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BLUE-COLLAR CRIME AND FINANCE

ABSTRACT

We examine the reputational and persistent costs of blue-collar crime against firms. Blue-collar crime negatively affects firms' reputations regarding credit risk, which persists over time and worsens future access to and external financing conditions (even if firms are financially healthy again in the future, and even if current crime events are unrelated to future crime incidence). Blue-collar crime does not need to be disclosed to lenders, but revelation is more likely among firms with more employees and in smaller communities, due to potential information leakages. However, the CEO's work experience mitigates the impact of blue-collar crime on future financing conditions.

JEL Codes: G21, K14

Keywords: Blue-Collar Crime, External Financing, Credit Risk, Information Leakages, CEO's Work Experience.

1. INTRODUCTION

The incidence of blue-collar crime (i.e., theft, burglary, robbery, assaults, and/or threats) against firms has been, and will continue to be, an important impediment to their economic performance. For instance, 17.7 percent of the firms covered in the World Bank Enterprise Surveys (WBES) had experienced blue-collar crime incidents in the year prior to the date they were surveyed (the WBES include over 135,000 firms from 139 countries between 2010 and 2017). Such events represented average losses of about 5.6 percent of annual sales, and 16.9 percent of firms identified blue-collar crime as a major constraint on the development of their businesses.

Regarding this issue, innovative prior empirical literature has focused on either the negative effect of high regional crime rates on economic performance (e.g., Lashitew et al., 2019; Allard and Williams, 2020), or the negative impact on private firm growth of managers' perceptions of street crime as a business obstacle (which does not mean that these firms have actually experienced a crime event).[1] However, there has been a dearth of attention paid to the effects of the actual experience of blue-collar crime events (rather than regional crime rates) on the firms' reputations regarding their credit risk, which could persist over time and worsen future access to, and the conditions of, external financing. This study contributes to filling this gap by empirically analyzing whether actual blue-collar crime incidents generate additional and persistent costs in future financing terms.[2] In addition, we explore potential channels through

[1] See, for example, studies that use data on regional rates of blue-collar crime and its effect on economic performance, including Thaler (1978), Gibbons (2004), Krkoska and Robeck (2006), Pshisva and Suarez (2006), Bonaccorsi di Patti (2009), Daniele and Marani (2011), Benyishay and Pearlman (2013) and Montoya (2016). For studies that use data related to firm managers' perceptions of street crime as a business obstacle, see Gaviria (2002) and Ayyagari et al. (2008).

[2] We do not claim that regional crime rates and managers' perceptions are not important. In fact, they can be relevant because, for example, they convey signals of the firm's exposure to possible crime incidents that could affect its ability to service new debt. However, the actual experience of blue-collar crime by individual firms is what directly matters for their performance and risk.

which crime may impact future financing by examining mechanisms in relation to how a lender could more likely be aware of a firm's history of being subject to crime.

Specifically, we analyze whether blue-collar crime events not only generate losses to firms (direct damages), but also cause indirect costs (such as increased costs of external financing). We assess whether crime incidents affect firms' future reputations that, in turn, may increase their credit risk, with persistent worsened access to, and conditions of, any prospective external financing. In such a case, potential borrowers would be worse off if lenders knew that they were victims of crime.[3] We also examine information leakages as potential mediating factors that could provide a framework for understanding how and in what contexts lenders might be more likely to find out about blue-collar crime events that firms do not have to disclose to creditors. Furthermore, we examine private firms' features that might be effective in mitigating the persistent negative impact of blue-collar crime on external financing.

We exploit a unique, private, firm-level, panel database that was collected in both 2009 and 2012. This is the productivity, technology and innovation (PROTEqIN) survey, developed by the Inter-American Development Bank (IDB) through the Compete Caribbean Partnership Facility.[4] The PROTEqIN survey is an improved version (i.e., featuring additional information) of the WBES and covers 13 Caribbean countries.[5] In particular, the PROTEqIN survey provides information on loan interest rates and loan maturities, which are not included in the WBES. Information about loan interest rates (maturities) is very important for our analysis of blue-collar crime and financing terms because such information reflects the default risk of firms, which

[3] In other contexts, it has been shown that firms engage in bad news hoarding to protect their reputations; see, for example, Jiang et al. (2020).
[4] The Compete Caribbean Partnership Facility (CCPF) is an organization that promotes economic growth and productivity, and fosters innovation and competitiveness, in the Caribbean region. It is a partnership between the Caribbean Development Bank, the IDB and the UK Department for International Development.
[5] These countries are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago.

should increase (decrease) if blue-collar crime events have a negative impact on the reputations of firms in terms of their credit risk.

We show evidence that blue-collar crime negatively affects future external financing terms, after accounting for potential endogeneity issues. We use data on blue-collar crime events in 2009, and we assess whether such events affected the financing terms of the loans to these firms in 2012. For those firms that faced blue-collar crime in 2009, such events represented damages equivalent to 3.8 percent of their profit margins in the same year. Thus, these damages (due to blue-collar crime) should affect the firms' reputations in 2009 in terms of an increase in their credit risk (i.e., firms should suffer in 2009 an additional indirect cost since it will now be more onerous to obtain external financing). However, we find that firms suffering blue-collar crime in 2009 recovered their financial performance by 2012, since those that were and were not subject to blue-collar crime in 2009 were statistically equivalent in their profit margins in 2012. Therefore, we may expect that firms that were subject to blue-collar crime in 2009 should also have recovered their reputations and improved their credit risk by 2012.

Nevertheless, reputations may not necessarily recover immediately, even if firms become financially healthy again in the years following a blue-collar crime event. This is because lenders may update firms' financial status through a learning process that gradually incorporates new information, which takes time. This intuitive idea of firm reputation is summed up well by Warren Buffett (1995), who states: "*It takes twenty years to build a reputation and five minutes to ruin it*". For instance, Lang and Nakamura (1990) argue that learning affects credit markets, since learning makes the level of credit activity persistent over time, even after transitory shocks.

Consistent with the arguments that reputation is persistent, we show that a firm's experience of blue-collar crime in 2009 reduces its future chances of obtaining external financing in 2012 (even if firms are financially healthy again in 2012, and if crime incidence in 2009 does not imply future crime incidence in 2012). Furthermore, blue-collar crime negatively affects future external financing conditions by raising interest rates and reducing both the size and maturity of the future loans granted to firms.

Even though firms do not have to reveal to potential lenders whether they have experienced blue-collar crime, lenders may learn about such crime events through alternative sources of information. We find evidence suggesting that the negative effects of blue-collar crime on future financing terms are affected by learning from information leakages. We show that information leakages are more likely among firms with more employees and those in smaller communities. We also show that the CEO's work experience mitigates the negative impact of blue-collar crime on the conditions of future external financing.

The analysis of whether current blue-collar crime events affect a firm's future reputation in terms of an increase in its credit risk is important for at least two reasons. First, this analysis connects the literature on a firm's reputation and organizational learning (see, e.g., Schulz, 2002). In this context, the distinction between resources invested in developing a reputation (i.e., firm attributes) and the reputation itself is crucial. In our analysis, the absence of blue-collar crime is the firm attribute, which is not directly observable by lenders. Thus, lenders need to follow a learning process (which takes time) to acquire the knowledge of the incidence of blue-collar crime that would affect the firm's reputation concerning its credit risk. Second, the literature has mainly studied the impact of internal firm attributes, such as quality of management, quality of products or services, community and environmental responsibility, innovativeness, and firm's prior performance, on the development of reputation (e.g., Deutsch and Ross, 2003; Jensen and Roy, 2008). However, the incidence of a blue-collar crime is an external firm determinant, in the sense that such crime events cannot be completely controlled by firms (of course, in our analysis, we control for firms that invest in security and insurance).

One might think that, even though firms do not have to reveal to potential lenders whether they have experienced blue-collar crime, lenders could still observe the negative impact of blue-collar crime on *future* profitability and/or collateral. However, as explained above, we show that blue-collar crime in 2009 is unrelated to both the profit margin and the firms' physical assets in 2012.

We also rule out alternative explanations related to the possibility of a blue-collar crime incident in 2009 increasing the likelihood of firms suffering blue-collar crime in 2012. Thus, we show evidence that the incidence of blue-collar crime is not persistent over time. Moreover, although we control for geographic location in our results, we also perform an additional analysis to rule out the possibility of lenders identifying regions with high incidences of blue-collar crime and interpreting this as a signal of increased crime risk for all firms located in these areas, thus providing loans with worse conditions to all these firms, albeit they may not all have suffered crime events.

We explicitly discuss the possibility of unobserved characteristics being correlated with both blue-collar crime and future financing terms. Even though it is very difficult in general to establish a clean causal link (without endogeneity issues) between blue-collar crime events and financing terms, we report a consistent and vast set of results that support our arguments that blue-collar crime matters. First, given that we use *lagged* blue-collar crime incidence, this accounts for the possibility of unobserved variables being contemporaneously correlated with crime and financing terms. Second, we show that our results are robust to controlling for economic conditions and several private firm characteristics, including manager's gender and experience, geographic location, industry, firm age, number of full-time workers, ownership structure, presence of temporary workers, and the level of informality of the market in which the firm operates.

Third, our results are robust to using a two-step Heckman selection model (Heckman, 1976, 1979) to account for potential self-selection in access to credit, where we also control for firm growth, alternative sources of credit, the competitive environment in which the firm operates, transparency of financial statements, innovation levels, manager's perceptions of business obstacles, and whether the firm invests in security and insurance (since firms may act strategically by doing so, if they know that blue-collar crime affects external financing). Fourth, consistent with the conditional exogeneity of blue-collar crime events, our results remain qualitatively unchanged when we implement alternative identification strategies, such as the propensity score matching (PSM) and instrumental variable (IV) approaches, which are designed to control for potential endogeneity issues induced by unobserved variables.

The paper is organized as follows. The next section discusses prior work and develops new hypotheses. Thereafter we describe the empirical strategy and data. The main results and robustness checks are then presented. Finally, the last section offers concluding remarks and suggestions for future research.

2. HYPOTHESIS DEVELOPMENT

2.1. Prior Research

Despite the large literature on different forms of crime (see, e.g., Becker, 1968; Witte, 1980; Glaeser et al., 1996; Levitt, 2017), the number of studies on the relationship between actual blue-collar crime events in private firms and financial decisions is limited. Nevertheless, this study is connected to the scarce literature on the effects of different forms of crime on financial outcomes.

The paper is part of the literature on the adverse effects of other forms of crime, such as cybercrime, on private firms. For instance, Kamiya et al. (2021) and Tosun (2021) show that cyberattacks are associated with negative stock-market reactions, reductions in sales growth, and decreases in investment in the short run. However, cybercrime differs from blue-collar crime in its opaqueness. In general, firms must disclose cyberattacks that damage their businesses, especially those involving personal information of workers and customers, which is not the case for blue-collar crime incidents. In the Caribbean context, for example, in Barbados and Jamaica, firms must disclose cyberattacks involving personal information, as per each country's Data Protection Act.[6]

The analysis of the effect of blue-collar crime on financing conditions is associated with the literature studying the effects of corporate, or white-collar, crime on firm performance (see, e.g., Ivancevich et al., 2003). There is evidence of negative consequences of managerial misconduct, such as "cooking the books", in terms of firms' growth (see, e.g., Karpoff and Lott, 1993). Thus, companies face significant long-term reputational costs when caught, which are reflected in permanent reductions in the expected present value of future cash flows. However, white-collar crime is also different from blue-collar crime with respect to the sources of the incidents and the individuals involved. White-collar crime is generated within the firm and

[6] Disclosure enforcement in the event of cyberattacks is also found in other countries outside of the Caribbean region. In the United States, for example, firms must disclose cyberattacks under the State Security Breach Notification Laws and the SEC Cybersecurity Disclosure Guidance.

involves managers and/or owners, while blue-collar crime tends to consist of an external event in which the perpetrators do not necessarily have an insider relationship with the affected company.

This study relates to the literature that examines the effects of bribes and corruption on financial markets. For example, Asiedu and Freeman (2009) show that corruption has an adverse effect on investment growth in transition countries, while Shleifer and Vishny (1993) describe how corruption emerges and why corruption levels are high and costly to development. Moreover, this study is associated with the literature on the role of property rights in financial markets (La Porta et al., 1998). For instance, Qi et al. (2011, 2017) show that creditor rights enhance the size and quality of debt markets. Qian et al. (2018) confirm that legal institutions are particularly important in developing countries.

This paper is connected to studies that examine the negative impact of high regional crime rates on economic performance. For instance, Thaler (1978) and Gibbons (2004) show that high regional crime rates reduce housing prices. Benyishay and Pearlman (2013) find that high regional crime rates have negative effects on the growth of microenterprises. Bonaccorsi di Patti (2009) shows that regions with higher crime rates are associated with more uncertain earnings and higher financing costs. Pshisva and Suarez (2006) and Montoya (2016) show that crime and violence in a region cause subsequent declines in economic activity and investment.[7] However, these studies' topics differ from our main research question, as we analyze whether blue-collar crime events *per se* suffered by private firms (rather than exposure to high-crime-level environments) affect those firms' financial outcomes.

[7] In addition, Daniele and Marani (2011) report that high regional crime rates have a deterrent effect on foreign direct investment, while Krkoska and Robeck (2006) find that higher rates of crime are associated with the weak development of microenterprises in the services sector, in large countries with high unemployment.

We also contribute to the literature related to managers' perceptions of street crime as a business obstacle. For example, Gaviria (2002) and Ayyagari et al. (2008) find that such perceptions affect growth. These studies differ from ours in that we analyze the impact of actual blue-collar crime events, rather than perceptions of crime as a business difficulty, on financial outcomes.[8]

Finally, the study is particularly related to Hanedar et al. (2014), who analyze whether collateral requirements for loans in year τ_1, which are granted to small and medium-sized enterprises, are affected by potential determinants also observed in year τ_1 (e.g., number of employees or even crime events). However, this study differs from that of Hanedar et al. (2014) in several dimensions; thus, our findings complement their results. First, we analyze whether a blue-collar crime incident in year τ_1 affects firms' reputations regarding their credit risk, which may persist over time and worsen future access to, and the conditions of, external financing in year $\tau_2 > \tau_1$ (even if firms are financially healthy again in year τ_2). This is because lenders might update the firms' financial status through a learning process that gradually incorporates new information, which takes time. Second, given that blue-collar crime events do not need to be disclosed by firms to lenders, we also analyze whether lenders may learn about such crime events from potential information leakages. Third, we examine private firms' features that are useful in mitigating the persistent negative impact of information leakages about crime, on these firms' access to external financing.

[8] Fernandes (2008) also finds that high protection payments (defined as payments to organized crime to prevent violence) affect the productivity of firms. However, Fernandes (2008) does not use data on whether firms have actually experienced crime, as we do.

2.2. Hypotheses

Blue-collar crime incidents can be quite important for firms' performance because such criminal events not only induce direct costs due to losses but may also generate indirect costs that could persist over time. For instance, suppose that a firm is the victim of a blue-collar crime act in year τ_1, which generates losses (i.e., direct costs). The negative shock on cash flows, due to crime losses, might also affect the firm's reputation in the same year τ_1, in terms of an increased credit risk (i.e., the firm suffers an *indirect* cost since it will now be more onerous for it to obtain external financing). However, reputation may not necessarily recover immediately (i.e., reputation can be persistent until year τ_2, where $\tau_2 > \tau_1$), even if the firm becomes financially healthy again in the years following the crime.

The reputation of a firm, in terms of its credit risk, can be persistent for several reasons. For instance, it is well known that the beliefs of individuals can take time to change due to the learning process followed by agents (see, e.g., Arrow, 1962). Thus, Lang and Nakamura (1990) show evidence that learning can affect credit markets, which can make the level of credit activity persistent over time, after temporary shocks. Moreover, there is evidence that the learning process followed by agents is not as smooth as we would like, since agents also have cognition biases. For example, there is evidence that agents assign more weight to negative news than positive (Meyer and Pagel, 2021). In addition, agents may stop paying attention to new information that contradicts their previous personal opinions (i.e., there is a confirmatory bias; see, e.g., Darley and Gross, 1983; Rabin and Schrag, 1999), which can be exacerbated in the credit market, where lenders face an environment of asymmetric information and adverse selection.[9] Thus, our first testable hypothesis follows:

Hypothesis 1: *A firm that experiences blue-collar crime is less likely to obtain debt finance in the future, and if debt finance is obtained, then the amount of finance obtained will be lower, while the firm will face less advantageous terms reflected in higher interest rates and lower loan maturities.*

It is worth noting that firms may also act strategically, in the sense that they do not have to reveal to the community (especially to potential lenders) whether they have experienced blue-collar crime. Thus, in principle, we should not expect any pervasive relation between blue-collar crime and future indirect costs in terms of worsened external financing conditions. Nevertheless, lenders may learn from alternative sources of information (e.g., firm information leakages), about unrevealed firm characteristics, which could include information on whether firms have experienced blue-collar criminal acts.

Therefore, the potential negative effects of blue-collar crime on future financing terms may be affected by information flows. It is well known that firms would like to control the information flows out of the company that will go into the pool of publicly available information, especially internal information that affects firm competitiveness (Cassiman and Veugelers, 2002). Critical internal information includes clients' sensitive information, unpatented production ideas, business plans, customer lists, the financial situation, and a firm's risks (Demski et al., 1999). As explained in the introduction, blue-collar crime incidence is part of the potential risk

[9] There are several studies related to the fact that reputation is persistent over time. For instance, firms that face criminal acts related to corporate data breaches or corrupt practices, which induce a negative reputational effect that can last for years, increase their corporate social responsibility (CSR) investments to reduce the persistence of their bad reputations (see, e.g., Hong et al., 2019).

that companies face, as such criminal events generate losses that might constrain their business development.

Internal information leakages can be generated by employee conversations outside the firm, betrayal of client confidences by legal advisors, and the careless management of internal information (i.e., lack of information protocols). For instance, Rajan and Zingales (2001), Zabojnik (2002), Baccara (2007), Baccara and Razin (2007), Baccara and Bar-Isaac (2008), and Buss and Peukert (2015) provide examples of internal information leaking to outside the firm. Accordingly, we expect larger negative effects of blue-collar crime on financing conditions in firms that are more exposed to information leakages, as described in the second hypothesis:

Hypothesis 2: *The impact of blue-collar crime on debt finance is more pronounced among firms with a greater likelihood of internal information leakages.*

Finally, as we have hypothesized about a potential channel through which the potential negative effects of blue-collar crime on future financing terms might be exacerbated (i.e., through information leakages), it is natural to examine whether there is any element firms might use as a mitigating factor against such potential negative effects.

A firm feature that may mitigate the impact of blue-collar crime on future external financing terms is related to the CEO's work experience. There are several reasons why the CEO's experience might help to ameliorate the harmful effects of blue-collar crime on financing conditions. Firstly, experienced CEOs may reduce flows of internal information from the company, in the sense of explicitly asking workers and police officers to conceal information and avoiding interviews with the press about blue-collar crime incidents (i.e., by establishing information protocols). Secondly, experienced CEOs may have better access to external financing, through their better financial networks. Thirdly, experienced CEOs should be more skilled at negotiating lending contracts.

The mitigating consequences of having an experienced CEO, on the potential effect of blue-collar crime on financing conditions, are in line with previous empirical literature that has documented positive reputational effects of the CEO's experience on the performance of firms (see, e.g., Deutsch and Ross, 2003; Falato et al., 2015). Thus, we suggest that the CEO's work experience reduces the negative impact of blue-collar crime on the conditions of future external financing, which is reflected in our third testable hypothesis:

Hypothesis 3: *The impact of blue-collar crime on debt finance is less pronounced for firms with more experienced CEOs.*

3. EMPIRICAL STRATEGY AND DATA

Identifying the causal effects of blue-collar crime on firms' future financing terms entails several challenges, due to potential endogeneity issues with blue-collar crime events. In this section, and across the paper, we will explicitly discuss potential endogeneity issues, and present the empirical analyses we use to deal with them. Of course, we must recognize that, as in any non-experimental empirical study, it is difficult to eliminate all endogeneity concerns, even applying appropriate econometric techniques. However, we will show over the different sections of this study a coherent and large set of evidence and robustness checks, which support the argument that blue-collar crime matters for future external financing terms.

3.1. Main Empirical Strategy

Before describing the main empirical strategy, and as explained in the introduction, it is worth noting that we use data on blue-collar crime events in 2009, and we assess whether such events affected the financing terms of the loans in the portfolios of firms in 2012 (details of the data used in our study will be explained in the following Section 3.2). This should largely account for contemporaneous endogeneity of firm-level crime events because, if there were unobserved characteristics systematically and contemporaneously correlated with both blue-collar crime and financing terms, measuring them in different time periods would ameliorate this potential source of bias.

In terms of the main empirical strategy, the first endogeneity issue relates to the potential selection bias among firms that apply for and obtain loans (and therefore for which we observe the financial outcomes of interest). As such, in our main specification aimed at exploring the relation between blue-collar crime and future financial terms, we will model the non-randomness of accessibility of external financing with a two-step Heckman selection model (Heckman, 1976, 1979). Besides controlling for potential selection into accessing external financing, this model exploits all observations (regardless of the accessibility of external financing) to inform the relation between blue-collar crime and financial outcomes.

Formally, in the first step, we estimate the probability that a firm has access to financing in 2012 with a probit specification as follows:

$$Prob\left(EF_{i,2012} = 1 | Z_{i,2009}\right) = \Phi\left(Z'_{i,2009}\gamma\right), \tag{1}$$

where $EF_{i,2012}$ indicates access to external financing in 2012 ($EF_{i,2012} = 1$ if firm i had access and $EF_{i,2012} = 0$ otherwise), $Z_{i,2009}$ is a vector of determinants of access to external financing that is measured in 2009, γ is a vector of unknown parameters, and $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution.

In the second step of the Heckman model, we estimate the relation between blue-collar crime experienced in 2009 and financing terms observed in 2012, which is the main objective of our study, by estimating the following regression:

$$Y_{ijc,2012} = \beta \cdot Crime_{i,2009} + X'_{i,2009}\delta + FEs + \lambda\left(Z'_{i,2009}\hat{\gamma}\right) + \varepsilon_{ijc}. \tag{2}$$

Here, $Y_{ijc,2012}$ denotes the financial outcomes observed in 2012 for firm i operating in industry j, which is located in country c. In equation (2), $Crime_{i,2009}$ denotes variables related to blue-collar crime experienced in 2009 by firm i. The term $X'_{i,2009}$ is a vector of firm-level characteristics, which we include as controls in all our specifications.

The term FEs denotes country*industry (cross) fixed effects that control for unobserved determinants of financial terms, common to firms operating in the same industry within the same country. Therefore, we can exploit the variation within each country-industry cell, which allows us to control for unobserved variables related to the country heterogeneity and industry heterogeneity. The term $\lambda\left(Z'_{i,2009}\hat{\gamma}\right)$ denotes the inverse Mills ratio evaluated at $Z'_{i,2009}\hat{\gamma}$, where $\hat{\gamma}$ is the vector of estimated parameters obtained in step (1) above. Hence, the inclusion of $\lambda\left(Z'_{i,2009}\hat{\gamma}\right)$ accounts for selection into financial access.

3.2. Data Description and Summary Statistics

3.2.1 *Main Dependent Variables, Explanatory Variables, and Firm Controls*

Within the empirical strategy explained in Section 3.1, the β parameter in equation (2) captures the main relation of interest between blue-collar crime and future financing terms. Therefore, in this section, we begin explaining the data used for the key components of that equation: dependent variables concerning financing conditions observed in 2012, explanatory variables related to blue-collar crime events in 2009, and firm-specific characteristics used as controls.

We use a firm-level panel of 1,324 enterprises observed in both 2009 and 2012 across 13 Caribbean nations. The first wave of data collection corresponds to the 2009 WBES, and the 2012 follow-up data collection corresponds to the PROTEqIN survey.[10] The samples were purposely designed (by the World Bank and the IDB) to be nationally representative of the private sector within each country included in the survey. The panel dataset provides rich information on the performance and characteristics of the firms, which includes information on blue-collar crime events. Furthermore, the PROTEqIN survey has the advantage over other similar surveys, such as the WBES, that it provides loan interest rates and maturities. Information regarding interest rates and loan maturities is very relevant for our main research question since, as explained in the introduction, they reflect the default risk of firms.

Table 1 presents the description and summary statistics of the variables used in this study. To test our hypotheses (as described in Section 2.2), the key dependent variables include the financing terms of firm loans in 2012: the annual interest rate on the loan, the natural logarithm

[10] The PROTEqIN survey covers Caribbean economies: Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago.

of the loan amount (converted to USD), and the maturity of the loan (in years). Notice that 375 firms out of the 1,324 surveyed firms obtained external financing in 2012. The average annual interest rate was about 10.6 percent for an average loan amount of roughly 30,000 USD with 3.6 years maturity. Table A1 in Appendix A shows the sample breakdown by country and industry.[11]

[Insert Table 1 here]

The main explanatory variables are related to blue-collar crime events (incidence and cost of crime) experienced by the firms in 2009. We consider crime at the extensive margin with an indicator for whether the firm suffered a blue-collar crime event or not (i.e., a blue-collar crime dummy), and at the intensive margin by computing the ratio of the direct costs of the blue-collar crime to the firm's annual sales.

It is important to note that blue-collar crime events were self-reported by firms to an independent surveyor under a confidentiality agreement. Therefore, our data contains *real* blue-collar crime experiences, some of which were reported and some not reported to the police. To reduce potential data noisiness regarding small-crime events, we consider a firm to have experienced a blue-collar crime incident if the incident caused damages larger than 1 percent of annual sales. We observe that 15.3 percent of firms experienced blue-collar crime events in 2009. The overall average cost of blue-collar crime (including all firms in the sample) is 0.6 percent of annual sales. However, among the firms that were victims of blue-collar crime, the damages represented an average of 3.8 percent of their annual sales.

[11] The sampling design of the survey considers a stratification approach, where industries are agglomerated into two industrial groups within each country: services and manufacturing. For more details on the sampling design, please see https://publications.iadb.org/en/productivity-technology-innovation-caribbean. Therefore, there are 26 country-industry cells (see Table A1 in Appendix A). When considering all 1,324 observed firms, the average cell size accounts for 45.7 firms, and when considering the 375 firms that applied for external financing (and for which we therefore observe financial outcomes in 2012), the average cell size accounts for 14.4 firms. Therefore, this sampling design allows for the inclusion of country-industry (cross) fixed effects.

Table 1 also presents firm characteristics observed in 2009, which are used as controls when assessing the relation between blue-collar crime and financial outcomes (i.e., contained in the vector $X'_{i,2009}$ in equation (2)). The first firm control is related to whether the firm is (or is not) in a capital city, enabling us to consider the effect of big/small communities in our results. In this table, we observe that 14.3 percent of firms are in a capital city. It is important to notice that, as the largest (smallest) country in our sample is Jamaica (Saint Kitts and Nevis), with an area of 10,991 km^2 (261 km^2), which is 38.8 (0.9) percent of the area of Hawaii, locations that are not capital cities can be considered small towns or rural areas.

We include firm age as a control since mature firms may be more prepared for crime and they may receive better financing conditions.[12] In our sample, the average firm age is almost 18 years. We also control for the size of the company using as a proxy the number of full-time workers. This is because firms with more employees are larger and thus less risky than small firms. Our data show that firms have on average 44 full-time workers. In addition, we control for both the gender of the CEO and the CEO's business-governmental networks, the latter proxied by the CEO's experience.[13] Table 1 shows that firms are disproportionally managed by males (80 percent) with an average experience of about 17 years.

Furthermore, we control for the potential impact of political connections on corporate governance, using as a proxy the government participation in firms, which is on average 12.1 percent in our sample. We control for the use of an external workforce, with on average 42 percent of our firms employing temporary workers. We also control for whether firms operate

[12] In terms of the effect of a firm's maturity, Mählmann (2011) provides evidence that firms with long credit rating histories will receive superior ratings in relation to firms with shorter histories. This is because mature firms know better how to strategically release private information to lenders to improve their credit status.

[13] The CEO's work experience might also affect their decision-making process. For instance, there is evidence that CEOs with a lot of work experience (especially CEOs that are closer to retirement, who have shorter career horizons) are more willing to accept takeover bids than young ones (Jenter and Lewellen, 2015).

within environments where competitors have workers without formal contracts. Table 1 shows that 28.5 percent of firms operate within competitive environments where there are informal workers. Moreover, and finally, we control for the ownership concentration in terms of the percentage owned by the largest shareholder/owner. In our data, firm ownership is heavily concentrated in the main owner, who has an average of 87.5 percent ownership.[14]

In relation to firm controls, Table 2 analyzes whether such firm characteristics differ between firms with and without blue-collar crime, after we control for country*industry (cross) fixed effects. This table shows that, out of nine firm characteristics measured in 2009, six differ significantly between firms with and without blue-collar crime at the 10 percent level or lower. Therefore, it will be important to control for them within our empirical approach.

[Insert Table 2 here]

3.2.2 *Determinants of Access to External Financing*

As explained in Section 3.1, we use a Heckman selection model to account for the non-randomness of access to external financing, exploiting data concerning all the 1,324 surveyed firms. Thus, here we describe the firm determinants in 2009 that are used to control for potential selection bias in relation to access to finance in 2012 (i.e., the vector $Z_{i,2009}$ in the first stage of the Heckman model).

Following Cosh et al. (2009), within the $Z_{i,2009}$ vector in equation (1), we include a set of determinants of credit access, which are listed in Table A3 of Appendix A. In particular, we

[14] Table A2 in Appendix A presents a correlation analysis of the main variables used in this study. It shows that, in general, the correlations between the explanatory variables are low in absolute terms, although there are exceptions, such as that between firm age and manager experience, which is 0.48.

consider corporate governance characteristics by including an indicator for whether the legal status of the firm is that of a private or public shareholding company, an indicator for incorporated firms, and an indicator for whether the firm had its annual statements certified by an external auditor. We include market risk proxies by considering the gross profit margin, an indicator for high competition, and an indicator for whether the firm's main market is local. In relation to proxies for regulatory risk, we include an indicator for whether the manager perceives business licensing and permits as an obstacle, an indicator for whether the manager perceives the political environment as a business obstacle, and an indicator for whether the manager perceives corruption as a business obstacle. In terms of determinants used as proxies for credit risk, we consider an indicator for whether the firm applied for a loan within the last year and this application was rejected, and an indicator for whether the manager perceives access to finance as a business obstacle. Moreover, we include proxies for the firm's debt structure by considering the percentage of working capital financed with external funds and an indicator for whether the firm has an overdraft account.

We also account for proxies related to the CEO's risk appetite by including an indicator for whether the firm has introduced new patents and an indicator for whether the firm has introduced new products or services. In addition, we include a determinant to proxy for the risk aversion of the CEO in relation to crime incidence, namely, an indicator for whether the firm has invested in security and insurance. This is because firms may act strategically by investing in security and insurance if they know that blue-collar crime may affect their external financing prospects.

Table A3 of Appendix A also reports summary statistics of these firm determinants of credit access. For instance, Table A3 shows that the average gross profit margin was 44.5 percent with almost 48 percent of firms having their own country as their main market. The majority (66.8 percent) had their financial statements certified by an external auditor, and an average of 39.7 percent of their working capital was financed with external funds. The business environment is relatively competitive, with 78.4 percent of firms having more than five competitors. However, innovation levels are relatively low, with only 2.3 (14) percent of firms having introduced new patents (new products or services). Although many firms have an overdraft account (66.8 percent), access to longer-term external finance at convenient terms is the more prevalent obstacle, as perceived by managers (58.9 percent).[15]

4. RESULTS

In this section, we first provide evidence that blue-collar crime does, in fact, negatively impact future external financing terms. Subsequently, we provide evidence suggesting that the negative effects of blue-collar crime on future financing terms are affected by firms' internal information leakages. Then, we perform an analysis to rule out alternative explanations, such as an endogenous reduction in either *future* profitability or the firm's collateral after a blue-collar crime incident (i.e., lenders may observe that victimized firms are not financially healthy), and the potentially endogenous impact of regions with high levels of blue-collar crime. Finally, we analyze whether there are firm features that ameliorate the negative impact of blue-collar crime on the conditions of future external financing.

[15] Table A4 of Appendix A presents an analysis concerning whether these firm determinants of credit access differ between firms with and without blue-collar crime in 2009, after we control for country*industry (cross) fixed effects. Table A4 shows that, out of 16 firm determinants of credit access, only one differs significantly between firms with and without blue-collar crime at the 10 percent level or lower.

4.1. Effect of Blue-collar Crime on Future External Financing

4.1.1. *Impact of Blue-collar Crime on Financing Conditions and Credit Access*

In this section, we present evidence that blue-collar crime negatively affects future external financing terms. Table 3 presents results from the Heckman model regarding the effects of blue-collar crime on future external financing conditions (as explained in Section 3.1). In this table, the dependent variables are the interest rates, the natural logarithms of the loan amount and loan maturity. All our analyses include firm-specific controls. We show the results with country*industry (cross) fixed effects, and those when country and industry fixed effects are independently included.

[Insert Table 3 here]

Table 3 shows that firms subject to blue-collar crime events in 2009 have worse financing terms in 2012. For instance, in terms of interest rates in 2012, with firm controls and country*industry fixed effects, the variable crime/sales in 2009 (i.e., the total cost of blue-collar crime divided by the total sales of the firm) displays a significant coefficient of 16.17. This implies that a one-standard-deviation increase in crime divided by sales in 2009 results in an average interest rate increase of 0.36 percentage points in 2012 (equivalent to a 3.4 percent increase in interest rates relative to the average 10.56 percent interest rate).

Table 3 also shows that blue-collar crime reduces the future size and maturity of loans from external financing sources. For example, the crime/sales variable displays a significant coefficient of -8.96 (-11.92) when the dependent variable is the natural logarithm of the loan amount (loan maturity), in the model with firm controls and country*industry fixed effects. This implies that a one-standard-deviation increase in crime divided by sales in 2009 has on average a

2.0 (7.5) percent reduction in the size (maturity) of loans obtained in the subsequent three years. The results in Table 3 are strongly consistent with Hypothesis 1.

One might think that blue-collar crime would not only affect financing conditions (i.e., interest rates, loan amounts, and loan maturity), but also *access* to external financing *per se*. To test whether blue-collar crime affects access to external financing, we take the sub-sample of firms that indicated in the PROTEqIN survey 2012 their *intention* to seek external financing, regardless of whether they obtained a loan in the end. Then, we create a dummy variable, $Access\ to\ Credit$, which takes the value 1 if a firm had at least one loan approved and 0 otherwise.[16] The results from both the probit and logit models are presented in Table 4.[17] In this table, the dependent variable is the dummy variable, $Access\ to\ Credit$ in 2012, while the explanatory variables are related to blue-collar crime events that firms experienced in 2009.

[Insert Table 4 here]

Table 4 shows that being subject to blue-collar crime reduces the likelihood of a firm obtaining external financing. For the fully saturated models, the estimated marginal effects in the probit (logit) analysis indicate that the likelihood of obtaining a loan in 2012 is reduced by 9.1 (8.9) percentage points for firms that experienced a blue-collar crime in 2009 and hoped to obtain a loan. Thus, the analysis presented in Table 4 provides further evidence that blue-collar crime induces a negative impact on firms' future access to financing, which provides further support to Hypothesis 1.

[16] In the dummy variable $Access\ to\ Credit$, we drop from the analysis (i) firms that did not obtain a loan due to the incompleteness of their loan application or another unspecified objection, and (ii) firms that wanted to obtain a loan but did not submit a credit application because they considered the application procedure to be complex or for another unspecified reason.

[17] Please notice that Table 4 does not include all 1,324 surveyed firms, since this analysis only considers the sub-sample of 586 firms that expressed their *intention* to seek external financing in 2012, independent of whether they finally obtained such funding.

4.1.2. *Robustness Checks for the Impact of Blue-collar Crime on Future Financing Conditions*

To evidence the robustness of our main specification, we also present results using three alternative strategies, comparing the financial outcomes of firms that were subject to blue-collar crime to those of firms that were not, which are reported in Appendix B. We estimate an OLS model that is conditional on applying for a loan (see Table B1). Second, to control for the potential endogeneity of blue-collar crime, we estimate a propensity score matching, PSM, model and an instrumental variable, IV, strategy (see Tables B2 and B3, respectively).

In the PSM model, crime-affected firms are matched to observationally similar non-crime-affected firms, and the differences in financing terms between the matched firms are estimated (see Table B2). In the IV strategy, we consider two instruments for blue-collar crime suffered in 2009 (see Table B3). The first instrument is the incidence of crime events within the geographical vicinity of the firm. Therefore, we compute the variable, $CrimeAround$, which measures the percentage of firms that have been victims of blue-collar crime within the region of each firm. The second instrument is an indicator that takes the value 1 if the firm's manager perceives crime, theft, and disorder as business obstacles for the firm. In all these robustness checks, we find that blue-collar crime damages external financing conditions.

These additional robustness checks are, however, restricted to firms that obtained access to financing (i.e., for which financing terms are observed), and do not control for selection into access to financing, as the Heckman model does (as explained in Section 3.1). Therefore, these models also serve as an indirect test of the extent to which selection into access to financing distorts the measured effects of blue-collar crime. Since both the PSM and IV approaches aim at controlling for the potential endogeneity of blue-collar crime, the similarity of the estimated effects resulting from the Heckman model would suggest that, after considering endogeneity concerns, selection into financing did not alter the measured impacts of blue-collar crime on financial outcomes.

We perform an additional robustness check, reported in Table B4 of Appendix B, where we execute a Heckman analysis in which the dependent variable is the difference between the firm's loan interest rate and the local Treasury Bill rate of the respective country, observed in the year in which the loan was granted. This robustness check is important because the global financial crisis of 2008/2009 overlaps with the sample period of our analysis. Therefore, the potentially different effects of the global financial crisis on each country should be reflected in the local Treasury Bill rate of each economy. Thus, Table B4 controls for the potentially different impacts of that crisis period on each country, in terms of the relationship between blue-collar crime and future financing conditions.[18] Taken together, Table 3 and Tables B1-B4 show that blue-collar crime negatively affects external financing conditions, which is in line with Hypothesis 1.

One might wonder if this result is only observable in the 13 Caribbean countries of the 2012 PROTEqIN survey. Thus, in Table B5 of Appendix B, we replicate the Heckman analysis presented in Table 3 for other countries, by exploiting the WBES and taking samples from multiple years (and thus building a panel dataset akin to the one described in Section 3). We select countries that are similar to those we focus on in this study, in terms of their *per capita* income and regulatory governance.

[18] Notice that we also include country*industry fixed effects, which should capture different economic conditions in each country and industry.

To select similar countries in Table B5, we obtain the level of *per capita* income and the consolidated regulatory governance score from the World Bank Global Indicators of Regulatory Governance. In the 13 Caribbean countries included in this study, 92.3 percent have a high or upper-middle level of income, and the regulatory governance scores range from 0 to 2.8. Consequently, we selected countries from the WBES that appeared in two different years, had high or middle levels of income, and had regulatory governance scores between 0 and 3.0. The countries that complied with such selection requirements were Angola, Argentina, Azerbaijan, Belarus, Botswana, the Dominican Republic, Ecuador, Mongolia, Paraguay, Peru, Turkey, and Uruguay. In Table B5, we present results for two samples: (i) all similar countries (as described above) and (ii) all similar countries excluding Angola, Argentina, and Turkey because they have larger populations relative to the Caribbean countries in our dataset, which could lead to a misleading comparison.

The problem with using only the WBES is that there is no information on loan interest rates and maturities. Nevertheless, we have data on the sizes of loans, which we use to analyze the effect of blue-collar crime on financing terms.[19] Table B5 shows that blue-collar crime reduces the sizes of the loans obtained by firms in other countries. This suggests that the negative effects of blue-collar crime on loan sizes are also observable in other similar economies.

One may also argue that our analysis might have a source of bias related to whether crime events are reported to the police. This is important because, if blue-collar crime negatively affected the access to and conditions of financing, then firms might strategically decide not to report blue-collar crime to the police. This strategic behavior would be aimed at reducing the

[19] In addition to the controls and fixed effects applied in Table 3, we also included year fixed effects to account for the fact that WBES was executed in various years (as opposed to our panel of Caribbean countries for all of which interviews took place in both 2009 and 2012).

chances of a potential lender being informed about such crime incidence. Therefore, if one were using blue-collar crime reported to the police to estimate the potential effects on financing terms, such analysis would suffer from reporting bias.

Regarding the previous point, the advantage of our analysis is that we do not rely on data from police crime reports. Instead, as explained in Section 3.2, we work with the WBES and the PROTEqIN surveys, which contain crime incidences self-reported to an independent surveyor under a confidentiality agreement. Thus, our data account for *real* blue-collar crime incidents, some of which were reported and some not reported to the police. Indeed, in Table B6 of Appendix B, we assess whether *real* blue-collar crime suffered in 2009 affects the likelihood of firms reporting crime events in 2012 to the police, using logit and probit analyses. In this table, the dependent variable is an indicator for whether the firm reported a blue-collar crime event suffered in 2012 to the police (conditional on the firm suffering a *real* crime event in 2012), while the key explanatory variable is the *real* incidence of blue-collar crime in 2009. Table B6 shows that there is no significant relationship between *real* crime in 2009 and the likelihood of reporting crime suffered in 2012 to the police. This result implies that the average firm does not appear to strategically underreport real crime suffered to the police (in which case a negative and significant coefficient would be observed). Notice also that there is a relatively high rate of reporting crime to the police. For example, of 254 firms with real blue-collar crime events in 2012, 229 firms (or 90.2 percent) reported these crime incidents to the police.[20] This evidence suggests that, even though our analysis is not contaminated by possible strategic underreporting of crime, crime underreporting seems to be low, thus not constituting a systematic source of bias.

[20] While we know whether firms report (or do not report) real blue-collar crime to the police in 2012 (and thus we can calculate the percentage of crime events reported in this year), the same information was not asked in the survey in 2009, but we do not expect the reporting rate in 2009 to have been too different.

One may also argue that our findings could be biased if blue-collar crime was mainly observed in firms with CEOs with relatively less extended business-government networks and/or in firms with lower political connections. To account for this possibility, all our models control for the firm-specific CEO's experience (which is a proxy for the CEO's business-governmental networks). In addition, we control for the percentage of each firm owned by the government (which proxies for the firm's political connections). However, as shown in Table 2, firms with blue-collar crime have more experienced CEOs and are more politically connected (on average, CEOs have 21.3 years of experience and 12.5 percent of these firms is owned by the government) than firms without blue-collar crime (which have, on average, CEOs with 16.7 years of experience and are 9.9 percent owned by the government). While this evidence goes against the initial intuition, it shows the importance of controlling for these characteristics when estimating the relation between blue-collar crime and financial outcomes.

Nevertheless, we perform an additional robustness check to examine the extent to which the business-government networks of CEOs might be biasing our results. In Table B7, we examine whether blue-collar crime in 2009 affects the likelihood of the firm replacing the CEO between 2009 and 2012. If blue-collar crime were mainly observed in firms with less business-government-connected CEOs, who can easily be replaced, we should observe that blue-collar crime events induce CEO replacements (as crime incidence negatively affects financing conditions). In Table B7, the dependent variable is an indicator for whether the CEO was replaced between 2009 and 2012, while the key explanatory variable is the incidence of blue-collar crime in 2009. The evidence reported in Table B7 indicates that the incidence of blue-collar crime does not trigger CEO replacements and, therefore, suggests that potential biases related to the CEO's connectedness are not pervasive.

4.2. Evidence on Information Leakages about Blue-collar Crime Events

As explained previously, firms do not have to reveal to lenders whether they have been subject to blue-collar crime. However, lenders may seek alternative sources of information to discover features that firms have not revealed, including any blue-collar crime events they may have experienced. Alternative sources of information about unrevealed firm characteristics include internal information leakages. Therefore, the potential negative effects of blue-collar crime on future financing terms may be explained by information flows, as described in Hypothesis 2.

To analyze the effect of alternative sources of information related to blue-collar crime on external financing conditions, we would need to use variables that capture information flows within companies, which are difficult to obtain. Nevertheless, we can use proxies for information flows that may provide insights related to lenders' use of alternative sources of information to discover unrevealed firm features such as blue-collar crime incidence.

4.2.1. *Information Flows through Firms' Employees*

The first source of information flows can be generated by the firm's own workers through information leakages. For instance, Zabojnik (2002), Baccara and Razin (2007), and Baccara and Bar-Isaac (2008) examine conditions that might induce employees to leak internal information. Accordingly, we expect that the negative effects of blue-collar crime on future financing conditions should mainly be observed within the sub-group of firms with many workers.

To analyze whether the effect of blue-collar crime on financing terms is larger among firms with more employees, we perform the following two econometric approaches: Firstly, we perform a sub-sample analysis. We divide firms into two sub-groups: (i) companies that are above the 50th percentile in terms of the number of workers; and (ii) those that are below the 50th percentile in terms of the number of workers. Then, we conduct the same Heckman analysis as described in equations (1) and (2) of Section 3.1, for each sub-group independently, the results of which are reported in Table 5. The left (right) panel shows estimates from the sub-sample of firms above (below) the 50th percentile in number of employees.[21]

[Insert Table 5 here]

Secondly, we perform another Heckman analysis similar to the one explained in equations (1) and (2), but considering a variant of equation (2), where we estimate a fully interacted model. In this second Heckman analysis, equation (1) is unaltered, and the variant of equation (2) has the following expression:

$$\begin{aligned} Y_{ijc,2012} \; = \; & \beta_1 \cdot Crime_{i,2009} + \beta_2 \cdot Crime_{i,2009} \cdot DumH + DumH \\ & + X'_{i,2009}\delta + \text{FEs} + \lambda\left(Z'_{i,2009}\hat{\gamma}\right) + \varepsilon_{ijr}, \end{aligned} \tag{3}$$

where $DumH$ denotes an indicator defined over a dichotomous firm-specific characteristic such that it takes the value of unity for firms that share that characteristic and zero otherwise. Other terms were defined in equation (2). In this second Heckman analysis, we estimate equations (1) and (3) with the full sample.

In the context of the heterogeneous effects with respect to the number of employees, $DumH$ equals unity if the firm is above the 50th percentile in terms of the number of workers, and 0 otherwise. This second Heckman analysis is important, because it allows us to test whether the coefficients in the left panel of Table 5 are statistically different from the coefficients in the

[21] In Table 5, and in the following tables in the main body of this study, we only show the effect of blue-collar crime on loan *interest rates* due to space limitations, but results for loan size and loan maturity are reported in Appendix C.

right panel. The main outcomes of this second Heckman analysis are also reported in Table 5. Here, ^{aaa}, ^{aa}, and ^{a} denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3) with the full sample, as described above).

Table 5 shows that the effect of blue-collar crime on the future interest rate is mainly observed in the sub-group of firms with more workers. For example, interest rates are significantly and positively related to the variable crime/sales, with a coefficient of 29.85, when the number of workers is above the 50th percentile. This implies that a one-standard-deviation increase in crime divided by sales in 2009, results in an average interest rate increase of 0.67 percentage points in 2012 (equivalent to a 6.4 percent increase in interest rates relative to the average 10.56 percent interest rate). However, in the same analysis for the sub-group of firms employing fewer workers, the coefficient is only 2.53 and not significant. Notice that these two estimated coefficients are statistically different from each other (using the second Heckman fully interacted model).

The results in Table 5 are surprising because firms with more employees are larger and thus less risky than small firms, meaning that a lower (not higher) effect of blue-collar crime on future interest rates should be expected for large firms. However, these results can be explained by the fact that, in firms with more workers, there are more opportunities for information related to blue-collar crime to be leaked. This is consistent with our argument that, even though firms are not required to reveal blue-collar crime incidents perpetrated against them, information leakages can help lenders find out anyway, which is consistent with Hypothesis 2. These results are also in line with previous empirical literature on information leakages regarding R&D. For example, Buss and Peukert (2015) find that firms with more employees face a greater likelihood of leakages about technical inventions than firms with fewer employees.

One could also conjecture that companies with many employees are more important and that blue-collar crime events perpetrated against them likely appear more often in the press. Thus, lenders may know about the occurrence of blue-collar crime incidents in larger firms due to press coverage, rather than through information leakages from the firms' own employees. We do not claim that information flows are restricted to internal information leakages alone. In fact, information leakages and press coverage are complementary sources of information flows.

4.2.2. *Information Flows in Small Communities*

Another potential factor that could exacerbate the rate at which information about being victim to blue-collar crime might reach creditors has to do with the context of the communities where the firms operate. One relevant contextual characteristic is the size of the city where the firm is located. If city size affects the rate at which informal communication, such as rumors, travels, this will affect the likelihood of creditors being aware of individual firms' experience of blue-collar crime.

There are at least three reasons why information flows could be relatively more intense in small towns than big cities. Firstly, in small towns, there is more chance people know each other, which will lead rumors to propagate faster (Kapferer, 2013). Secondly, in small towns, since important *local* events are rare, the local press will tend to report any blue-collar crime events suffered by firms in the geographical vicinity (since such crime is important local news), constituting a complementary source of quick information dissemination.

Thirdly, immediately after a blue-collar crime event occurs in a firm, the proportion of the population in the geographical vicinity of that firm that is aware of the crime event will in general be larger in small towns than big cities. Despite the fact that (by construction) a bigger and denser city will have a greater population within the vicinity than a small town, the *initial proportion* of the population that is aware of the event will be lower in the big city than in the small town. In this context, it is well known that the speed of rumor transmission towards reaching the complete population is positively related to the *initial proportion* of the population with that information (see Daley and Kendall, 1965). Therefore, the likelihood that crime rumors reach financial institutions will be relatively higher within small towns than big cities, since in the former the *initial proportion* of the population knowing the rumor will be larger than in the latter.

These arguments about differences in information flows between small and large communities are consistent with Dodd (1958), who finds that people engage in rumor transmission in small towns more than in larger cities. Consequently, a second proxy for information flows is related to the larger chances of rumor transmission in small communities. Thus, we explore the differential impacts with respect to the size of the city in which the firm is located. As in Table 5, we perform two econometric approaches to examine the heterogeneous effects of small communities on the relations between crime and future financial terms: a Heckman sub-sample analysis and a Heckman fully interacted model, which are reported in Table 6.

[Insert Table 6 here]

In Table 6, we divide the sample into two sub-groups: (i) firms located in capital cities and (ii) firms located in other areas. For each sub-group, as reported in Table 5, we estimate the same first Heckman models for the interest rate (i.e., by estimating equations (1) and (2) for each sub-group independently). Afterwards, in Table 6, we run the second Heckman interacted model (i.e., by estimating equations (1) and (3) with the full sample), but this time where $DumH$ equals 1 if the firm is in a capital city, and 0 otherwise.

This table shows that the effect of blue-collar crime on interest rates is mainly observed in small cities.[22] This finding provides additional support to our argument that information flows may be a reason why lenders find out about blue-collar crime events and therefore increase interest rates for firms that have been victims of them. The evidence presented in Table 6 is also consistent with Hypothesis 2.

4.3. Analyzing Alternative Explanations for the Relationship between Blue-collar Crime and Financing Terms

4.3.1. *Endogenous Reduction in Future Profitability and/or a Firm's Collateral*

One might argue that blue-collar crime events could negatively affect the value of physical assets (e.g., machinery, vehicles, equipment, land, or buildings) and future firm profitability. Thus, even though firms do not have to reveal to potential lenders whether they have experienced blue-collar crime, lenders may observe the reduced value of physical assets (which can be used as collateral) and firm profitability. Any such potential reduction in the future value of the physical assets and profitability of the company should negatively affect the external financing terms provided by lenders (i.e., lenders may observe that such firms are not financially healthy), which may, rather than information leakages, drive our results.

[22] Corresponding to Table 6, in Table C2 of Appendix C, we also present an analysis where the dependent variables are the loan amount and the loan maturity.

To assess this possibility, Table 7 presents PSM analyses on the relation between blue-collar crime in 2009 and the level of physical assets and profit margins in 2012. Table 7 shows that blue-collar crime in 2009 does not significantly affect the value of the firms' physical assets or their profit margins in 2012; and therefore, firms are financially healthy again in 2012.

[Insert Table 7 here]

One might think that, since crime in 2009 does not affect profitability in 2012, this finding could also suggest that worsened access to financing (due to crime in 2009) does not have *real effects* on crime-affected firms in 2012, raising concerns on the validity of the results. However, the results reported in Table 7 do not imply that worsened financing conditions in 2012 have no *real impact* on affected firms, due to two main reasons, which are explained as follows.

Firstly, in terms of physical assets in 2012, firms would not necessarily have to use the potential external funding in 2012 to buy physical assets in the same year. Instead, firms could use such external funding for developing new foreign markets, to improve the quality of services, or to increase workforce skills, amongst other possible alternative business investments. Therefore, Table 7 does not account for whether deteriorated financing conditions in 2012 (as a consequence of blue-collar crime) affect alternative business investments than those in physical assets.

Secondly, in terms of profits in 2012, suppose that firms would invest potential external funding in 2012 to develop new foreign markets (or to develop alternative business investments, such as those described in the previous paragraph). Nevertheless, firms would not necessarily recover such business investments in the same year (and it is even more unlikely that firms would immediately obtain *profits* in 2012). This is because, in any investment, there is a payback period that elapses before one recovers the funds expended (see, e.g., Boardman et al., 1982). Therefore, Table 7 does not say anything about whether deteriorated financing conditions in 2012 (due to crime) will have a *real future* effect on profit margins (i.e., after 2012).

Instead, the results in Table 7 suggest that crime-affected firms in 2009 (for which crime generated direct damages of 3.8 percent of annual sales in 2009) are financially healthy again in 2012. Thus, lenders in 2012 do not observe the direct damages of the crime from 2009, which could have been driving our results if they were observed.

Moreover, we rule out alternative explanations related to the fact that the incidence of blue-collar crime may increase the probability of blue-collar crime in the future. In Table B8 of Appendix B, we present logit and probit analyses for the effects of blue-collar crime suffered in 2009 on the likelihood of experiencing blue-collar crime in 2012. The dependent variable is an indicator of whether the firm was a victim of blue-collar crime in 2012, while the key explanatory variable is the incidence of blue-collar crime in 2009.

We show in Table B8 that the incidence of blue-collar crime is not persistent over time. The evidence reported in Tables 7 and B8 shows that the deleterious effects of blue-collar crime on the access to and conditions of external financing are present even if firms are financially healthy again in the future, and current crime events are not related to future crime incidence.

4.3.2. *Endogenous Effect of Regions with High Rates of Blue-collar Crime*

One might also think that the results in this study may not be driven by information flows from individual firms, but by lenders identifying regions with higher incidences of blue-collar crime, and thus offering loans with worsened conditions to firms operating within those areas.

Thus, we run an exercise using only firms that *did not* experience blue-collar crime in 2009. If lenders cannot individually identify firms that have experienced blue-collar crime (i.e., lenders only identify regions with high rates of blue-collar crime), we should observe worsened financing conditions for 'non-crime' firms in regions with high rates of blue-collar crime.

Then, we run a Heckman analysis where the dependent variable is the interest rate, and the main explanatory variable is $CrimeAround$.[23] This analysis is presented in Table 8. Similar analyses are reported in Table C3 of Appendix C, where the dependent variables are the loan amount and loan maturity respectively.

[Insert Table 8 here]

In Table 8, we run the Heckman analysis using three sub-samples. In the first column, we use all firms that did not experience blue-collar crime in 2009. In the second column, we only use non-crime firms located on small islands (i.e., we exclude Jamaica and the Bahamas). In the third column, we only use non-crime firms located in small countries, as measured by population (i.e., we exclude Jamaica, the Bahamas, and Trinidad & Tobago).

Table 8 evidences that a larger level of blue-collar crime happening in the region around non-crime firms does not increase their interest rates. The estimated coefficients on $CrimeAround$ are all statistically indistinguishable from zero. This means that lenders do not identify regions with higher chances of blue-collar crime to increase interest rates offered to firms in those regions. Thus, the results in Table 8 suggest that lenders are looking for blue-collar crime events relevant to each firm (i.e., firm-specific crime acts) and reflecting them in the cost of financing offered to such firms.

[23] As described in Section 4.1.2, $CrimeAround$ denotes the percentage of firms that have been victims of blue-collar crime within the geographical vicinity of each firm.

4.4. Firm Features that Mitigate the Negative Impact of Blue-collar Crime on Financing Conditions

In previous sections, we have reported that blue-collar crime events negatively affect future external financing. We have shown evidence suggesting that the negative effects of blue-collar crime on future financing terms are affected by information flows and we have ruled out alternative explanations. Thus, it is natural to analyze whether there is any element that firms may use as a mitigating factor against the negative effect of blue-collar crime on future external financing conditions.

We analyze, therefore, whether the CEO's work experience may ameliorate this negative impact, as described in Hypothesis 3. Thus, as for Table 5, we perform two econometric approaches: a Heckman sub-sample analysis and a Heckman fully interacted model, which are reported in Table 9.

[Insert Table 9 here]

In the first econometric approach, we split firms into two groups: (i) firms whose CEOs have less than (or equal to) 15 years of work experience, and (ii) firms whose CEOs have more than 15 years of work experience.[24] We estimate the Heckman models for the interest rate for each sub-sample, as we did for the results in Table 5 (see equations (1) and (2) in Section 3.1). In the second econometric approach, we run the second Heckman interacted model (i.e., we estimate equations (1) and (3) with the full sample), but this time $DumH$ equals 1 if the firm's CEO's work experience is less than (or equal to) 15 years, and 0 otherwise.

[24] Notice that the cutoff of 15 years of experience corresponds to the median CEO experience level in the sample.

Table 9 (right panel) shows that the undesirable effect of blue-collar crime on future interest rates is not observed in firms with experienced CEOs.[25] However, the undesirable effects are strong and significant in firms with less experienced CEOs (left panel). Moreover, the estimated coefficients in the right and left panels are statistically different from each other (based on running the second Heckman fully interacted model). This evidence is consistent with Hypothesis 3.

The findings observed in Table 9 are not surprising and are in line with previous empirical literature about the positive effects of the CEO's experience on firm performance (Deutsch and Ross, 2003; Falato et al., 2015). The results reported in Table 9 are as expected, due to at least three important elements related to the CEO's experience, which should help to mitigate the negative impact of blue-collar crime on future external financing terms. First, CEOs with more experience should have more control over internal information flows, as they are likely to establish information protocols concerning the critical information of the company. Second, a CEO with more experience should be better connected to financial institutions than a young CEO. Thus, the former should improve their firms' access to and conditions of external financing more than the latter. Moreover, and third, CEOs with more experience should have more bargaining skills with which to negotiate the conditions of external financing.

5. CONCLUDING REMARKS AND FUTURE RESEARCH

Despite the large literature on different forms of crime, the number of studies on the relationship between blue-collar crime and finance is limited. An important feature of blue-collar

[25] Corresponding to Table 9, in Table C4 of Appendix C, we report results where the dependent variables are the loan amount and loan maturity respectively.

crime events is that they do not need to be disclosed by the affected firms. Based on information leakages, we developed new hypotheses that conjectured that blue-collar crime would nevertheless impose costs (apart from the obvious direct costs of the crime) on a firm’s long-term reputation, thereby worsening its future business prospects. We empirically examined the impact of actual blue-collar crime events on one type of business prospect, namely a firm’s ability to access external finance and to obtain reasonable financing conditions. Our empirical analysis is different to that carried out in the previous literature on crime, which has focused either on the perception of crime as a business obstacle or on regional crime rates.

The evidence indicates that blue-collar crime not only induces losses (direct damages) for private firms, but also generates indirect costs that are persistent over time. We show that today's incidents of blue-collar crime affect the firms' reputations in the future, through increases in their credit risk (indirect costs), which persist in the following years and worsen the access to and conditions of future external financing. This is observed even if the firms are financially healthy in the future, at the time when the credit is required (and even if current crime events are unrelated to future crime incidence). The persistence of the credit status can be explained by the learning process followed by lenders, which takes time and is also affected by cognition biases.

We also show that, even though firms do not have to disclose to lenders that they have experienced blue-collar crime events, lenders may search through firms’ internal information leakages to find out whether firms have been subject to such crime incidents. Finally, we show that the CEO's work experience mitigates the negative impact of blue-collar crime on the conditions of future external financing.

The results suggest a rich agenda for further research. For instance, future research endeavors could include examinations of the effects of blue-collar crime on private firm innovation in terms of R&D, and investigations into how blue-collar crime might affect long-term management orientation, human resource decisions, marketing choices, business strategies, and other management decisions.

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Table 1: Summary Statistics. This table displays statistics of all the firms included in this study. We split the variables into three groups: Financial outcomes observed in 2012 (restricted to firms that obtained external financing), crime incidence observed in 2009, and firm characteristics observed in 2009.

Variable ID	Description	Mean	Median	SD	Min	Max	N
	Financial outcomes observed in 2012						
Interest rate	Average annual interest rate obtained from the loan/credit (%)	10.555	10.000	3.165	5.000	20.000	375
Log (loan amount)	The natural logarithm of the amount in $USD obtained from the most recent loan/credit that is still current	10.314	10.021	1.710	6.670	16.629	375
Loan maturity	Loan maturity in years	3.599	3.083	2.053	1.000	12.000	375
	Crime incidence observed in 2009						
Crime dummy	Dummy equals to 1 if the firm was subject to blue-collar crime in 2009	0.153	0.000	0.360	0.000	1.000	1324
Cost crime / sales	Total cost of blue-collar crime divided by the total firm sales in 2009	0.006	0.000	0.023	0.000	0.250	1324
	Firm characteristics observed in 2009						
Dummy capital city	Dummy variable equals to 1 if the firm is located in a capital city	0.143	0.000	0.350	0.000	1.000	1324
Firm age	Age of the firm in 2009 (in years)	17.747	14.000	12.911	1.000	59.000	1324
Number full-time workers	Number of workers in 2009	44.050	18.000	84.433	5.000	1313.00	1324
Dummy top manager male	The gender of the firm's top manager: 1=male, 0=female	0.800	1.000	0.400	0.000	1.000	1324
Years top manager experience	Years of top manager's experience in the industry	17.410	15.000	11.431	1.000	50.000	1324
Percentage own by government	Percentage of the firm that is owned by the government	0.121	0.000	1.877	0.000	51.000	1324
Dummy temporary workers	Dummy variable equals to 1 if the firm has temporary workers	0.417	0.000	0.493	0.000	1.000	1324
Dummy environment with informal workers	Dummy variable equals to 1 if the firm compete in an environment where workers do not have formal contracts	0.285	0.000	0.452	0.000	1.000	1324
Percentage own by largest	Percentage owned by the largest shareholder/owner in 2009	87.479	100.000	23.540	2.000	100.000	1324

Table 2: Differences in Firm-Specific Controls between Firms with and without Blue-Collar Crime. The first two columns display firm characteristics observed in 2009, separated by blue-collar crime incidence in 2009. The third column reports the p-value of the estimated coefficient on the crime dummy from a regression of each characteristic on the crime dummy, and country*industry fixed effects.

Firm characteristics observed in 2009	Mean (Std Dev) for firms that experienced crime	Mean (Std Dev) for firms that did not experience crime	p-value
Dummy capital city	0.163	0.139	0.826
	(0.37)	(0.346)	
Firm age	20.123	17.317	0.078
	(14.228)	(12.617)	
Number full-time workers	45.584	43.773	0.706
	(85.955)	(84.19)	
Dummy top manager male	0.739	0.811	0.063
	(0.44)	(0.392)	
Years top manager experience	21.300	16.706	0.078
	(12.042)	(11.178)	
Percentage own by government	0.125	0.099	0.767
	-1.951	-1.403	
Dummy temporary workers	0.557	0.392	0.004
	(0.498)	(0.488)	
Dummy environment with informal workers	0.389	0.267	0.001
	(0.489)	(0.442)	
Percentage own by largest	84.537	88.012	0.052
	(25.474)	(23.144)	

Table 3: Heckman Analysis for the Effect of Blue-Collar Crime on External Financing. This table presents a Heckman analysis (accounting for selection on loan approval). The dependent variables are the loan interest rate, the natural logarithm of the loan amount and the loan maturity granted by the financial institution. We employ two different analyses. The first has the dummy of the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. Firm controls are those listed in Table 1. We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

The Effect of Blue-Collar Crime on Interest Rates, Loan Amounts and Loan's Duration												
	Heckman Analysis											
	Interest rate				*Log (loan amount)*				*Loan maturity*			
Crime dummy	1.506***	1.448***			-0.302	-0.286			-0.503	-0.742**		
	(0.391)	(0.417)			(0.282)	(0.290)			(0.329)	(0.361)		
Cost crime / sales			17.03**	16.17*			-8.628***	-8.956***			-10.87**	-11.92**
			(8.636)	(8.678)			(3.157)	(3.202)			(5.000)	(5.342)
Constant	14.07***	14.33***	14.28***	14.53***	10.05***	10.30***	10.00***	9.663***	1.837	1.706	1.765	1.608
	(1.629)	(1.638)	(1.582)	(1.593)	(1.011)	(1.079)	(1.015)	(0.880)	(1.676)	(1.586)	(1.681)	(1.581)
Observations	1,324	1,324	1,324	1,324	1,324	1,324	1,324	1,324	1,324	1,324	1,324	1,324
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES		YES		YES		YES		YES		YES	
Industry FE	YES		YES		YES		YES		YES		YES	
Country*Industry FE		YES		YES		YES		YES		YES		YES

Table 4: Logit and Probit Analyses on the Access to External Financing. This table presents the estimated effects of blue-collar crime on the likelihood of obtaining external financing (conditional on having expressed the *intention* to obtain external financing). The dependent variable is an indicator of whether the firm obtained financing from a financial institution in 2012. We conduct two different analyses. The first has the dummy of the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. Firm controls are those listed in Table 1. We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-Collar Crime on Access to External Financing							
	Acess to Credit							
	Probit analysis				Logit analysis			
Crime dummy	-0.673**	-0.647*			-1.479**	-1.469**		
	(0.339)	(0.331)			(0.644)	(0.646)		
Cost crime / sales			-31.63***	-30.55***			-59.14***	-58.80***
			(11.15)	(10.58)			(21.50)	(21.32)
Constant	-0.872	-1.003*	-0.948	-1.078*	-1.606	-1.865	-1.720	-1.971*
	(0.651)	(0.609)	(0.650)	(0.605)	(1.191)	(1.154)	(1.173)	(1.130)
Observations	586	586	586	586	586	586	586	586
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES		YES		YES		YES	
Industry FE	YES		YES		YES		YES	
Country*Industry FE		YES		YES		YES		YES
	Marginal Effects							
	(Delta method for estimated standard errors)							
Crime dummy	-0.0838**	-0.0910**			-0.0793***	-0.0887***		
	(0.0384)	(0.0413)			(0.0306)	(0.0313)		
Cost crime / sales			-3.561***	-3.883***			-2.907***	-3.228***
			(1.120)	(1.197)			(0.954)	(1.052)

Table 5: Heterogeneity Analysis of Interest Rates with Respect to the Number of Workers. This table presents a Heckman analysis (accounting for selection on loan approval) exploring differential effects with respect to the number of workers. The dependent variable is the loan interest rate granted by the financial institution. The table reflects outcomes from two sub-groups: (i) companies that are above the 50th percentile in terms of the number of workers; and (ii) those that are below the 50th percentile in terms of the number of workers. For each sub-group, we estimate the Heckman models for the interest rate (i.e., by estimating equations (1) and (2) for each sub-group independently). We conduct two different analyses. The first has the dummy of the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. Firm controls are those listed in Table 1. We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. In addition, [aaa], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3), which reflect a second Heckman fully interacted model).

	Heterogeneity by Number of Workers			
	Heckman Analysis			
	Firms above the 50th percent. # workers		Firms below the 50th percent. # workers	
	Interest rate			
Crime dummy	1.993***		1.278*	
	(0.512)		(0.659)	
Cost crime / sales		29.85***,[aa]		2.525[aa]
		(7.133)		(9.710)
Constant	17.28***	17.19***	15.16***	15.71***
	(2.078)	(2.021)	(1.263)	(1.312)
Observations	643	643	681	681
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES

Table 6: Heterogeneity Analysis of Interest Rates with Respect to Size of City in which Firm is Located. This table presents a Heckman analysis (accounting for selection on loan approval) exploring differential effects with respect to the size of the city in which the firm is located. The dependent variable is the loan interest rate granted by the financial institution. The table reflects outcomes from two sub-groups: (i) firms located in capital cities; and (ii) firms located in other areas. For each sub-group, we estimate the Heckman models for the interest rate (i.e., by estimating equations (1) and (2) for each sub-group independently). We employ two different analyses. The first has the dummy of the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. Firm controls are those listed in Table 1. We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. In addition, ^{aaa}, ^{aa}, and ^{a} denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3), which reflect a second Heckman fully interacted model).

	Heterogeneity by Size of City in which Firm is Located			
	Heckman Analysis			
	Small city or rural area		Capital city	
	Interest rate			
Crime dummy	1.896***,aaa		0.765aaa	
	(0.431)		(1.291)	
Cost crime / total sales		18.91*		19.96
		(10.38)		(14.27)
Constant	13.51***	14.30***	19.10***	19.01***
	(1.773)	(1.736)	(2.259)	(2.060)
Observations	1,154	1,154	189	189
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES

Table 7: Propensity Score Matching Analysis of Physical Assets and Profit Margins after Blue-Collar Crime Events. In this table, we analyze the level of physical assets and the profit margin after blue-collar crime events have taken place. We present regressions using a propensity-score-matched model in which crime-experiencing firms are matched to non-crime firms using the firm characteristics summarized in Table 1. We run the regressions using two different matching models, one with probit and the other logit, and each with two different specifications of neighbors, for robustness. The dependent variables are the levels of physical assets and profit margins observed in 2012. Physical assets reflect the value of machinery, vehicles, equipment, land, and buildings. The profit margin is calculated as (Sales-Costs)/Sales. The explanatory variable is the dummy for the presence of crime in 2009. Robust standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-Collar Crime on Physical Assets and Profit Margins							
	Propensity Score Matching Analysis (matching based on firm characteristics)							
	Ln (physical assets in 2012)				*Profit margin in* 2012			
Crime dummy	0.303	0.176	0.133	0.172	-0.00650	-0.0180	-0.0200	-0.0182
	(0.187)	(0.165)	(0.118)	(0.141)	(0.0200)	(0.0200)	(0.0205)	(0.0205)
Observations	1,324	1,324	1,324	1,324	1,324	1,324	1,324	1,324
Matching model	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Nearest neighbors	1	1	10	10	1	1	10	10
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 8. Impact of Crime Externalities Caused by Victim Firms on Interest Rates of Non-crime Firms. This table presents a Heckman analysis of the effect of externalities caused by firms that suffer from blue-collar crime on non-crime firms. Specifically, we create a new variable, *CrimeAround*, which measures the percentage of firms that were the victim of crime in 2009, within each country-region. In this analysis, we only include firms that were not affected by a blue-collar crime event in 2009. All models control for industry fixed effects (FEs). We also control for the loans in the portfolios of firms in 2012 in terms of the use of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six groups, 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and up to 100 workers. Country considers Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Impact of Crime (caused by the victim firms) on Non-crime Firms		
	Heckman Analysis		
	All non-crime firms	Non-crime firms (small islands)	Non-crime firms (small countries)
	Interest Rate		
CrimeAround	-0.904	-1.512	0.317
	(0.972)	(1.249)	(1.633)
Constant	13.64***	8.616***	9.753***
	(1.548)	(1.679)	(1.614)
Observations	1104	956	748
Firm controls	YES	YES	YES
Industry FE	YES	YES	YES

Table 9: Heterogeneity Analysis of Interest Rates with Respect to CEO's Work Experience. This table presents a Heckman analysis (accounting for selection on loan approval) exploring differential effects with respect to the CEO's work experience. The dependent variable is the loan interest rate charged by the financial institution. The table reflects outcomes from two sub-groups: (i) firms whose CEOs have less than (or equal to) 15 years of work experience, and (ii) firms whose CEOs have more than 15 years of work experience. For each sub-group, we estimate the Heckman models for the loan interest rate (i.e., by estimating equations (1) and (2) for each sub-group independently). We conduct two different analyses. The first has the dummy for the occurrence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. Firm controls are those listed in Table 1. We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. In addition, ^{aaa}, ^{aa}, and ^{a} denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3), which reflect a second Heckman fully interacted model).

	Heterogeneity by CEO's Work Experience			
	Heckman Analysis			
	Firms whose CEO's experience ≤ 15 years		Firms whose CEO's experience > 15 years	
	Interest rate			
Crime dummy	2.201***^{,aa}		0.978^{aa}	
	(0.698)		(0.643)	
Cost crime / sales		26.33**^{,aa}		14.54^{aa}
		(10.25)		(10.41)
Constant	15.23***	15.93***	14.26***	14.05***
	(1.761)	(1.707)	(2.030)	(1.939)
Observations	704	704	620	620
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES

Appendix A

(Additional Data Analyses and Summary Statistics)

Table A1: Sample Breakdown by Country and Industry. This table shows the number of firms, by country and industry, analyzed in this study.

	Number of firms by country and industry			
	All firms		Firms with financial outcomes observed in 2012	
	Services	Manufacturing	Services	Manufacturing
Jamaica	70	54	22	23
Antigua Barbuda	75	21	15	5
Bahamas	47	25	16	8
Belize	53	49	24	22
Barbados	33	31	20	13
Dominica	92	16	21	6
Grenada	75	14	23	5
Guyana	28	16	7	4
St-Kitts and Nevis	71	22	13	8
Saint Lucia	62	51	15	12
St-Vincent and the Grenadines	62	51	21	3
Suriname	68	30	4	2
Trinidad & Tobago	36	36	42	21
Total	1324		375	

Table A2: Correlation Analysis. This table reports a correlation analysis of the main variables used in this study

	Interest rate	Log (loan amount)	Loan maturity	Crime dummy	Cost crime / sales	Dummy capital city	Firm age	# full-time workers	Dummy manager male	Manager experience	% own by gov.	Dummy temp. workers	Dummy informal workers	% own by largest
Interest rate	1.00													
Log (loan amount)	0.06	1.00												
Loan maturity	-0.03	-0.06	1.00											
Crime dummy	0.18	0.00	0.00	1.00										
Cost crime / sales	0.13	-0.05	-0.02	0.61	1.00									
Dummy capital city	0.35	-0.01	-0.06	0.02	0.02	1.00								
Firm age	0.02	0.16	-0.07	0.08	0.05	0.07	1.00							
# full-time workers	0.01	0.42	-0.01	0.01	0.03	0.08	0.24	1.00						
Dummy manager male	0.02	0.09	-0.08	-0.06	-0.05	0.04	0.08	0.07	1.00					
Manager experience	0.00	0.16	0.00	0.15	0.16	0.09	0.48	0.14	0.05	1.00				
% own by gov.	0.09	0.00	-0.06	0.00	0.07	0.07	0.03	0.16	0.01	0.05	1.00			
Dummy temp. workers	-0.04	0.10	-0.01	0.12	0.03	0.05	0.15	0.19	0.05	0.17	0.03	1.00		
Dummy informal workers	-0.03	0.02	-0.02	0.10	0.10	0.04	0.07	0.04	0.03	0.07	-0.03	0.12	1.00	
% own by largest	-0.01	0.04	-0.01	-0.05	-0.01	-0.05	-0.03	-0.06	0.01	-0.01	-0.01	-0.07	-0.07	1.00

Table A3: Summary Statistics of the Firm Determinants of Credit Access for the First Step of the Heckman Selection Model. This table contains statistics on of the firm determinants of credit access, which are used in the first step of the Heckman selection model (see equation (1)).

Variables used in the first-stage of the Heckman analysis for access to financing in 2012							
Variable ID	Description	Mean	Median	SD	Min	Max	N
	Firm characteristics observed in 2009						
G. profit margin	Gross profit margin of the firm in 2009 (without considering the costs of blue-collar crime in 2009), calculated as [Sales-Costs]/Sales	0.445	0.392	0.281	-2.000	1.000	1324
Dummy main market local	A dummy variable equals to 1 if the main market of the firm is local	0.476	0.000	0.500	0.000	1.000	1324
Dummy shareholding company	A dummy variable equals to 1 if the legal status of the firm is a private or public shareholding company	0.348	0.000	0.477	0.000	1.000	1324
Dummy external auditor	A dummy variable equals to 1 if the firm had its annual statements checked and certified by an external auditor in 2009	0.668	1.000	0.471	0.000	1.000	1324
Dummy corporation	A dummy variable equals to 1 for incorporated firms as of 2009	0.124	0.000	0.330	0.000	1.000	1324
% work. cap. financ. by external funds	% of working capital financed by external funds in the 2009 last fiscal year	39.723	35.000	28.578	0.000	100.000	1324
Dummy obst.: business licensing-permits	Dummy if manager perceive as an obstacle: business licensing and permits	0.316	0.000	0.465	0.000	1.000	1324
Dummy obst.: political environment	Dummy equals to 1 if manager perceive as an obstacle: political environment	0.357	0.000	0.479	0.000	1.000	1324
Dummy previous loan rejection	Dummy equals to 1 if the firm applied for a loan the last year, and this application	0.064	0.000	0.245	0.000	1.000	1324
Dummy high competition	Dummy equals to 1 if the firm has more than five competitors	0.784	1.000	0.412	0.000	1.000	1324
Dummy new patents	Dummy equals to 1 if the firm has introduced new patents	0.023	0.000	0.151	0.000	1.000	1324
Dummy obst.: access to finance	Dummy equals to 1 if manager perceive as an obstacle: access to finance	0.589	1.000	0.492	0.000	1.000	1324
Dummy obst.: corruption	Dummy equals to 1 if manager perceive as an obstacle: corruption	0.466	0.000	0.499	0.000	1.000	1324
Dummy security and insurances	Dummy equals to 1 if the firm invests in security and insurances	0.627	1.000	0.484	0.000	1.000	1324
Dummy innovation	Dummy equals to 1 if the firm has introduced new products or services	0.140	0.000	0.347	0.000	1.000	1324
Dummy overdraft account	Dummy equals to 1 if the firm has firm has an overdraft account	0.668	1.000	0.471	0.000	1.000	1324

Table A4: Differences between Firms with and without Blue-Collar Crime in Terms of the Firm Determinants of Credit Access for the First Step of the Heckman Selection Model. This table presents an analysis concerning whether firm determinants of credit access (which are used in the first step of the Heckman selection model, see equation (1)) differ between firms with and without blue-collar crime in 2009. The third column reports the p-value of the estimated coefficient on the crime dummy from a regression of each characteristic on the crime dummy and country*industry fixed effects.

Variables used in the first-stage of the Heckman analysis for access to financing in 2012			
Firm characteristics observed in 2009	Mean (Std Dev) for firms that experienced crime	Mean (Std Dev) for firms that did not experience crime	p-value
G. profit margin	0.449	0.425	0.729
	(0.282)	(0.270)	
Dummy main market local	0.473	0.493	0.136
	(0.499)	(0.501)	
Dummy shareholding company	0.345	0.365	0.669
	(0.476)	(0.482)	
Dummy external auditor	0.66	0.714	0.638
	(0.474)	(0.453)	
Dummy corporation	0.115	0.172	0.424
	(0.319)	(0.379)	
% work. cap. financ. by external funds	38.85	44.57	0.459
	(28.430)	(29.000)	
Dummy obst.: business licensing-permits	0.309	0.355	0.197
	(0.462)	(0.480)	
Dummy obst.: political environment	0.356	0.365	0.930
	(0.479)	(0.482)	
Dummy previous loan rejection	0.0598	0.0887	0.137
	(0.237)	(0.285)	
Dummy high competition	0.781	0.803	0.281
	(0.414)	(0.399)	
Dummy new patents	0.0205	0.0394	0.265
	(0.142)	(0.195)	
Dummy obst.: access to finance	0.603	0.512	0.547
	(0.489)	(0.501)	
Dummy obst.: corruption	0.458	0.512	0.270
	(0.498)	(0.501)	
Dummy security and insurances	0.606	0.744	0.010
	(0.489)	(0.438)	
Dummy innovation	0.145	0.108	0.190
	(0.353)	(0.312)	
Dummy overdraft account	0.664	0.695	0.566
	(0.473)	(0.462)	

Appendix B

(Robustness Checks)

Table B1: OLS Analysis of the Effect of Blue-Collar Crime on External Financing. This table presents OLS analyses restricted to firms that applied for and obtained a loan. The dependent variables are the loan interest rate, the natural logarithm of the loan amount, and the loan maturity granted by the financial institution. We carry out two different analyses. The first has the dummy for the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. Firm controls are those listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

The Effect of Blue-Collar Crime on Interest Rates, Loan Amounts and Loan's Duration												
	OLS Analysis											
	Interest rate				*Ln (loan amount)*				*Loan maturity*			
Crime dummy	1.533***	1.477***			-0.304	-0.287			-0.482	-0.717*		
	(0.415)	(0.450)			(0.285)	(0.299)			(0.337)	(0.376)		
Cost crime / sales			17.43*	16.51*			-8.600***	-8.854**			-10.56**	-11.63**
			(9.465)	(9.694)			(3.220)	(3.354)			(5.023)	(5.398)
Constant	15.90***	16.09***	16.19***	16.40***	9.341***	9.544***	9.307***	9.511***	3.375***	3.380***	3.307***	3.248***
	(0.889)	(0.884)	(0.919)	(0.927)	(0.450)	(0.490)	(0.422)	(0.478)	(0.781)	(0.788)	(0.750)	(0.750)
R-squared	0.472	0.498	0.460	0.488	0.370	0.385	0.376	0.391	0.128	0.182	0.131	0.182
Observations	375	375	375	375	375	375	375	375	375	375	375	375
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES		YES		YES		YES		YES		YES	
Industry FE	YES		YES		YES		YES		YES		YES	
Country*Industry FE		YES		YES		YES		YES		YES		YES

Table B2: Propensity Score Matching Analysis for the Effect of Blue-Collar Crime on External Financing. This table presents regressions using a propensity-score-matched sample in which crime-experiencing firms are matched to non-crime firms using the firm characteristics summarized in Table 1. This analysis is restricted to firms that applied for and obtained a loan. We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. We run the regressions using two different matching models, one probit and the other logit, and each with two different specifications of neighbors, for robustness. The dependent variables are the loan interest rate, the natural logarithm of the loan amount, and the loan maturity granted by the financial institution. The explanatory variable is the dummy for the presence of crime in 2009. Robust standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

The Effect of Blue-Collar Crime on Interest Rates, Loan Amounts and Loan's Duration												
	Propensity Score Matching Analysis (matching based on firm characteristics)											
	Interest rate				*Log (loan amount)*				*Loan maturity*			
Crime dummy	1.616***	1.488***	1.846***	1.845***	-0.327	-0.295	-0.405***	-0.408**	-0.268	-0.317	-0.311	-0.295
	(0.492)	(0.503)	(0.547)	(0.555)	(0.247)	(0.231)	(0.140)	(0.177)	(0.342)	(0.332)	(0.390)	(0.392)
Observations	375	375	375	375	375	375	375	375	375	375	375	375
Matching model	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Nearest neighbors	1	1	10	10	1	1	10	10	1	1	10	10
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table B3: Instrumental Variable Analysis for the Effect of Blue-Collar Crime on External Financing. This table presents an instrumental variable (IV) approach, restricted to firms that applied for and obtained a loan. In this IV analysis, firm-specific crime variables are instrumented with both the incidence of crime events within the vicinity of the firm, and whether the firm's manager perceives crime, theft, and disorder as business obstacles. The dependent variables are the loan interest rate, the natural logarithm of the loan amount, and the loan maturity granted by the financial institution. We carry out two different analyses. The first has the dummy for the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. All models control for country*industry cross fixed effects (FEs). We also control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

The Effect of Blue-Collar Crime on Interest Rates, Loan Amounts and Loan's Duration						
	Instrumental Variable Analysis					
	Interest rate		*Log (loan amount)*		*Loan maturity*	
	Second-stage					
Crime dummy	1.541*		-0.977*		-1.404**	
	(0.927)		(0.521)		(0.669)	
Cost crime / sales		30.609*		-19.414*		-27.887**
		(17.365)		(10.201)		(14.091)
Constant	16.073***	16.330***	9.725***	9.562***	3.560***	3.326***
	(0.905)	(0.874)	(0.491)	(0.475)	(0.724)	(0.704)
	First-stage instrument					
Crime around	0.780***	0.039***	0.780***	0.039***	0.780***	0.039***
	(0.132)	(0.008)	(0.132)	(0.008)	(0.132)	(0.008)
Dummy manager perceive as obst. crime and disorder	0.154***	0.007***	0.154***	0.007***	0.154***	0.007***
	(0.032)	(0.002)	(0.032)	(0.002)	(0.032)	(0.002)
First stage's F-stat	40.452	9.71	40.452	9.71	40.452	9.71
Observations	375	375	375	375	375	375
Firm controls	YES	YES	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES	YES	YES

Table B4: Heckman Analysis of Interest Rates - Local Treasury Bill (t-bill). This table presents a Heckman analysis (accounting for selection on loan approval). The dependent variable is the difference between the interest rate on the loans granted to the firm and the t-bill rate of the respective country, for the year in which the loan was granted. The t-bill rates were obtained from the World Bank's website. We carry out two different analyses. The first has the dummy for the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. We control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-collar Crime on Interest Rate Spreads			
	Heckman Analysis			
	Interest rate - local t-bill (*respective country*)			
Crime dummy	1.517***	1.463***		
	(0.406)	(0.433)		
Cost crime / sales			15.95*	15.16*
			(8.769)	(8.895)
Constant	-5.298***	-5.063***	-5.091***	-4.859***
	(1.725)	(1.705)	(1.687)	(1.669)
Observations	1,324	1,324	1,324	1,324
Firm controls	YES	YES	YES	YES
Country FE	YES		YES	
Industry FE	YES		YES	
Country*Industry FE		YES		YES

Table B5: Heckman Analysis of Loan Amounts Obtained in External Financing – Other Similar Countries. This table presents a Heckman analysis (accounting for selection on loan approval). The dependent variable is the natural logarithm of the loan amount granted by the financial institution. We include firms (interviewed in the WBES) whose countries are similar in terms of income and regulatory governance to those covered in the PROTEqIN survey. To select similar countries, we obtain the level of income and the consolidated regulatory governance score from the World Bank Global Indicators of Regulatory Governance. In the 13 countries included in this study (see Table A1), 92.3 percent have a high or upper-middle level of income, and the regulatory governance scores range from 0 to 2.8. We selected countries from the WBES in two different years, in the high or middle levels of income, and with regulatory governance scores between 0 and 3.0. The countries selected were Angola, Argentina, Azerbaijan, Belarus, Botswana, the Dominican Republic, Ecuador, Mongolia, Paraguay, Peru, Turkey, and Uruguay. We present results for two samples: (i) with all similar countries (as described above); and (ii) with all similar countries excluding Angola, Argentina, and Turkey, because they have larger populations relative to the Caribbean countries in this study, which could potentially provide a misleading comparison. We employ two different analyses. The first has the dummy for the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales. Both key explanatory variables were obtained from the first time that the firm was interviewed in the WBES. We control for the loans in the portfolios of the firms in terms of the use of collateral and year in which the loan was granted. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Angola, Argentina, Azerbaijan, Belarus, Botswana, the Dominican Republic, Ecuador, Mongolia, Paraguay, Peru, Turkey, and Uruguay. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-Collar Crime on Loan Amounts							
	Heckman Analysis							
	Other similar countries from WBES				Other similar countries from WBES (without Angola, Argentina and Turkey)			
	Ln (loan amount)							
Crime dummy	-0.239	-0.242			-0.316*	-0.307		
	(0.154)	(0.160)			(0.192)	(0.193)		
Cost crime / sales			-5.514**	-6.146***			-4.105***	-4.867***
			(2.149)	(2.204)			(1.480)	(1.694)
Constant	13.96***	12.96***	13.94***	12.94***	11.58***	11.89***	11.56***	11.88***
	(0.664)	(0.573)	(0.665)	(0.574)	(0.765)	(0.772)	(0.768)	(0.787)
Observations	1,946	1,946	1,946	1,946	1,235	1,235	1,235	1,235
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES		YES		YES		YES	
Industry FE	YES		YES		YES		YES	
Country*Industry FE		YES		YES		YES		YES

Table B6: Logit and Probit Analyses on the effect of Previous Blue-Collar Crime on the Reporting of New Crime Events to the Police. This table presents the estimated effects of blue-collar crime suffered in 2009 on the likelihood of firms reporting crime events in 2012 to the police. The dependent variable is an indicator for whether the firm reported to the police a blue-crime event in 2012 (conditional on the firm experiencing crime in 2012), while the explanatory variable is the incidence of blue-collar crime in 2009. We control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-Collar Crime in 2009 on Reported Blue-Collar Crime in 2012			
	Police report dummy (2012)			
	Probit analysis		Logit analysis	
Crime dummy (2009)	0.451	0.441	0.716	0.698
	(0.275)	(0.270)	(0.482)	(0.472)
Constant	-0.637***	-0.796***	-0.936**	-1.241***
	(0.236)	(0.220)	(0.403)	(0.384)
Observations	1324	1324	1324	1324
Firm controls	YES	YES	YES	YES
Country FE	YES		YES	
Industry FE	YES		YES	
Country*Industry FE		YES		YES
	Marginal Effects (Delta method for estimated standard errors)			
Crime dummy (2009)	0.117	0.112	0.105	0.101
	(0.0724)	(0.0696)	(0.0719)	(0.0691)
	Sample characteristics			
Firms with crime incidence in 2012	254			
Firms with crime incidence reported in 2012	229			
Percentage of police reporting in 2012	90.2%			

Table B7: Logit and Probit Analyses on the effect of Blue-Collar Crime on CEO Replacement. This table presents the estimated effects of blue-collar crime suffered in 2009 on the likelihood of CEO replacement between 2009 and 2012. The dependent variable is a dummy that equals 1 if the firm's CEO's is replaced between 2009 and 2012, and 0 otherwise, while the explanatory variable is the incidence of blue-collar crime in 2009. We control for all firm characteristics listed in Table 1. Despite the identity of the manager not being available in our data, we obtained a proxy for the CEO's replacement by calculating the difference between the CEO's years of experience in 2009 and that in 2012, which should be equal to three years (± one year). Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-Collar Crime in 2009 on Manager Replacement between 2009 y 2012			
	Dummy manager replacement between 2009 y 2012			
	Probit analysis		Logit analysis	
Crime dummy (2009)	-0.0412	-0.0439	-0.113	-0.115
	(0.125)	(0.117)	(0.235)	(0.217)
Constant	-0.955***	-0.974***	-1.599***	-1.624***
	(0.294)	(0.327)	(0.529)	(0.591)
Observations	1,324	1324	1,324	1324
Firm controls	YES	YES	YES	YES
Country FE	YES		YES	
Industry FE	YES		YES	
Country*Industry FE		YES		YES
	Marginal Effects (Delta method for estimated standard errors)			
Crime dummy (2009)	-0.0105	-0.0107	-0.0159	-0.0152
	(0.0318)	(0.0284)	(0.0330)	(0.0287)
	Sample characteristics			
Percentage of manager replacement (2009-2012) across all firms	18.8%			
Percentage of manager replacement (2009-2012) conditional on crime incidence in 2009	18.2%			

Table B8: Logit and Probit Analyses on the Incidence of Future Crime. This table presents the estimated effects of blue-collar crime suffered in 2009 on the likelihood of experiencing blue-collar crime in 2012. The dependent variable is an indicator for whether the firm was a victim of blue-collar crime in 2012. We control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Effect of Blue-Collar Crime in 2009 on Blue-Collar Crime in 2012			
	Crime dummy (2012)			
	Probit analysis		Logit analysis	
Crime dummy (2009)	0.406	0.397	0.628	0.609
	(0.260)	(0.255)	(0.448)	(0.438)
Constant	-0.658***	-0.830***	-0.977**	-1.306***
	(0.253)	(0.244)	(0.431)	(0.425)
Observations	1324	1324	1324	1324
Firm controls	YES	YES	YES	YES
Country FE	YES		YES	
Industry FE	YES		YES	
Country*Industry FE		YES		YES
	Marginal Effects (Delta method for estimated standard errors)			
Crime dummy (2009)	0.107	0.104	0.0961	0.0920
	(0.0669)	(0.0645)	(0.0669)	(0.0645)

Appendix C:

(Additional Results for Loan Size and Loan Maturity)

Table C1: Heterogeneity Analysis of Loan Size and Loan Maturity with Respect to the Number of Workers. This table presents a Heckman analysis (accounting for selection on loan approval) exploring differential effects with respect to the number of workers. The dependent variables are the loan size and the loan maturity granted by the financial institution. The table reflects outcomes from two sub-groups: (i) companies that are above the 50th percentile in terms of the number of workers and (ii) those that are below the 50th percentile in terms of the number of workers. For each sub-group, we estimate the Heckman models for the loan size and the loan maturity (i.e., by estimating equations (1) and (2) for each sub-group independently). We conduct two different analyses. The first has the dummy for the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. We control for the loans in the portfolios of the firms in 2012 in terms of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. In addition, [aaa], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3), which reflect a second Heckman fully interacted model).

	Heterogeneity by Number of Workers			
	Heckman Analysis			
	Firms above the 50th percent. # workers		Firms below the 50th percent. # workers	
	Log (loan amount)			
Crime dummy	-0.375		-0.105	
	(0.361)		(0.507)	
Cost crime / sales		-14.26***		-2.432
		(4.062)		(5.520)
Constant	10.11***	10.14***	9.317***	9.327***
	(1.431)	(1.397)	(0.929)	(0.982)
Observations	643	643	681	681
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES
	Loan maturity			
Crime dummy	-0.812		-0.994**	
	(0.568)		(0.499)	
Cost crime / sales		-10.29		-15.50**
		(9.121)		(7.136)
Constant	3.051	3.081*	0.710	0.615
	(1.903)	(1.873)	(2.272)	(2.197)
Observations	643	643	681	681
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES

Table C2: Heterogeneity Analysis of Loan Size and Loan Maturity with Respect to the Size of the City in which the Firm is Located. This table presents a Heckman analysis (accounting for selection on loan approval) exploring differential effects with respect to the size of the city in which the firm is located. The dependent variables are the loan size and the loan maturity granted by the financial institution. The table reflects outcomes from two sub-groups: (i) firms located in capital cities and (ii) firms located in other areas. For each sub-group, we estimate the Heckman models for the loan size and the loan maturity (i.e., by estimating equations (1) and (2) for each sub-group independently). We employ two different analyses. The first has the dummy for the presence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. We control for the loans in the portfolios of the firms in 2012 in terms of the use of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. In addition, ^{aaa}, ^{aa}, and ^{a} denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3), which reflect a second Heckman fully interacted model).

	Heterogeneity by Size of City in which Firm is Located			
	Heckman Analysis			
	Small city or rural area		Capital city	
	Log (loan amount)			
Crime dummy	-0.675***,^{aaa}		2.418***,^{aaa}	
	(0.237)		(0.553)	
Cost crime / sales		-11.96***		23.55*
		(2.736)		(14.05)
Constant	10.84***	10.55***	8.622***	7.985***
	(1.120)	(1.121)	(0.837)	(0.848)
Observations	1,154	1,154	189	189
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES
	Loan maturity			
Crime dummy	-0.673		-1.023	
	(0.430)		(0.800)	
Cost crime / sales		-12.40**		5.448
		(6.047)		(11.73)
Constant	1.625	1.345	2.443**	2.848**
	(1.818)	(1.788)	(1.202)	(1.215)
Observations	1,154	1,154	189	189
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES

Table C3. Impact of Crime Externalities Caused by Victim Firms on Loan Size and Maturity of Non-crime Firms. This table presents a Heckman analysis of the effect of externalities caused by firms that suffer from blue-collar crime on non-crime firms. Specifically, we create a new variable, *CrimeAround*, which measures the percentage of firms that were the victim of crime in 2009, within each country-region. In this analysis, we only include firms that were not affected by a blue-collar crime event in 2009. All models control for industry fixed effects (FEs). We also control for the loans in the portfolios of firms in 2012 in terms of the use of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six groups, 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and up to 100 workers. Country considers Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	The Impact of Crime (caused by the victim firms) on Non-crime Firms		
		Heckman Analysis	
	All non-crime firms	Non-crime firms (small islands)	Non-crime firms (small countries)
		Log (loan amount)	
CrimeAround	-0.380	-0.905	-0.981
	(0.485)	(0.654)	(0.854)
Constant	10.82***	9.801***	9.950***
	(1.088)	(1.014)	(0.855)
Observations	1104	956	748
Firm controls	YES	YES	YES
Industry FE	YES	YES	YES
		Loan maturity	
CrimeAround	-0.416	-0.846	-0.107
	(1.182)	(1.663)	(2.456)
Constant	1.449	3.841**	2.470
	(1.401)	(1.694)	(1.862)
Observations	1104	956	748
Firm controls	YES	YES	YES
Industry FE	YES	YES	YES

Table C4: Heterogeneity Analysis of Loan Size and Maturity with Respect to CEO's Work Experience. This table presents a Heckman analysis (accounting for selection on loan approval) exploring differential effects with respect to the CEO's work experience. The dependent variables are the loan size and the loan maturity. The table reflect outcomes from two sub-groups: (i) firms whose CEOs have less than (or equal to) 15 years of work experience, and (ii) firms whose CEOs have more than 15 years of work experience. For each sub-group, we estimate the Heckman models for the loan size and the loan maturity (i.e., by estimating equations (1) and (2) for each sub-group independently). We conduct two different analyses. The first has the dummy for the occurrence of crime against the company as the key explanatory variable. The second uses the total cost of crime against the company divided by its total sales in 2009. We control for the loans in the portfolios of the firms in 2012, in terms of the use of collateral. In addition, we control for all firm characteristics listed in Table 1. Estimated standard errors, shown in parentheses, are two-way clustered by the size and country of the firm. Size considers six strata: 0 to 19 workers, 20 to 39, 40 to 59, 60 to 79, 80 to 99, and above 100 workers. Countries included are Antigua-Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, Saint Lucia, St Kitts and Nevis, St Vincent and Grenadines, Suriname, the Bahamas, and Trinidad & Tobago. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. In addition, [aaa], [aa], and [a] denote significance at 1%, 5%, and 10%, respectively, regarding whether the coefficients in the left panel are different from the respective coefficients in the right panel (i.e., based on estimating equations (1) and (3), which reflect a second Heckman fully interacted model).

	Heterogeneity by CEO's Work Experience			
	Heckman Analysis			
	Firms whose CEO's experience ≤ 15 years		Firms whose CEO's experience > 15 years	
	Log (loan amount)			
Crime dummy	-0.773**		-0.158	
	(0.342)		(0.339)	
Cost crime / sales		-12.47**		-7.959**
		(5.341)		(3.575)
Constant	9.068***	8.871***	8.875***	8.960***
	(1.135)	(1.119)	(1.019)	(1.034)
Observations	704	704	620	620
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES
	Loan maturity			
Crime dummy	-0.339		-0.854*	
	(0.497)		(0.453)	
Cost crime / sales		-29.08***,[aaa]		-6.975[aaa]
		(6.512)		(6.405)
Constant	2.636**	2.921**	5.316***	5.450***
	(1.285)	(1.280)	(1.352)	(1.433)
Observations	704	704	620	620
Firm controls	YES	YES	YES	YES
Country*Industry FE	YES	YES	YES	YES