no significant difference in level of abnormal personnel expenses between LMFs after confiscation and LWFs or this difference is significantly lower than that between LMFs before confiscation and LWFs.*

__Hypothesis 2b__. Ceteris paribus, there is no significant difference in level of abnormal material expenses between LMFs after confiscation and LWFs or this difference is significantly lower than that between LMFs before confiscation and LWFs.

__Hypothesis 3b__. Ceteris paribus, there is no significant difference in level of abnormal service expenses between LMFs after confiscation and LWFs or this difference is significantly lower than that between LMFs before confiscation and LWFs.

__Hypothesis 4b__. Ceteris paribus, there is no significant difference in level of abnormal CFO between LMFs after confiscation and LWFs.

3.5 Methodology

3.5.1 Estimation of Expenses Manipulation Proxies (Dependent Variables)

In order to calculate our EXM proxies we first estimate normal material expenses, including both raw materials and trading goods, and normal personnel expenses using the model adopted by prior studies (e.g., Cohen et al., 2008; Kim et al., 2012; Roychowdhury, 2006) for normal production costs:

$$\frac{MAT_t(PER_t)}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \beta_4 \frac{\Delta S_{t-1}}{TA_{t-1}} + \varepsilon_t \tag{1}$$

Where in year t (or t - 1), MAT_t and PER_t are respectively material expenses and personnel expenses that we assume mostly related to production; *TA*, S_t, and ΔS_t respectively represent total assets, net sales and change in net sales relative to previous year. Parameters of Eq. (1) are estimated cross-sectionally for each industry-year with at least 15 observations in order to control for industry-wide changes under different economic conditions (Jeter and

Shivakumar, 1999) that affect our variables while allowing the coefficients to vary across time (e.g., DeFond and Jiambalvo, 1994; Kasznik, 1999). We use all active unlisted firms in AIDA (excluding LMFs) with financial statements available for 10 years from 2003 to 2012. The total number of these firms at the moment of its retrieval from AIDA is 78,340. The abnormal levels of material expenses (*ABMAT*) and personnel expense (*ABPER*) are measured as the estimated residuals from Eq. (1).

Additionally, we estimate abnormal service expenses (*ABSERV*) as the residuals from the following Eq. (2) employed by prior studies (e.g., Cohen et al., 2008; Kim et al., 2012; Roychowdhury, 2006) for discretionary expenses with parameters estimated in the same way as for Eq. (1):

$$\frac{SERV_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_{t-1}}{TA_{t-1}} + \varepsilon_t \tag{2}$$

Finally, in line with Dechow et al. (1998) and Roychowdhury (2006) we estimate abnormal CFO (*ABCFO*) as the residuals from the following Eq. (3) with parameters estimated in the same way as for Eq. (1):

$$\frac{CFO_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \varepsilon_t \tag{3}$$

As the statement of CFO is not legally required for unlisted firms in Italy, CFO is computed as:

$$CFO = Earnings\ before\ tax - Total\ accruals \tag{4}$$

Consistent with previous studies on EM (Bergstresser & Philippon, 2006; Dechow, Sloan, & Sweeney, 1995; Jones, 1991), total accruals (*ACCR*), are computed as:

$$ACCR_t = \Delta CA_t - \Delta CL_t - \Delta CASH_t + \Delta STD_t - DEP_t \tag{5}$$

Where ΔCA is change in current assets, ΔCL is change in current liabilities, $\Delta CASH$ is change in cash and cash equivalents, ΔSTD is change in debt included in current liabilities, *DEP* is depreciation and amortization expenses.

3.5.2 Other Variables and Base Regression Model

As independent variables strictly related to our hypotheses we use binary variables *LMF_PRE* taking value of 1 for LMFs before confiscation, *LMF_POST* taking value of 1 for LMFs after confiscation, and *LWF* taking value of 1 for LWFs. The latter is excluded as a base variable from the final regression model. Furthermore, we consider other control variables shown in the prior literature to be associated with different EM practices (e.g., Alissa et al., 2013; Duellman et al., 2013; Gunny, 2010; Kim et al., 2012; Klein, 2002; Roychowdhury, 2006; Zhao et al., 2012). Because of previous inconsistent evidences and the peculiarities of our sample and EXM proxies we do not make any sign prediction. Specifically, we include absolute change in net income (*ABSΔNI), s*ize (*SIZE*), long-term indebtedness (*LEVLONG*), sum of inventory and receivables (*INVREC*), assets growth (*GROWTH*), financial performance (*ROA)*, and an indicator variable for firms reporting losses (*LOSS*).

Furthermore, we include the current effective tax rate (*ETR*) (Hanlon and Heitzman, 2010; Lanis and Richardson, 2012; Richardson and Lanis, 2007) consistent with the stronger tax avoidance incentive in private firms.

We also consider the case of firms just meeting zero earnings benchmark that previous studies find to be more likely to engage in EM (Gunny, 2010; Roychowdhury, 2006; Zang, 2012). Therefore, we indicate as suspect (*SUSPECT*) firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 (Gunny, 2010).

Previous research documents that firms use a mix of EM techniques and trade-off between them based on their relative costs (Badertscher, 2011; Cohen et al., 2008; Cohen and Zarowin, 2010; Zang, 2012). Hence, we include a proxy for AM represented by discretionary accruals (*DAC*). It is calculated using the modified Jones model (Dechow et al., 1995) with a control for performance (Kothari et al., 2005) as the residuals from the following Eq. (6) whose parameters are estimated similarly to Eq. (1):

$$\frac{ACCR_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t - \Delta AR_t}{TA_{t-1}} + \beta_3 \frac{PPE_t}{TA_{t-1}} + \beta_4 ROA_{t-1} + \varepsilon_t \qquad (6)$$

Where in year t (or t - 1) Δ*REV*, Δ*AR*, *PPE*, and *ROA* represent changes in net revenue, changes in accounts receivables, property, plant, and equipment, and return on assets, respectively.

In a recent study Stubben (2010) finds that discretionary revenue models are more likely than aggregate discretionary accrual models to detect a combination of revenue and expense manipulation especially in growth firms. Hence, we include discretionary revenue accruals (*DREV*) as an additional proxy for AM. Following Stubben (2010) and Caylor (2010), we calculate *DREV* as the residuals from the following Eq. (7) with parameters estimated similarly to Eq. (1):

$$\frac{\Delta AR_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t}{TA_{t-1}} + \beta_3 \frac{\Delta CFO_{t+1}}{TA_{t-1}} \varepsilon_t \qquad (7)$$

We also include change in inventory (*CH_INV*) which may be affected by EM practices through overproduction (Cohen and Zarowin, 2010; Gunny, 2010; Roychowdhury, 2006; Zang, 2012)

Finally, we include dummy variables representing industry (*INDSEC)* and year *(YEAR).*

Therefore, in order to contrast our hypotheses we estimate the following model for our EXM proxies:

$$EXM\_PROXY_t = \beta_0 + \beta_1 LMF\_PRE_t + \beta_2 LMF\_POST_t + \beta_3 ABS\Delta NI_t + \beta_4 SIZE_{t-1} + \beta_5 LEVLONG_{t-1} + \beta_6 INVREC_{t-1} + \beta_7 GROWTH_t + \beta_8 ROA_{t-1} + \beta_9 ETR_t + \beta_{10} DAC_t + \beta_{11} DREV_t + \beta_{12} CH\_INV_t + \beta_{13} LOSS_t + \beta_{14} SUSPECT_t + \sum \emptyset_i INDSEC_{it} + \sum \alpha_i YEAR_i + \varepsilon_t \quad (8)$$

Where the variables, whose firm subscript is suppressed for simplicity, are:

EXM_PROXY is *ABPER*, *ABMAT*, *ABSERV* or *ABCFO*:

ABPER is abnormal personnel expenses equal to residuals from Eq. (1);

ABMAT is abnormal material expenses equal to residuals from Eq. (1);

ABSERV is abnormal service expenses equal to residuals from Eq. (2);

ABCFO is abnormal CFO equals to residuals from Eq. (3) .

LMF_PRE is a dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise.

LMF_POST is a dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise.

ABSΔNI is absolute value of change in net income relative to previous year divided by lagged total assets.

SIZE is natural logarithm of total assets.

LEVLONG is long-term liabilities divided by total assets.

INVREC is total inventories and receivables divided by total assets.

GROWTH is change in total assets relative to previous year divided by lagged total assets.

ROA is income before tax divided by total assets.

ETR is current tax expense divided by income before tax.

DAC is discretionary total accruals equal to residuals from Eq. (6).

DREV is discretionary revenue accruals equal to residuals from Eq. (7).

CH_INV is change in inventory relative to previous year divided by lagged total assets.

LOSS is a dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise.

SUSPECT is a dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise.

INDSEC is a dummy variables representing industry defined by the two-digit SIC code.

YEAR is dummy variables representing the fiscal year.

3.5.3 Data and Sample Selection

LMFs sample consists of 224 firms confiscated to organized crime, some of them provided by ANBSC and others found in online newspapers and AIDA database. The financial statements for all firms are obtained from AIDA, the Italian Bureau Van Dijk database. It contains comprehensive information on 1 million companies with a turnover above € 500,000 in Italy, including the indication for some of them of the confiscation status and date of confiscation. Firms provided by ANBSC have all been confiscated by final judgment but their small size or their liquidation means that only 54 out of 1663 have financial statements available on AIDA. In addition, we include firms confiscated in first instance and found on AIDA database (118) and online newspapers (52) until reaching a total of 224. For the 224 LMFs we obtain from AIDA available financial statement data for the year of confiscation and for the years prior to and following the confiscation within the period of 2003 to 2012. Hence, for some LMFs we only have available either financial data prior to confiscation or financial data after confiscation. We then estimate our base regression model of Eq. (8) including LMF-years and AIDA population of active unlisted firm-years from 2003 to 2012 in LMFs industries. We initially avoid the matched sample procedure although in our base regression model we control for year, size and two-digit industry SIC code. Table 3.1 summarizes the sample selection procedure that yields the 224 LMFs and the 78,340 LWFs.

Table 3.1. Sample selection

	Number of firms
LMFs sample	
LMFs definitively confiscated at November 5th 2012 provided by ANBSC	1,663
Less: firms provided by ANBSC with data unavailable on AIDA database	-1,609
Add: firms found in AIDA database with status confiscated	118
Add: confiscated firms found in online newspapers with data available in AIDA	52
Final LMFs sample	**224**
LMFs year observations in base regression model (*ABMAT*)	**890**
LWFs control sample	
Aida population of active and unlisted firms with available financial data from 2003 to 2012 in the same two-digit SIC industries as LMFs	**78,340**
LWFs year observations in base regression model (*ABMAT*)	**518,001**

Source: ANBSC and AIDA database, 2013.

Table 3.2 presents the industry distribution by two-digit SIC groups of LMFs in our sample and AIDA population of active unlisted firms with available financial data from 2003 to 2012 in the same industries as those of LMFs.

Table 3.2. Industry Distribution of LMFs and AIDA population of active unlisted firms with available financial data from 2003 to 2012 restricted to LMFs industries

Sic code	Industry description	AIDA population		LMFs	
		Freq.	Percent	Freq.	Percent
01	Agricultural production-crops	644	0.82%	4	1.79%
14	Mining and quarrying of nonmetallic minerals, except fuels	463	0.59%	9	4.02%
15	Building construction-general contractors and operative builders	5,486	7.00%	41	18.30%
16	Heavy construction other than building construction-contractors	524	0.67%	3	1.34%
17	Construction-special trade contractors	4,032	5.15%	8	3.57%
20	Food and kindred products	3,224	4.12%	6	2.68%
					(Continued on the next page)

Sic code	Industry description	AIDA population		LMFs	
		Freq.	Percent	Freq.	Percent
25	Furniture and fixtures manufacturing	829	1.06%	3	1.34%
28	Chemicals and allied products manufacturing	1,598	2.04%	1	0.45%
29	Petroleum refining and related industries	158	0.20%	2	0.89%
32	Stone, clay, glass and concrete products manufacturing	1,960	2.50%	13	5.80%
34	Fabricated metal products, except machinery and transportation equipment	7,038	8.98%	2	0.89%
42	Motor freight transportation and warehousing	2,894	3.69%	18	8.04%
44	Water transportation	586	0.75%	1	0.45%
45	Transportation by air	95	0.12%	1	0.45%
47	Transportation services	1,884	2.40%	3	1.34%
49	Electric, gas and sanitary services	1,419	1.81%	7	3.13%
50	Wholesale trade, durable goods	14,064	17.95%	23	10.27%
51	Wholesale trade, nondurable goods wholesale dealing in	7,821	9.98%	19	8.48%
52	Building materials, hardware, garden supply, and mobile home dealers wholesale dealing in	1,018	1.30%	1	0.45%
53	General merchandise stores	324	0.41%	1	0.45%
54	Food stores	1,737	2.22%	16	7.14%
55	Automotive dealers and gasoline service stations	536	0.68%	4	1.79%
56	Apparel and accessory stores	1,920	2.45%	3	1.34%
57	Home furniture, furnishings, and equipment stores	872	1.11%	1	0.45%
58	Eating and drinking places	1,007	1.29%	2	0.89%
59	Miscellaneous retail	1,475	1.88%	1	0.45%
65	Real estate	2,239	2.86%	7	3.13%
70	Hotels, rooming houses, camps, and other lodging places	1,600	2.04%	3	1.34%
72	Personal services	327	0.42%	1	0.45%
73	Business services	5,001	6.38%	2	0.89%
75	Automotive repair, services, and parking	882	1.13%	1	0.45%
79	Amusement and recreation services	744	0.95%	5	2.23%
(Continued on the next page)					

Sic code	Industry description	AIDA population		LMFs	
		Freq.	**Percent**	**Freq.**	**Percent**
80	Health services	1,165	1.49%	9	4.02%
81	Legal services	19	0.02%	1	0.45%
87	Engineering, accounting, research, management, and related services	2,755	3.52%	2	0.89%
Total		**78,340**	**100.00**%	**224**	**100.00**%

Source: AIDA database, 2013.

Compared to the AIDA population, LMFs are especially more abundant in industry groups: building construction-general contractors and operative builders (18.30% of LMFs versus 7.00% of AIDA population), food stores (7.14% versus 2.22%) and Motor freight transportation and warehousing (8.04% versus 3.69%). On the other hand, there is a lower proportion of LMFs mostly in wholesale trade, durable goods (10.27% versus 17.95%), business services (0.89% versus 6.38%) and fabricated metal products, except machinery and transportation equipment (0.89 versus 8.98%). It is noteworthy that Construction (SIC codes 15, 16 and 17) is the sector with the highest cumulative percentage (23.21%) of LMFs. This sector presents most of the characteristics of sectors in which previous research finds a higher presence of undeclared work (e.g., Pfau-Effinger, 2009) such as high work intensity and low technology. Indeed, usage of undeclared work may be an explanation of the hypothesized lower abnormal personnel expenses in LMFs.

3.6 Results and Discussions

3.6.1 Descriptive Statistics and Univariate Analysis

Table 3.3 presents descriptive statistics for each variable considered in our base regression model comparing LMF-years to LWF-years both before and after confiscation. We report medians because they are less likely than means to be influenced by extreme observations. All continuous variables are winsorized at the top and bottom 1 percent of their distributions to avoid the influence of outliers.

Table 3.3. Descriptive statistics and variable comparison between LMFs and LWFs

	LMFs before confiscation		LMFs after confiscation		LWFs		LMFs before confisc. - LWFs		LMFs after confisc. - LWFs	
	N	**Median**	**N**	**Median**	**N**	**Median**	**Difference**	**Test**	**Difference**	**Test**
Dependent Variables										
ABPER	622	-0.047	490	-0.017	661,712	-0.019	-0.028	***	0.002	
ABMAT	622	0.060	490	0.053	661,717	-0.004	0.064	***	0.057	***
ABSERV	750	-0.072	517	-0.053	671,047	-0.037	-0.034	***	-0.015	
ABCFO	647	-0.009	473	-0.018	567,262	-0.004	-0.004	*	-0.013	**
Control Variables										
ABSΔNI	750	0.014	517	0.023	671,114	0.014	0.000	**	0.009	***
SIZE	967	7.944	553	8.230	753,484	7.802	0.142		0.428	***
LEVLONG	967	0.024	553	0.064	753,480	0.030	-0.006		0.035	***
INVREC	928	0.644	529	0.588	705,084	0.614	0.030	*	-0.026	
GROWTH	750	0.109	517	0.004	671,352	0.037	0.072	***	-0.033	***
ROA	967	0.022	553	0.011	753,371	0.028	-0.006	***	-0.016	***
ETR	966	0.423	553	0.334	751,630	0.515	-0.092	***	-0.181	***
DAC	631	0.000	463	-0.004	541,446	-0.001	0.000		-0.003	
DREV	573	0.011	438	0.001	534,121	-0.009	0.020	***	0.010	***
CH_INV	750	0.000	517	0.000	671,298	0.000	0.000	***	0.000	
%LOSS	3.90%		15.05%		6.34%		-2.44%	***	8.71%	***
%SUSPECT	6.75%		6.34%		10.32%		-3.57%	***	-3.98%	***

*Notes: The sample full period spans 2003–2012. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed Mann–Whitney–Wilcoxon test for the differences in medians of continuous variables. Pearson chi-squared test of independence for categorical variables: %LOSS is percentage of firms with two or more consecutive years of negative income; %SUSPECT is percentage of firms just beating/meeting the zero earnings before tax benchmark. Continuous variables: ABPER is abnormal personnel expenses equal to residuals from Eq. (1); ABMAT is abnormal material expenses equal to residuals from Eq. (1); ABSERV is abnormal service expenses equal to residuals from Eq. (2); ABCFO is abnormal CFO equals to residuals from Eq. (4); ABS∆NI is absolute value of change in net income relative to previous year divided by lagged total assets; SIZE is natural logarithm of total assets; LEVLONG is long-term liabilities divided by total assets; INVREC is total inventories and receivables divided by total assets; GROWTH is change in total assets relative to previous year divided by lagged total assets; ROA is income before tax divided by total assets; ETR is current tax expense divided by income before tax; DAC is discretionary total accruals equal to residuals from Eq. (6); DREV is discretionary revenue accruals equal to residuals from Eq. (7); CH_INV is change in inventory relative to previous year divided by lagged total assets.*

As regards dependent variables, medians of variables *ABPER* and *ABSERV* are both negative and significantly ($p<0.01$) lower for LMFs before confiscation relative to LWFs providing a first indication in support of our hypotheses H1a and H3a, respectively. On the other hand, there is no significant difference in levels of *ABPER* and *ABSERV* between LWFs and LMFs after confiscation consistent with hypotheses H1b and H3b, respectively. Expense-decreasing manipulation of LMFs before confiscation resulting from these first two variables is offset by an expense-increasing manipulation suggested by positive and significantly ($p<0.01$) higher variable *ABMAT*, consistent with hypothesis H2a. This variable remains positive and significantly ($p<0.01$) higher for LMFs after confiscation. However, difference in medians decreases by 10.85% from 0.0636 to 0.0567 providing an indication in support of hypothesis H2b.

Furthermore, variable *ABCFO* is negative for LMFs before confiscation but only marginally significantly ($p<0.10$) lower than that for LWFs. On the other hand, after confiscation the magnitude of this difference increases and becomes significant at the 0.05 level. These results fail to support hypotheses H4a and H4b that do not predict any significant difference in level of *ABCFO*.

Turning to control variables, variable *ABS*Δ*NI* is significantly ($p<0.05$) lower for LMFs before confiscation, whereas it is significantly ($p<0.01$) higher after confiscation. Furthermore, before confiscation variable *LEVLONG* is not significantly different between the two types of firm. In contrast, after confiscation LMFs appear significantly ($p<0.01$) more long term indebted than LWFs because of the likely loss of the criminal support granting financial resources and competitive advantages (Arlacchi, 1983; Fantò, 1999). In addition, LMFs are significantly ($p<0.01$) less profitable (*ROA*) than LWFs both before and after confiscation. An overinvestment of financial resources stemming from illegal activities as well as a poor management and an income-decreasing EM for tax avoidance may explain the lower profitability of LMFs before confiscation. On the other hand, the cost of the reinstatement of legality and the loss of business opportunities and competitive advantages (Arlacchi, 1983; Fantò, 1999) may be the causes after confiscation. A further consistent indication is the significantly ($p<0.01$) higher total assets growth rate (*GROWTH*) for LMFs before confiscation, presumably financed with dirty money, that becomes significantly ($p<0.01$) lower after confiscation. Interestingly, significantly ($p<0.01$) lower variable *ETR* for LMFs both before and after confiscation provides evidence of a higher tax avoidance in the former firms. As regards AM variables, variable *DAC* does not show any significant difference between both types of firm, whereas variable *DREV* is positive and significantly ($p<0.01$) higher for LMFs both before and after confiscation. Consistent with Stubben's (2010) findings, these latter results suggest that discretionary revenue accruals are more likely than aggregate discretionary accruals to detect a combination of revenue and expense manipulation. Interestingly, the unadjusted accrual variable *CH_INV* is positive and significantly higher for LMFs before confiscation, whereas it does not show any significant difference after confiscation. This result may be a consequence of the higher growth of LMFs before confiscation relative to LWFs.

In addition, it is noteworthy the significantly ($p<0.01$) lower percentage of LMFs before confiscation with two or more consecutive years of negative income (*%LOSS*). However, after confiscation the situation is completely reversed consistent with the average decline of financial performance of LMFs. Finally, the percentage of LMFs just meeting/beating the zero earnings benchmark (*%SUSPECT*), both before and after confiscation, is significantly ($p<0.01$) lower suggesting that LMFs may have a weaker motivation to hit that benchmark.

Table 3.4 displays Pearson correlations between independent variables of our base regression model in Eq. (8). Correlations among variables appearing jointly as independent in regression models are low (below 0.43), thus providing a first indication that collinearity is unlikely to affect estimations.

Table 3.4. Pearson correlations between independent variables

	1		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*		*10*
1.ABSΔNI	1																		
2.SIZE	-0.113	***	1																
3.LEVLONG	-0.066	***	0.170	***	1														
4.INVREC	-0.085	***	0.003	**	-0.180	***	1												
5.GROWTH	0.123	***	0.060	***	0.021	***	-0.009	***	1										
6.ROA	0.098	***	-0.105	***	-0.195	***	-0.056	***	0.098	***	1								
7.ETR	-0.112	***	-0.038	***	-0.015	***	0.034	***	0.010	***	0.026	***	1						
8.DAC	-0.023	***	0.032	***	0.025	***	0.024	***	0.181	***	-0.016	***	0.006	***	1				
9.DREV	0.032	***	0.063	***	-0.013	***	0.233	***	0.385	***	-0.001		0.004	***	0.077	***	1		
10.CH_INV	-0.005	***	0.043	***	0.027	***	0.121	***	0.429	***	-0.018	***	0.017	***	0.280	***	0.026	***	1

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. ABSΔNI is absolute value of change in net income relative to previous year divided by lagged total assets; SIZE is natural logarithm of total assets; LEVLONG is long-term liabilities divided by total assets; INVREC is total inventories and receivables divided by total assets; GROWTH is change in total assets relative to previous year divided by lagged total assets; ROA is income before tax divided by total assets; ETR is current tax expense divided by income before tax; DAC is discretionary total accruals equal to residuals from Eq. (6); DREV is discretionary revenue accruals equal to residuals from Eq. (7); CH_INV is change in inventory relative to previous year divided by lagged total assets.*

3.6.2 Regression Results

In order to test our hypotheses, we estimate our model in Eq. (8) through a linear regression with panel-corrected standard errors to consider heteroskedasticity and contemporaneous correlation across panels. Table 3.5 presents the results for our estimations.

Table 3.5. Multiple Regressions of expenses manipulation proxies

	ABPER			*ABMAT*			*ABSERV*			*ABCFO*		
	Coef.	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
Variables of interest:												
LMF_PRE	-0.025	(0.002)	***	0.107	(0.000)	***	-0.053	(0.000)	***	-0.009	(0.029)	**
(Hypothesis/Exp. Sign)	H1a/–			H2a/+			H3a/–			H4a/0		
LMF_POST	-0.005	(0.519)		0.062	(0.000)	***	-0.015	(0.279)		-0.006	(0.349)	
(Hypothesis/Exp. Sign)	H1b/0			H2b/0			H3b/0			H4b/0		
Control variables:												
ABSΔNI	0.213	(0.000)	***	-0.366	(0.000)	***	0.207	(0.000)	***	0.083	(0.000)	***
SIZE	-0.005	(0.000)	***	0.002	(0.000)	***	0.010	(0.000)	***	0.004	(0.000)	***
LEVLONG	-0.040	(0.000)	***	0.058	(0.000)	***	-0.122	(0.000)	***	0.028	(0.000)	***
INVREC	0.002	(0.037)	**	0.043	(0.000)	***	0.029	(0.000)	***	-0.059	(0.000)	***
GROWTH	0.001	(0.362)		-0.041	(0.000)	***	0.246	(0.000)	***	0.037	(0.000)	***
ROA	0.021	(0.000)	***	-0.570	(0.000)	***	-0.166	(0.000)	***	0.565	(0.000)	***
ETR	0.015	(0.000)	***	-0.018	(0.000)	***	0.005	(0.000)	***	-0.001	(0.000)	***
DAC	-0.022	(0.000)	***	0.056	(0.000)	***	-0.026	(0.000)	***	-0.992	(0.000)	***
DREV	0.022	(0.000)	***	-0.012	(0.001)	***	-0.055	(0.000)	***	-0.006	(0.000)	***
CH_INV	0.053	(0.000)	***	0.731	(0.000)	***	-0.102	(0.000)	***	-0.069	(0.000)	***
LOSS	0.028	(0.000)	***	-0.030	(0.000)	***	-0.001	(0.642)		-0.034	(0.000)	***
SUSPECT	-0.056	(0.000)	***	0.063	(0.000)	***	-0.014	(0.000)	***	-0.006	(0.000)	***
INDSEC	Yes			Yes			Yes			Yes		
YEAR	Yes			Yes			Yes			Yes		
												(Continued on the next page)

	ABPER			*ABMAT*			*ABSERV*			*ABCFO*		
	Coef.	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
Intercept	0.032	(0.000)	***	-0.062	(0.000)	***	-0.115	(0.000)	***	0.019	(0.000)	***
Number of obs.	518,891			518,891			525,109			525,109		
R^2	0.022			0.090			0.044			0.862		
Wald $\chi 2$	12,298	(0.000)	***	44,502	(0.000)	***	16,311	(0.000)	***	2,080,000	(0.000)	***

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. All test statistics and significance levels are calculated based on panel-corrected standard errors to consider heteroskedasticity and contemporaneous correlation across panels. LMF_PRE is a dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; LMF_POST is a dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; ABSΔNI is absolute value of change in net income relative to previous year divided by lagged total assets; SIZE is natural logarithm of total assets; LEVLONG is long-term liabilities divided by total assets; INVREC is total inventories and receivables divided by total assets; GROWTH is change in total assets relative to previous year divided by lagged total assets; ROA is income before tax divided by total assets; ETR is current tax expense divided by income before tax; DAC is discretionary total accruals equal to residuals from Eq. (6); DREV is discretionary revenue accruals equal to residuals from Eq. (7); CH_INV is change in inventory relative to previous year divided by lagged total assets; LOSS is a dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT is a dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise; INDSEC is a dummy variables representing industry defined by the two-digit SIC code; YEAR is a dummy variables representing the fiscal year.*

First of all, it is noteworthy that all the estimated regressions are significant at the 0.01 level according to the chi-square tests. As regards variables relevant for our hypotheses, coefficient on *LMF_PRE* is negative and significant ($p<0.01$) both in *ABPER* and *ABSERV* regression, whereas it is positive and significant ($p<0.01$) in *ABMAT* regression. These results provide support for hypotheses H1a, H2a and H3a, indicating that LMFs before confiscation downward manage personnel expenses, upward manage material expenses and downward manage service expenses, respectively. It should be noted that having controlled for change in inventory (*CH_INV*) allows inferring that other reasons than overproduction, including fraudulent manipulations, may explain higher *ABMAT* in LMFs before confiscation. Furthermore, coefficient on *LMF_PRE* is negative and significant ($p<0.05$) in *ABCFO* regression failing to support null hypothesis H4a. Hence, EXM performed by LMFs before confiscation has a cumulative decreasing effect on their CFO relative to sales.

On the other hand, coefficient on *LMF_POST* is not significant in all regressions except in *ABMAT* regression where it is positive and significant ($p<0.01$). However, in the latter regression an untabulated test shows that it is significantly ($p<0.05$) lower than coefficient on *LMF_PRE*, thus suggesting a less intensive material EXM of LMFs after confiscation relative to before confiscation. In summary, our results support all hypotheses related to LMFs after confiscation (H1b, H2b, H3b, H4b) and provide further evidence on the significant impact of legal administration on their practices.

As regards the rest of control variables, it is noteworthy that all their coefficients are mostly significant at the 0.01 level although their sign differ across the regressions. This provides evidence of a different EXM strategy associated with each type of expense. Focusing on AM variables, in *ABMAT* regression coefficients on *DAC* and *CH_INV* are positive and significant ($p<0.01$), whereas coefficient on *DREV* is negative and significant ($p<0.01$). Consistent with previous findings on substitutive use of different EM strategies (Badertscher, 2011; Cohen et al., 2008; Cohen and Zarowin, 2010; Zang, 2012), these results suggest that firms may upward manage material expenses and earnings through overproduction, increasing inventory and aggregate accruals, as a substitute for upward managing revenue accruals. Hence, *DREV* may be a better AM proxy than *DAC* whether the objective is to clearly distinguish effects on earnings of EXM strategies from those of AM strategies. Indeed, *DREV* is less likely to be affected by overproduction EXM strategy which necessarily implies an increase in inventory accruals included in aggregate accruals.

3.6.3 Additional Analyses

3.6.3.1 Regression Analysis with Interactions

In order to determine the effect of each control variable on EXM of LMFs before confiscation, we estimate additional regressions including the interactions of control variables with the binary variable *LMF_PRE*. We present the results of our additional estimations in Table 3.6.

Table 3.6. Multiple regressions of expenses manipulation proxies with interaction variables

	ABPER			*ABMAT*			*ABSERV*		
	Coef.	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
Variables of interest:									
LMF_PRE	-0.165	(0.023)	**	0.281	(0.006)	***	-0.145	(0.220)	
LMF_POST	-0.005	(0.516)		0.062	(0.000)	***	-0.015	(0.274)	
Control variables:									
ABSΔNI	0.213	(0.000)	***	-0.366	(0.000)	***	0.206	(0.000)	***
*ABSΔNI *LMF_PRE*	-0.113	(0.490)		0.137	(0.584)		0.623	(0.009)	***
SIZE	-0.005	(0.000)	***	0.002	(0.000)	***	0.010	(0.000)	***
*SIZE*LMF_PRE*	0.010	(0.176)		-0.023	**(0.045)**	**	0.005	(0.687)	
LEVLONG	-0.040	(0.000)	***	0.058	(0.000)	***	-0.122	(0.000)	***
*LEVLONG*LMF_PRE*	0.008	(0.820)		0.006	(0.942)		0.090	(0.235)	
INVREC	0.002	(0.043)	**	0.043	(0.000)	***	0.029	(0.000)	***
*INVREC*LMF_PRE*	0.060	(0.060)	*	0.023	(0.648)		-0.025	(0.684)	
GROWTH	0.001	(0.358)		-0.041	(0.000)	***	0.246	(0.000)	***
*GROWTH*LMF_PRE*	0.033	(0.329)		0.063	(0.245)		0.103	(0.081)	*
ROA	0.021	(0.000)	***	-0.570	(0.000)	***	-0.165	(0.000)	***
*ROA*LMF_PRE*	0.066	(0.673)		-0.207	(0.259)		0.074	(0.763)	
ETR	0.015	(0.000)	***	-0.018	(0.000)	***	0.005	(0.000)	***
*ETR*LMF_PRE*	0.007	(0.391)		-0.019	(0.145)		0.019	(0.172)	
DAC	-0.022	(0.000)	***	0.056	(0.000)	***	-0.026	(0.000)	***
*DAC*LMF_PRE*	-0.106	(0.030)	**	-0.153	**(0.036)**	**	0.070	(0.377)	

(Continued on the next page)

	ABPER			*ABMAT*			*ABSERV*		
	Coef.	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
DREV	0.022	(0.000)	***	-0.012	(0.001)	***	-0.054	(0.000)	***
*DREV*LMF_PRE*	-0.014	(0.801)		0.230	**(0.017)**	**	-0.107	(0.291)	
CH_INV	0.053	(0.000)	***	0.731	(0.000)	***	-0.102	(0.000)	***
*CH_INV*LMF_PRE*	0.106	(0.158)		-0.088	(0.528)		0.054	(0.713)	
LOSS	0.028	(0.000)	***	-0.030	(0.000)	***	-0.001	(0.686)	
*LOSS*LMF_PRE*	0.071	(0.112)		-0.029	(0.577)		-0.106	(0.075)	*
SUSPECT	-0.057	(0.000)	***	0.063	(0.000)	***	-0.014	(0.000)	***
*SUSPECT*LMF_PRE*	0.033	(0.110)		-0.002	(0.955)		-0.014	(0.716)	
INDSEC	Yes			Yes			Yes		
YEAR	Yes			Yes			Yes		
Intercept	0.032	(0.000)	***	-0.063	(0.000)	***	-0.115	(0.000)	***
Number of obs.	518,891			518,891			525,109		
R^2	0.023			0.090			0.044		
Wald $\chi 2$	12,324	(0.000)	***	44,544	(0.000)	***	16,345	(0.000)	***

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. All test statistics and significance levels are calculated based on panel-corrected standard errors to consider heteroskedasticity and contemporaneous correlation across panels. LMF_PRE is a dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; LMF_POST is a dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; ABSΔNI is absolute value of change in net income relative to previous year divided by lagged total assets; SIZE is natural logarithm of total assets; LEVLONG is long-term liabilities divided by total assets; INVREC is total inventories and* *receivables divided by total assets; GROWTH is change in total assets relative to previous year divided by lagged total assets; ROA is income before tax divided by total assets; ETR is current tax expense divided by income before tax; DAC is discretionary total accruals equal to residuals from Eq. (6); DREV is discretionary revenue accruals equal to residuals from Eq. (7); CH_INV is change in inventory relative to previous year divided by lagged total assets; LOSS is a dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT is a dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise; INDSEC is a dummy variables representing industry defined by the two-digit SIC code; YEAR is a dummy variables representing the fiscal year.*

Interestingly, in *ABMAT* regression coefficients on interaction variables *SIZE*LMF_PRE*, *DAC*LMF_PRE* are negative and significant ($p<0.05$), whereas coefficient on variable *DREV*LMF_PRE* is positive and significant ($p<0.05$). These results suggest that before confiscation larger LMFs showing higher discretionary aggregate accruals are less likely to upward manage material expenses. On the other hand, LMFs exhibiting higher discretionary revenue accruals are more likely to upward manage material expenses. It can be inferred a simultaneity in revenue and expense manipulations in LMFs that makes the directional effect on earnings hardly predictable.

3.6.3.2 Matched Sample Estimations

We perform a robustness test of our results by estimating our base regression model within a matched sample. So as to define a control sample, researchers choose from a wide range of firm characteristics on which to match such as: cash flows, year, industry, net income, size proxied by sales or total assets, ROA, etc. (Defond and Jiambalvo, 1994; Defond and Subramanyam, 1998; Kothari et al., 2005; Perry and Williams, 1994; Teoh et al., 1998). We match each LMF-year with three LWF-years on year, industry, sign of ROA and size proxied by total assets. Matching is performed for both pre-confiscation LMF-years and for post-confiscation LMF-years. We include the new dummy variables *LWF_PRE* and *LWF_POST* as well as the dummy variables *LMF_PRE* and *LMF_POST*. *LWF_PRE* takes value of 1 for LWF-years matched to pre-confiscation LMF-years and 0 otherwise, whereas *LWF_POST* takes value of 1 for LWF-years matched to post-confiscation LMF-years. For each EXM proxy we estimate two regressions excluding as base dummy variable *LWF_PRE* or *LWF_POST*, alternatively. However, we present a result column for each dependent variable and only report values for variables *LMF_PRE* (versus base *LWF_PRE*) and *LMF_POST* (versus base *LWF_POST*). Indeed, switching base from *LWF_PRE* to *LWF_POST* does not affect value and significance of the other independent variables. Table 3.7 shows the results of our estimations with standard errors adjusted by a two dimensional cluster at the firm and year levels (Colin et al., 2011; Gow et al., 2010).

Table 3.7. Multiple regressions of expenses manipulation proxies within a matched sample

	ABPER			*ABMAT*			*ABSERV*			*ABCFO*		
	Coef.	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
Variables of interest:												
LMF_PRE (base LWF_PRE)	-0.032	(0.017)	**	0.106	(0.000)	***	-0.071	(0.004)	***	0.000	(0.981)	
(Hypothesis/Exp. Sign)	H1a/–			H2a/+			H3a/–			H4a/0		
LMF_POST (base LWF_POST)	-0.003	(0.813)		0.054	(0.008)	***	-0.010	(0.657)		0.004	(0.387)	
(Hypothesis/Exp. Sign)	H1b/0			H2b/0			H3b/0			H4b/0		
Control variables:												
ABSΔNI	0.238	(0.001)	***	-0.204	(0.148)		0.250	(0.071)	*	-0.091	(0.009)	***
SIZE	-0.006	(0.088)	*	-0.001	(0.853)		0.008	(0.060)	*	0.007	(0.000)	***
LEVLONG	-0.031	(0.029)	**	0.034	(0.330)		-0.104	(0.004)	***	0.033	(0.003)	***
INVREC	0.032	(0.018)	**	0.028	(0.332)		0.047	(0.234)		-0.047	(0.000)	***
GROWTH	0.030	(0.058)	*	0.012	(0.687)		0.259	(0.000)	***	-0.007	(0.786)	
ROA	-0.076	(0.074)	*	-0.558	(0.000)	***	-0.022	(0.792)		0.917	(0.000)	***
ETR	0.008	(0.001)	***	-0.006	(0.152)		0.004	(0.496)		-0.002	(0.150	
DAC	-0.038	(0.100)		-0.023	(0.590)		0.081	(0.024)	**	-0.981	(0.000)	***
DREV	-0.014	(0.596)		0.070	(0.096)	*	-0.167	(0.012)	**	0.020	(0.730)	
CH_INV	0.055	(0.029)	**	0.610	(0.000)	***	-0.121	(0.053)	*	0.022	(0.570)	
LOSS	0.013	(0.244)		-0.021	(0.397)		-0.002	(0.904)		0.007	(0.056)	*
SUSPECT	-0.037	(0.000)	***	0.058	(0.000)	***	-0.022	(0.126)		0.010	(0.000)	***
INDSEC	Yes			Yes			Yes			Yes		

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	ABPER			*ABMAT*			*ABSERV*			*ABCFO*		
	Coef.	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**		**Coef.**	**p-value**	
YEAR	Yes			Yes			Yes			Yes		
Number of obs.	3,560			3,560			3,560			3,560		
R^2	0.075			0.134			0.082			0.906		
Wald $\chi 2$	55,911	(0.000)	***	180000	(0.000)	***	200000	(0.000)	***	62000000	(0.000)	***

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. All test statistics and significance levels are calculated based on the standard errors adjusted by a two-dimensional cluster at the firm and year levels. LMF_PRE is a dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; LWF_PRE is a dummy variable taking value of 1 for LWF-years matched to pre-confiscation LMF-years and 0 otherwise; LMF_POST is a dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; LWF_POST is a dummy variable taking value of 1 for LWF-years matched to post-confiscation LMF-years and 0 otherwise; ABSΔNI is absolute value of change in net income relative to previous year divided by lagged total assets; SIZE is natural logarithm of total assets; LEVLONG is long-term liabilities divided by total assets; INVREC is total inventories and receivables divided by total assets; GROWTH is change in total assets relative to previous year divided by lagged total assets; ROA is income before tax divided by total assets; ETR is current tax expense divided by income before tax; DAC is discretionary total accruals equal to residuals from Eq. (6); DREV is discretionary revenue accruals equal to residuals from Eq. (7); CH_INV is change in inventory relative to previous year divided by lagged total assets; LOSS is a dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT is a dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or* *equal to zero but less than 0.01 and 0 otherwise; INDSEC is a dummy variables representing industry defined by the two-digit SIC code; YEAR is a dummy variables representing the fiscal year.*

Results of matched sample estimations are mostly consistent with those of the unmatched sample. Indeed, coefficient on *LMF_PRE* is negative and significant ($p<0.05$ and $p<0.01$, respectively) in regressions *ABPER* and *ABSERV*, it is positive and significant ($p<0.01$) in *ABMAT* regression, and it is not significant in *ABCFO* regression. These results provide further support for hypotheses H1a, H2a, H3a and H4a. On the other hand, coefficient on *LMF_POST* is not significant in any regression but in *ABMAT* regression, where it is positive and significant ($p<0.01$). However, its magnitude (0.054) is 49.48% lower than magnitude (0.106) of coefficient on *LMF_PRE (*versus base *LWF_PRE)*. Once again, these results support hypothesis H1b, H2b, H3b and H4b.

In summary, the documented robustness of our results to different estimation methods can relieve concerns that our findings are driven by uncontrolled factors.

3.7 Conclusions

In this paper we examine EXM within a sample of 224 Italian firms defined as legally registered Mafia firms, due to having been confiscated at some point by judicial authorities in relation to alleged connections of their owners with Italian organized crime. For this purpose, we develop EXM proxies using expenses classified by nature rather than by function in accordance with the legal structure of the income statement in Italy.

Overall, our results reveal that before confiscation LMFs upward manage material expenses and downward manage personnel and service expenses with a cumulative negative effect on reported CFO relative to sales. In contrast, following the confiscation and intervention of legal administrators, differences in abnormal personnel and service expenses between LMFs and LWFs become statistically insignificant, whereas difference in abnormal material expenses significantly decreases.

These findings, however, are subject to several limitations. We cannot reject the possibility of a bias in the selection of our sample of LMFs considering that undetected LMFs are unobservable and smaller LMFs, unavailable on AIDA, are excluded. Furthermore, there could be selection biases in LMFs pursued and confiscated by Italian judicial authorities. Our measures of EXM in LMFs, based on abnormal expenses by nature, greatly depend on the reliability of reported financial statement figures. The likely manipulation of these figures may affect the correct interpretation of our measures.

We propose several opportunities for future research. First, our proxies could be tested on other types of firm that are expected to engage in EXM in order to gain further insight into their measurement ability. Second, future studies could examine the directional effect on earnings of EXM in unlisted firms which, especially in certain circumstances, might be different from that in listed firms. Third, AM and EXM proxies jointly with other financial and non-financial variables could be included in a logistic model which may be able to detect LMFs. Finally, this study could be replicated in other countries, where organized crime is deeply rooted, in order to determine whether its results are confirmed in a different cultural, legal and institutional context.

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Chapter 4: Accrual Management within Legally Registered Mafia Firms in Italy

4.1 Abstract

We examine discretionary revenue, expense and aggregate accruals within a sample of 224 Italian firms defined as legally registered Mafia firms (LMFs), due to having been confiscated at some point by judicial authorities in relation to alleged connections with organized crime.

Overall, our results reveal that, both before and after confiscation, LMFs engage more in revenue, expense and aggregate accrual management than lawful firms (LWFs) do. Several factors significantly influence the likelihood of LMFs engaging in accrual management. Furthermore, there is no significant difference between LMFs before and after confiscation and LWFs in the directional income management through discretionary aggregate accruals. Nonetheless, after confiscation LMFs simultaneously upward manage revenue and expense accruals with a null cumulative effect on aggregate accruals and income relative to LWFs.

LMFs are private and socially irresponsible by nature. In addition, their incentives, *modus operandi* and financial statement formats differ from those of listed companies. Hence, our study allows inferring conclusions on the relation between corporate social responsibility and accrual management. More importantly, it can help practitioners and regulators to identify accounting signals that can be used in risk assessment models or in the prevention of criminal infiltrations, especially in countries with a strong criminal presence.

4.2 Introduction

In this study we examine discretionary revenue, expense and aggregate accruals within a sample of 224 Italian firms defined as legally registered Mafia firms (LMFs), due to having been confiscated at some point by judicial authorities in relation to alleged connections with Italian organized crime. More specifically, LMFs are compared with a population of 78,340 unlisted lawful firms (LWFs) for which there is no evidence of any criminal connection. We carry out the comparison for LMFs both before and after their confiscation and assignment to legal administrators. Therefore, we identify two main time periods: the pre-confiscation period and the post-confiscation period within a time frame of 10 years from 2003 to 2012 for which financial statements are available on AIDA database. In this way, we aim to assess whether the confiscation of LMFs has a significant impact on their accrual management (AM) behavior. More importantly, we examine discretionary revenue and expense accruals as well as discretionary aggregate accruals. Indeed, our further objective is to determine which types of accruals LMFs manage and whether specific accrual models can provide additional insight compared to aggregate accrual models mostly used in previous research. More generally, we aim to understand whether Accounting can contribute to understanding the mechanisms of the criminal economy and terrorist funding. In this regard, Compin (2008) suggests that one of the role of Accounting in a criminal business is to mask the crime by ensuring that the accounting information, although deceptive, contains all the necessary virtues and in turn maintains an impression of rationality and economic credibility. Indeed, the Mafias, which are considered to be the most sophisticated form of criminal organization, also run businesses in the lawful economic sphere in which they usually invest proceeds from illicit trafficking (money laundering). LMFs, according to criminologists' terminology, can be defined as firms that are legally registered and apparently engage in lawful activities but are owned by a Mafia family (Champeyrache, 2004). LMFs differ from lawful firms in three main ways (Gambetta, 1993; Fantò, 1999): the owners are members of a criminal organization; total or partial funding comes from illegal activities; and criminal methods involving violence, intimidation or corruption may be used while doing business. Legal and illegal activities are therefore closely intertwined within LMFs as the legal activities mostly serve to launder profits stemming from illegal ones (Fantò, 1999).

Overall, our results reveal that both before and after confiscation LMFs manage aggregate, revenue and expense accruals more than LWFs do. Furthermore, several factors significantly influence the likelihood of LMFs engaging in AM such as: size, level of inventories and receivables, profitability and intensity of real activities manipulation. In terms of directional income management through discretionary aggregate accruals there is no significant difference between LWFs and LMFs both before and after confiscation. Nonetheless, after confiscation LMFs simultaneously upward manage revenue and expense accruals with a null cumulative effect on aggregate accruals and income relative to LWFs. These results confirm previous findings (e.g., Stubben, 2010) on the informative superiority of specific accrual models over aggregate accrual models in detecting a combination of revenue and expense manipulation.

Prior research examines AM in varying types of firms and in diverse contexts. For example, different studies find a significant relation between AM and firms committing financial statement fraud, considering that firms with income-increasing accruals in prior years must either deal with the consequences of the accrual reversals or commit fraud to offset the reversals (Perols and Lougee, 2011; Jones et al., 2008; Lee et al., 1999; Beneish, 1997). Chaney et al. (2011) find that the quality of reported accounting information measured by discretionary accruals is systematically poorer for firms with political connections than for firms lacking such connections. Other studies examine the AM behavior pattern of socially responsible firms with inconsistent results (Kim et al., 2012; Chih et al., 2008; Gargouri et al., 2010). Prencipe (2012) shows that US multinational firms manage earnings through discretionary accruals less than domestic companies do. Wang and Yung (2011) find lower levels of AM among state-owned enterprises than privately-owned firms in China even after controlling for the effect of tunneling. García Lara et al. (2009) provide evidence that failed firms manage earnings upwards through accruals and real activities in the four years prior to failure. Coppens and Peek (2005) find the tax incentives reduce the benefits of engaging in income-increasing AM especially in private firms located in countries with strong tax alignment. Finally, Prencipe et al. (2008), using a sample of Italian listed companies, provides empirical evidence on the motivations for AM in publicly listed family companies, highlighting the differences from public nonfamily firms.

Although some traits of LMFs can be identified in the aforementioned studies on AM, our study contributes to the accounting literature given that, to the best of our knowledge, it is the first that specifically examines AM within LMFs. These firms may particularly interest the scientific community due to their singularities. Indeed, they are private and socially irresponsible by nature because of their illicit purposes. In addition, their incentives, *modus operandi* and financial statement formats differ from those of listed companies. Hence, our study allows inferring conclusions on the relation between corporate social responsibility (CSR) and AM. Moreover, it adopts AM proxies based on specific revenue and expense accruals that provide additional insight into the simultaneous manipulation of revenues and expenses that may not be detected by traditional aggregate accrual models. Finally, our paper can aid practitioners and regulators in identifying accounting signals in firm management that can be used in risk assessment models or in the prevention of criminal infiltrations, especially in those countries where organized crime is deeply rooted.

The remainder of the paper proceeds as follows: the next section introduces LMFs; "Related Research and Hypothesis Development" section reviews the literature and develops the hypotheses; “Methodology” section describes the research design and sample data; “Results and Discussions” section presents empirical results and their discussion; “Conclusions” section includes concluding remarks.

4.3 Legally Registered Mafia Firms

For the purpose of this study, we define “organized crime” according to the Italian legal provision of “associazione a delinquere di tipo mafioso” (article 416-bis of the Italian criminal code). Furthermore, art. 416-bis states that:

“A mafia-type association consists of three or more individuals and those who belong to it make use of the power of intimidation afforded by the associative bond and the state of subjugation and criminal silence (omertà) which derives from it to commit crimes, to acquire directly or indirectly the management or control of economic activities, concessions, authorizations or public contracts and services, either to gain unjust profits or advantages for themselves or for others, or to prevent or obstruct the free exercise of the vote, or to procure votes for themselves or to others at a time or electoral consultation”.

Ever since their appearance in the middle of the 19th century, Italian criminal organizations have infiltrated the social and economic life of many regions only in Southern Italy. There are several known mafia-like organizations in Italy: Cosa Nostra of Sicily and Ndrangheta of Calabria are considered among the biggest cocaine smugglers in Europe and, together with Camorra of Naples, began to develop between 1500 and 1800. More recently in the 1980s, two new organizations, Stidda and Sacra Corona Unita of Puglia, also appeared.

One of the main reasons for criminal organizations to take on new businesses is so as to be able to invest and launder significant financial resources coming from illegal activities, such as usury, extortion, drug, waste and arms trafficking and so on. This form of investment of illicit capital is a way to break into legal markets in order to obtain high profits and launder so-called "dirty" money. Another very important aspect is the need to achieve social consensus through activities that ensure employment and income for the population in the areas in which the criminal organization exercises control of the territory.

Several authors in Sociology have analyzed characteristics of LMFs. Fantò (1999) suggests that the main trait of LMFs is not the type of business run but the nature of the capital accumulation process that led to their formation as well as the strength of intimidation on which they are hinged. This force of intimidation, according to the same author, in addition to being the precondition that allows LMFs to take a dominant position in a territory, it is also a kind of surplus value that is added to what normally yields the legal capital invested in the same area and under the same conditions. The mafia-style intimidation is the point of greatest strength, the source of the competitive advantages of firms and economies of the Mafias over firms and the legal economy.

Arlacchi (1983) identifies the following competitive advantages of the LMFs over the LWFs: discouragement of competition (securing goods and raw materials at favorable prices, as well as orders, contracts and commercial outlets using criminal intimidation); wage compression (evasion of social security contributions and insurance, non-payment of overtime, denial of trade union rights); availability of financial resources (investment of huge proceeds coming from illegal activities (money laundering) without bearing the cost of credit).

In this study a firm is classified as LMF if, at some point during its existence, it has been confiscated by Italian judicial authorities because of alleged connections to one of the Italian criminal organizations. After the first instance of court confiscation the LMF is entrusted to one or more legal administrators. The Legal Administration (LA) is an institution designed to protect and manage confiscated assets and firms and to avoid their progressive impoverishment. The LA is based on strong principles of corporate social responsibility and public interest. The main objectives of legal administrators are: the reinstatement of legality in the management of the firm, the reorganization and turnaround of the firm according to sound management principles. However the administration of these firms in not always sufficiently dynamic and market-oriented and conservatism may prevail. Furthermore, it ought to be noted that the confiscation of first instance is a temporary measure that can be followed, even after several years, by the definitive confiscation as the last phase of the trial.

The body currently in charge of the administration and assignment of assets (including firms) definitively confiscated due to organized crime is the Italian agency Agenzia Nazionale Beni Sequestrati e Confiscati (ANBSC) which was created through Decree Law on February 4th 2010. The main concern of the agency is to ensure the continuation of firms after confiscation, as most of them risk bankruptcy with the consequent loss of employment resulting in a hugely negative impact on their workforce and subsequently social stability. According to the most recent available data on the ANBSC official website (http://www.benisequestraticonfiscati.it) the number of confiscated firms on January 7th 2013 was 1,708. After confiscation firms can be sold, leased or liquidated and although the efforts of ANBSC to ensure the continuation of the business, the most of the firms end up being liquidated or going bankrupt as they are unable to face the market competition after losing the support of organized crime and banks.

LMFs are mainly created as limited-liability companies (Società a responsabilità limitata (Srl)) with a reduced number of owners that exercise a close control on operations directly or indirectly through trusted managers that are often affiliates of the same criminal organization. One might then assume that the potential misalignment of interests and goals between them is reduced, with no significant agency problems. The minimum required starting equity for a

SRL is € 10,000. Its capital is divided into shares which can be bought or sold just by notarial act. SRLs can issue corporate bonds but are subject to many limitations. Organized crime may prefer this corporate structure because the initial investment is lower than alternative legal forms, audit committee is not required, and even from a fiscal point of view there are fewer charges.

4.4 Related Research and Hypothesis Development

4.4.1 AM Definition and Its Proxies

Healy and Wahlen (1999: 368) consider that "earnings management (EM) occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that rely on reported accounting numbers".

This definition is broad enough in scope to include the two types of EM that previous studies have mostly examined: AM and real activities manipulation (RM). More specifically, the large amount of research carried out thus far indicates that managers exercise discretion and manage earnings for different purposes using a wide variety of methods, ranging from carrying out special transactions (RM) (e.g., Roychowdhury, 2006; Cohen et al., 2008; Zang, 2012) that usually affect firm's operating activities and cash flow (CFO) to the discretionary manipulation of accruals (AM) with no CFO impact (Dechow and Dichev, 2002; Dechow et al., 2010).

Indeed, total accruals (*ACCR*) can be decomposed into two different parts: 1) normal or non-discretionary accruals (*NDAC*), which are associated with a firm's operating and investment activities and are meant to capture adjustments reflecting fundamental performance; and 2) abnormal or discretionary accruals (*DAC*) that reflect the results of managers' discretionary accounting choices that, within generally accepted accounting principles (GAAP), try to ‘‘obscure’’ or ‘‘mask’’ true economic performance (Dechow and Skinner, 2000).

Prior studies use a wide variety of measures of *DAC* as surrogates for EM (Jones, 1991; Subramanyam, 1996; DeFond and Subramanyam, 1998; Kothari et al., 2005). However, these studies mostly focus on aggregate accruals rather than considering each specific type of accruals. In this regard, previous research questions aggregate accrual models for providing biased and noisy estimates of discretion (Dechow et al., 1995; Bernard and Skinner, 1996; Stubben, 2010; Wilson, 2011). Furthermore, McNichols (2000) suggests that future progress in the EM literature is more likely to come from the examination of specific accruals. In confirmation of this, in a recent study Stubben (2010), using a sample of firms subject to SEC enforcement actions for a mix of revenue- and expense related misstatements, finds that revenue accrual models are more likely than aggregate accrual models to detect a combination of revenue and expense manipulation especially in growth firms. Hence, following Stubben (2010) and Caylor (2010) we also use discretionary revenue accruals (*DREV*) to measure revenue AM (REAM) as well as aggregate discretionary accruals (*DAC*) to measure aggregate AM (AGAM). In addition, we build a new measure of discretionary expense accruals (*DEXP*) to measure expense AM (EXAM). In essence, we consider that LMFs may resort to a combination of revenue and expense manipulation, for example through fictitious transactions, in order to achieve their illicit purposes. As manipulation of revenues and expenses can be performed in the same direction, increasing revenues and expenses or vice versa, the total effect may not be detected in discretionary aggregate accrual models that they do not provide information as to which components of earnings firms manage and how the AM is achieved (Marquardt and Wiedman, 2004; Stubben, 2010). Moreover, differently from other specific accruals (allowance for bad debts, depreciations, etc.), revenue and expense accruals are common across industries and represent a large portion of the earnings discretion available to firms (Stubben, 2010). Finally, similar to previous studies (Warfield et al., 1995; Klein, 2002; Kim et al., 2012) we mainly use the unsigned value of the aforementioned AM proxies, given that AM can be either income-increasing or income-decreasing and we do not have reasons for expecting any of them to be prevalent in LMFs relative to LWFs.

4.4.2 AM within LMFs and Hypothesis Formulation

Prior to carrying out our research we expect a higher AM intensity within LMFs before confiscation relative to LWFs. Our expectations are based both on the characteristics of LMFs and on some previous studies examining firms with similarities in certain aspects.

In general, assuming the presence of fictitious transactions beyond a normal business logic disguising money laundering or pursuing tax avoidance, we expect AM within LMFs to be mostly used to adjust the financial statements at year end while keeping an impression of rationality and economic credibility (Compin, 2008).

On the other hand, several empirical studies show that poor accrual quality results in a number of negative consequences at the firm level, including larger costs of debt and equity (Francis et al., 2005), or a higher likelihood of a lawsuit. Nonetheless, LMFs can usually count on financial resources coming from illegal activities (money laundering) which reduce the need for bank financing relative to LWFs and the related incentive to report a positive financial performance or an acceptable accrual quality.

Moreover, we expect a higher level of AM for LMFs due to the low level of scrutiny from outsiders of these firms compared to the LWFs, in connection with the protection ensured by their criminal ties often associated with political ties. In this aspect, some analogy may be found with the case of politically connected firms studied by Chaney et al. (2011) which exhibit higher AM than firms lacking such connections. Additionally, previous studies find that a low external monitoring intensity is associated with a higher level of AM and RM (Duellman et al., 2013; Wongsunwai, 2013).

Furthermore, and similar to the hypothesis built by Chaney et al. (2011) for politically connected firms, to the extent that organized crime provides protection to LMFs so that low quality accounting information is not penalized, LMFs might simply care less about the quality of the information they disclose and invest less time to accurately portray their accruals. In this case, the quality of information would be low due to inattention on the part of the firm's managers. In addition, lack of managerial competencies may also negatively affect the quality of accounting information in comparison with LWFs. Indeed, in LMFs allegiance to the Mafia family is often considered as the essential criterion for appointing future agents that are recruited from a relatively small pool of affiliates and surrogates (Duplat et al., 2012). On the other hand, in LWFs the selection process is largely driven by the skills and abilities of these candidates to run the business.

Finally, a further indication on the AM pattern of LMFs may come from some prior research on the relation between CSR and AM, given that LMFs are assumed to be socially irresponsible. In this regard, previous studies find that more socially responsible U.S. public firms, based on Kinder Lydenburg and Domini database, are less likely to engage in AM and to be the subject of SEC investigations (Hong and Andersen, 2011; Kim et al., 2012). Previously Chih et al. (2008) examines the relationships between CSR and AM across 1,653 companies in 46 countries. They provide inconsistent results across different EM proxies since they find that a firm with CSR in mind tends not to smooth earnings, and displays less interest in avoiding earnings losses and decreases. It is, however, prone to engage in more earnings aggressiveness defined, according to Bhattacharya et al. (2003), as the tendency to delay the recognition of losses and accelerate the recognition of gains. This tendency can be mitigated in a country with strong legal enforcement. On the other hand, Prior et al. (2008) examine whether firm managers who engage in AM practices use CSR strategically to gain support from stakeholders and reduce their activism and vigilance. Using archival data from a multi-national panel sample of 593 firms from 26 countries between 2002 and 2004, they find a positive relation between AM and CSR for regulated firms, but this result is not statistically significant for unregulated firms. More recently, Gargouri et al. (2010) assess the relationship between corporate social performance (CSP) and AM. Based on a sample of 109 Canadian companies they find a positive association between firm's CSP ratings related to environment and employees, and the AM activities. According to the authors this could be attributed to the costs borne by firms engaged in environmental activities, which reduce the financial performance and give managers an incentive to manage earnings. CSP appears to create collusion between managers and employees, the aim of which is to share the benefits of AM.

That said, given the inconsistent evidence from prior research with mixed implications on the relation between CSR and AM, in this study we also aim to provide additional insight into this relation.

Based on previous considerations we empirically test the following research hypotheses:

> ***H1a****: Ceteris paribus, before confiscation LMFs engage more in AGAM than LWFs do.*
>
> ***H2a****: Ceteris paribus, before confiscation LMFs engage more in REAM than LWFs do.*
>
> ***H3a****: Ceteris paribus, before confiscation LMFs engage more in EXAM than LWFs do.*

According to ANBSC statistics, after confiscation most of the LMFs fall into financial distress and often end up in liquidation. The main reasons for that may be: the loss of privileged and illegal business opportunities, the increase in operating expenses (e.g., regularization of undeclared workers and increase in service expenses for external support) and the shortage of funding as the dirty money flow (money laundering) is interrupted and the banks are more reluctant to grant credit. In this respect, previous studies find that distressed firms prior to bankruptcy engage in income-increasing AM in order to conceal the deteriorating financial conditions until they improve (Smith et al., 2001; Rosner, 2003; Charitou et al., 2007; García Lara et al., 2009). Moreover, after the confiscation one of the tasks of legal administrators is the reinstatement of legality within LMFs. Hence, accounting adjustments, including accrual reversals, to correct previous misreporting and the regularization and settlement of some transactions may still lead to higher AM measures relative to LWFs even though for reasons which may differ from those prior to confiscation. Thus, the further hypotheses of our study are:

H1b*: Ceteris paribus, after confiscation LMFs engage more in AGAM than LWFs do.*

H2b*: Ceteris paribus, after confiscation LMFs engage more in REAM than LWFs do.*

H3b*: Ceteris paribus, after confiscation LMFs engage more in EXAM than LWFs do.*

4.5 Methodology

4.5.1 AM Proxies (Dependent Variables)

In order to test our hypotheses, we need to build our measures of AGAM, REAM and EXAM to input as dependent variables in our base regression model. Hence, we calculate *DAC* as the residuals from the following Eq. (1) based on the modified Jones model (Dechow et al., 1995) with a control for performance (Kothari et al., 2005):

$$\frac{ACCR_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t - \Delta AR_t}{TA_{t-1}} + \beta_3 \frac{PPE_t}{TA_{t-1}} + \beta_4 ROA_{t-1} + \varepsilon_t \qquad (1)$$

Where in year t (or t - 1), *ACCR* denotes total accruals; *TA*, Δ*REV*, Δ*AR*, *PPE*, and ROA represent total assets, changes in net revenue, changes in accounts receivables, property, plant, and equipment, and return on assets, respectively. The firm subscript is suppressed for simplicity. Parameters of Eq. (1) are estimated cross-sectionally for each industry-year with at least 15 observations in order to control for industry-wide changes under different economic conditions (Jeter and Shivakumar, 1999) that affect our variables while allowing the coefficients to vary across time (Kasznik, 1999; DeFond and Jiambalvo, 1994). We use all active firms in AIDA (excluding LMFs) which are not listed on the stock exchange and with financial statements available for 10 years from 2003 to 2012. The total number of these firms at the moment of its retrieval from AIDA is 78,340.

Similar to Stubben (2010) and Caylor (2010), we calculate *DREV* as the residuals from the following Eq. (2) estimated in the same way as Eq. (1). In line with Caylor (2010), we assume that changes in accounts receivables are positively related to future changes in *CFO* as well as contemporaneous changes in revenues, since the receivable amounts will be collected in the next period:

$$\frac{\Delta AR_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t}{TA_{t-1}} + \beta_3 \frac{\Delta CFO_{t+1}}{TA_{t-1}} \varepsilon_t \qquad (2)$$

Following the same rationale as *DREV* we additionally calculate a new measure *DEXP* as the residuals from the following Eq. (3) estimated in the same way as Eq. (1):

$$\frac{\Delta AP_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t}{TA_{t-1}} + \beta_3 \frac{\Delta CFO_{t+1}}{TA_{t-1}} \varepsilon_t \tag{3}$$

Where ΔAP represents change in accounts payables.

As the statement of CFO is not legally required for private firms in Italy, CFO is computed as:

$$CFO = Earnings\ before\ tax - Total\ accruals \tag{4}$$

Consistent with previous studies on AM (Healy, 1985; Jones, 1991; Dechow et al., 1995; Bergstresser and Philippon, 2006), *ACCR* are computed as:

$$ACCR_t = \Delta CA_t - \Delta CL_t - \Delta CASH_t + \Delta STD_t - DEP_t \tag{5}$$

Where:

ΔCA = change in current assets, ΔCL = change in current liabilities, $\Delta CASH$ = change in cash and cash equivalents, ΔSTD = change in debt included in current liabilities, *DEP* = depreciation and amortization expenses.

4.5.2 Control Variables and Base Regression Model

We explain AM proxies as depending on firm type (LMF or LWF), period (pre-confiscation and post-confiscation) and other control variables shown in the prior literature to be associated with AM (Klein, 2002; Kim et al., 2012; Zang, 2012). As independent variables strictly related to our hypotheses we use binary variables *CRIME1* taking value of 1 for LMFs before confiscation, *CRIME2* taking value of 1 for LMFs after confiscation, and *CRIME3* taking value of 1 for LWFs. The latter is excluded from the final regression model as a base variable.

Turning to control variables we include the following and, where possible, we make a prediction on the sign of their association with AM:

1. Absolute change in net income divided by lagged total assets (*ABSΔNI*). Previous studies suggest that *ABSΔNI* is positively associated with AM (Warfield et al., 1995; Dechow et al., 1996; Klein, 2002) and our prediction is consistent with them.
2. Size *(SIZE)*. Prior research finds that *SIZE* is negatively correlated with AM due to internal control deficiencies associated with small firms (Kinney and McDaniel, 1989; Ge and McVay, 2005; Doyle et al., 2007; Ashbaugh-Skaife et al., 2007) and because larger firms are more easily scrutinized by investors or regulators than smaller firms (Siregar and Utama, 2008; Zhao et al., 2012). On the other hand, other studies find a positive relation between AM and *SIZE* in public listed companies due to a greater pressure to meet earnings targets (Dechow et al., 1995; Kim et al., 2012; Duellman et al., 2013). As our sample is based on unlisted private firms we expect a negative association between *SIZE* and AM.
3. Long-term indebtedness (*LEVLONG*). Prior studies find that companies with long-term debts are associated with higher level of income-increasing AM because of incentives to avoid violating debt covenants (Sweeney, 1994; DeFond and Jiambalvo, 1994; Alissa et al., 2013). On the other hand, other studies find firms in financial distress exhibiting their financial troubles through large negative accruals in order to signal their willingness to deal with them, or to obtain concessions and renegotiations from lenders and labor unions as well as subsidies from government (DeAngelo et al., 1994; Peltier-Rivest, 1999; Saleh and Ahmed, 2005). In our study, long-term debts commonly include bank debts which represent a primary source of funding for private firms. Hence, we expect a positive correlation between *LEVLONG* and income-increasing AM assuming an incentive for private firms to report a better financial performance in order to gain an easier and cheaper

access to bank credit. In contrast, the directional income-increasing AM may result in a negative relation between *LEVLONG* and the unsigned AM proxies on which our analysis is mainly based.

4. Sum of inventory and receivables (*INVREC*). The extent of AM may vary with the flexibility managers have to undertake such activities (Roychowdhury, 2006). A high level of stock of current assets, and in particular inventories and receivables, may give more opportunities for AM which is more likely to escape detection. Hence, we expect a positive association between *INVREC* and AM.
5. Growth (*GROWTH*). A firm's growth in assets may come from two sources: external financing (including both debt and equity issuance) and internal operating results. Higher leverage from borrowing activities may affect a firm's AM behavior as already mentioned. With regards to equity issuance, Teoh et al. (1998a, 1998b) find significantly more active AM when firms raise capital either in the IPO or seasoned equity market. Therefore, we do not make any prediction on the relation between AM and *GROWTH* given that it may greatly depend on the way the growth is financed.
6. Financial performance (*ROA*). Previous studies show that weak performance provides incentives to engage in AM (DeFond and Park, 1997; Keating and Zimmerman, 1999; Doyle et al., 2007; Kim et al., 2012). Accordingly, we predict a negative association between *ROA* and AM.
7. Effective tax rate (*ETR*). We adopt the current *ETR* (current tax expense divided by pre-tax book income) (Richardson and Lanis, 2007; Hanlon and Heitzman, 2010; Lanis and Richardson, 2012) as a variable which is likely to affect AM. Indeed, a higher *ETR* indicates a lower income tax avoidance that may be associated with a lower AM consistent with a more socially responsible behavior.

8. Loss (*LOSS*). Similar to previous studies we consider the particular situation of firms reporting losses (Klein, 2003; Alissa et al., 2013). Due to the inconsistent prior findings, we do not make any prediction on the relation between *LOSS* and AM.
9. Firms just meeting zero earnings benchmark (*SUSPECT*). Prior research finds that income-increasing AM is more likely to occur when firms just beat/meet an important earnings benchmark (Burgstahler and Dichev, 1997; Degeorge et al., 1999; Zang, 2012). Although tax avoidance may be an important incentive for AM in our firms, these might still have incentives to report small earnings rather than losses in order to avoid raising suspicions of tax authorities or to have an easier access to bank credit. Similar to previous studies (Graham et al., 2005; Roychowdhury, 2006; Zang, 2012) and considering the specifications of our firms in the sample, we indicate as suspect (*SUSPECT*) firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 (Gunny, 2010). We predict a positive association between *SUSPECT* and income-increasing AM which may result in a negative association between *SUSPECT* and the unsigned AM proxies.
10. Unsigned abnormal CFO (*AABCFO*). We expect firms to use a mix of AM and RM as tools to manage their reported earnings. Previous studies find that listed public firms choose between the two mechanisms using the technique that is less costly to them (Cohen et al., 2008; Cohen and Zarowin, 2010; Badertscher, 2011; Zang, 2012). To control for the interactions between these two EM methods, as in Cohen et al. (2008) and in Kim et al. (2012), we include in the AM regressions a proxy for RM represented by variable *AABCFO*. Following Dechow et al. (1998) and Roychowdhury (2006), It is calculated as the unsigned residuals from the following Eq. (6) whose parameters are estimated similarly to Eq. (1):

$$\frac{CFO_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \varepsilon_t \tag{6}$$

Because our tests on EM are not directional and we use unsigned proxies for AM and RM, we expect a positive association between *AABCFO* and AM.

11. Industry (*INDSEC*). Dummy variables representing industry defined by the two-digit SIC code. We do not make any specific sign prediction for the *INDSEC* dummies.
12. Year (*YEAR*). Dummy variables to control for year effects. Again, we do not make any sign prediction for the *YEAR* dummies.

In summary, to test our hypotheses and similar to previous studies (Roychowdhury, 2006; Cohen et al., 2008; Cohen and Zarowin, 2010; Zang, 2012; Kim et al., 2012; Alissa et al., 2013) we estimate the following base regression model for our AM proxies adapting the independent variables to the specific characteristics of the sample firms:

$$AM\_PROXY_t = \beta_0 + \beta_1 CRIME1_t + \beta_2 CRIME2_t + \beta_3 ABS\Delta NI_t + \beta_4 SIZE_{t-1} + \tag{7}$$

$$\beta_5 LEVLONG_{t-1} + \beta_6 INVREC_{t-1} + \beta_7 GROWTH_t + \beta_8 ROA_{t-1} + \beta_9 ETR_t +$$

$$\beta_{10} AABCFO_t + \beta_{11} LOSS_t + \beta_{12} SUSPECT_t + \sum \emptyset_i INDSEC_{it} + \sum \alpha_i YEAR_i + \varepsilon_t$$

The variables, whose firm subscript is suppressed for simplicity, are defined in the Appendix.

4.5.3 Data and Sample Selection

LMFs sample consists of 224 firms confiscated to organized crime, some of them provided by ANBSC and others found in online newspapers and AIDA database. The financial statements for all firms are obtained from AIDA, the Italian Bureau Van Dijk database. It contains comprehensive information on 1 million companies with a turnover above € 500,000 in Italy, including the indication for some of them of the confiscation status and date of confiscation.

Firms provided by ANBSC have all been confiscated by final judgment but their small size or their liquidation means that only 54 out of 1,663 have financial statements available on AIDA. In addition, we include firms confiscated in first instance and found on AIDA database (118) and online newspapers (52) until reaching a total of 224. For the 224 LMFs we obtain from AIDA available financial statement data for the year of confiscation and for the years prior to and following the confiscation within the period of 2003 to 2012. Hence, for some LMFs we only have available either financial data prior to confiscation or financial data after confiscation. We then estimate our base regression model of Eq. (7) including LMFs firm-years and AIDA population of active unlisted firm-years from 2003 to 2012 in LMFs industries. We initially avoid the matched sample procedure although in our base regression model we control for year, size and two-digit industry SIC code. Table 4.1 summarizes the sample selection procedure that yields the 224 LMFs and the 78,340 LWFs.

Table 4.1. Sample selection

	Number of firms
LMFs sample	
LMFs definitively confiscated at November 5th 2012 provided by ANBSC	1,663
Less: LMFs provided by ANBSC with data unavailable on AIDA database	-1,609
Add: LMFs found on AIDA database with status confiscated	118
Add: confiscated LMFs found in online newspapers with data available in AIDA	52
Final LMFs sample	**224**
LMFs year observations in base regression model (*ABSDAC*)	**1,094**
LWFs control sample	
Aida population of active and unlisted firms with available financial data from 2003 to 2012 in the same two-digit SIC industries as LMFs	**78,340**
LWFs year observations in base regression model (*ABSDAC*)	**540,339**

Source: ANBSC and AIDA database, 2013.

Table 4.2 presents the industry distribution by two-digit SIC groups of LMFs in our sample and AIDA population of active unlisted firms with available financial data from 2003 to 2012 in the same industries as the LMFs.

Table 4.2. Industry Distribution of LMFs and AIDA population of active unlisted firms with available financial data from 2003 to 2012 restricted to LMFs industries (LWFs)

Sic code	Industry description	AIDA population		LMFs	
		Freq.	Percent	Freq.	Percent
01	Agricultural production-crops	644	0.82%	4	1.79%
14	Mining and quarrying of nonmetallic minerals, except fuels	463	0.59%	9	4.02%
15	Building construction-general contractors and operative builders	5,486	7.00%	41	18.30%
16	Heavy construction other than building construction-contractors	524	0.67%	3	1.34%
17	Construction-special trade contractors	4,032	5.15%	8	3.57%
20	Food and kindred products	3,224	4.12%	6	2.68%
25	Furniture and fixtures manufacturing	829	1.06%	3	1.34%
28	Chemicals and allied products manufacturing	1,598	2.04%	1	0.45%
29	Petroleum refining and related industries	158	0.20%	2	0.89%
32	Stone, clay, glass and concrete products manufacturing	1,960	2.50%	13	5.80%
34	Fabricated metal products, except machinery and transportation equipment	7,038	8.98%	2	0.89%
42	Motor freight transportation and warehousing	2,894	3.69%	18	8.04%
44	Water transportation	586	0.75%	1	0.45%
45	Transportation by air	95	0.12%	1	0.45%
47	Transportation services	1,884	2.40%	3	1.34%
49	Electric, gas and sanitary services	1,419	1.81%	7	3.13%
50	Wholesale trade, durable goods	14,064	17.95%	23	10.27%

(Continued on the next page)

Sic code	Industry description	AIDA population		LMFs	
		Freq.	**Percent**	**Freq.**	**Percent**
51	Wholesale trade, nondurable goods wholesale dealing in	7,821	9.98%	19	8.48%
52	Building materials, hardware, garden supply, and mobile home dealers wholesale dealing in	1,018	1.30%	1	0.45%
53	General merchandise stores	324	0.41%	1	0.45%
54	Food stores	1,737	2.22%	16	7.14%
55	Automotive dealers and gasoline service stations	536	0.68%	4	1.79%
56	Apparel and accessory stores	1,920	2.45%	3	1.34%
57	Home furniture, furnishings, and equipment stores	872	1.11%	1	0.45%
58	Eating and drinking places	1,007	1.29%	2	0.89%
59	Miscellaneous retail	1,475	1.88%	1	0.45%
65	Real estate	2,239	2.86%	7	3.13%
70	Hotels, rooming houses, camps, and other lodging places	1,600	2.04%	3	1.34%
72	Personal services	327	0.42%	1	0.45%
73	Business services	5,001	6.38%	2	0.89%
75	Automotive repair, services, and parking	882	1.13%	1	0.45%
79	Amusement and recreation services	744	0.95%	5	2.23%
80	Health services	1,165	1.49%	9	4.02%
81	Legal services	19	0.02%	1	0.45%
87	Engineering, accounting, research, management, and related services	2,755	3.52%	2	0.89%
Total		**78,340**	**100.00**%	**224**	**100.00**%

Source: AIDA database, 2013.

Compared to the population of active and unlisted firms on AIDA with available financial data from 2003 to 2012, the sample LMFs are especially more abundant in industry groups: building construction-general contractors and operative builders (18.30% of LMFs sample versus 7.00% of population), food stores (7.14% versus 2.22%) and Motor freight transportation and warehousing (8.04% versus 3.69%). On the other hand, there is a lower proportion of LMFs mostly in wholesale trade, durable goods (10.27% versus 17.95%), business services (0.89% versus 6.38%) and fabricated metal products, except machinery and transportation equipment (0.89 versus 8.98%). It is noteworthy that Construction (SIC codes 15, 16 and 17) is the sector with the higher cumulative percentage (23.21%) of LMFs in our sample.

Table 4.3 shows the distribution of LMFs by Italian region where they are legally registered and indicates the Mafia organization with major presence in that region based on a recent study of Transcrime (2013). Because of their different locations we can reasonably assume that LMFs in our sample represent a variety of Mafia organizations with a predominance of Cosa Nostra. Indeed, 50.89% of LMFs are located in Sicily where Cosa Nostra is largely dominant.

Table 4.3. LMFs by Italian region and Mafia organization

Italian Region	Number of LMFs	Percentage of LMFs	Mafia organization with major presence in the region*
Sicily	114	50.89%	Cosa Nostra
Calabria	61	27.23%	Ndrangheta
Campania	20	8.93%	Camorra
Lazio	13	5.80%	Camorra
Apulia	6	2.68%	Sacra Corona Unita
Lombardy	4	1.79%	Ndrangheta
Abruzzo	3	1.34%	Camorra
Piedmont	2	0.89%	Ndrangheta
Emilia-Romagna	1	0.45%	Ndrangheta
Total	**224**	**100.00%**	

**Source: Transcrime (2013)*

Some features of our sample selection may affect our results and generate biases limiting the generalization to other settings. We just consider LMFs that have been confiscated and with available financial data on AIDA. This database only includes companies with a turnover above € 500,000. For some firms confiscation year is not available and we find it out through a Google search for articles in local online newspapers including details on confiscation and whose correctness is reasonable but cannot be corroborated. Several preventive confiscations may have been carried out for the same firm and subsequently cancelled by the court. Criminal connection is in these cases uncertain.

Finally, Table 4.4 includes number of LMFs by confiscation year. It can be seen that 2012 is the year with largest number of confiscated firms and more than 50% of firms have been confiscated from 2010 to 2013.

Table 4.4. LMFs by confiscation year

Confiscation year	Number of confiscated LMFs	Percentage
1994	3	1.33%
1995	1	0.44%
1996	1	0.44%
1997	1	0.44%
1998	2	0.89%
1999	1	0.44%
2000	2	0.89%
2001	3	1.33%
2002	2	0.89%
2004	10	4.45%
2005	1	0.45%
2006	9	4.01%
2007	18	8.03%
2008	24	10.71%
2009	19	8.48%
2010	24	10.72%
2011	35	15.64%
2012	37	16.54%
2013	31	13.87%
Total	**224**	**100.00%**

Source: ANBSC and AIDA database, 2013.

4.6 Results and Discussions

4.6.1 Descriptive Statistics and Univariate Analysis

The following Table 4.5 presents descriptive statistics for each variable considered in our base regression model comparing the LMFs firm-years to the LWFs firm-years before and after confiscation. We report medians because they are less likely than means to be influenced by extreme observations. All continuous variables are winsorized at the top and bottom 1 percent of their distributions to avoid the influence of outliers.

Table 4.5. Descriptive statistics and variable comparison between LMFs and LWFs

	LMFs before confisc.		LMFs after confisc.		LWFs		LMFs before confisc. - LWFs		LMFs after confisc. - LWFs	
	N	**Median**	**N**	**Median**	**N**	**Median**	**Difference**	**Test**	**Difference**	**Test**
Dependent Variables										
DAC	631	-0.0004	463	-0.0036	541,446	-0.0006	0.0002		-0.0030	
ABSDAC	631	0.1197	463	0.0652	541,446	0.0780	0.0416	***	-0.0129	*
DREV	573	0.0110	438	0.0011	534,121	-0.0085	0.0195	***	0.0096	***
ABSDREV	573	0.0962	438	0.0589	534,121	0.0611	0.0351	***	-0.0022	
DEXP	585	0.0086	437	0.0013	549,070	-0.0077	0.0163	***	0.0090	***
ABSDEXP	585	0.0970	437	0.0691	549,070	0.0647	0.0323	***	0.0044	**
Control Variables										
ABSΔNI	750	0.0136	517	0.0229	671,114	0.0138	-0.0002	**	0.0091	***
SIZE	967	7.9444	553	8.2300	753,484	7.8023	0.1421		0.4277	***
LEVLONG	967	0.0238	553	0.0643	753,480	0.0296	-0.0058		0.0347	***
INVREC	928	0.6439	529	0.5883	705,084	0.6141	0.0298	*	-0.0258	
GROWTH	750	0.1089	517	0.0043	671,352	0.0371	0.0718	***	-0.0328	***
ROA	967	0.0220	553	0.0113	753,371	0.0276	-0.0055	***	-0.0163	***
ETR	966	0.4229	553	0.3340	751,630	0.5153	-0.0924	***	-0.1813	***
ABCFO	647	-0.0087	473	-0.0179	567,262	-0.0044	-0.0042	*	-0.0135	**
AABCFO	647	0.1244	473	0.0663	567,262	0.0960	0.0284	***	-0.0297	***
%LOSS	3.90%		15.05%		6.34%		-2.44%	***	8.71%	***
%SUSPECT	6.75%		6.34%		10.32%		-3.57%	***	-3.98%	***

*Notes: The sample full period spans 2003–2012. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed Mann–Whitney–Wilcoxon test for the differences in medians of continuous variables. Pearson chi-squared test of independence for categorical variables: %LOSS = % of firms with two or more consecutive years of negative income; %SUSPECT = % of firms just beating/meeting the zero earnings before tax benchmark. DAC = aggregate discretionary accruals equal to residuals from Eq. (1); ABSDAC = absolute value of DAC; DREV = discretionary revenue accruals equal to residuals from Eq. (2); ABSDREV = absolute values of DREV; DEXP = discretionary expense accruals equal to residuals from Eq. (3); ABSDEXP = absolute value of DEXP; ABSΔNI = absolute value of (net income – lagged net income)/ lagged total assets; SIZE = natural logarithm of total assets; LEVLONG = long-term liabilities divided by total assets; INVREC = total inventories and receivables divided by total assets; GROWTH = (total assets − lagged total assets)/ lagged total assets; ROA = income before tax divided by total assets; ETR = current tax expense divided by income before tax; ABCFO = abnormal CFO equal to residuals from Eq. (6); AABCFO = absolute value of ABCFO.*

As regards dependent variables, medians of variables *ABSDAC*, *ABSDREV* and *ABSDEXP* are all significantly ($p<0.01$) higher for LMFs before confiscation relative to LWFs, providing a first indication in support of our hypotheses H1a, H2a and H3a, respectively. On the other hand, variable *ABSDAC* is marginally significantly ($p<0.10$) lower for LMFs after confiscation compared to LWFs, whereas there is no significant difference in level of *ABSDREV* between LWFs and LMFs after confiscation. These results are not consistent with hypotheses H1b and H2b, respectively. In contrast, variable *ABSDEXP* remains significantly ($p<0.01$) higher for LMFs after confiscation relative to LWFs providing a first support for hypothesis H3b. As regards the signed values of our AM proxies, there is no significant difference in level of *DAC* between LWFs and LMFs both before and after confiscation, indicating a null directional effect on income of AM practices in LMFs compared to LWFs. However, variables *DREV* and *DEXP* are both positive and significantly ($p<0.01$) higher for LMFs both before and after confiscation relative to LWFs. This suggests that LMFs may simultaneously engage in an income-increasing REAM and an income-decreasing EXAM with a null cumulative effect on income which is not reflected in the AGAM proxy. Overall, these results provide a first confirmation of Stubben's (2010) findings on the superiority of specific accrual models over aggregate accrual models in detecting a combination of revenue and expense manipulation especially in growth firms such as LMFs are.

Turning to control variables, variable *ABSΔNI* is significantly ($p<0.05$) lower for LMFs before confiscation relative to LWFs, whereas it is significantly ($p<0.01$) higher after confiscation. Furthermore, before confiscation variable *LEVLONG* is not significantly different between the two types of firm. In contrast, after confiscation LMFs appear significantly ($p<0.01$) more long term indebted than LWFs because of the likely loss of the criminal organization support granting financial resources and competitive advantages (Arlacchi, 1983; Fantò, 1999). A consequent increased need of LMFs to resort to bank financing may additionally explain the significant rise in their long term indebtedness after confiscation. In addition, LMFs are significantly ($p<0.01$) less profitable (*ROA*) than LWFs both before and after confiscation. An overinvestment of financial resources stemming from illegal activities (money laundering) may explain the lower profitability of LMFs before confiscation. On the other hand, the cost of the reinstatement of legality and the loss of business opportunities and competitive advantages (Arlacchi, 1983; Fantò, 1999) may be the causes after confiscation. A further consistent indication is the significantly ($p<0.01$) higher total assets growth rate (*GROWTH*) of LMFs before confiscation, presumably financed with dirty money, that becomes significantly ($p<0.01$) lower after confiscation because of the likely suspension of any money laundering activity. Interestingly, significantly ($p<0.01$) lower variable *ETR* for LMFs both before and after confiscation relative to LWFs provides evidence of a higher tax avoidance in the former firms. As regards RM variables, variable *ABCFO* is negative for LMFs before confiscation but only marginally significantly ($p<0.10$) lower relative to LWFs, whereas after confiscation the magnitude of this difference increases and becomes significant at the 0.05 level. On the other hand, variable *AABCFO* for LMFs before confiscation is significantly ($p<0.01$) higher than that for LWFs, suggesting a more intensive RM of the former firms which becomes significantly ($p<0.01$) less intensive after confiscation. In addition, it is noteworthy the significantly ($p<0.01$) lower percentage of LMFs before confiscation with two or more consecutive years of negative income (*%LOSS*) compared to LWFs. Nonetheless, after confiscation the situation is completely reversed consistent with the average decline of financial performance of LMFs once out of the full control of the criminal organization. Finally, the percentage of LMFs just meeting/beating the zero earnings benchmark (*%SUSPECT*), both before and after confiscation, is significantly ($p<0.01$) lower than that of LWFs, suggesting that LMFs may have a weaker motivation to hit that benchmark. Indeed, LMFs before confiscation can count on financial resources coming from illegal activities reducing the need for bank financing and the related incentive to report a positive financial performance. On the other hand, after confiscation the steep decline of LMFs financial performance, the conservatism and the higher CSR standards of legal administrators may hinder that achievement.

Finally, Table 4.6 shows that Pearson correlations among independent variables appearing jointly in our base regression model are low (below 0.33), thus providing a first indication that collinearity is unlikely to affect estimations.

Table 4.6. Pearson correlations between independent variables

	1		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*
1.ABSΔNI	1																
2.SIZE	-0.113	***	1														
3.LEVLONG	-0.066	***	0.170	***	1												
4.INVREC	-0.085	***	0.003	**	-0.180	***	1										
5.GROWTH	0.123	***	0.060	***	0.021	***	-0.009	***	1								
6.ROA	0.098	***	-0.105	***	-0.195	***	-0.056	***	0.098	***	1						
7.ETR	-0.112	***	-0.038	***	-0.015	***	0.034	***	0.010	***	0.026	***	1				
8.ABCFO	0.052	***	-0.021	***	-0.038	***	-0.078	***	-0.119	***	0.328	***	-0.007	***	1		
9.AABCFO	0.185	***	-0.182	***	-0.116	***	-0.060	***	0.276	***	0.158	***	-0.007	***	-0.021	***	1

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. ABSΔNI = absolute value of (net income – lagged net income)/ lagged total assets; SIZE = natural logarithm of total assets; LEVLONG = long-term liabilities divided by total assets; INVREC = total inventories and receivables divided by total assets; GROWTH = (total assets − lagged total assets)/ lagged total assets; ROA = income before tax divided by total assets; ETR = current tax expense divided by income before tax; ABCFO = abnormal CFO equal to residuals from Eq. (6); AABCFO = absolute value of ABCFO.*

4.6.2 Multivariate Regression Analysis

In order to test our hypotheses, we estimate our model in Eq. (7) through a linear regression with standard errors adjusted by a two dimensional cluster at the firm and year levels (Gow et al., 2010; Colin et al., 2011; Kim et al., 2012), considering the likely correlation of the residuals across firm and/or over time. Table 4.7 presents the results for our unsigned AM proxies.

Table 4.7. Two dimensional cluster corrected standard errors regression of unsigned AM proxies

		ABSDAC		***ABSDREV***		***ABSDEXP***	
	Exp. Sign	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
Variables of interest:							
CRIME1	+	0.018	0.000	0.028	0.000	0.021	0.000
Hypothesis		H1a		H2a		H3a	
CRIME2	+	0.017	0.000	0.024	0.000	0.031	0.000
Hypothesis		H1b		H2b		H3b	
Control variables:							
ABSΔNI	+	-0.022	0.363	0.148	0.000	0.110	0.000
SIZE	–	-0.003	0.000	-0.011	0.000	-0.009	0.000
LEVLONG	–	-0.010	0.022	-0.067	0.000	-0.049	0.000
INVREC	+	-0.005	0.240	0.012	0.422	0.020	0.002
GROWTH	?	0.011	0.006	0.067	0.000	0.067	0.000
ROA	–	-0.172	0.000	-0.055	0.000	-0.111	0.000
ETR	–	0.000	0.942	0.000	0.998	-0.001	0.000
AABCFO	+	0.782	0.000	0.190	0.000	0.222	0.000
LOSS	?	-0.020	0.000	-0.010	0.000	-0.009	0.000
SUSPECT	–	-0.002	0.177	0.001	0.487	0.006	0.000
INDSEC	?	Yes		Yes		Yes	
YEAR	?	Yes		Yes		Yes	
Intercept	?	0.068	0.000	0.188	0.000	0.146	0.000
Number of obs.		541,433		525,145		534,743	
R^2		0.758		0.215		0.227	
Wald $\chi 2$		3.4E+09	0.000	6.8E+07	0.000	9.8E+06	0.000

Notes: The p-values are two-tailed. ABSDAC = absolute value of aggregate discretionary accruals equal to residuals from Eq. (1); ABSDREV = absolute values of discretionary revenue accruals equal to residuals from Eq. (2); ABSDEXP = absolute value of discretionary expense accruals equal to residuals from Eq. (3); CRIME1 = dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; CRIME2 = dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; ABSΔNI = absolute value of (net income – lagged net income)/ lagged total assets; SIZE = natural logarithm of total assets; LEVLONG = long-term liabilities divided by total assets; INVREC = total inventories and receivables divided by total assets; GROWTH = (total assets − lagged total assets)/ lagged total assets; ROA = income before tax divided by total assets; ETR = current tax expense divided by income before tax; AABCFO = absolute value of abnormal CFO equal to residuals from Eq. (6); LOSS = dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT = dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise; INDSEC = dummy variables representing industry defined by the two-digit SIC code; YEAR = dummy variables representing the fiscal year.

First of all, it is noteworthy that all the estimated regressions are significant at the 0.01 level according to the chi-square tests. As regards variables relevant for our hypotheses, coefficient on *CRIME1* is positive and significant ($p<0.01$) in all regressions. These results provide support for hypotheses H1a, H2a and H3a, indicating that LMFs before confiscation engage more than LWFs in AGAM, REAM and EXAM, respectively. On the other hand, coefficient on *CRIME2* is also positive and significant ($p<0.01$) in all regressions consistent with hypotheses H1b, H2b and H3b. Hence, LMFs after confiscation continue engaging more in AM than LWFs do.

As regards the rest of control variables, it is noteworthy that all their coefficients are mostly significant at the 0.01 level and with the expected sign in all regressions with some exceptions. In particular, unpredicted coefficient on *GROWTH* is positive and significant ($p<0.01$) in all regressions indicating that AM is more intensive in faster growing firms. Coefficient on *ETR* is not significant at conventional levels in *ABSDAC* and *ABSDREV* regressions, whereas it is negative and significant ($p<0.01$) as expected in *ABSDEXP* regression. More importantly, coefficient on *AABCFO* is positive and significant ($p<0.01$) in all regressions suggesting that AM and RM is simultaneously carried out consistent with previous studies (Cohen et al., 2008; Cohen and Zarowin, 2010; Badertscher, 2011; Zang, 2012). In addition, negative and significant ($p<0.01$) coefficient on *LOSS* in all regressions suggest that firms with losses engage less in AM. Finally, coefficient on *SUSPECT* is only significant ($p<0.01$) in *ABSDEXP* regression where it is positive, indicating that firms just meeting zero earnings benchmark engage more in EXAM.

In summary, our multiple regression analysis suggests that LMFs both before and after confiscation engage more in AGAM, REAM and EXAM than LWFs do**.** Therefore, the assignment of LMFs to legal administrators after their confiscation has no significant impact on the intensity of AM, although adjustments to prior to confiscation misreporting and the regularization of some transactions may explain these results.

4.6.3 Additional Analyses

4.6.3.1 Regression Analysis with Interactions

In order to empirically determine the effect of each control variable on AM in LMFs before confiscation we estimate an additional regression including the interactions of control variables with the binary variable *CRIME1*. In Table 4.8 we present the results of our additional regression analysis with standard errors adjusted by a two dimensional cluster at the firm and year levels.

Table 4.8. Two dimensional cluster corrected standard errors regression of unsigned AM proxies with interaction variables

	ABSDAC		*ABSDREV*		*ABSDEXP*	
Variable	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
CRIME1	-0.003	0.869	0.061	0.178	0.130	0.003
CRIME2	0.017	0.000	0.024	0.001	0.031	0.000
ABSΔNI	-0.023	0.363	0.148	0.000	0.110	0.000
*ABSΔNI*CRIME1*	0.106	0.189	0.074	0.521	-0.015	0.793
SIZE	-0.003	0.000	-0.011	0.000	-0.009	0.000
*SIZE*CRIME1*	-0.002	0.339	-0.004	0.419	**-0.013**	**0.001**
LEVLONG	-0.010	0.025	-0.067	0.000	-0.049	0.000
*LEVLONG*CRIME1*	-0.005	0.666	-0.048	0.277	-0.018	0.587
INVREC	-0.005	0.245	0.012	0.435	0.020	0.003
*INVREC*CRIME1*	**0.018**	**0.022**	-0.006	0.858	0.006	0.859
GROWTH	0.011	0.007	0.067	0.000	0.067	0.000
*GROWTH*CRIME1*	-0.003	0.815	0.009	0.742	0.014	0.190
ROA	-0.172	0.000	-0.055	0.000	-0.111	0.000
*ROA*CRIME1*	**0.172**	**0.021**	-0.020	0.789	-0.052	0.453
ETR	0.000	0.957	0.000	0.991	-0.001	0.000
*ETR*CRIME1*	-0.005	0.216	0.005	0.417	0.005	0.412
AABCFO	0.782	0.000	0.190	0.000	0.222	0.000
*AABCFO*CRIME1*	**0.066**	**0.010**	0.013	0.776	-0.043	0.279
LOSS	-0.020	0.000	-0.010	0.000	-0.009	0.000
*LOSS*CRIME1*	0.032	0.267	**-0.061**	**0.001**	**-0.048**	**0.026**
SUSPECT	-0.002	0.176	0.001	0.478	0.006	0.000
*SUSPECT*CRIME1*	**0.019**	**0.022**	-0.018	0.289	0.007	0.548
INDSEC	Yes		Yes		Yes	
YEAR	Yes		Yes		Yes	
Intercept	0.068	0.000	0.188	0.000	0.146	0.000
Number of obs.	541,433		525,145		534,743	
R^2	0.758		0.215		0.227	
Wald $\chi 2$	1.1E+07	0.000	4.2E+06	0.000	2.1E+05	0.000

Notes: The p-values are two-tailed. ABSDAC = absolute value of aggregate discretionary accruals equal to residuals from Eq. (1); ABSDREV = absolute values of discretionary *revenue accruals equal to residuals from Eq. (2); ABSDEXP = absolute value of discretionary expense accruals equal to residuals from Eq. (3); CRIME1 = dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; CRIME2 = dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; ABSΔNI = absolute value of (net income – lagged net income)/ lagged total assets; SIZE = natural logarithm of total assets; LEVLONG = long-term liabilities divided by total assets; INVREC = total inventories and receivables divided by total assets; GROWTH = (total assets − lagged total assets)/ lagged total assets; ROA = income before tax divided by total assets; ETR = current tax expense divided by income before tax; AABCFO = absolute value of abnormal CFO equal to residuals from Eq. (6); LOSS = dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT = dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise; INDSEC = dummy variables representing industry defined by the two-digit SIC code; YEAR = dummy variables representing the fiscal year.*

Interestingly, variables that have a significant effect on AM in LMFs before confiscation relative to LWFs are different across the three regressions. More specifically, in *ABSDAC* regression coefficients on the interaction variables *INVREC*CRIME1*, *ROA*CRIME1*, *AABCFO*CRIME1* and *SUSPECT*CRIME1* are positive and significant ($p<0.05$), respectively suggesting that LMFs with higher level of inventories and receivables, higher profitability, more intensive RM and just meeting zero earnings benchmark are more likely to engage in AGAM. On the other hand, in *ABSDREV* and *ABSDEXP* regressions coefficients on variable *LOSS*CRIME1* are negative and significant ($p<0.01$ and $p<0.05$, respectively), indicating that LMFs reporting losses are less likely to engage in REAM and EXAM, respectively. Finally, coefficient on *SIZE*CRIME1* is negative and significant ($p<0.01$) in

ABSDEXP regression, providing evidence that larger LMFs are less likely to engage in EXAM.

4.6.3.2 Matching Procedure

We perform a robustness test of our results by estimating our base regression model within a matched sample. So as to define a control sample, researchers choose from a wide range of firm characteristics on which to match such as: cash flows, year, industry, net income, size proxied by sales or total assets, ROA, etc. (Defond and Jiambalvo, 1994; Perry and Williams, 1994; Defond and Subramanyam, 1998; Teoh et al., 1998; Kothari et al., 2005). We match each LMF with three LWFs on year, industry (two-digit SIC code), sign of profitability (ROA) and size proxied by total assets. We adopt total assets as a measure of size rather than net sales or total number of employees because we believe that it is less likely to be significantly manipulated in the financial statements. Indeed, number of employees might be underreported because LMFs are likely to resort to undeclared work in order to avoid payment of social security for employees, whereas net sales may be either fictitious or underreported for tax avoidance purposes. Matching is performed for both LMF pre-confiscation firm-years and for LMF post-confiscation firm-years. We add to the dummy variables *CRIME1* and *CRIME2* the new dummy variables *LAW1* and *LAW2*. *LAW1* takes value of 1 for LWF observations matched to LMF pre-confiscation firm-years and 0 otherwise, whereas *LAW2* takes value of 1 for LWF observations matched to LMF post-confiscation firm-years. For each AM proxy we estimate two regressions excluding as base dummy variable *LAW1* or *LAW2*, alternatively. However, we present a result column for each dependent variable and only report values for variables *CRIME1* (versus base *LAW1)* and *CRIME2* (versus base *LAW2).* Indeed, switching base from *LAW1* to *LAW2* does not affect value and significance of the other independent variables except for the intercept whose values and significances are separately reported for each base. Table 4.9 shows the results of our estimations with standard errors adjusted by a two dimensional cluster at the firm and year levels.

Table 4.9. Two dimensional cluster corrected standard errors regression of unsigned AM proxies within a matched sample

		ABSDAC		***ABSDREV***		***ABSDEXP***	
	Exp. Sign	**Coef.**	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
Variables of interest:							
CRIME1 (base LAW1)	+	0.013	0.000	0.026	0.000	0.018	0.001
Hypothesis		H1a		H2a		H3a	
CRIME2 (base LAW2)	+	0.015	0.000	0.024	0.000	0.028	0.000
Hypothesis		H1b		H2b		H3b	
Control variables:							
ABSΔNI	+	0.067	0.223	0.182	0.003	0.147	0.000
SIZE	–	-0.002	0.038	-0.014	0.000	-0.017	0.000
LEVLONG	–	-0.004	0.403	-0.071	0.000	-0.039	0.000
INVREC	+	0.004	0.569	0.038	0.005	0.043	0.000
GROWTH	?	0.015	0.009	0.089	0.000	0.097	0.000
ROA	–	-0.089	0.062	-0.031	0.256	-0.067	0.130
ETR	–	-0.001	0.388	-0.001	0.532	0.003	0.008
AABCFO	+	0.805	0.000	0.213	0.000	0.224	0.000
LOSS	?	-0.011	0.011	-0.012	0.018	-0.004	0.723
SUSPECT	–	-0.001	0.781	0.005	0.510	0.009	0.132
INDSEC	?	Yes		Yes		Yes	
YEAR	?	Yes		Yes		Yes	
Intercept (base LAW1)	?	0.046	0.000	0.179	0.000	0.203	0.000
Intercept (base LAW2)	?	0.049	0.000	0.181	0.000	0.207	0.000
Number of obs.		3,739		3,560		3,598	
R^2		0.774		0.273		0.301	
Wald $\chi 2$		5.6E+07	0.000	7.0E+05	0.000	4.4E+05	0.000

Notes: The p-values are two-tailed. ABSDAC = absolute value of aggregate discretionary accruals equal to residuals from Eq. (1); ABSDREV = absolute values of discretionary revenue accruals equal to residuals from Eq. (2); ABSDEXP = absolute value of discretionary expense accruals equal to residuals from Eq. (3); CRIME1 = dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; CRIME2 = dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; LAW1 = dummy variable taking value of 1 for LWFs observations matched to LMFs pre-confiscation firm-years and 0 otherwise; LAW2 = dummy variable taking value of 1 for LWFs observations matched to LMFs post-confiscation firm-years and 0 otherwise; ABSΔNI = absolute value of (net income – lagged net income)/ lagged total assets; SIZE = natural logarithm of total assets; LEVLONG = long-term liabilities divided by total assets; INVREC = total inventories and receivables divided by total assets; GROWTH = (total assets − lagged total assets)/ lagged total assets; ROA = income before tax divided by total assets; ETR = current tax expense divided by income before tax; AABCFO = absolute value of abnormal CFO equal to residuals from Eq. (6); LOSS = dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT = dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise; INDSEC = dummy variables representing industry defined by the two-digit SIC code; YEAR = dummy variables representing the fiscal year.

All the estimated regressions are significant at the 0.01 level according to the chi-square tests. Results of matched sample estimations are mostly consistent with those of the unmatched sample. Indeed, coefficients on variables *CRIME1* and *CRIME2* are positive and significant ($p<0.01$) in all regressions providing further support for all our hypotheses. As regards the rest of control variables, signs of coefficients are mostly consistent with our expectations although some coefficients are not significant at conventional levels.

In summary, the documented robustness of our results to different estimation methods can relieve concerns that our findings are driven by uncontrolled factors.

4.6.3.3 Regression Analysis with Signed AM Proxies

To test our hypotheses and similar to previous studies (Warfield et al., 1995; Klein, 2002; Kim et al., 2012), we use the unsigned value of our proxies as AM can be either income-increasing or income-decreasing. However, to address the possibility that the difference in AM between LMFs and LWFs is also directional in terms of impact on the income, we re-estimate our base regression model in Eq. (7) using the signed measures of AM. Furthermore, we replace variable *AABCFO* with signed *ABCFO* in the model. Table 4.10 shows the results of our estimations with standard errors adjusted by a two dimensional cluster at the firm and year levels.

Table 4.10. Two dimensional cluster corrected standard errors regression of signed AM proxies

	DAC		***DREV***		***DEXP***	
	Coef.	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
Variables of interest:						
CRIME1	-0.005	0.322	-0.008	0.391	-0.007	0.074
CRIME2	-0.007	0.325	0.027	0.000	0.027	0.006
Control variables:						
ABSΔNI	0.051	0.346	-0.065	0.016	-0.136	0.004
SIZE	0.004	0.000	0.005	0.001	0.007	0.000
LEVLONG	0.028	0.000	-0.045	0.019	-0.016	0.132
INVREC	-0.042	0.000	-0.113	0.000	-0.025	0.053
GROWTH	0.045	0.000	0.257	0.000	0.320	0.000
ROA	0.468	0.000	-0.061	0.041	-0.116	0.000

(Continued on the next page)

	DAC		*DREV*		*DEXP*	
	Coef.	**p-value**	**Coef.**	**p-value**	**Coef.**	**p-value**
ETR	-0.001	0.000	0.000	0.019	-0.001	0.001
ABCFO	-0.848	0.000	-0.009	0.763	0.208	0.000
LOSS	-0.030	0.000	-0.005	0.019	0.032	0.000
SUSPECT	-0.004	0.001	0.001	0.430	0.015	0.000
INDSEC	Yes		Yes		Yes	
YEAR	Yes		Yes		Yes	
Intercept	0.003	0.615	0.012	0.639	-0.083	0.000
Number of obs.	541,433		525,145		534,743	
R^2	0.854		0.185		0.316	
Wald $\chi 2$	5.3E+07	0.000	2.3E+05	0.000	1.3E+05	0.000

Notes: The p-values are two-tailed. DAC = aggregate discretionary accruals equal to residuals from Eq. (1); DREV = discretionary revenue accruals equal to residuals from Eq. (2); DEXP = discretionary expense accruals equal to residuals from Eq. (3); CRIME1 = dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise; CRIME2 = dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise; ABSΔNI = absolute value of (net income – lagged net income)/ lagged total assets; SIZE = natural logarithm of total assets; LEVLONG = long-term liabilities divided by total assets; INVREC = total inventories and receivables divided by total assets; GROWTH = (total assets − lagged total assets)/ lagged total assets; ROA = income before tax divided by total assets; ETR = current tax expense divided by income before tax; ABCFO = abnormal CFO equal to residuals from Eq. (6); LOSS = dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise; SUSPECT = dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise; INDSEC = dummy variables representing industry defined by the two-digit SIC code; YEAR = dummy variables representing the fiscal year.

Again, all the estimated regressions are significant at the 0.01 level according to the chi-square tests. Interestingly, coefficient on variable *CRIME1* is not significant at conventional levels in both *DAC* and *DREV* regression, whereas it is negative and only marginally significant ($p<0.10$) in *DEXP* regression. Overall, these results suggest that there is no significant difference in accrual-based EM between LMFs before confiscation and LWFs. On the other hand, coefficient on variable *CRIME2* is not significant in *DAC* regression, whereas it is positive and significant ($p<0.01$) in both *DREV* and *DEXP* regression. This provides evidence that LMFs after confiscation upward manage both revenue and expense accruals with a null cumulative effect on aggregate accruals and income. Adjustments of prior to confiscation misreporting and the regularization of some transactions carried out by legal administrators may explain these results. Furthermore, these results confirm Stubben's (2010) findings on the informative superiority of specific accrual models over aggregate accrual models in detecting a combination of revenue and expense manipulation especially in growth firms. Finally, we find similar results by repeating the estimations within a matched sample.

4.7 Conclusions

In this study we analyze AM within a sample of 224 Italian firms defined as LMFs, due to having been confiscated at some point by judicial authorities in relation to alleged connections with Italian organized crime. We specifically examine discretionary expense and revenue accruals as well as discretionary aggregate accruals, which previous studies mostly consider, in order to determine which types of accruals LMFs manage and detect a possible combination of revenue and expense manipulation that may not be showed in aggregate accrual models.

Overall, our results reveal that both before and after confiscation LMFs manage aggregate, revenue and expense accruals more than LWFs do. In addition, several factors significantly influence the likelihood of LMFs engaging in AM such as: size, level of inventories and receivables, profitability and intensity of RM. On the other hand, in terms of directional impact on income through aggregate discretionary accruals there is no significant difference between LWFs and LMFs before and after confiscation. Nonetheless, after confiscation LMFs simultaneously upward manage revenue and expense accruals with a null cumulative effect on aggregate accruals and income relative to LWFs. Adjustments of prior to confiscation misreporting and the regularization of some transactions carried out by legal administrators may explain this behavior after confiscation. In addition, these results confirm previous findings (Stubben, 2010) on the superiority of specific accrual models over aggregate accrual models in detecting a combination of revenue and expense manipulation.

However, these findings are subject to several limitations. Firstly, we cannot reject the possibility of a bias in the selection of our sample of LMFs considering that undetected LMFs are unobservable and smaller LMFs, unavailable on AIDA, are excluded. Furthermore, there could be selection biases in LMFs pursued and confiscated by Italian judicial authorities. Finally, our measures of AM in LMFs greatly depend on the reliability of reported financial statement figures. Indeed, the likely manipulation of these figures and the consequent endogenity in the calculation models may affect the correct interpretation of our measures, although the consistent results of the estimations within a matched sample may partially relieve this concern.

We propose several opportunities for future research. First, this study could be replicated in other countries, where organized crime is deeply rooted, in order to determine whether its results are confirmed in a different cultural, legal and institutional context. Second, a further analysis of RM using specific measures of abnormal expenses could reveal whether and how

LMFs manipulate real activities as well as accruals. Finally, AM and RM proxies jointly with other financial and non-financial variables could be included in a logistic model which may be able to detect LMFs.

4.8 Appendix

Definition of variables of the base regression model (Eq. (7)):

AM_PROXY = *DAC*, *ABSDAC*, *DREV*, *ABSDREV*, *DEXP*, *ABSDEXP*:

DAC = aggregate discretionary accruals equal to residuals from Eq. (1)

ABSDAC = absolute value of *DAC*

DREV = discretionary revenue accruals equal to residuals from Eq. (2)

ABSDREV = absolute values of *DREV*

DEXP = discretionary expense accruals equal to residuals from Eq. (3)

ABSDEXP = absolute value of *DEXP*

CRIME1 = dummy variable taking value of 1 for LMFs before confiscation and 0 otherwise

CRIME2 = dummy variable taking value of 1 for LMFs after confiscation and 0 otherwise

$ABS\Delta NI$ = absolute value of (net income – lagged net income)/ lagged total assets

SIZE = natural logarithm of total assets

LEVLONG = long-term liabilities divided by total assets

INVREC = total inventories and receivables divided by total assets

GROWTH = (total assets − lagged total assets)/ lagged total assets

ROA = income before tax divided by total assets

ETR = current tax expense divided by income before tax

ABCFO = abnormal CFO equal to residuals from Eq. (6)

AABCFO = absolute value of *ABCFO*

LOSS = dummy variable that that takes a value of 1 if the firm had two or more consecutive years of negative income including the current and 0 otherwise

SUSPECT = dummy variable that takes a value of 1 for firm-years with earnings before tax over lagged assets greater than or equal to zero but less than 0.01 and 0 otherwise

INDSEC = dummy variables representing industry defined by the two-digit SIC code

YEAR = dummy variables representing the fiscal year

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Chapter 5: Detection Model of Legally Registered Mafia Firms in Italy

5.1 Abstract

This paper develops a model that can contribute to the detection of legally registered firms defined as Mafia firms (LMFs) due to having been confiscated by judicial authorities, in relation to alleged connections of their owners with Italian organized crime. The model correctly classifies 76.41% of firms within a matched sample of 852 firm-years including LMFs and lawful firms.

Furthermore, we present an analysis of financial statement characteristics of singular private firms which are socially irresponsible by nature and whose incentives, *modus operandi* and legal financial statement formats differ from those of listed companies. In particular, we show that specific accruals and earnings management proxies may provide more insight into accounting manipulation patterns of LMFs.

More importantly, our paper can help practitioners and regulators identify accounting signals that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices.

5.2 Introduction

The Mafias, which are considered to be the most sophisticated form of criminal organization, also run businesses in the lawful economic sphere in which they usually invest proceeds from illicit trafficking (money laundering). Legally registered Mafia firms (LMFs), according to criminologists' terminology, can be defined as firms that are legally registered and apparently engage in lawful activities but are owned by a Mafia family (Champeyrache, 2004). LMFs differ from lawful firms (LWFs) in three main ways (Gambetta, 1993; Fantò, 1999): the owners are members of a criminal organization; funding partially or totally comes from illegal activities; and criminal methods involving violence, intimidation or corruption might be used while doing business. Legal and illegal activities are therefore closely intertwined within LMFs as the legal activities mostly serve to launder profits stemming from illegal ones (Fantò, 1999).

In this study we develop a logistic regression model that can contribute to detecting LMFs in Italy based on their financial statement characteristics. Our test is based on a sample of 198 Italian legally registered firms defined as LMFs due to having been confiscated at some point by judicial authorities, in relation to alleged connections of their owners with Italian organized crime.

In essence, in this paper we aim to understand whether Accounting can contribute to disclosing the mechanisms of the criminal economy and terrorist funding. In this regard, Compin (2008) suggests that one of the role of Accounting in a criminal business is to make the crime invisible by ensuring that the accounting information, although deceptive, contains all the necessary virtues maintaining an impression of rationality and economic credibility.

We specifically investigate whether accounting information of LMFs embeds some significant differences from that of similar firms for which there is no evidence of any criminal connection (LWFs). Based on these differences we develop an accounting detection model of LMFs that could find practical application in forensic accounting. Among the different financial variables we test to predict criminal connections, we particularly focus on earnings management (EM) proxies. The large amount of research on EM carried out thus far indicates that managers discretionally manage earnings for different purposes using a wide variety of methods, ranging from carrying out special transactions (so-called real activities manipulation (RM)) that usually affect cash flows from operations (CFO) (e.g., Roychowdhury, 2006) to the discretionary manipulation of accruals (accrual-based EM) with no CFO impact (e.g., Dechow and Dichev, 2002; Dechow et al., 2010). Hence, in this study we examine both methods of EM as well as developing some new proxies for EM in order to reflect specific characteristics of LMFs.

As far as we know there are no previous studies in the literature that seek to develop an accounting detection model of LMFs. Nonetheless, considering the supposed fraudulent purposes of LMFs such as money laundering and tax evasion we refer to previous studies that develop prediction models of financial statement frauds and related manipulations using financial and non-financial variables (Beneish, 1997; Summers and Sweeney, 1998; Lee et al., 1999; Marquardt and Wiedman, 2004; Erickson et al., 2005; Jones et al., 2008; Brazel et al., 2009; Perols and Lougee, 2011; Dechow et al., 2011). A main difference between LMFs and firms committing financial statement fraud examined in previous research is that in the former the fraudulent purpose is genetic and strictly related to their existence, whereas in the latter fraud is subsequently committed due to specific circumstances.

Overall, our results reveal that our detection model is able to correctly classify 76.41% of firms within a matched sample of 852 firm-year observations including LMFs and LWFs. More specifically, our model detects 76.29% of LMFs (sensitivity) and 76.53% of LWFs (specificity). Out-of-sample tests confirm the robustness of the predictions and an additional analysis shows that undetected LMFs are significantly larger than detected LMFs. Additionally, consistent with previous studies (Beneish, 1997; Dechow et al., 2011) on fraud prediction our model shows that unadjusted specific accruals have more predictive power than discretionary accruals and a specific RM proxy such as abnormal material expenses is also a significant predictor of criminal connections. Finally, we find that LMFs relative to LWFs are more likely to engage in accrual-based EM and to manage material expenses upwards and personnel and service expenses downwards through RM.

Our study contributes to the accounting literature given that, to our knowledge, it is the first to develop an accounting detection model of LMFs. These firms, whose financial statement characteristics are examined in details, may particularly interest the scientific community due to their singularities. Indeed, they are private and socially irresponsible by nature because of their illicit purposes. Moreover, their incentives, *modus operandi* and financial statement formats differ from those of listed companies. More importantly, our paper can aid practitioners and regulators in identifying accounting signals in firm management that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices, especially in countries where organized crime is deeply rooted. Moreover, our study proposes a more detailed taxonomy on EM given that within EM it distinguishes accrual-based EM from RM, and within accrual-based EM it identifies three subcategories: aggregate accrual-based EM, revenue accrual-based EM and expense accrual-based EM. In relation to that, it adopts new EM proxies such as discretionary expense accruals measuring expense accrual-based EM and more specific RM proxies such as abnormal personnel, material and service expenses. Furthermore, it shows that analysis of specific accruals and RM proxies may provide more insight into EM patterns of these types of firms. Finally, it contributes to research on corporate social responsibility (CSR) in the way suggested by previous studies (e.g., Jenkins, 2006; Guthrie and Durand, 2008; Carroll and Shabana, 2010), indicating that socially irresponsible firms, such as LMFs, tend to engage more in EM.

The remainder of the paper proceeds as follows: the next section introduces LMFs; “Related Research” section reviews research on financial statement fraud and relation between EM and CSR in order to infer expectations on LMFs; “Research Design” section describes the research design and sample data; “Results and Discussions” section presents empirical results and their discussion; “Conclusions” section includes concluding remarks.

5.3 Legally Registered Mafia Firms

For the purpose of this study, we define “organized crime” according to the Italian legal provision of “associazione a delinquere di tipo mafioso” (article 416-bis of the Italian criminal code). Furthermore, art. 416-bis states that:

“A mafia-type association consists of three or more individuals and those who belong to it make use of the power of intimidation afforded by the associative bond and the state of subjugation and criminal silence (omertà) which derives from it to commit crimes, to acquire directly or indirectly the management or control of economic activities, concessions, authorizations or public contracts and services, either to gain unjust profits or advantages for themselves or for others, or to prevent or obstruct the free exercise of the vote, or to procure votes for themselves or to others at a time or electoral consultation”.

Ever since their appearance in the middle of the 19th century, Italian criminal organizations have infiltrated the social and economic life of many regions only in Southern Italy. There are several known mafia-like organizations in Italy: Cosa Nostra of Sicily and 'Ndrangheta of Calabria are considered among the biggest cocaine smugglers in Europe and, together with

Camorra of Naples, began to develop between 1500 and 1800. More recently in the 1980s, two new organizations, Stidda and Sacra Corona Unita of Puglia, also appeared.

One of the main reasons for criminal organizations to take on new businesses is so as to be able to invest and launder significant financial resources coming from illegal activities, such as usury, extortion, drug, waste and arms trafficking and so on. This form of investment of illicit capital is a way to break into legal markets in order to obtain high profits and launder so-called "dirty" money. Another very important aspect is the need to achieve social consensus through activities that ensure employment and income for the population in the areas in which the criminal organization exercises control of the territory.

Several authors in Sociology have analyzed characteristics of LMFs. Fantò (1999) suggests that the main trait of LMFs is not the type of business run but the nature of the capital accumulation process that led to their formation as well as the strength of intimidation on which they are hinged. This force of intimidation, according to the same author, in addition to being the precondition that allows LMFs to take a dominant position in a territory, it is also a kind of surplus value that is added to what normally yields the legal capital invested in the same area and under the same conditions. The mafia-style intimidation is the point of greatest strength, the source of the competitive advantages of firms and economies of the Mafias over firms and the legal economy.

Arlacchi (1983) identifies the following competitive advantages of the LMFs over the LWFs: discouragement of competition (securing goods and raw materials at favorable prices, as well as orders, contracts and commercial outlets using criminal intimidation); wage compression (evasion of social security contributions and insurance, non-payment of overtime, denial of trade union rights); availability of financial resources (investment of huge proceeds coming from illegal activities (money laundering) without bearing the cost of credit).

After the first instance of court confiscation LMFs are entrusted to one or more legal administrators. The Legal Administration is an institution designed to reinstate the legality, protect and manage confiscated LMFs and avoid their progressive impoverishment. However, the confiscation of first instance is a temporary measure that can be followed, even after several years, by the definitive confiscation as the last phase of the trial. The body currently in charge of the administration and assignment of assets (including firms) definitively confiscated due to organized crime is the Italian agency Agenzia Nazionale Beni Sequestrati e Confiscati (ANBSC). According to the most recent available data on the ANBSC official website (http://www.benisequestraticonfiscati.it) the number of confiscated firms on January 7th 2013 was 1,708. After definitive confiscation firms can be sold, leased or liquidated and although the efforts of ANBSC to ensure the continuation of the business, most of the firms end up being liquidated or going bankrupt as they are unable to face the market competition after losing the support of organized crime and banks.

LMFs are mainly created as limited-liability companies (Società a responsabilità limitata (Srl)) with a reduced number of owners that exercise a close control on operations directly or indirectly through trusted managers that are often affiliates of the same criminal organization. One might then assume that the potential misalignment of interests and goals between them is reduced, with no significant agency problems. Organized crime may prefer this corporate structure because the minimum required starting equity (€ 10,000) is lower than alternative legal forms, audit committee is not required, and even from a fiscal point of view there are fewer charges.

5.4 Related Research

5.4.1 Financial Statement Fraud

We are not aware of previous studies in the accounting literature that seek to specifically develop an accounting detection model of LMFs. Nonetheless, we expect LMFs to resort to financial statement manipulations in order to disguise money laundering activities and/or to evade tax. Hence, in order to identify the most predictive variables of our model we mainly refer to previous studies which develop prediction models of financial statement frauds and related manipulations using financial and non-financial variables (Beneish, 1997; Summers and Sweeney, 1998; Lee et al., 1999; Marquardt and Wiedman, 2004; Erickson et al., 2005; Jones et al., 2008; Brazel et al., 2009; Perols and Lougee, 2011; Dechow et al., 1996, 2011). In this regard, Beneish (1997, 1999) estimates a model for detecting earnings manipulation violating generally accepted accounting principles (GAAP) using financial statement variables. He finds a positive relation between aggregate accruals and likelihood of fraud, confirming Dechow et al.'s (1996) previous finding. Beneish (1999) considers that a limitation of the model is that it is estimated using financial information for publicly traded companies and cannot be reliably used to study privately-held firms. Additionally, the earnings manipulation in the sample involves earnings overstatement and consequently the model cannot be reliably used to study firms engaged in understatement of earnings. Through our study we specifically aim to overcome these limitations. Lee et al. (1999) subsequently find that the excess of earnings over CFO (income increasing accruals) is significantly greater for a sample of 56 firms committing financial statement fraud relative to a broad control sample of non-fraud firms. Marquardt and Wiedman (2004) document that the specific accruals used in EM violating GAAP vary with the context and related incentives (motivations), and consequently provide support for the usefulness of examining individual accruals as well as aggregate accruals in specific EM contexts. Jones et al. (2008) find that some measures of discretionary accruals have predictive power for fraudulent restatements of financial statements in 118 firms charged by the Securities and Exchange Commission (SEC) between 1988 and 2001. Brazel et al. (2009) provide evidence that inconsistencies between nonfinancial measures and financial measure can help detect firms with high fraud risk. More recently, Perols and Lougee (2011), using a sample of 54 fraud and 54 non-fraud firms, show that fraud firms are more likely to have managed earnings in prior years through discretionary accruals. Finally, Dechow et al. (2011) analyze the characteristics of firms investigated by the SEC for misstating earnings on various dimensions and find that, at the time of misstatements, accrual quality is low, both financial and nonfinancial measures of performance are deteriorating and financing activities and related off-balance-sheet activities are much more likely.

5.4.2 Earnings Management within LMFs

In most of the aforementioned studies EM, measured by several proxies, is a significant variable of the prediction model of financial statement frauds. Hence, we expect EM pattern, including both accrual-based EM and RM, to be significantly different between LMFs and LWFs. Accrual-based EM involves within GAAP accounting choices that try to ‘‘obscure’’ or ‘‘mask’’ true economic performance (Dechow and Skinner, 2000). On the other hand, Roychowdhury (2006) finds that managers engage in RM by providing price discounts to temporarily boost sales, reducing discretionary expenditures in order to improve reported margins, and overproducing to lower the cost of goods sold. We examine both types of EM activities because recent studies suggest that firms choose between the two mechanisms using the technique that is less costly to them (e.g., Roychowdhury, 2006; Cohen et al., 2008;

Cohen and Zarowin, 2010; Badertscher, 2011; Zang, 2012). In this regard, RM, as a departure from optimal operational decisions, is unlikely to increase firms' long-term value. Hence, some managers might find RM particularly costly because their firms face intense competition in the industry (Zang, 2012). However, these considerations may not be applicable to LMFs which usually face a weak market competition and benefit from significant competitive advantages (Arlacchi, 1983; Fantò, 1999). Additional reasons may lead LMFs to engage in EM practices more than LWFs do. First, RM can be used to permanently reduce taxable income, even more effectively than accrual-based EM, by fraudulently removing certain cash flows from the balance sheets. Second, money laundering may require recording fictitious transactions that may lead to EM pattern detected in our proxies. Third, the great availability of financial resources stemming from illegal activities (money laundering) may reduce the need of bank financing and the related incentive to avoid EM practices in order to exhibit an acceptable earnings quality. Finally, a more intensive EM in LMFs may be fostered by the low level of scrutiny from outsiders of these firms compared to LWFs, in connection with the protection ensured by their criminal ties often associated with political ties. In this aspect, some analogy might be found with the case of politically connected firms studied by Chaney et al. (2011) which engage more in EM than firms lacking such connections. Additionally, previous studies find that a low external monitoring intensity is associated with a higher level of EM (e.g., Duellman et al. 2013, Wongsunwai 2013).

5.4.3 Earnings Management and Corporate Social Responsibility

A further indication on the different EM pattern between LMFs and LWFs may come from some previous research on the relation between CSR and EM. Indeed, LMFs can be assumed to be socially irresponsible whether we refer to the widely accepted Carroll's (1979) definition of CSR implying that, in order to meet social expectations, CSR firms work to make a profit, obey the law, behave ethically, and be a good corporate citizen by financially supporting worthy social causes (Carroll, 1991).

In practice, a variety of methods are used to measure CSR in the academic and business communities. In this regard, Turker (2009) identifies the following categories: reputation indices or databases, single and multiple issue indicators, content analysis of corporate publications, scales measuring CSR at the individual or at the organizational level. Some widely employed reputation indices and databases are: The Kinder, Lydenberg, and Domini (KLD) Database, the Fortune Index, the Canadian Social Investment Database (CSID) and the French ARESE. In particular, KLD, ‘‘the de facto research standard’’ in scholarly research (Waddock, 2003, p. 369), rates US listed companies through scores based on several attributes of social activities including human rights, corporate governance, community relations, diversity, employee relations, environment and product characteristics. As regards CSR measure through issue indicators, previous studies adopt corporate crime (Baucus and Baucus, 1997; Davidson and Worrell, 1990) and tax avoidance (Lanis and Richardson, 2012; Dowling, 2013) indicators which are particularly relevant for our research. Another CSR measure method is content analysis of corporate publications on their practices regarding environmental, community, employee, and consumer issues (Gray et al., 1995; Turker, 2009). More importantly, a further method applicable to our study uses scales that measure the CSR perceptions and values of managers (Aupperle, 1984; Singhapakdi et al., 1996; Ruf et al., 1998; Quazi and O’Brien, 2000). Finally, scales measuring CSR at the organizational level consider the extent to which businesses meet the economic, legal, ethical, and discretionary responsibilities imposed on them by their stakeholders (Maignan and Ferrell, 2000; Turker, 2009).

We do not directly measure CSR in LMFs. Nonetheless, based on the CSR measures applied in previous research, we can reasonably assume LMFs to be socially irresponsible taking into account their aforementioned common practices, the nature of their owners and their supposed questionable values. Based on this assumption, previous findings on the relation between CSR and EM may support our research.

In this regard, previous studies find that more socially responsible U.S. public firms, based on KLD database, are less likely to manage earnings through discretionary accruals, to manipulate real operating activities, and to be the subject of SEC investigations (Hong and Andersen, 2011; *Kim et al.,* 2012). Previously Chih et al. (2008) examine the relationships between CSR and EM across 1,653 companies in 46 countries and find inconsistent results across different EM proxies. On the other hand, Prior et al. (2008) find that firm managers who engage in EM practices use CSR strategically to gain support from stakeholders and reduce their activism and vigilance. More recently, based on a sample of 109 Canadian companies, Gargouri et al. (2010) find a positive association between firm's corporate social performance ratings related to environment and employees and EM activities. Finally, based on a survey of professional accountants within private industry in Hong Kong, Shafer (2013) finds a significant association between perceptions of the organizational ethical climate and belief in the importance of CSR and between the latter and accountants' ethical judgments and behavioral intentions regarding accounting and operating earnings manipulation.

In summary, given the inconsistent evidence from prior research with mixed implications on the relation between CSR and EM, in this study we also aim to provide additional insight into this relation.

5.5 Research Design

5.5.1 Variable Definition

Previous studies on business failure prediction are based on the assumption that successful prediction models should include some carefully chosen variables from the whole spectrum of financial analysis (liquidity, indebtedness, profitability, and activity) and that they should use these variables in the intuitively right sense (Karels and Prakash, 1987; Dambolena and Khoury, 1980; Balcaen and Ooghe, 2006; Åstebro and Winter, 2012). Consistently, we believe that exploring a wide range of financial characteristics of LMFs as well as their EM behavior will more likely lead us to the best detection model.

5.5.1.1 Earnings Management Variables

Prior studies (Roychowdhury 2006; Cohen et al. 2008; Cohen and Zarowin 2010; Badertscher 2011; Zang 2012; Kim et al., 2012) use different proxies for RM including: abnormal levels of CFO, abnormal productions costs, abnormal discretionary expenses (R&D, advertising, and selling, general, and administrative expenditures) and a combined proxy of the previous. In Italy legal format of income statement classifies expenses by nature rather than by function and production costs cannot be distinguished from discretionary expenditures. Therefore, we adopt three new measures of RM as well as the usual abnormal CFO (*ABCFO*): abnormal material expenses (*ABMAT*), including both raw materials and trading goods, abnormal service expenses (*ABSERV*) and abnormal personnel expenses (*ABPER*).

Prior studies (Roychowdhury, 2006; Zang, 2012; Kim et al., 2012) assume that RM is mainly performed to boost earnings given that they analyze listed companies. On the other hand, LMFs are private firms whose incentives to decrease earnings or manipulate, even fraudulently, expenses of different nature (personnel, raw materials, service, etc.) may be prevalent in accordance with their supposed illicit purposes. In particular, in LMFs we expect higher *ABMAT* due to fraudulent sales underreporting and the record of fictitious transactions with related parties in order to disguise money laundering and evade taxes. Furthermore, we expect lower *ABPER* due to wage compression practices (Arlacchi, 1983) including evasion of social security contributions. Finally, we expect lower *ABSERV* given that LMFs may be less prone to contract external services such as advertising, consultancy, maintenance etc. because of their aforementioned competitive advantages.

As a measure of accrual-based EM we calculate discretionary accruals (*DAC*) using the modified Jones model proposed by Dechow et al. (1995) with an additional control for firm performance (Kothari et al., 2005). Furthermore, following Stubben (2010) and Caylor (2010) we also use discretionary revenue accruals (*DREV*) and a new measure of discretionary expense accruals (*DEXP*) as further proxies of accrual-based EM. Indeed, we consider that LMFs may simultaneously manipulate revenues and expenses and the related cumulative effect may not be detected in aggregate discretionary accrual models which do not provide information as to which components of earnings firms manage and how the EM is achieved (Marquardt and Wiedman, 2004).

In summary, within EM we distinguish accrual-based EM from RM and within accrual-based EM we distinguish as subcategories aggregate accrual-based EM from revenue accrual-based EM and expense accrual-based EM.

Previous studies find that discretionary accrual models have less power to identify manipulation than unadjusted accrual measures supplemented with other financial statement ratios (Beneish, 1997; Dechow et al., 2011). Hence, based on previous research (Beneish, 1997; Dechow et al., 2011; Rosner, 2003) we additionally test in our model, deflated by lagged total assets, unadjusted aggregate accruals (*ACCR*) and some unadjusted specific accruals that are more likely to be manipulated such as: change in receivables (*CH_REC*), change in inventory (*CH_INV*) and change in payables (*CH_PAY*). Following the same reasoning for accrual-based EM we also examine unadjusted proxies for RM by including in our model personnel, material and service expenses deflated by lagged total assets in order to determine whether they show more predictive power than commonly used abnormal RM measures.

5.5.1.2 Other Variables

Besides accrual-based EM and RM measures we test in our model the following variables, grouped by category, used in prior works on fraudulent financial statements and adapted to the singularities of LMFs.

***Asset composition*.** Previous studies **(**Loebbecke et al., 1989**;** Persons, 1995; Summer and Sweeney, 1998; Beneish, 1999; Dechow *et al*., 2011) examine asset composition with special regard to receivables and inventories that can be an easy target for manipulation due to the subjective judgment involved in their valuation. Accordingly, we measure asset composition with variables *CATA* (current assets/total assets), *RECTA* (receivables/total assets), *INVTA* (inventory/total assets) and *INTA* (intangible assets/total assets). In comparison with LWFs in the same industry, we expect LMFs to exhibit higher receivables to account for incoming dirty money and lower inventory to avoid taxes (VAT and income tax) through stock underreporting and fictitious purchase transactions.

***Performance*. W**e examine some variables expressing the reported firm financial performance and try to detect inconsistencies and signals of possible fraudulent manipulations. More specifically, we expect LMFs to fraudulently manipulate reported revenues. In this regard, previous fraud research finds that firms that increase revenue fraudulently are more likely to have abnormally high sales growth rates (Erickson et al., 2006; Brazel et al., 2009). As firms use resources to generate sales, unusual relations between sales and resources used, such as assets (capital productivity) and employees (labor productivity) may be a signal of fraud. Based on that and in line with previous studies on prediction of financial statement frauds (Fanning and Cogger, 1998; Perols and Lougee, 2011), we include *Revenue to Assets* (*REVTA*) and *Revenue to Employee (REVEMPL)* as predictors in our model. We predict a negative relation between *REVTA* and probability of criminal connection (*CRIME*) since in LMFs revenue may be underreported for tax evasion and there may be a need to quickly overinvest in assets available financial resources coming from illicit sources without demanding an immediate competitive return. On the other hand, higher values of *REVEMPL* for LMFs relative to LWFs may be due not only to a fraudulent revenue manipulation but also to the underreporting of the number of employees because of the employment of undeclared workers.

We additionally test Return on Assets (*ROA*) as a predictor given that we expect LMFs to be less efficient and profitable than LWFs because they may downward manage earnings to avoid tax as well as being oversized and poorly managed. Change in ROA (ABS*_CH_ROA*) is also added following Dechow et al. (2011) although, differently from the latter, we consider the absolute value in order to reflect higher opportunistic profitability fluctuations not reflecting the actual business performance. In accordance with this higher volatility pattern in LMFs, we furthermore include and expect higher values for absolute changes in percentages of personnel (*ABS_CH_PERSREV*), material (*ABS_CH_MATREV*) and service expenses (*ABS_CH_SERVREV*) over sales and absolute changes in net income (*ABS_CH_NI*) and CFO (*ABS_CH_CFO)* deflated by lagged total assets.

In line with previous fraud research (Fanning and Cogger, 1998; Beneish, 1999; Summers and Sweeney, 1998; Lee et al., 1999) we additionally include the annual absolute change in the ratio receivables to sales (*ABS_CH_RECREV*) also called days' sales in receivables. A significant variation in days' sales in receivables could be the result of a change in credit policy but it may also be suggestive of a fraudulent revenue manipulation (Beneish, 1999). As we expect revenue manipulation to be either upwards or downwards we consider the absolute value of ratio variation. In order to detect a possible simultaneous expense manipulation, we also add a variable for the absolute change in payables to purchases (ABCH*_PAY_EXP).*

Debt. As regards the indebtedness, we expect a positive relation between leverage (*LEV*) (total liabilities/total assets) and *CRIME*. LMFs may be more indebted than LWFs because they may report fictitious business transactions for tax evasion or money laundering purposes or may obtain favorable payment terms from suppliers using the strength of criminal intimidation (Arlacchi, 1983; Fantò, 1999). More specifically, LMFs may prefer fictitious debt transactions to inject dirty money since regular contributions of capital from shareholders may raise suspicions on their origins. Nonetheless, we expect LMFs to show less bank indebtedness *(LEVBANK*) compared to the rest of LWFs because their access to alternative illegal source of funding (money laundering) may replace bank support.

Liquidity. Regarding liquidity we include current ratio (*CRATIO*: current assets/current liabilities) (Shih et al., 2011) and the absolute value of its annual change (*ABS_CH_CRATIO)*. We expect a worse and more fluctuating liquidity situation for LMFs given that current assets and liabilities balances may include fictitious fraudulent transactions, undermining the adequacy of these ratios to reflect the actual short-term debt-paying ability of the firms.

Growth. Previous research finds that the fast growth of a firm is an important warning of financial information fraud (Loebbecke et al., 1989; Beasley, 1996; Bell and Carcello, 2000;

Shih et al., 2011). Consistently, we include percentage increase of total assets (*GROWTH*) as a predictor in our model. Indeed, we expect LMFs to have a higher growth rate than LWFs because of the continuous investment (overinvestment) of financial resources stemming from illegal activities (money laundering).

Non-financial. Following Dechow et al. (2011) we add a measure of difference of percentage change in total assets less percentage change in number of employees (*DIF_GROWTH_EMPL*) under the assumption that physical assets and employees are complements and should follow a similar growth pattern. We expect this measure to be significantly lower for LMFs because, although they may overinvest to launder dirty money, a sustained underreporting of number of employees due to the undeclared employment may result in higher fluctuations in the number of employees and higher employee growth rates. Lastly, we include personnel expenses per employee *(PERSEMPL)* expecting a lower value for LMFs due not only to lower remunerations but also to the payment of undeclared envelope wages (Williams, 2009).

5.5.2 Earnings Management Variable Construction

We need to build measures of accrual-based EM and RM to input as independent variables in our prediction model. Hence, in order to decompose total accruals (*ACCR)* into non-discretionary accruals (*NDAC)* and discretionary accruals (*DAC)* we use the cross-sectional version of the modified Jones model proposed by Dechow et al. (1995) with an additional control for firm performance (Kothari et al., 2005) by including return on assets (*ROA*) as a regressor in the estimation model:

$$\frac{ACCR_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t - \Delta AR_t}{TA_{t-1}} + \beta_3 \frac{PPE_t}{TA_{t-1}} + \beta_4 ROA_{t-1} + \varepsilon_t \qquad (1)$$

Where in year t (or t - 1), *ACCR* denotes total accruals; *TA,* Δ*REV,* Δ*AR, PPE*, and *ROA* represent total assets, changes in net revenue, changes in accounts receivables, property, plant, and equipment, and return on assets, respectively. The firm subscript is suppressed for simplicity. Parameters of Eq. (1) are estimated cross-sectionally for each industry-year with at least 15 observations in order to control for industry-wide changes under different economic conditions (Jeter and Shivakumar, 1999) that affect total accruals while allowing the coefficients to vary across time (e.g., Kasznik, 1999; DeFond and Jiambalvo, 1994). We use all active firms in AIDA (excluding LMFs) which are not listed on the stock exchange and with financial statements available for 10 years from 2003 to 2012. The total number of these firms at the moment of its retrieval from AIDA is 78,340. Following DeFond and Subramanyam (1998) and Kothari et al. (2005) our measure of *DAC* is the residual of Eq. (1), which is the difference between *ACCR* deflated by lagged *TA* and *NDAC* estimated by the fitted values of Eq. (1):

$$DAC_t = \frac{ACCR_t}{TA_{t-1}} - NDAC_t \tag{2}$$

Consistent with previous studies of EM (Healy, 1985; Jones, 1991; Dechow et al., 1995), total accruals (*ACCR*), are computed as:

$$ACCR_t = \Delta CA_t - \Delta CL_t - \Delta CASH_t + \Delta STD_t - DEP_t \tag{3}$$

Where:

Δ*CA* = change in current assets, Δ*CL* = change in current liabilities, Δ*CASH* = change in cash and cash equivalents, Δ*STD* =change in debt included in current liabilities and *DEP* = depreciation and amortization expenses.

CFO is computed as:

$$CFO = Earnings\ before\ tax - ACCR \tag{4}$$

Following Dyreng, Hanlon, and Maydew (2012) the income and accruals measures that we examine in our tests are pre-tax and thus are not affected by reductions in tax expense as a result of any tax planning.

Similarly to Stubben (2010) and Caylor (2010), we calculate discretionary revenue accruals (*DREV)* as the residual from the following Eq. (5) estimated in the same way as *DAC.* In line with Caylor (2010), we assume that changes in accounts receivables are positively related to future changes in CFO as well as contemporaneous changes in revenues, since the receivable amounts will be collected in the next period:

$$\frac{\Delta AR_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t}{TA_{t-1}} + \beta_3 \frac{\Delta CFO_{t+1}}{TA_{t-1}} \varepsilon_t \tag{5}$$

Following the same rationale as *DREV* we additionally calculate a new measure of discretionary expense accruals (*DEXP*) as the residual from the following Eq. (6) estimated in the same way as *DAC:*

$$\frac{\Delta AP_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{\Delta REV_t}{TA_{t-1}} + \beta_3 \frac{\Delta CFO_{t+1}}{TA_{t-1}} \varepsilon_t \tag{6}$$

Where ΔAP represents change in accounts payables.

As regards RM proxies, we calculate abnormal CFO (*ABCFO)* based on Roychowdhury's (2006) study and new abnormal expense measures (*ABMAT*, *ABPER and ABSERV*) in order to identify the nature of expenses which are aim of the manipulation.

We estimate the normal level of material expenses and personnel expenses using the model adopted by Roychowdhury (2006) for production costs:

$$\frac{MAT_t(PER_t)}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \beta_4 \frac{\Delta S_{t-1}}{TA_{t-1}} + \varepsilon_t \tag{7}$$

Where MAT_t and PER_t are respectively material expenses and personnel expenses in year t that we assume mostly related to production; S_t is the net sales in year t; and ΔS_t is the change in net sales from year t-1 to t (S_t - S_{t-1}). Eq. (7) is estimated in the same way as *DAC*. The abnormal level of material expenses (*ABMAT)* and personnel expense (*ABPER*) are measured as the estimated residual from Eq. (7).

Additionally, we estimate the abnormal level of service expenses (*ABSER*V) as the residual from the following Eq. (8) used by Roychowdhury (2006) for discretionary expenses and estimated in the same way as *DAC*:

$$\frac{SERV_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_{t-1}}{TA_{t-1}} + \varepsilon_t \tag{8}$$

Finally, in line with Dechow et al. (1998) and Roychowdhury (2006) we estimate abnormal CFO (*ABCFO*) as the residual from the following Eq. (9) estimated in the same way as *DAC*:

$$\frac{CFO_t}{TA_{t-1}} = \beta_0 + \beta_1 \frac{1}{TA_{t-1}} + \beta_2 \frac{S_t}{TA_{t-1}} + \beta_3 \frac{\Delta S_t}{TA_{t-1}} + \varepsilon_t \tag{9}$$

5.5.3 Detection Model

In order to build our detection model we start with the estimation of the following logistic regression model (Eq. 10) where the dependent dummy variable *CRIME* takes a value of 1 for LMFs and 0 for LWFs:

Pr (CRIME) = f (EM variables, Asset composition variables, Performance variables, Debt variables, Liquidity variables, Growth variable, Nonfinancial variables) (10)

Following a similar approach adopted by Dechow et al. (2011) for prediction of accounting misstatements we group the variables in different categories. Table 5.1 describes the independent variables and their calculation, classifies them by category and indicates their predicted sign as previously discussed.

Table 5.1. Variable definitions

Variable	Description	Pred. Sign	Calculation
EARNINGS MANAGEMENT			
Aggregate accrual-based:			
DAC	Discretionary accruals	?	Residuals of modified Jones model (Dechow *et al*., 1995) with additional control for firm performance (Kothari *et al*., 2005) (Eq. 1)
ABSDAC	Absolute value of discretionary accruals	+	Absolute value of *DAC*
Revenue accrual-based:			
DREV	Discretionary revenue accruals	+	Residuals from Caylor's (2010) model (Eq. 5)
ABSDREV	Absolute value of discretionary revenue accruals	+	Absolute value of *DREV*
Expense accrual-based:			
DEXP	Discretionary expense accruals	+	Residuals from Eq. (6)
ABSDEXP	Absolute value of discretionary expense accruals	+	Absolute value of *DEXP*
RM:			
ABMAT	Abnornal material expenses	+	Residuals from Eq. (7)
			(Continued on the next page)

Variable	Description	Pred. Sign	Calculation
ABPER	Abnormal personnel expenses	–	Residuals from Eq. (7)
ABSERV	Abnormal service expenses	–	Residuals from Eq. (8)
ABCFO	Abnormal CFO	?	Residuals from Eq. (9) (Roychowdhury, 2006)
Unadjusted EM proxies:			
ACCR	Total accruals deflated by lagged total assets	?	Total accruals Eq. (3)/total assets_{t-1}
CH_REC	Change in receivables deflated by lagged total assets	+	$(\text{Receivables}_t$ - $\text{receivables}_{t-1})$/total assets_{t-1}
CH_INV	Change in inventory deflated by lagged total assets	?	$(\text{Inventory}_t$ - $\text{inventory}_{t-1})$/total assets_{t-1}
CH_PAY	Change in payables deflated by lagged total assets	+	$(\text{Payables}_t$ - $\text{payables}_{t-1})$/total assets_{t-1}
PERTA	Personnel expenses to lagged total assets	–	Personnel expenses/total assets_{t-1}
MATTA	Material expenses to lagged total assets	+	Material expenses/total assets_{t-1}
SERVTA	Service expenses to lagged total assets	–	Service expenses/total assets_{t-1}
ASSET COMPOSITION:			
INTA	Intangible assets to total assets	?	Intangible assets/total assets
CATA	Current assets to total assets	?	Current assets/total assets
RECTA	Receivables to total assets	+	Receivables/total assets
INVTA	Inventory to total assets	–	Inventory/total assets
PERFORMANCE:			
ROA	Return on assets	–	Earnings before interests and extraordinary items/total assets
ABS_CH_ROA	Absolute value of change in ROA	+	Absolute value of: ROA_t-ROA_{t-1}
REVTA	Revenue to assets	–	Revenue_t/total assets_{t-1}
			(Continued on the next page)

Variable	Description	Pred. Sign	Calculation
SERVREV	Service expenses to sales	–	Service expenses/sales
MATREV	Material expenses to sales	+	Material expenses/sales
PERSREV	Personnel expenses to sales	–	Personnel expenses/sales
ABS_CH_PERSREV	Absolute value of change in personnel expenses over sales	+	Absolute value of: (Personnel expenses/sales)$_t$ - (Personnel expenses/sales)$_{t-1}$
ABS_CH_MATREV	Absolute value of change in material expenses over sales	+	Absolute value of: (material expenses/sales)$_t$ - (material expenses/sales)$_{t-1}$
ABS_CH_SERVREV	Absolute value of change in service expenses over sales	+	Absolute value of: (service expenses/sales)$_t$ - (service expenses/sales)$_{t-1}$
ABS_CH_NI	Absolute value of change in net income	+	Absolute value of: (net income$_t$-net income$_{t-1}$)/total assets$_{t-1}$
ABS_CH_CFO	Absolute value of change in CFO	+	Absolute value of: (CFO$_t$-CFO$_{t-1}$)/total assets$_{t-1}$
ABS_CH_RECREV	Absolute value of change in receivables to sales	+	Absolute value of: (receivables/sales)$_t$-(receivables/sales)$_{t-1}$
ABS_CH_PAYEXP	Absolute value of change in payables to purchases	+	Absolute value of: (payables/expenses)$_t$-(payables/expenses)$_{t-1}$
DEBT:			
LEV	Leverage	+	Total liabilities/total assets
LEVBANK	Bank indebtedness	–	Bank debts/total assets
LIQUIDITY:			
CRATIO	Current ratio	–	Current assets/current liabilities
ABS_CH_CRATIO	Absolute value of change in current ratio	+	Absolute value of: $CRATIO_t$ - $CRATIO_{t-1}$
GROWTH:			
GROWTH	Percentage change in total assets	+	(Total assets$_t$-total assets$_{t-1}$)/total assets$_{t-1}$
NON-FINANCIAL:			
PERSEMPL	Personnel expenses to employees	–	Personnel expenses/number of employees
			(Continued on the next page)

Variable	Description	Pred. Sign	Calculation
REVEMPL	Revenue to employee	+	$Revenue_t/employees_{t-1}$
DIF_GROWTH_EMPL	Percentage change in total assets less percentage change in number of employees	–	$GROWTH-(employees_t-employees_{t-1})/employees_{t-1}$
YEAR	Fiscal year	?	Dummy variables representing the fiscal year
IND	Industry	?	Dummy variables representing industry defined by the two-digit SIC code

5.5.4 Data and Sample Selection

LMFs sample consists of 198 firms confiscated to organized crime, some of them provided by ANBSC and others found in online newspapers and AIDA database. The financial statements for all firms are obtained from AIDA, the Italian Bureau Van Dijk database. It contains comprehensive information on 1 million companies with a turnover above € 500,000 in Italy, including the indication for some of them of the confiscation status and date of confiscation. Firms provided by ANBSC have all been confiscated by final judgment but their small size or their liquidation means that only 54 out of 1,663 have financial statements available on AIDA. In addition, we include firms confiscated in first instance and found in AIDA database (118) and online newspapers (52) until reaching a total of 224. We only consider firm-year observations prior to the confiscation year as once confiscated and subject to legal administration LMFs may lose their distinctive characteristics. Hence, out of these 224 LMFs we eliminate 26 confiscated before 2005 whose needed financial statements are unavailable on AIDA which only includes years from 2003 to 2012. Finally, we end up with a sample of 198 LMFs. Moreover, some missing data on AIDA for the calculation of several tested variables in some years further reduce the number of firm-year observations in the final detection model which ends up being 426.

Table 5.2 presents the industry distribution by two-digit SIC groups of LMFs in our sample and AIDA population of active unlisted firms with available financial data from 2003 to 2012 in the same industries as LMFs.

Table 5.2. Industry distribution of LMFs and AIDA population of active unlisted firms with available financial data from 2003 to 2012 restricted to LMFs industries (LWFs)

Sic code	Industry description	AIDA population		LMFs	
		Freq.	%	Freq.	%
01	Agricultural production-crops	644	0.82%	4	2.02%
14	Mining and quarrying of nonmetallic minerals, except fuels	463	0.59%	8	4.04%
15	Building construction-general contractors and operative builders	5,486	7.00%	33	16.67%
16	Heavy construction other than building construction-contractors	524	0.67%	3	1.52%
17	Construction-special trade contractors	4,032	5.15%	8	4.04%
20	Food and kindred products	3,224	4.12%	6	3.03%
25	Furniture and fixtures manufacturing	829	1.06%	3	1.52%
28	Chemicals and allied products manufacturing	1,598	2.04%	1	0.51%
29	Petroleum refining and related industries	158	0.20%	2	1.01%
32	Stone, clay, glass and concrete products manufacturing	1,960	2.50%	11	5.56%
34	Fabricated metal products, except machinery and transportation equipment	7,038	8.98%	1	0.51%
42	Motor freight transportation and warehousing	2,894	3.69%	18	9.09%
44	Water transportation	586	0.75%	1	0.51%
45	Transportation by air	95	0.12%	1	0.51%
47	Transportation services	1,884	2.40%	3	1.52%
49	Electric, gas and sanitary services	1,419	1.81%	6	3.03%
50	Wholesale trade, durable goods	14,064	17.95%	22	11.11%
51	Wholesale trade, nondurable goods wholesale dealing in	7,821	9.98%	17	8.59%

(Continued on the next page)

Sic code	Industry description	AIDA population		LMFs	
52	Building materials, hardware, garden supply, and mobile home dealers wholesale dealing in	1,018	1.30%	1	0.51%
53	General merchandise stores	324	0.41%	1	0.51%
54	Food stores	1,737	2.22%	15	7.58%
55	Automotive dealers and gasoline service stations	536	0.68%	2	1.01%
56	Apparel and accessory stores	1,920	2.45%	2	1.01%
57	Home furniture, furnishings, and equipment stores	872	1.11%	1	0.51%
58	Eating and drinking places	1,007	1.29%	2	1.01%
59	Miscellaneous retail	1,475	1.88%	1	0.51%
65	Real estate	2,239	2.86%	6	3.03%
70	Hotels, rooming houses, camps, and other lodging places	1,600	2.04%	3	1.52%
72	Personal services	327	0.42%	1	0.51%
73	Business services	5,001	6.38%	2	1.01%
75	Automotive repair, services, and parking	882	1.13%	1	0.51%
79	Amusement and recreation services	744	0.95%	4	2.02%
80	Health services	1,165	1.49%	5	2.53%
81	Legal services	19	0.02%	1	0.51%
87	Engineering, accounting, research, management, and related services	2,755	3.52%	2	1.01%
Total		**78,340**	**100%**	**198**	**100%**

Source: AIDA database, 2013.

Compared to the population of active and unlisted firms in AIDA with available financial data from 2003 to 2012, the sample LMFs are especially more abundant in industry groups: building construction-general contractors and operative builders (16.67% of criminal sample versus 7.00% of population), food stores (7.58% versus 2.22%) and Motor freight transportation and warehousing (9.09% versus 3.69%). On the other hand, there is a lower proportion of LMFs mostly in wholesale trade, durable goods (11.11% versus 17.95%), business services (1.01% versus 6.38%) and fabricated metal products, except machinery and transportation equipment (0.51 versus 8.98%).

In order to build our full sample for the model estimate, we use a matched sample design. So as to define a control sample, researchers choose from a wide range of firm characteristics on which to match such as: cash flows, year, industry, net income, size proxied by sales or total assets, ROA, etc. (Defond and Jiambalvo 1994; Perry and Williams 1994; Defond and Subramanyam 1998; Teoh et al. 1998; Kothari et al. 2005). We match each LMF-year with a LWF-year on fiscal reporting year, industry (two-digit SIC code) and size proxied by total assets. Our aim is to mitigate the effects of seasonal earnings patterns, unique industry characteristics, concurrent economic conditions and firm size. We adopt total assets as a measure of size rather than net sales or total number of employees because we believe that it is less likely to be significantly misreported in the financial statements. Indeed, number of employees might be underreported because LMFs are likely to resort to undeclared work in order to avoid payment of social security.

Table 5.3 summarizes the sample selection procedure that yields the 198 LMFs and the 418 control LWFs.

Table 5.3. Sample selection

	Number of firms
LMFs sample	
LMFs definitively confiscated at November 5th 2012 provided by ANBSC	1,663
Less: LMFs provided by ANBSC with data unavailable on AIDA database	-1,609
Add: LMFs found in AIDA database with status confiscated	118
Add: confiscated LMFs found in online newspapers with data available on AIDA	52
Less: LMFs confiscated before 2005 with pre-confiscation data unavailable on AIDA	-26
Final LMFs sample	**198**
LMF-years in detection model	**426**
(Continued on the next page)	

	Number of firms
LWFs control sample	
Aida population of active and unlisted firms with available financial data from 2003 to 2012 in the same two-digit SIC industries as LMFs	78,340
Less: LWFs not matched to LMFs by year, sector and size	-77,922
Final LWFs in detection model	**418**
LWF-years in detection model	**426**

Source: ANBSC and AIDA database, 2013.

For the 616 total firms in our matched sample, we obtain from AIDA available financial statement data for the years prior to the confiscation within the period of 2003 to 2013. Table 5.4 includes number of LMFs by confiscation year. It can be seen that 2012 is the year with largest number of confiscated firms and more than 50% of firms have been confiscated from 2011 to 2013.

Table 5.4. LMFs by confiscation year

Confiscation year	Number of confiscated LMFs	Percentage
2005	1	0.51%
2006	9	4.55%
2007	18	9.09%
2008	24	12.12%
2009	19	9.60%
2010	24	12.12%
2011	35	17.68%
2012	37	18.69%
2013	31	15.66%
Total	**198**	**100.00%**

Source: ANBSC and AIDA database, 2013.

5.6 Results and Discussions

5.6.1 Descriptive Statistics and Univariate Analysis

Table 5.5 presents descriptive statistics for each variable considered for the development of our detection model comparing LMF-years to their matched LWF-years before confiscation. All continuous variables are winsorized at the top and bottom 1 percent of their distributions to avoid the influence of outliers.

Table 5.5. Descriptive statistics and pairwise variable comparison between LMFs and LWFs

		LMFs		LWFs		Difference (LMFs - LWFs)			
Variable	**N**	**Mean**	**Median**	**Mean**	**Median**	**Pred. Sign**	**Mean**	**Median**	**Test**
EARNINGS MANAGEMENT									
Aggregate accrual-based:									
DAC	516	0.012	-0.004	-0.006	0.003	?	0.018	-0.007	
ABSDAC	516	0.188	0.115	0.145	0.090	+	0.043	0.026	***
Revenue accrual-based:									
DREV	460	0.031	0.016	0.024	-0.005	+	0.007	0.020	
ABSDREV	460	0.146	0.089	0.115	0.064	+	0.032	0.026	***
Expense accrual-based:									
DEXP	478	0.028	0.009	0.001	-0.007	+	0.026	0.017	**
ABSDEXP	478	0.146	0.091	0.108	0.062	+	0.038	0.028	***
RM:									
ABMAT	601	0.107	0.061	-0.018	-0.017	+	0.125	0.078	***
ABPER	601	-0.024	-0.047	-0.012	-0.024	–	-0.012	-0.023	**
ABSERV	741	-0.012	-0.072	0.005	-0.035	–	-0.017	-0.037	***
ABCFO	543	-0.026	-0.005	0.013	-0.002	?	-0.039	-0.002	**
Unadjusted EM proxies:									
ACCR	543	0.012	-0.020	-0.015	-0.017	?	0.028	-0.003	
CH_REC	625	0.097	0.025	0.053	0.013	+	0.044	0.012	***
CH_INV	741	0.039	0.000	0.015	0.000	?	0.024	0.000	***

(Continued on the next page)

		LMFs		LWFs		Difference (LMFs - LWFs)			
Variable	**N**	**Mean**	**Median**	**Mean**	**Median**	**Pred. Sign**	**Mean**	**Median**	**Test**
CH_PAY	552	0.075	0.014	0.040	0.013	+	0.034	0.001	**
PERTA	741	0.202	0.108	0.214	0.144	–	-0.012	-0.036	***
MATTA	741	0.945	0.442	0.724	0.380	+	0.221	0.063	***
SERVTA	741	0.391	0.182	0.437	0.254	–	-0.046	-0.073	***
ASSET COMPOSITION									
INTA	967	0.035	0.004	0.025	0.004	?	0.010	0.000	*
CATA	966	0.743	0.819	0.734	0.807	?	0.010	0.012	*
RECTA	875	0.389	0.380	0.374	0.356	+	0.015	0.024	**
INVTA	967	0.184	0.054	0.185	0.097	–	-0.001	-0.044	**
PERFORMANCE									
ROA	967	0.040	0.035	0.059	0.041	–	-0.018	-0.007	***
ABS_CH_ROA	741	0.051	0.024	0.041	0.021	+	0.010	0.003	**
REVTA	741	1.585	1.041	1.503	1.165	–	0.082	-0.124	
SERVREV	908	0.292	0.176	0.340	0.266	–	-0.048	-0.090	***
MATREV	908	0.550	0.564	0.440	0.434	+	0.110	0.130	***
PERSREV	908	0.171	0.108	0.168	0.124	–	0.003	-0.016	**
ABS_CH_PERSREV	684	0.057	0.024	0.033	0.013	+	0.023	0.011	***
ABS_CH_MATREV	684	0.153	0.050	0.087	0.028	+	0.066	0.022	***
ABS_CH_SERVREV	684	0.121	0.033	0.083	0.026	+	0.038	0.007	***
ABS_CH_NI	741	0.046	0.013	0.032	0.013	+	0.014	0.000	***

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		LMFs		LWFs		Difference (LMFs - LWFs)			
Variable	**N**	**Mean**	**Median**	**Mean**	**Median**	**Pred. Sign**	**Mean**	**Median**	**Test**
ABS_CH_CFO	363	0.265	0.137	0.221	0.129	+	0.043	0.008	*
ABS_CH_RECREV	571	0.299	0.111	0.169	0.056	+	0.131	0.054	***
ABS_CH_PAYEXP	547	0.357	0.137	0.204	0.065	+	0.153	0.072	***
DEBT									
LEV	967	0.774	0.840	0.684	0.736	+	0.090	0.103	***
LEVBANK	807	0.134	0.046	0.164	0.100	–	-0.030	-0.054	***
LIQUIDITY									
CRATIO	962	1.365	1.054	1.457	1.175	–	-0.092	-0.122	***
ABS_CH_CRATIO	734	0.401	0.118	0.317	0.102	+	0.084	0.015	
GROWTH									
GROWTH	741	0.242	0.110	0.102	0.036	+	0.140	0.074	***
NON-FINANCIAL									
PERSEMPL	908	27.251	26.373	34.192	32.173	–	-6.941	-5.800	***
REVEMPL	703	781.379	280.656	533.141	274.466	+	248.238	6.190	
DIF_GROWTH_EMPL	697	-0.114	-0.014	0.037	0.033	–	-0.151	-0.048	***

*Notes: The sample full period spans 2003–2012. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed Wilcoxon signed-rank test for the differences in medians between paired samples. See Table 5.1 for variable definitions. We apply non parametric Wilcoxon signed-rank test rather than Student's t-test for differences in means given that untabulated Skewness/Kurtosis tests for Normality show non-normality of most of the variables. However, both tests mostly perform the same.*

As regards accrual-based EM variables, it is noteworthy that, as expected, *ABSDAC*, *ABSDREV* and *ABSDEXP* are significantly ($p<0.01$) higher for LMFs relative to LWFs, suggesting a higher degree of aggregate accrual-based, revenue-accrual based and expense accrual-based EM, respectively. As regards RM variables, variable *ABMAT* is positive and significantly ($p<0.01$) higher for LMFs indicating an income-decreasing RM that is offset by an income-increasing RM suggested by significantly ($p<0.05$) lower variables *ABPER* and *ABSERV*. Significantly ($p<0.05$) lower variable *ABCFO* for LMFs provides evidence that the cumulative effect of RM is a reduction of *CFO* relative to LWFs. As regards unadjusted EM proxies, variables *CH_REC*, *CH_INV* and *CH_PAY*, each representing a different specific accrual, are significantly ($p<0.05$) higher for LMFs, indicating that these firms are more likely to report both higher income-increasing accruals and higher income-decreasing accruals that cumulatively offset each other in terms of cumulatively impact on earnings. Indeed, consistent with variable *DAC*, variable *ACCR* is not significantly different between the two types of firms. Similar to the results of related RM proxies, variables *PERTA* and *SERVTA* are significantly ($p<0.01$) lower and variable *MATTA* is significantly ($p>0.01$) higher for LMFs. As regards asset composition variables, marginally significantly ($p<0.10$) higher variable *CATA* documents a higher liquidity in asset composition of LMFs. This is partially due to higher receivables as showed by significantly ($p<0.05$) higher variable *RECTA* and despite the significantly ($p<0.05$) lower variable *INVTA*. As far as performance variables are concerned, profitability variable *ROA* is significantly ($p<0.01$) lower for LMFs and more volatile as suggested by significantly ($p<0.05$) higher variable *ABS_CH_ROA*. Significantly ($p<0.05$) lower variables *SERVREV* and *PERSREV* and significantly ($p<0.01$) higher variable *MATREV* for LMFs provide further evidence on lower service and personnel expenses and higher material expenses with respect to sales, respectively. Significantly ($p<0.01$) higher variables *ABS_CH_PERSREV*, *ABS_CH_MATREV*, *ABS_CH_SERVREV*, *ABS_CH_NI*, *ABS_CH_RECREV* and *ABS_CH_PAYEXP* for LMFs provide further evidence on the higher volatility of their reported performance which foster suspicions on a underlying opportunistic and fraudulent manipulation. As expected, LMFs are significantly ($p<0.01$) more leveraged (*LEV*), although their bank indebtedness (*LEVBANK*) is significantly ($p<0.01$) lower. Variable *CRATIO* is significantly ($p<0.01$) lower for LMFs indicating a theoretical weakness in the ability to meet their short term debt obligations, without considering the alternative non-standard resources and advantages of LMFs. It is worth noting the expected significantly ($p<0.01$) higher total assets growth rate (*GROWTH*) of LMFs. Finally, according to our expectations, non-financial variable *PERSEMPL* is significantly ($p<0.01$) lower for LMFs providing indication of wage compression practices (Arlacchi, 1983; Fantò, 1999) and non-financial variable *DIF_GROWTH_EMPL* is negative and significantly ($p<0.01$) lower for LMFs.

Table 5.6 displays Pearson correlations among EM related variables taken into account for developing our detection model. High correlations identified among some variables warn against their simultaneous inclusion in the detection model. As expected, unadjusted specific accrual variables are highly correlated with the corresponding discretionary accrual variables: *DAC* with *ACCR* ($r=0.93$, $p<0.01$), *DREV* with *CH_REC* ($r=0.86$, $p<0.01$), *DEXP* with *CH_PAY* ($r=0.78$, $p<0.01$). Furthermore, some specific abnormal expenses RM proxies are highly correlated with the corresponding unadjusted measures: *ABPER* with *PERTA* ($r=0.72$, $p<0.01$) and *ABSERV* with *SERVTA* ($r=0.70$, $p<0.01$). In addition, change in receivables accruals (*CH_REC)* are highly positively correlated ($r=0.70$, $p<0.01$) with change in payables accruals (*CH_PAY)* and discretionary revenue accruals (*DREV*) are highly positively correlated ($r=0.57$, $p<0.01$) with discretionary expense accruals (*DEXP*). These results suggest that revenue accrual-based EM and expense accrual-based EM are carried out in the same direction with opposite effects on earnings by increasing both expenses and revenues or vice versa.

Table 5.6. Pearson correlations between EM related variables

	DAC	*ABSDAC*	*DREV*	*ABSDREV*	*DEXP*	*ABSDEXP*	*ABMAT*	*ABPER*	*ABSERV*	*ABCFO*	*ACCR*	*CH_REC*	*CH_PAY*	*CH_INV*	*PERTA*	*MATTA*	*SERVTA*
DAC	1																
ABSDAC	0.1 ***	1															
DREV	0.0	0.1 ***	1														
ABSDREV	0.0	0.4 ***	0.4 ***	1													
DEXP	-0.1 ***	0.1 ***	0.6 ***	0.3 ***	1												
ABSDEXP	0.0	0.4 ***	0.2 ***	0.5 ***	0.3 ***	1											
ABMAT	0.1 ***	0.1 **	0.0	0.0	0.1 ***	0.0	1										
ABPER	0.0	0.0	0.0	0.0	0.0	-0.1 ***	-0.2 ***	1									
ABSERV	0.1 *	0.2 ***	0.1 ***	0.2 ***	0.2 ***	0.2 ***	-0.5 ***	-0.2 ***	1								
ABCFO	-0.9 ***	-0.1 ***	0.0	0.0	0.1 ***	-0.1 **	-0.2 ***	0.0	0.0	1							
ACCR	0.9 ***	0.2 ***	0.0	0.0	-0.1 ***	0.0	0.1 ***	0.0	0.0	-0.9 ***	1						
CH_REC	0.0	0.2 ***	0.9 ***	0.5 ***	0.5 ***	0.3 ***	0.1 *	0.0	0.3 ***	0.0	0.0	1					
CH_PAY	-0.3 ***	0.2 ***	0.5 ***	0.4 ***	0.8 ***	0.3 ***	0.1 **	0.0	0.3 ***	0.3 ***	-0.4 ***	0.7 ***	1				
CH_INV	0.4 ***	0.3 ***	0.0	0.1 **	0.3 ***	0.1 ***	0.2 ***	0.1 ***	0.1 ***	-0.4 ***	0.5 ***	0.0	0.2 ***	1			
PERTA	0.0	0.1 ***	0.1 ***	0.2 ***	0.0	0.1 ***	-0.2 ***	0.7 ***	0.0	0.0	-0.1 **	0.2 ***	0.1 ***	0.0	1		
MATTA	0.0	0.1 ***	0.1 ***	0.2 ***	0.1 ***	0.2 ***	0.3 ***	-0.1 **	0.0	0.0	0.0	0.2 ***	0.2 ***	0.2 ***	0.1 ***	1	
SERVTA	0.0	0.3 ***	0.1 ***	0.4 ***	0.1 ***	0.3 ***	-0.5 ***	-0.1 ***	0.7 ***	0.0	0.0	0.2 ***	0.2 ***	0.1 ***	0.3 ***	0.0	1

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed test. See Table 5.1 for variable definitions.*

5.6.2 Multivariate Logistic Regression Analysis

We estimate a cross-sectional logistic regression to determine whether the variables examined in univariate tests are jointly significant in detecting LMF-years. We use a stepwise backward elimination technique to arrive at a model that best predicts LMFs within our sample. The backward elimination technique begins with all of our selected variables excluding those highly correlated in order to avoid collinearity. Results of univariate tests are also taken into account as a first indication of the expected predictive ability of each variable. Finally, we succeed in building a model with a more limited set of variables providing as much as possible, meaningful and non-over-lapping information on all aspects of financial performance and the EM pattern of sample firms. The model is displayed in Table 5.7. It additionally includes control variables for industry sectors and years which are untabulated.

Table 5.7. Logistic regression comparing LMFs with LWFs

Variable	Pred. Sign	Estimate	p-value
CH_REC	+	-1.249	0.024
CH_INV	?	-2.618	0.015
ABMAT	+	0.991	0.009
PERTA	–	-0.610	0.249
INTA	?	4.640	0.002
CATA	?	-0.630	0.382
RECTA	+	0.838	0.199
INVTA	–	-2.101	0.015
REVTA	–	-0.335	0.003
SERVREV	–	-1.383	0.008
ABS_CH_PERSREV	+	4.931	0.005
ABS_CH_MATREV	+	0.849	0.183
ABS_CH_NI	+	1.361	0.400
LEV	+	4.383	0.000
LEVBANK	–	-3.554	0.000
GROWTH	+	1.887	0.000
PERSEMPL	–	-0.023	0.000
(Continued on the next page)			

Variable	Pred. Sign	Estimate	p-value
REVEMPL	+	0.000	0.030
DIF_GROWTH_EMPL	–	-0.570	0.003
IND		Yes	
YEAR		Yes	
Intercept		-0.604	0.493
Number of obs.		852	
LR $\chi 2$ (57)		271.89	0.000
Pseudo R^2		0.230	
Area under ROC Curve		0.816	
Correctly classified (cut-off = 0.50)			
LMFs		76.29%	
LWFs		76.53%	
Overall		76.41%	

Notes: The p-values are two-tailed. See Table 5.1 for variable definitions.

The chi-square test indicates the significance of the overall model. As showed at the bottom of the Table, using a probability cut-off point of 0.50 the model correctly classifies 76.29% of the total LMF-years (sensitivity) and 76.53% of the total LWF-years (specificity) with a total rate of 76.41 firm-years correctly classified. To illustrate the possible tradeoffs between false positives and correctly predicted LMFs at various probability cutoff-points, Fig. 5.1 shows a receiver operating characteristic (ROC) curve for the detection model. An area under the ROC Curve of 0.50 represents a model that does not have discriminatory power beyond that of chance, while higher levels represent improved power (see Hosmer and Lemeshow, 2000). The ROC Curve has been used extensively in the bankruptcy literature (e.g., Chava and Jarrow, 2004; Åstebro and Winter, 2012) and finance and accounting literature (e.g., Demers and Joos, 2007; Lisowsky, 2010; Dimmock and Gerken, 2012) to estimate both the validity and predictive ability of logistic models. The area under the ROC Curve of our estimated model is approximately 0.82, indicating strong discriminatory power of the model to identify LMFs.

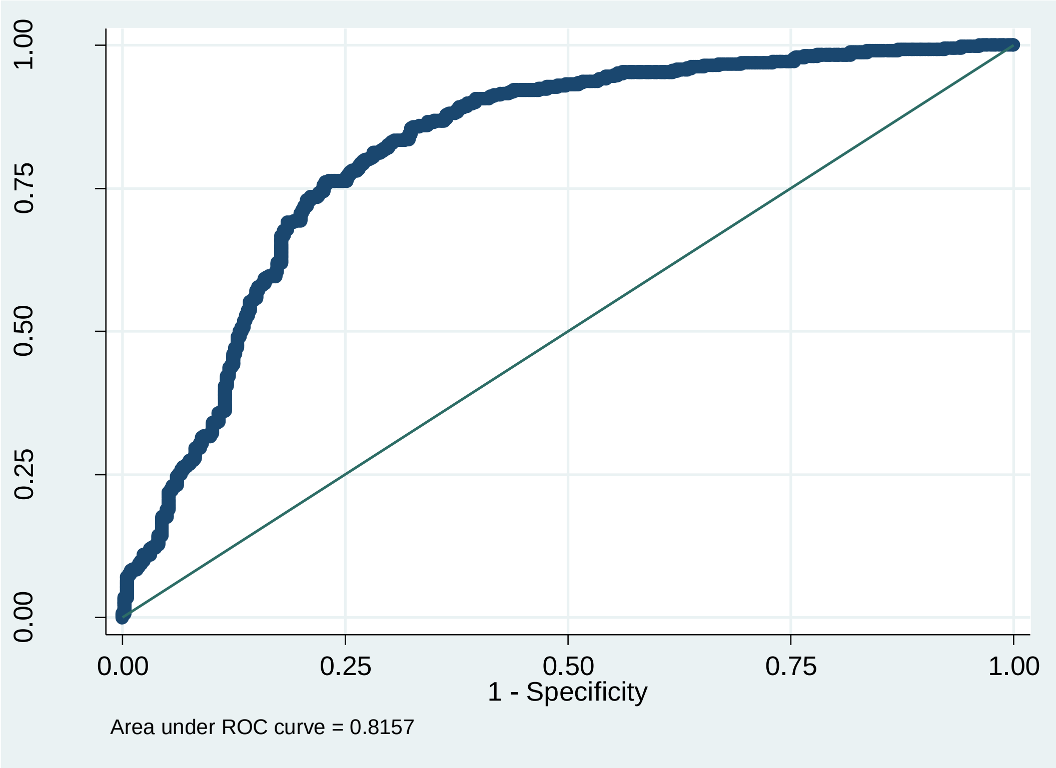

Fig. 5.1.This figure shows the receiver operating characteristic (ROC) curve for the logistic regression results of Table 5.7. The ROC curve shows the relation between the proportion of LMFs detected and the proportion of false positives for all possible classification probability cut-off points.

Fig. 5.2 shows the graph of sensitivity and specificity for each probability cut-off point for the detection model of Table 7. A reduction of the cut-off point increases the sensitivity and decreases the specificity. For example, a cut-off point of 0.35 scores a sensitivity of approximately 90% and a specificity of approximately 60%. Considering the higher misclassification cost for LMFs relative to LWFs, reducing the cut-off point from 0.5 might be a convenient option.

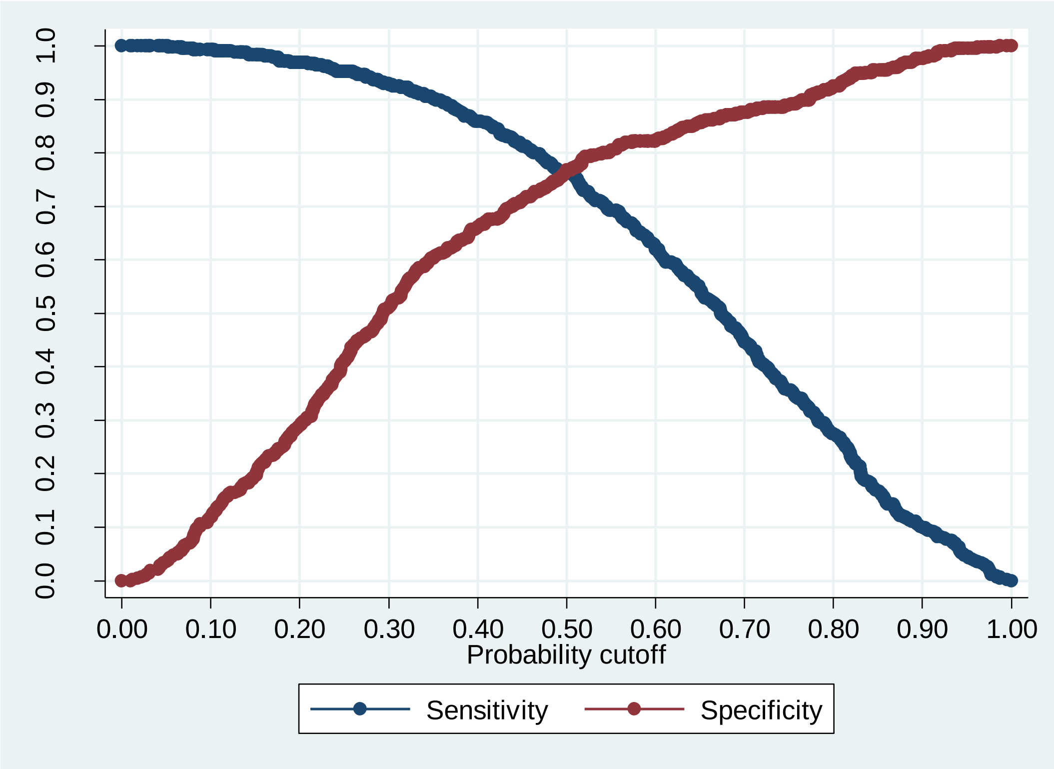

Fig. 5.2.This figure shows the graph of sensitivity and specificity versus probability cutoff-points.

Turning to the results of the estimated detection model in Table 5.7, it is noteworthy that, within the accrual-based EM variables, coefficients on *CH_REC* and *CH_INV* are negative and significant ($p<0.05$) suggesting that LMFs are more likely to report lower revenue and inventory valuation accruals than LWFs do. These results are consistent with previous studies on financial statement frauds finding that discretionary accruals have less power to identify manipulation than unadjusted specific accrual measures supplemented with other financial statement ratios (Beneish, 1997; Dechow et al., 2011). The latter are thus preferable also considering the fewer calculation efforts they require. Regarding RM variable *ABMAT*, its coefficient is positive and significant ($p<0.01$), as expected, providing evidence that LMFs are more likely to upward manage material expenses through real activities than LWFs do. On the other hand, positive and significant ($p<0.01$) coefficient on *INTA* and negative and significant

($p<0.05$) coefficient on *INVTA* respectively suggest that LMFs are more likely to report higher intangible assets and lower inventory with respect to total assets.

As far as performance variables are concerned, coefficient on *REVTA* is negative and significant ($p<0.01$) as expected and negative and significant ($p<0.01$) coefficient on *SERVREV* suggests lower service expenses with respect to sales in LMFs. For the rest of variables of the models, the results of univariate tests are mostly confirmed and the same considerations apply. Some exceptions are variables *ABS_CH_MATREV* and *ABS_CH_NI* whose coefficients are not significant at conventional levels in spite of improving the predictive power of the model. Another exception is the variable *REVEMPL* whose coefficient is positive and significant ($p<0.05$) apparently suggesting a higher labor productivity in LMFs relative to LWFs. Nonetheless, we are more inclined to believe that this result is mainly due to the underreporting of number of employees because of the employment of undeclared workers.

Finally, Table 5.8 shows the illicit activities which may be reflected by the variables included in the final detection model. Our analysis is mostly based on the assumptions made in the "Variable Definition" section. Money laundering as well as labor, income and value added tax evasion are assumed to be the primary incentives which should be considered whether additional variables are included in the model in order to improve its predictive power.

Table 5.8. Illicit activities and related reflecting variables of the detection model

Illicit activity	**Reflecting variables**
Fraudulent accounting manipulations	*CH_REC; CH_INV; ABMAT; INTA; CATA; RECTA; INVTA; REVTA; SERVREV; ABS_CH_MATREV; ABS_CH_NI; GROWTH*
	(Continued on the next page)

Illicit activity	Reflecting variables
Money laundering through fictitious transactions	*CH_REC; ABMAT; CATA; RECTA; REVTA; SERVREV; ABS_CH_MATREV; ABS_CH_NI; LEV; LEVBANK; GROWTH; DIF_GROWTH_EMPL*
Income tax/ value added tax evasion	*CH_REC; CH_INV; ABMAT; INVTA; REVTA; ABS_CH_MATREV; ABS_CH_NI*
Wage compression including evasion of social security contributions	*PERTA; ABS_CH_PERSREV; PERSEMPL; REVEMPL; DIF_GROWTH_EMPL*
Supplier intimidation	*LEV*

Notes: See Table 5.1 for variable definitions.

5.6.3 Robustness Tests

A key concern for any prediction model is out-of-sample validity. In this subsection we test whether the within-sample predictions are robust out-of-sample through a cross-validation. For this purpose we estimate three detection models excluding in turns LMFs confiscated in each year between 2011 and 2013 with their control firms and predicting values for each excluded hold-out sample. Related estimates and detection accuracy rates for each yearly hold-out sample are presented in the following Table 5.9.

Table 5.9. Logistic regressions excluding hold-out samples

	2013 excluded		2012 excluded		2011 excluded	
Variable	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
CH_REC	-1.532	0.022	-1.460	0.017	-1.579	0.012
CH_INV	-1.855	0.167	-1.836	0.137	-2.691	0.024
ABMAT	0.887	0.060	1.173	0.007	0.770	0.074
PERTA	-2.542	0.000	-0.261	0.675	-0.186	0.749
INTA	2.210	0.187	5.350	0.002	5.762	0.001
CATA	-0.575	0.527	-0.775	0.349	0.182	0.817
RECTA	0.347	0.683	0.996	0.164	0.811	0.255
INVTA	-3.430	0.002	-2.063	0.030	-1.995	0.036
(Continued on the next page)						

	2013 excluded		2012 excluded		2011 excluded	
Variable	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
REVTA	-0.164	0.257	-0.236	0.054	-0.300	0.009
SERVREV	-2.028	0.001	-0.830	0.178	-1.326	0.023
ABS_CH_PERSREV	3.079	0.154	6.520	0.001	3.518	0.079
ABS_CH_MATREV	1.661	0.052	-0.028	0.968	1.729	0.016
ABS_CH_NI	3.378	0.097	0.196	0.917	1.417	0.422
LEV	4.589	0.000	4.409	0.000	3.602	0.000
LEVBANK	-4.182	0.000	-3.091	0.000	-3.530	0.000
GROWTH	2.112	0.000	1.779	0.001	1.836	0.000
PERSEMPL	-0.025	0.000	-0.025	0.000	-0.022	0.000
REVEMPL	0.000	0.105	0.000	0.165	0.000	0.016
DIF_GROWTH_EMPL	-0.842	0.001	-0.555	0.009	-0.540	0.010
IND	Yes		Yes		Yes	
YEAR	Yes		Yes		Yes	
Intercept	0.098	0.927	-0.799	0.393	-1.173	0.267
Number of obs.	632		648		680	
LR $\chi 2$	221.8	0.000	207.9	0.000	196.51	0.000
Pseudo R^2	0.253		0.231		0.2085	
Area under ROC Curve	0.827		0.816		0.806	
Correctly classified hold-out samples (cut-off = 0.50):						
Confiscation year	**2013**		**2012**		**2011**	
Number of obs.	220		204		172	
LMFs	66.36%		75.49%		81.40%	
LWFs	72.73%		67.65%		74.42%	
Overall	69.55%		71.57%		77.91%	

Notes: The p-values are two-tailed. See Table 5.1 for variable definitions.

The results indicate that the overall predictive power of the models at cut-off of 0.50 is 69.55%, 71.57% and 77.91% in the hold-out samples of LMFs confiscated in 2013, 2012 and 2011, respectively. Due to the relatively small difference from our tested model we consider that the out-of-sample tests support the robustness of our detection model.

5.6.4 Analysis of Undetected LMFs

We perform a further analysis of LMFs undetected by our model in order to determine whether they present some significant differences from detected LMFs.

Table 5.10 shows the industry distribution of undetected and detected LMFs. An untabulated Pearson Chi-squared test of independence indicates that industry distribution of undetected LMFs is not significantly different from that of detected LMFs.

Table 5.10. Industry distribution of undetected and detected LMFs

Sic code	Industry description	Undetected LMFs		Detected LMFs	
		Freq.	%	Freq.	%
01	Agricultural production-crops	3	2.97%	4	1.23%
14	Mining and quarrying of nonmetallic minerals, except fuels	5	4.95%	13	4.00%
15	Building construction-general contractors and operative builders	21	20.79%	50	15.38%
16	Heavy construction other than building construction-contractors	2	1.98%	4	1.23%
17	Construction-special trade contractors	3	2.97%	22	6.77%
20	Food and kindred products	2	1.98%	5	1.54%
25	Furniture and fixtures manufacturing	2	1.98%	11	3.38%
28	Chemicals and allied products manufacturing	0	0.00%	1	0.31%
29	Petroleum refining and related industries	1	0.99%	6	1.85%
32	Stone, clay, glass and concrete products manufacturing	7	6.93%	21	6.46%
34	Fabricated metal products, except machinery and transportation equipment	0	0.00%	5	1.54%
42	Motor freight transportation and warehousing	11	10.89%	32	9.85%
44	Water transportation	2	1.98%	4	1.23%
47	Transportation services	1	0.99%	2	0.62%
49	Electric, gas and sanitary services	5	4.95%	9	2.77%
					(Continued on the next page)

Sic code	Industry description	Undetected LMFs		Detected LMFs	
		Freq.	**%**	**Freq.**	**%**
50	Wholesale trade, durable goods	16	15.84%	47	14.46%
51	Wholesale trade, nondurable goods wholesale dealing in	9	8.91%	27	8.31%
53	General merchandise stores	0	0.00%	1	0.31%
54	Food stores	4	3.96%	10	3.08%
55	Automotive dealers and gasoline service stations	0	0.00%	6	1.85%
56	Apparel and accessory stores	0	0.00%	4	1.23%
59	Miscellaneous retail	0	0.00%	2	0.62%
65	Real estate	0	0.00%	5	1.54%
70	Hotels, rooming houses, camps, and other lodging places	0	0.00%	5	1.54%
72	Personal services	1	0.99%	2	0.62%
73	Business services	2	1.98%	3	0.92%
75	Automotive repair, services, and parking	0	0.00%	6	1.85%
79	Amusement and recreation services	0	0.00%	1	0.31%
80	Health services	2	1.98%	8	2.46%
81	Legal services	1	0.99%	6	1.85%
87	Engineering, accounting, research, management, and related services	1	0.99%	3	0.92%
Total		**101**	**100.00%**	**325**	**100.00%**

Table 5.11 presents univariate tests of differences between undetected and detected LMFs including detection model variables and two additional variables measuring firm size.

Table 5.11. Comparison of variables between undetected and detected LMFs

	Undetected LMFs			Detected LMFs			Difference (Undetected - Detected)		
Variable	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**Mean**	**Median**	**Test**
Total assets (logarithm)	101	8.508	8.493	325	8.216	8.222	0.291	0.271	**
Number employees	101	30.943	13.000	325	23.455	11.000	7.488	2.000	**
CH_REC	101	0.049	0.024	325	0.084	0.034	-0.035	-0.010	
CH_INV	101	0.025	0.000	325	0.006	0.000	0.019	0.000	**
ABMAT	101	-0.023	-0.011	325	0.157	0.111	-0.180	-0.122	***
PERTA	101	0.212	0.101	325	0.190	0.106	0.023	-0.005	
INTA	101	0.015	0.001	325	0.048	0.004	-0.032	-0.003	***
CATA	101	0.759	0.867	325	0.725	0.766	0.034	0.100	**
RECTA	101	0.464	0.469	325	0.452	0.476	0.012	-0.006	
INVTA	101	0.170	0.050	325	0.140	0.042	0.031	0.008	
REVTA	101	1.338	1.042	325	1.546	1.043	-0.209	-0.001	
SERVREV	101	0.362	0.226	325	0.243	0.169	0.119	0.057	***
ABS_CH_PERSREV	101	0.039	0.018	325	0.054	0.024	-0.015	-0.005	
ABS_CH_MATREV	101	0.081	0.022	325	0.149	0.056	-0.068	-0.034	***
ABS_CH_NI	101	0.030	0.013	325	0.040	0.012	-0.010	0.001	
LEV	101	0.679	0.709	325	0.794	0.841	-0.115	-0.132	***
LEVBANK	101	0.192	0.166	325	0.147	0.075	0.045	0.091	***
GROWTH	101	0.084	0.065	325	0.189	0.087	-0.104	-0.022	
PERSEMPL	101	38.732	30.529	325	27.641	26.343	11.092	4.187	***
(Continued on the next page)									

	Undetected LMFs			Detected LMFs			Difference (Undetected - Detected)		
Variable	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**Mean**	**Median**	**Test**
REVEMPL	101	522.278	253.141	325	848.794	293.083	-326.516	-39.942	
DIF_GROWTH_EMPL	101	0.080	0.029	325	-0.164	-0.063	0.244	0.092	***

*Notes: *, ** and *** denote significance levels at 10%, 5% and 1%, respectively, based on a two-tailed Mann–Whitney–Wilcoxon test for the differences in medians. See Table 5.1 for variable definitions.*

It is noteworthy that undetected LMFs are significantly ($p<0.05$) larger than detected LMFs in terms of both logarithm of total assets and number of employees. Indeed, larger firms are more easily scrutinized by regulators (Siregar and Utama, 2008) and may have more resources and incentives to better disguise illicit practices by enhancing the rationality and economic credibility of accounting information (Compin, 2008). Interestingly, as regards detection model variables, *ABMAT* is significantly ($p<0.01$) lower for undetected LMFs suggesting a less intensive RM. Furthermore, undetected LMFs exhibit a significantly ($p<0.01$) lower total indebtedness (*LEV*) and a significantly ($p<0.01$) higher bank indebtedness (*LEVBANK*). Finally, significantly ($p<0.01$) higher variables *PERSEMPL* and *DIF_GROWTH_EMPL* for undetected LMFs may indicate less adoption of wage compression practices (Arlacchi, 1983).

5.7 Conclusions

In this study we develop a logistic regression model that can contribute to the detection of LMFs in Italy based on their financial statement characteristics. Our test is based on a sample of 198 Italian legally registered firms defined as LMFs due to having been confiscated at some point by judicial authorities, in relation to alleged connections of their owners with Italian organized crime.

Overall, our results reveal that our model is able to detect 76.29% of LMF-years (sensitivity) and 76.53% of LWF-years (specificity) within a matched sample of 852 firm-years including both LMFs and LWFs. Additionally, we find that LMFs are more likely than LWFs to engage in accrual-based EM and to manage material expenses upwards and personnel and service expenses downwards through RM.

As a primary contribution, our paper can aid practitioners and regulators in identifying accounting signals that can be used in risk assessment models or in the detection of criminal infiltrations and related illicit practices. For example, our model could be used by authorities as a selection criterion of firms to be inspected in order to unmask illegal activities such as money laundering, tax evasion and fraudulent accounting manipulations. In particular, a high probability score resulting from the model may be considered as a red flag of criminal infiltration deserving further investigation.

We recognize that in the future our detection model might need to be adapted to the continuous evolution of Mafia practices. Nonetheless, we do not expect any significant change in the practices of LMFs as an immediate reaction aiming to undermine the effectiveness of an auditing procedure based on our model. Indeed, LMFs are already engaged in disguising their illicit practices such as money laundering and tax evasion and the patterns disclosed by our model are a necessary consequence of these attempts. Furthermore, confiscations of LMFs are mostly based on investigations carried out by authorities on parallel illicit activities and criminal bonds of the owners that significantly benefit LMFs by granting them sources of funding and business opportunities. The imputation of the owners for mafia-type association automatically implies the confiscation of all their assets including firms. Hence, a change in the internal LMFs practices would not prevent authorities from accomplishing their investigations.

However, our findings are subject to several limitations. We cannot be completely sure that control sample LWFs are not connected to criminal organizations despite having never been confiscated. It cannot be denied that organized crime is deeply infiltrated in the Italian economy. Nonetheless, considering the large population of 78,340 firms from which control sample LWFs have been selected, we assume a very low probability of a significant presence of LMFs in our control sample. Although we conduct extensive out-of-sample tests, we cannot reject the possibility that our detection model is biased because undetected LMFs are unobservable and smaller LMFs unavailable on AIDA are excluded. Furthermore, there could be selection biases in LMFs pursued by Italian authorities.

We propose several opportunities for future research. First, other detection techniques (multiple discriminant analysis, neural networks, decision trees, etc.) could be tested in order to find out whether they perform better than our logistic model. Second, additional information from other sources may be used to improve the predictive power of the model through the inclusion of additional non-financial variables. Third, the model could be applied to other types of illegal firms such as simple tax evaders that, although not directly connected to any criminal organization, may have behavior patterns similar to LMFs. Finally, this study could be replicated in other countries, where organized crime is deeply rooted, in order to determine whether the results are confirmed in a different cultural, legal and institutional context.

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Chapter 6: Conclusions

6.1 Conclusions, Limitations and Future Research

In this dissertation we perform some inferences from financial statements of 224 Italian firms defined as LMFs, due to having been confiscated at some point by judicial authorities in relation to alleged connections of their owners with Italian organized crime. Our studies are included in four papers which are closely related because of the main object of study, represented by LMFs, on which we apply our constructs and test our hypotheses.

Specifically, in the first study we develop two new measures of labor tax avoidance, based on social contribution expenses reported in financial statements, and test them and their determinants within our sample of LMFs. Overall, our results reveal that before confiscation LMFs engage more in labor tax avoidance than LWFs do, whereas after confiscation there is no significant difference between both types of firm. Furthermore, we find that several factors have a significant influence on the probability of engaging in such a practice. This study can enhance further research on the effectiveness of our measures and on the determinants of labor tax avoidance in other contexts and for other types of firm. Moreover, these measures can be added to the other direct and indirect methods commonly employed to measure and detect undeclared work representing a primary means of labor tax avoidance.

In the second study, we examine expenses manipulation within LMFs by developing new proxies that provide information on which expense by nature is manipulated without precluding most of the conclusions allowed by proxies classifying expenses by function and mostly applied in prior studies. We find that that, before being confiscated, LMFs upward manage material expenses and downward manage personnel and service expenses with a cumulative negative effect on reported cash flow relative to sales. In contrast, following the confiscation and the intervention of legal administrators, personnel and service expenses manipulation becomes insignificant, whereas material expenses manipulation significantly decreases relative to before confiscation.

In the third study, we analyze accrual management by measuring discretionary revenue, expense and aggregate accruals within LMFs. We report that both before and after confiscation LMFs engage more in revenue, expense and aggregate accrual management than LWFs do. Several factors significantly influence the likelihood of LMFs engaging in accrual management. Furthermore, there is no significant difference between LMFs before and after confiscation and LWFs in the directional income management through discretionary aggregate accruals. Nonetheless, after confiscation LMFs simultaneously upward manage revenue and expense accruals with a null cumulative effect on aggregate accruals and income relative to LWFs.

In the last study, based on the insights gained from previous analyses, we develop a detection model of LMFs that correctly classifies 76.41% of firms within a matched sample of 852 firm-years including LMFs and LWFs. Furthermore, we show that specific accruals and earnings management proxies may provide more insight into accounting manipulation patterns of LMFs.

However, our findings are subject to several limitations. First, we cannot be completely sure that control sample LWFs are not connected to criminal organizations despite having never been confiscated. It cannot be denied that organized crime is deeply infiltrated in the Italian economy. Nonetheless, considering the large population of 78,340 firms from which control sample LWFs have been selected, we assume a very low probability of a significant presence of LMFs in our control sample. Second, we cannot reject the possibility of a bias in the selection of our sample of LMFs considering that undetected LMFs are unobservable and smaller LMFs, unavailable on AIDA, are excluded. Third, there could be selection biases in LMFs pursued and confiscated by Italian judicial authorities. Finally, our measures in LMFs greatly depend on the reliability of reported financial statement figures. Indeed, the likely manipulation of these figures and the consequent endogenity in the calculation models may affect the correct interpretation of our measures.

We propose several opportunities for future research. First, our proxies and models could be tested on other types of firm that are expected to engage in earnings management, expenses manipulation, labor tax avoidance and other illicit practices ascribed to LMFs, in order to gain further insight into their measurement abilities. Second, additional variables could be added to our models in order to improve their predictive power and reduce the risk of omitted-variable bias. Third, these studies could be replicated in other countries, where organized crime is deeply rooted and related illicit practices are largely widespread, in order to determine whether their results are confirmed in a different cultural, legal and institutional context. Finally, the results of this dissertation could be used to empirically corroborate social theories on corporate social responsibility, management and organizational behaviors which, in turn, might strengthen our conclusions.

Annex: Peer-Reviewed Outcomes of the Ph.D. Dissertation

Peer-Reviewed Outcomes of the Ph.D. Dissertation

Following the requirements of the Section 3, Article 36 of the regulation governing the Ph.D. programs under the RD 99/2011 (approved by the Governing Board of the Universitat de Barcelona on 16th of March, 2012 and amended on 9th of May and 19th of July, 2012; 29th of May and 3rd of October, 2013; 17th of July, 2014), the peer-reviewed outcomes for each chapter of this Ph.D. dissertation are summarized below.

Chapter 2: Labor Tax Avoidance and Its Determinants: The Case of Mafia Firms in Italy

The following paper has been published:

Ravenda, D., Argilés-Bosch, J. M., & Valencia-Silva, M. M. (2014). Labor Tax Avoidance and Its Determinants: The Case of Mafia Firms in Italy. *Journal of Business Ethics, (forthcoming), DOI 10.1007/s10551-014-2304-7*.

Journal indexed in: Journal Citation Reports/Social Sciences Edition (2013 JCR impact factor: 1.552).

Chapter 3: Expenses Manipulation within Legally Registered Mafia Firms in Italy

The following paper has been submitted to a journal indexed in ISI-Web of Science and it is currently under review:

Ravenda, D., Valencia-Silva, M. M., & Argilés-Bosch, J. M. (2014). Expenses Manipulation within Legally Registered Mafia Firms in Italy.

Chapter 4: Accrual Management within Legally Registered Mafia Firms in Italy

The following paper has been submitted to a journal indexed in ISI-Web of Science and it is currently under review:

Ravenda, D., Valencia-Silva, M. M., & Argilés-Bosch, J. M. (2014). Accrual Management within Legally Registered Mafia Firms in Italy.

Chapter 5: Detection Model of Legally Registered Mafia Firms in Italy

The following paper has been conditionally accepted for publication in *European Management Review* (2013 JCR impact factor: 0.9):

Ravenda, D., Argilés-Bosch, J. M., & Valencia-Silva, M. M. (2014). Detection Model of Legally Registered Mafia Firms in Italy.