Accepted for publication in the Journal of Financial Regulation and Compliance. Date of acceptance: 04-Dec-2024. Published online: 06-Jan-2025. DOI: 10.1108/JFRC-10-2024-0193. Please cite as: "Rose, K.J. and Jensen, R.I.T. (2025), "Transaction monitoring in search of professional money launderers – a microeconomic model", Journal of Financial Regulation and Compliance, Vol. ahead-of-print No. ahead-of-print."

Transaction Monitoring in Search of Professional Money Launderers – a Microeconomic Model

Kalle Johannes Rose

Copenhagen Business School, Frederiksberg, Denmark

Rasmus Ingemann Tuffveson Jensen

Independent Researcher, Skanderborg, Denmark

Abstract

Purpose - We formulate a microeconomic model to investigate the effects of current anti-money laundering regulation. Our model is motivated by the requirement that banks undertake risk-based transaction monitoring, using "risk signals" to separate benevolent bank clients and money launderers.

Design/methodology/approach - We employ methodology from the functional school of law and economics, holding that structural forces may hinder the development of efficient legal rules. Our goal is to offer economic insights to address inefficiencies at a meta-level. Assuming money launderers have specific preferences and strategies, we model how they hide their activities. Our model allows us to investigate how money launderers respond to external shocks and policy changes.

Findings - As money launderers use resources to hide their activities, we find several noteworthy effects. For instance, increasing criminal penalties may decrease the amount of money laundering that is detected. Furthermore, wealthy money launderers may rarely be detected.

Originality - The academic literature on anti-money laundering is still relatively limited. Our results suggest regulators should be aware of unintended and potentially adverse effects of current regulation.

Research limitations/implications - Our paper only presents theoretical results.

Keywords Anti-money laundering, financial crime, risk-based regulation.

Paper type Research paper.

1 Introduction

Money laundering is a significant problem for banks, regulators, and law enforcement agencies worldwide, estimated to amount to 2.1-4 percent of the world economy (Pietschmann *et al.*, 2011). To prevent and detect money laundering, banks play an important role. In particular, banks are required to monitor client behavior using a risk-based approach. The idea is that banks should flag and report "unusual" or "suspicious" transactions. This is most often done with automatic transaction monitoring systems, using simple and confidential rules to raise alerts for investigation by bank officers (Verhage, 2009; Demetis, 2018).

In this paper, we frame transaction monitoring as a microeconomic problem faced by money launderers. Our methodology follows the functional school of law and economics (Klick and Parisi, 2015), holding that structural forces may hinder the development of efficient legal rules. Our goal is to offer economic insights to address inefficiencies at a meta-level. Our motivating idea is inspired by work of Pellegrina *et al.* (2023) and Rizzolli and Saraceno (2013). In particular, we imagine a launderer L (with a given amount of money M to be laundered) and a benevolent bank client B. Through their behavior, L and B emit "risk signals" s with probability density functions $l_M(s)$ and $b(s)$. Note that $l_M(s)$ may depend on the launderer's amount of money M. We are intentionally vague about how the risk signals are emitted; they simply serve to rank behavior in terms of money laundering risk. Banks, doing risk-based transaction monitoring, report a client if they emit a signal s over some threshold T (exogenously given from the launderer's perspective). However, knowing this and having access to a set of strategies with different costs, L may try to reduce their signal.

This effectively pushes $l_M(s)$ to the left, reducing the launderer's probability of detection. An illustration is given in Fig. 1. We stress that the ideas presented in this paragraph only motivate our model, presented in full in Section 4.

Our actual model builds on two main assumptions. First, costlier strategies have non-decreasing (and generally higher) probabilities of avoiding detection. Second, launderers have increasing and concave utility functions, displaying diminishing marginal utility. Given the assumptions (discussed in Section 5), our model yields several noteworthy results. In particular, increasing criminal penalties for money laundering may reduce the amount of laundering that is detected. Furthermore, introducing publicly known transaction monitoring rules may lower a launderer's expected utility. Finally, wealthy launderers pose a significant challenge; based on our model, we hypothesize that they rarely are detected. Our results suggest regulators should be aware of unintended and potentially adverse effects of anti-money laundering (AML) regulation.

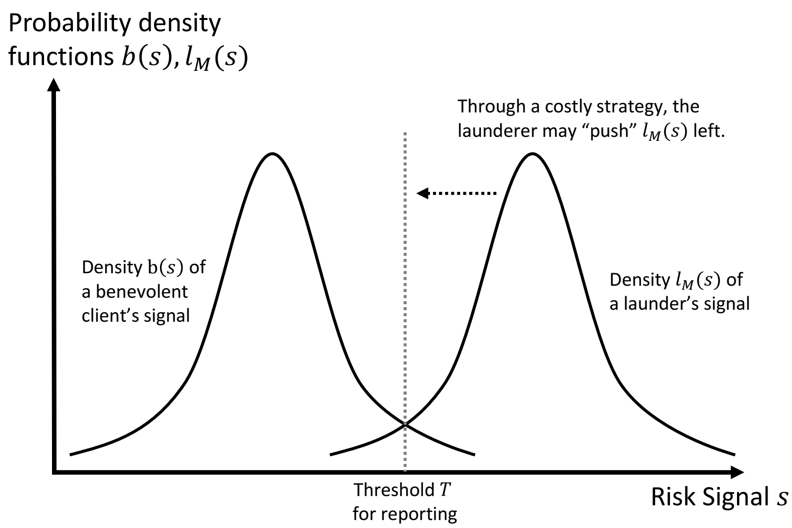

Fig. 1: Illustration of our motivating idea. We imagine a money launderer L (with an amount of money M to be laundered) and a benevolent bank client B emit risk signals s with probability density functions $l_M(s)$ and $b(s)$. A bank will report a client emitting a signal s over some threshold T. However, having access to a set of strategies with different costs, the launderer may try to reduce their signal, effectively pushing $l_M(s)$ to the left.

The rest of our paper is structured as follows. Section 2 provides an introduction to AML regulation. Section 3 reviews, discusses, and reflects on related literature. Section 4 presents and develops our model. Finally, Section 5 contains a discussion and conclusion.

2 Anti-money Laundering Regulation

In this section, we give an introduction to AML regulation in the European Union (EU). Subsection 2.1 provides an overview while Subsection 2.2 elaborates on due diligence and transaction monitoring requirements.

2.1 Anti-money Laundering and the Risk-Based Approach

Money laundering is the process whereby illicit funds are channeled through the financial system to conceal their true origin. The process allows illicit funds to be reinvested into illegal enterprises or to be used to acquire otherwise unattainable goods and services. Money laundering is often thought to involve three stages: placement, layering, and integration (Reuter and Truman, 2004). During placement, illicit funds are introduced into the financial system. During layering, funds are moved around to hide their origin. Finally, during integration, funds are used to buy products or services. This simplified view of the money laundering process is motivated by the wide variety of methods used to launder money. However, while common, the usefulness of the "placement-layering-integration" terminology is questionable (Reuter and Truman, 2004). For example, imagine a launderer with a large amount of cash. If the launderer can convince a bank in Denmark that they have obtained the cash in a legitimate way, they may deposit (and later use) the cash without being reported. Thus, it is possible to do money laundering without layering.

In 1991, the EU introduced its first directive to combat money laundering (1AMLD, 1991). Since then, several regulatory packages have been adopted, most recently in 2024 (6AMLD, 2024). According to the current EU definition of money laundering, dictated by the fourth AML directive, the concept can be defined as "the conversion or transfer of property (...) for the purpose of concealing or disguising the illicit origin of the property (...)" (4AMLD, 2015). The definition aligns with the framework and recommendations of the Financial Action Task Force, an intergovernmental organization established to combat money laundering in 1989 (FATF, 2023).

Regulatory approaches to AML have evolved in line with digitization and globalization. Early EU regulation used a rule-based approach (Unger and van Waarden, 2009). With the introduction of the fourth AML directive in 2015, the EU changed its approach to be risk-based. The intention was to obtain a more dynamic regulatory framework. Some elements in the present regulatory approach are, however, still rule-based and involve minimal thresholds. For example, banks are required to employ due diligence measures when they make an (even one-off) transfer of more than €1000. The basic principle of risk-based regulation is to control relevant risks rather than enforce "checkbox compliance." The key objective is to allocate resources effectively. Hence, banks should allocate more resources to high-risk areas than low-risk areas.

2.2 Due Diligence and Transaction Monitoring Requirements

Before establishing a relationship with a client, a bank is required to collect information about said client in a due diligence process (FATF, 2023). This is commonly known as Know-Your-Customer or Know-Your-Client (KYC) information and includes, e.g., a client's full name and place of residence for physical persons and ownership and beneficiary information for legal persons. KYC information serves multiple purposes, most notably confirming a client's identity and the origin of their funds. Furthermore, it enables banks to make risk assessments and profiles for ongoing (transaction) monitoring.

After a bank has established a relationship with a client, it must regularly update its KYC information on said client (FATF, 2023; 4AMLD, 2015). This is known as Ongoing Due Diligence (ODD). The bank must also monitor the behavior of the client. To this end, the bank will usually employ an automatic transaction monitoring system, relying on simple and confidential rules to raise alerts for bank officers (Verhage, 2009; Demetis, 2018). The KYC information collected during onboarding and ODD serves as a baseline against which the client's behavior is assessed. If the bank observes behavior it cannot rule out to be money laundering, it must file a suspicious activity report (SAR) to a national Financial Intelligence Unit (FIU). FIUs are then intended to allocate cases to appropriate authorities for further investigation.

The risk-based approach in modern AML regulation extends to transaction monitoring; SARs are intended to be filed on outlier, suspicious, or in-explainable behavior. Within Fig. 1, such behavior corresponds to a risk signal over the T threshold, denoted as an outlier in the rest of our paper. Thus, a money launderer is incentivized to make their activities appear normal and unsuspicious, decreasing their risk signal and probability of detection. While the EU's fourth AML directive (4AMLD, 2015) requires banks to monitor client behavior to ensure consistency with knowledge of a client and KYC information, we stress that abnormal or unexpected client behavior need not be suspicious from a money laundering perspective. Indeed, a pensioner suddenly spending their life savings on an expensive car from a reputable dealer might be both abnormal and unexpected. However, it is hardly a money laundering risk in and of itself.

Our model employs an abstract view of money laundering. While it is motivated by transaction monitoring, the model applies to regulation on both the placement, layering, and integration stages of laundering. Consequently, our model is also relevant to KYC and ODD regulation and processes. The model's generalizability is due to the abstract nature of our assumptions (described in Subsection 4.1); we assume a launderer has a utility function with diminishing marginal utility and a set of strategies with different costs and probabilities of avoiding detection. Such strategies may be very general. They can, for example, involve setting up a new bank account, going through a due diligence process, or using an existing account, only subject to transaction monitoring. Furthermore, they may involve both physical and legal persons (why the model also applies to both physical and legal persons).

3 Related Literature

In this section, we present and discuss related literature. Subsection 3.1 focuses on models of criminal activity. Subsection 3.2 focuses on risk-based AML regulation.

3.1 Criminal Activity and Anti-Money Laundering Efforts

Becker (1968) proposed a seminal model of criminal activity, assuming individuals are rational and weigh the costs and benefits of committing crime. The model considers factors such as a criminal's probability of getting caught, the severity of punishments, and the cost of law enforcement. The model provides insight into policies aiming to minimize the social loss of criminal activities. In particular, it highlights that there is a balance between the cost of law enforcement, criminal punishment, and deterrence.

Masciandaro (1999) proposes a model of money laundering, highlighting its multiplier effect on criminal activities. The model considers factors such as the cost of laundering, the proportion of funds reinvested in illegal activities, and the difference in expected returns from legal and illegal investments. Applying the model to data from Italy, the study evaluates Italian AML regulation, pointing out its inefficiency due to misaligned incentives for financial intermediaries.

Takáts (2011) utilizes game theory to model the principal-agent problem between governments and banks in AML regulation. The problem (abstracted away in our model) arises as banks must be incentivized to undertake costly transaction monitoring. To this end, the author imagines that banks are fined if they fail to report transactions later prosecuted as money laundering. The model suggests fines for non-reporting banks can be too big, leading to excessive reporting that dilutes the value of reports (i.e., a "crying-wolf" phenomenon). The suggestion is supported by empirical data from the United States, seeing an increase in SARs without a corresponding increase in money laundering prosecutions.

Pellegrina *et al.* (2023) investigate the impact of the risk-based AML regulation on the accuracy of SARs and deterrence of money laundering in Italy. The study develops a model to examine the relationship between reporting thresholds, type-I errors (false positives), type-II errors (false negatives), and the overall accuracy of SARs. Empirical analysis suggests that financial intermediaries in Italy likely lowered their reporting threshold after risk-based AML regulation was introduced, leading to increased type-I errors (i.e., a "crying wolf" effect). However, it likely also contributed to reduced type-II errors, enhancing deterrence.

3.2 Risk-based Anti-money Laundering Regulation

Unger and van Waarden (2009) examine the effects of shifting from rule-based to risk-based AML regulation. The shift, intended to curb over-reporting (i.e., the "crying wolf" problem), paradoxically coincides with increased reporting in many countries. However, in the Netherlands, it coincides with fewer reports. The authors attribute the difference to contrasting legal traditions. The United States, in particular, has an adversarial tradition with strict penalties for non-compliance. The Netherlands, by contrast, has a cooperative tradition, with regulators and supervisors focusing on informing and advising. The authors underscore the need for AML recommendations to be adaptable to specific legal frameworks. Furthermore, they hypothesize that risk-based regulation, over time, might revert to be de facto rule-based, as courts and supervisors operationalize what "suspicious" or "risky" behavior means.

Pellegrina and Masciandaro (2009) investigate risk-based AML regulation, using a principal-agent model to analyze the incentives of lawmakers, supervisors, and banks. They argue the effectiveness of AML regulation can be enhanced by aligning interests through a balanced scheme of rewards and penalties, ensuring the difference between private costs and public benefits is minimized. The paper also notes the need for national guidelines to tailor risk assessments. Additionally, the authors suggest high-quality supervision can be a substitute for severe non-compliance penalties for banks.

Ferwerda and Reuter (2022) evaluate NRAs from eight systemically important countries. The authors highlight significant discrepancies in how the NRAs conceptualize and analyze risks. Furthermore, the NRAs rely heavily on expert opinions solicited without the well-developed methodological framework to do so. The authors also note the NRAs misinterpret SARs and lack transparent methodologies.

Ogbeide *et al.* (2023) compare AML risk assessments by novices and AML professionals. The study employs a survey with 155 participants from 13 countries (primarily Nigeria and the United Kingdom).

Participants were presented with 12 case descriptions, asking if a case contained activity that might lead to a conviction. Notably, novices achieved a higher rate of correctly predicted outcomes, with both experts and novices exhibiting overconfidence. The finding raises fundamental questions about the feasibility of a risk-based approach to AML. For instance, if experts cannot assess AML risk better than novices, is it even possible to effectively implement a risk-based approach?

4 A Microeconomic Model

In this section, we develop our microeconomic model of transaction monitoring. Subsection 4.1 presents our assumptions. Subsection 4.2 builds our model. Subsection 4.3 analyzes penalties and risks. Subsection 4.4 investigates publicly known transaction monitoring rules. Finally, Subsection 4.5 hypothesizes why wealthy money launderers may be hard to detect.

4.1 Assumptions

Consider a money launderer with a given amount of money M to be laundered through bank transactions. We assume the launderer is rational and has a set of strategies with different costs c (direct and indirect), reducing their probability of detection. For a given cost c, let $q_M(c)$ denote the launderer's probability of avoiding detection.[1] For example, making a large lump-sum transaction might have a relatively low cost c_L. However, it also has a low probability of avoiding detection $q_M(c_L)$, as any transaction monitoring system is likely to flag it. We stress that the probabilities $q_M(c)$ may not be correct; the launderer simply holds them as beliefs. In turn, a launderer does not need to know exactly how a transaction monitoring system works. We assume costlier strategies have non-decreasing (and generally higher) probabilities of avoiding detection. This aligns with the launderer being rational; if success probabilities were declining at some point, we imagine they could choose a cheaper strategy and intentionally "waste resources" (e.g., burn cash) to keep $q_M(c)$ constant as c increases. Thus, $q_M(c)$ is a non-decreasing function of c. An illustration is given in Fig. 2, assuming a continuous spectrum of strategies (something that is not necessary for our model). If undetected, the launderer gets a net profit $m = M - c$. If detected, they must pay a penalty P. Motivated by the one-to-one relation between m and c, we also consider the probability that the launderer avoids detection as a function of m, denoted as $p_M(m)$. This must be non-increasing; see Fig. 3. Motivated by the

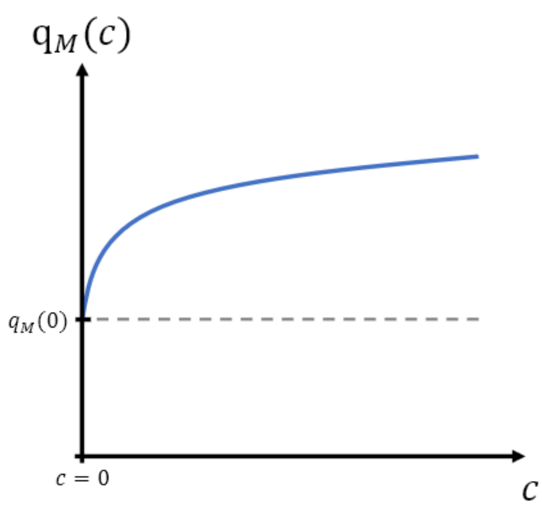

Fig. 2: A launderer's probability of avoiding detection $q_M(c)$ as a function of their strategy's cost c.

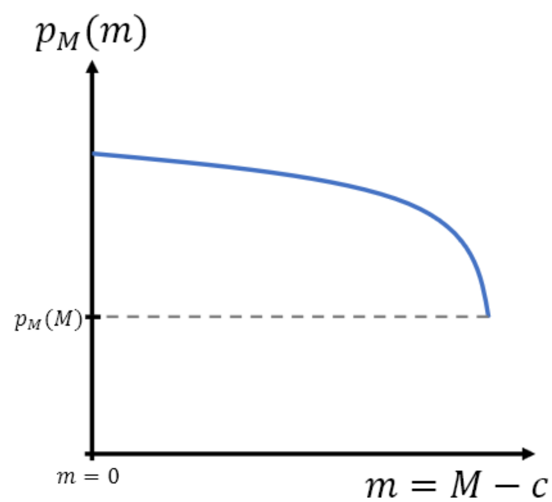

Fig. 3: A launderer's probability of avoiding detection $p_M(m)$ as a function of their net profit $m = M - c$.

[1] A launderer could have multiple strategies with identical costs. However, for a given cost c, it is only rational to consider the one with the highest $q_M(c)$. We do the same in our model, treating strategies with identical $(c, q_M(c))$ pairs as identical.

law of diminishing marginal utility (Berkman *et al.*, 2016), we assume the launderer has an increasing and concave utility function $u(m)$. The launderer's expected utility is now given as

$$E[u(m)] = p_M(m)u(m) - (1 - p_M(m))u(P). \tag{1}$$

We note that a non-strategic launderer (doing nothing to hide their activity) faces a net profit M and a probability of avoiding detection $p_M(m)$, equal to $\int_{-\infty}^{T} l_M(s)\, ds$ in our motivating setup in Section 1.

By assuming launderers have increasing and concave utility functions, we also assume they are risk-averse. This contrasts with (i) previous literature, often assuming launderers are risk-neutral, and (ii) conventional wisdom in criminology, holding that criminals are deterred more by increases in their probability of detection than penalties, implying they are risk-lovers (Becker, 1968). We depart from these views for several reasons. In particular, the idea of diminishing marginal utility (i.e., that each additional unit of consumption should yield comparatively less utility) is so well established in microeconomics that it is known as the "law of diminishing marginal utility" (Berkman *et al.*, 2016). In an expected-utility maximization framework, this implies risk-aversion. Furthermore, people are generally thought to be risk-averse, especially when stakes are high (Bombardini and Trebbi, 2012; Binswanger, 1980). Finally, prospect theory (Kahneman and Tversky, 1979) aligns with the idea that loss aversion in mixed gambles (where both a gain and a loss are possible; comparable to a money laundering situation) causes risk-averse choices.[2] We also highlight Shepherd (2006), providing some (though far from conclusive) empirical evidence that criminals are risk-averse, and Bar-Ilan and Sacerdote (2004), showing that criminals are not special in their response to fines. We refer to Mungan and Klick (2016) for an extensive discussion as to why criminals may be risk-averse despite conventional wisdom. As noted by Mungan and Klick (2016), the scientific literature is yet to come to a conclusion about criminals' risk profiles. Notably, it is possible that white collar criminals (including money launderers) have risk profiles that differ from other types of criminals.

4.2 Building and Solving the Model

A strategic money launderer may adopt a strategy with a non-zero cost c. This way, they effectively choose a combination of net profit $m = M - c$ and probability of avoiding detection $p_M(m)$. In $(m, p_M(m))$-space, we can illustrate the choice with indifference curves. These show combinations of m and $p_M(m)$ that lead to fixed levels of expected utility $E[u]$. Curves further in the upper-right corner represent higher levels of expected utility. To maximize their expected utility, a launderer will seek the highest indifference curve that intersects with $p_M(m)$, representing their available strategies; see Fig. 4. We note that a launderer's expected utility only may increase when they strategize (as they, otherwise, would use $c = 0$).

Given that $u(m)$ is increasing and concave, we generally expect a strategizing launderer to trade some net profit m for a higher probability of avoiding detection $p_M(m)$. We can characterize a launderer's optimal strategy by its net profit m^* (equivalent to an optimal strategy cost c^*). Note that we, here, conflate a strategy with its net profit m, denoting the strategy itself as m. This is due to the one-to-one relation between net profits m and costs c, and the idea that a launderer will consider just one strategy for a given cost c; see Footnote 1. From the first-order condition

$$\frac{\delta E[u(m)]}{\delta m} = p'_M(m)u(m) + p_M(m)u'(m) + p'_M(m)u(P) = 0 \tag{2}$$

we have that

$$p'_M(m^*)\left(u(m^*) + u(P)\right) = -u'(m^*)p_M(m^*). \tag{3}$$

Thus, the launderer's optimal strategy balances a marginal change in the probability of avoiding detection (on the left-hand side) against a marginal change in the utility if undetected (on the right-hand side). To engage in money laundering, we imagine someone (unless forced) must obtain a positive expected utility. Rearranging equation (1), this means that

$$u(m^*) > \frac{(1 - p_M(m^*))}{p_M(m^*)} u(P) \tag{4}$$

[2] To illustrate this idea, consider the following two gambles. Gamble 1 guarantees a gain of \$10 million with certainty. Gamble 2 offers a 95% chance to gain \$12 million and a 5% chance to lose \$28 million. Both gambles have the same expected value (\$10 million). If launderers are risk-averse, they will prefer Gamble 1 over Gamble 2 (something we find inherently reasonable).

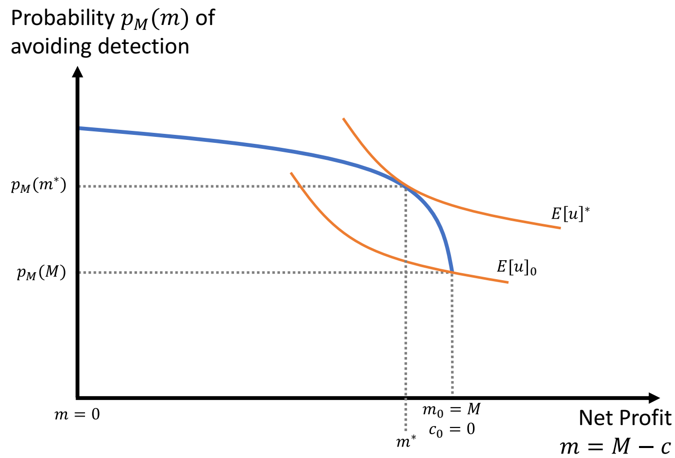

Fig. 4: Two indifference curves, representing utility levels $E[u]^*$ and $E[u]_0$. A launderer will seek the indifference curve furthest in the upper-right corner intersecting with $p_M(m)$. Doing so, they use c^* to hide their activity, obtain a net profit $m^* = M - c^*$, probability of avoiding detection $p_M(m^*)$, and expected utility $E[u]^*$. If they do not strategize, the launderer faces a net profit $m_0 = M$, probability of avoiding detection $p_M(m)$, and expected utility $E[u]_0$.

must hold, implying that an undetected launderer's utility is greater than the probability-weighted penalty they face if detected.

4.3 Changing Penalties and Risks

The penalty P affects the shape of a money launderer's indifference curves. Increasing P makes the launderer more willing to trade net profit m for a higher probability of avoiding detection $p_M(m)$; see Fig. 5. Thus, the launderer is pushed towards a strategy that (they believe) is harder to detect. In turn, we would expect less money laundering to be detected by transaction monitoring systems (assuming the launderer's beliefs about $p_M(c)$ are correct). Still, the launderer's expected utility must decrease, as any new optimal strategy was previously suboptimal (and P now is larger). Some launderers may also decide to stop their activities entirely if equation (4) no longer holds. Opposite effects apply if P decreases.

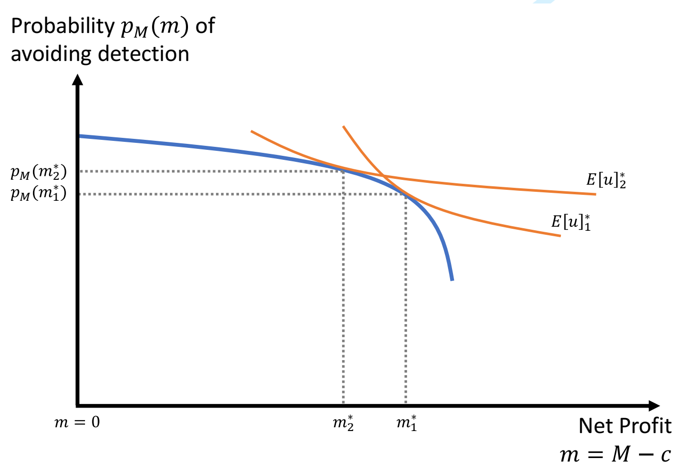

Fig. 5: Increasing the penalty P_1 to P_2 affects a launderer's indifference curves; see lines $E[u]_1^*$ and $E[u]_2^*$. The launderer becomes more willing to trade net profit m for a higher probability of avoiding detection $p_M(m)$.

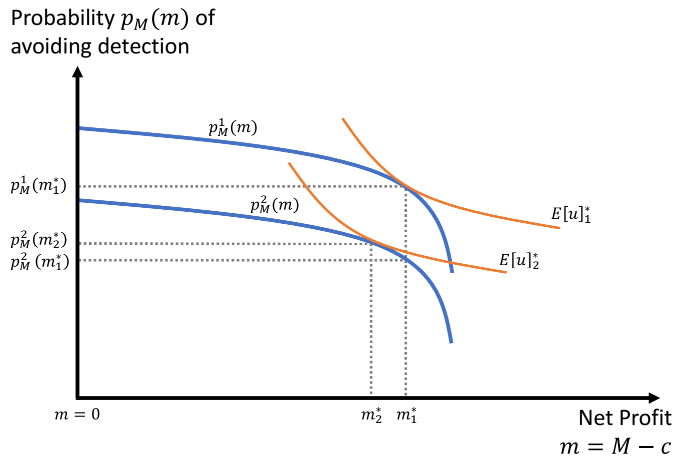

Fig. 6: A general decrease in the probabilities of avoiding detection $p_M^1(m)$ to $p_M^2(m)$ has two effects. It causes a direct shift; see the shift from $p_M^1(m_1^*)$ to $p_M^2(m_1^*)$. Furthermore, it causes a shift in a launderer's optimal strategy, going from a net profit m_1^* to m_2^*. The net effect is a "smaller-than-initially-believed" reduction in the optimally chosen probability of avoiding detection

Imagine a launderer comes to believe there is a higher risk they may be detected. This could, for example, be the result of a (publicly known) improvement in transaction monitoring systems. If the change applies across all strategies, it corresponds to a downwards shift of the $p_M(m)$ function; see Fig. 6. We now have two effects. First, any given net profit is associated with a lower probability of avoiding detection. Second, the launderer is pushed to change their strategy, exchanging net profit for a higher probability of avoiding detection. The net effect is a "smaller-than-initially-believed" reduction in the optimally chosen probability of avoiding detection. Note that the launderer's expected utility must decrease as the probability of avoiding detection associated with any strategy decreases. Some launderers may also decide to stop their activities entirely if equation (4) no longer holds. Opposite effects apply if the launderer generally becomes more confident about their strategies.

4.4 Introducing Publicly Known Transaction Monitoring Rules

Suppose a regulator such as the EU requires banks to implement publicly known transaction monitoring rules (e.g., the previously described KYC requirement associated with transferring funds over €1000). This means that a money launderer may know if some of their strategies will be flagged. In turn, the $p_M(m)$ function may change, dropping to zero for some net profits m.[3] An illustration is given in Fig. 7, assuming cheap strategies are targeted. A launderer previously using an affected strategy is now (heavily) incentivized to adopt a new. The launderer's new optimal strategy might have a higher probability of avoiding detection $p_M(m)$. However, we note that the launderer's expected utility must be lower (as any new strategy previously was suboptimal).[4] Some launderers may also decide to stop their activities entirely if equation (4) no longer holds. We stress that our analysis ignores any costs associated with publicly known transaction monitoring rules.

4.5 Modelling Wealthy Money Launderers

The amount of money M a money launderer seeks to launder affects the shape of their indifference curves. The effect is analog to that described at the start of Subsection 4.3, considering penalties. Notably, M may

[3]We stress that not all publicly known transaction monitoring rules will change the $p_M(m)$ function; some may not change it, and, in this sense, be useless. Furthermore, it may require many rules to change $p_M(m)$ for a single value of m. However, a single rule could also affect $p_M(m)$ for many different values of m.

[4]Denote the launderer's initial optimal strategy as m_1^* and its expected utility as $E[u]_1^*$. When the publicly known transaction monitoring rules are introduced, the launderer knows m_1^* will be flagged and they switch to a new optimal strategy m_2^* with an expected utility $E[u]_2^*$. Now, it must hold that $E[u]_2^* < E[u]_1^*$, as the launderer, otherwise, initially would have chosen m_2^* as their optimal strategy.

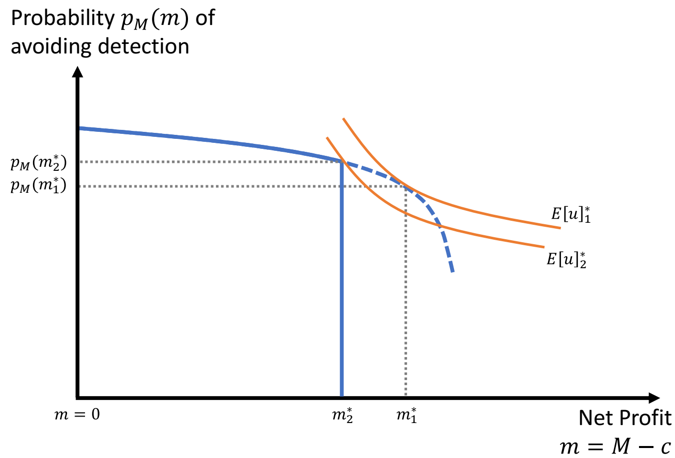

Fig. 7: Introducing publicly known transaction monitoring rules may change the $p_M(m)$ function, making it drop to zero for some net profits m (corresponding to "cheap" strategies here). A launderer previously using an affected strategy will, in turn, seek a new optimal strategy, going from a net profit m_1^* to m_2^*.

also influence the penalty P a launderer gets if detected. Thus, M may exert a direct (through itself) and indirect (through P) effect on indifference curves. In addition, M affects the launderer's probabilities of avoiding detection $p_M(m)$. As a baseline (using $c = 0$ costs to hide their activity), we imagine a wealthy launderer has a low probability of avoiding detection due to their large amount of money. However, we also imagine they have access to strategies that differ substantially from those of a poorer launderer. Specifically, we imagine the wealthy launderer's strategies exhibit scaling effects (potentially after a "barrier to entry"). For example, a wealthy launderer might employ a corrupt lawyer to set up a shell company at a high one-time cost that may be used to launderer large amounts of money with relatively low risk. An illustration is given in Fig 8. Note that M also may have an impact on $p_M(m)$ in and of itself; not just though the strategies it allows access to. As the wealthy launderer uses funds to hide their activity, em-

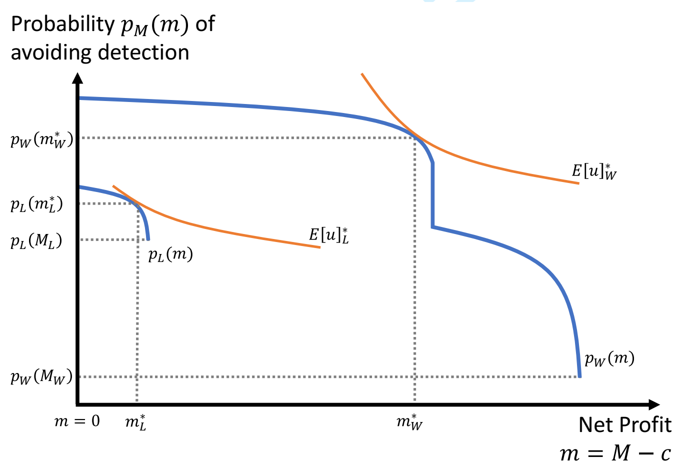

Fig. 8: A wealthy launderer's probabilities of avoiding detection $p_W(m)$ may differ substantially from a poorer launderer's $p_L(m)$. As the wealthy launderer employs a corrupt lawyer at a high one-time cost, we imagine a vertical increase in $p_W(m)$; before the discontinuity, the launderer cannot afford the lawyer, using strategies without them. After the discontinuity, however, the launderer uses them in all their strategies.

ploying (corrupt) professional help, their probability of avoiding detection can increase drastically. Thus, the wealthy launderer may have an optimal strategy with (what they believe is) a very high probability of avoiding detection. In turn, we hypothesize that wealthy launderers rarely are detected. It is technically possible for a poor launderer to choose an optimal strategy with a higher probability of avoiding detection than a wealthy launderer. This might, for example, happen if the poor launderer is extremely risk-averse while that wealthy launderer is very little risk-averse. However, we argue the situation is unlikely given (i) a continuous spectrum of strategies, (ii) scaling effects of the wealthy launderer's strategies, (iii) diminishing marginal utility, and (iv) penalties that increase with the amount of money laundered.

5 Discussion and Conclusion

We have developed a micro-economic model to analyze current AML regulation. Our model builds on two main assumptions, driving our results. First, we assume costlier money laundering strategies have non-decreasing (and generally higher) probabilities of avoiding detection. We argue this aligns with the EU's fourth AML directive, ascribing higher risk to complex (and thus costly) transaction patterns and structures. Furthermore, it aligns with launderers being rational; if success probabilities were declining at some point, we imagine launderers could choose a cheaper strategy and intentionally "waste resources" (e.g., burn cash) to keep probabilities constant. Second, we assume launderers have increasing and concave utility functions. We argue this is reasonable, as (i) launderers should get higher utility as their wealth increases and (ii) each marginal unit of wealth should yield comparatively less utility than the previous. The latter is so well established in microeconomics that it is referred to as the "law of diminishing marginal utility" (Berkman *et al.*, 2016). Our second assumption implies that launderers are risk-averse. We stress that launderers, however, still may "tolerate" risk considerably more than benevolent clients (being less risk-averse than them). Our model diverges from previous literature, often (explicitly) assuming launderers are risk neutral. We offer an alternative approach, contrasting and challenging the assumption of risk neutrality.

Our model yields several key insights. First, policymakers should be aware that while raising penalties for money laundering may have a deterring effect, it can also mean that less money laundering will be detected. Furthermore, publicly known transaction monitoring rules may shift launderers' strategies. For instance, mandatory reporting thresholds can push launderers to adopt more complex and costlier strategies. This increases the overall cost of laundering and might deter some individuals from engaging in money laundering. Overall, affected launderers will see their expected utility decrease. Whether or not this is worth pursuing depends on the costs associated with publicly known transaction monitoring rules. Based on our assumption that wealthy launderers can afford complex strategies unavailable to poor launderers (e.g., using corrupt professional advisors), we also hypothesize that wealthy launderers rarely are detected. Further research is warranted to determine if this is true and wealthy launderers can be found in pools of "inlier" behavior (i.e., behavior well below any transaction monitoring thresholds).

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