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Hugo Marin

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THÈSE DE DOCTORAT
DE L'UNIVERSITÉ PSL

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Soutenu par

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Introduction générale

Cette thèse est composée de trois travaux empiriques portant sur la finance d'entreprise, répartis en trois chapitres. Deux thèmes distincts sont abordés au travers de ces travaux : deux essais traitent du financement participatif par des investisseurs particuliers à destination des petites et moyennes entreprises, et un essai se rapporte au thème de la gouvernance d'entreprise. Cette introduction de thèse se structure en deux parties distinctes présentant les deux thèmes dans lesquels mes travaux s'inscrivent.

.1. Le prêt participatif aux entreprises

Dans cette section, je définis le prêt participatif et explique pourquoi il est particulièrement utile aux petites et moyennes entreprises. Je passe ensuite en revue les grands courants de recherche portant sur ce financement alternatif. Enfin, je présente mes deux travaux traitant de ce type de financement. Ces travaux, co-réalisés avec Madame le Professeur Carole Gresse, constituent deux chapitres de la présente thèse.

.1.1. La dépendance des petites et moyennes entreprises au système bancaire

Les marchés financiers sont un lieu de rencontre entre des agents économiques à capacité de financement et d'autres à besoin de financement. Les marchés financiers assurent de fait la mission double de financement de l'économie et de placement de

l'épargne des investisseurs.

Parmi les agents économiques à besoin de financement figurent les petites et moyennes entreprises. Néanmoins, ces entreprises ne disposent pas d'un accès direct et aisé aux marchés financiers, qu'il s'agisse des marchés de dettes ou bien de fonds propres. De ce fait, les petites et moyennes entreprises sont dépendantes du système bancaire pour combler leurs besoins de financement externe. Cette dépendance financière des petites et moyennes entreprises vis-à-vis du système bancaire peut conduire à un manque de financement¹ de ces entreprises vitales pour le dynamisme de l'économie². Le prêt participatif, une forme particulière de financement participatif, permet d'offrir une source alternative de financement externe aux petites et moyennes entreprises.

.1.2. Le prêt participatif : définition et présentation

Le financement participatif, ou *crowdfunding* en anglais, peut être défini comme une méthode de levée de fonds auprès d'un important nombre d'investisseurs particuliers, et ce sans faire appel à une institution bancaire. Cette levée de fonds se fait généralement par le biais d'une plateforme numérique. Le prêt participatif, ou *crowdlending*, est une forme particulière de financement participatif. Un emprunteur ayant recours au prêt participatif pour financer son projet contracte un emprunt auprès d'un grand nombre d'investisseurs désirant lui prêter de l'argent. L'emprunteur rembourse le capital et les intérêts auprès de ses multiples créanciers selon les termes définis avant la levée de fonds. Le prêt participatif diffère notamment du prêt bancaire par le nombre de créanciers associés à un seul et unique prêt³.

¹L'écart entre la demande de financement des petites et moyennes entreprises françaises et l'offre de prêts bancaires s'est établi à 9% du produit intérieur brut en 2019. Source : *Filling the Bank Financing Gap, Allianz, Euler Hermes, 2019*, figure 3 page 6.

²En 2019, les petites et moyennes entreprises représentaient 99.8% du nombre total d'entreprises, employaient 48.1% de la population salariée et étaient responsables de 42.5% de la création totale de valeur ajoutée en France. Source : *Les Entreprises en France – Insee Références – Édition 2021, INSEE*, tableau page 71.

³Une autre différence d'importance entre le prêt bancaire et le prêt participatif tient à l'absence de caution ou garantie demandée à l'emprunteur lors de l'octroi du prêt participatif.

Le prêt participatif a fait ses premiers pas au milieu des années 2000 au Royaume-Uni et aux Etats-Unis avec l'apparition des plateformes Zopa, Prosper et Lending Club. Ces plateformes se spécialisent initialement dans l'origination de prêts participatifs de particulier à particulier. A partir de 2010, les prêts participatifs à destination des petites et moyennes entreprises américaines deviennent possibles avec la création de la plateforme Funding Circle⁴. En France, le développement de cette source de financement alternative au prêt bancaire s'est fait plus tardivement : à partir de 2010 pour les prêts participatifs entre particuliers, par l'intermédiaire de la plateforme Younited Credit, et à partir de 2014 pour les prêts participatifs à destination des petites et moyennes entreprises grâce aux plateformes October, anciennement Lendix, et Unilend.

En 2018, le volume mondial des prêts participatifs entre particuliers s'est élevé à 195 milliards de dollars, tandis que les prêts participatifs à destination des entreprises ont compté pour 50 milliards de dollars. La Chine est le principal moteur de l'essor du prêt participatif puisqu'elle est responsable de 84% du volume global, suivie par les Etats-Unis⁵. Bien que ces volumes soient importants et en progression d'année en année, ils sont infimes en comparaison de la taille des marchés traditionnels de capitaux.

.1.3. Deux mécanismes de fixation du taux d'intérêt : la fixation unilatérale ou les enchères

Le prêt participatif, à l'instar du prêt bancaire, est caractérisé par une durée et par un taux d'intérêt. La durée du prêt est systématiquement déterminée avant la levée de fonds alors que le taux d'intérêt peut être fixé avant ou pendant la levée de fonds selon le mécanisme de fixation de taux choisi. Deux mécanismes d'établissement du taux d'intérêt d'un prêt participatif existent.

⁴Lire Shneor et al. (2020) pour un historique détaillé de l'essor du financement participatif dans le monde.

⁵Lire *The Global Alternative Finance Market Benchmarking Report, University of Cambridge – Judge Business School, April 2020.*

Le mécanisme le plus couramment utilisé est celui de la fixation unilatérale du taux d'intérêt avant la levée de fonds. La plateforme de financement participatif étant responsable de l'origination du prêt détermine le niveau de risque du projet de l'emprunteur et, sur cette base, fixe unilatéralement le taux d'intérêt du prêt participatif. Selon ce mécanisme, tous les prêteurs particuliers finançant un même projet sont rémunérés à un taux d'intérêt unique.

Un autre mécanisme, moins courant, de détermination du taux d'intérêt d'un prêt participatif est l'enchère. Le montant et la durée de l'emprunt sont annoncés aux investisseurs avant le début de l'enchère, ainsi que des informations diverses concernant l'emprunteur et le projet à financer. Les investisseurs soumettent leurs offres, caractérisées par le taux d'intérêt auquel ils souhaitent être rémunérés couplé au montant d'argent qu'ils acceptent de prêter, durant l'enchère. Les offres s'accumulant au fil de l'enchère, le montant global soumissionné par les investisseurs peut dépasser le montant de l'emprunt initialement fixé. Les investisseurs impliqués dans l'enchère entrent alors en compétition les uns avec les autres. A la fin de l'enchère, les offres sont classées par ordre croissant de taux d'intérêt. Les montants des offres sont alors cumulés en commençant par l'offre au taux d'intérêt le plus faible jusqu'à ce que le montant de l'emprunt fixé avant l'enchère soit atteint. Les offres dont les montants ont ainsi été additionnés sont déclarées gagnantes tandis que le reste des offres soumises durant l'enchère sont rejetées. Les investisseurs victorieux prêtent à l'emprunteur le montant promis durant l'enchère et sont rémunérés au taux qu'ils ont demandé⁶. Selon ce mécanisme, les investisseurs particuliers finançant un projet ne sont donc pas nécessairement tous rémunérés au même taux d'intérêt.

Bien que le système d'enchère soit plus complexe à mettre en place par la plateforme de prêt participatif, et à utiliser par les investisseurs particuliers, que la fixation unilatérale du taux d'intérêt, ce mécanisme a l'avantage d'organiser un processus de découverte des prix. Ce processus peut s'avérer informateur pour

⁶Le système d'enchère décrit dans ce paragraphe est celui de l'enchère à la hollandaise, ou enchère à prix demandé.

l'emprunteur capable de déduire du taux d'intérêt l'engouement de la demande pour son projet ainsi que l'appréciation du degré de risque de ce dernier par les investisseurs.

.1.4. La littérature associée au prêt participatif

Le financement participatif, en tant que nouvelle source de financement et de placement, a suscité un vif intérêt de la communauté académique. Un riche et vaste panel de travaux en a été le fruit⁷. Par souci de concision, la revue de littérature qui suit présente de façon sommaire les principaux courants de recherche dans lesquels s'inscrivent les travaux académiques portant sur le prêt participatif⁸.

Le premier grand courant de recherche attaché à l'étude du prêt participatif traite de l'asymétrie d'information entre emprunteurs et prêteurs particuliers, pouvant aboutir à un phénomène d'antisélection. Vallée et Zeng (2019) et Mohammadi et Shafi (2017) mettent en exergue cette asymétrie d'information en soulignant la capacité supérieure des investisseurs institutionnels à inférer la qualité de crédit d'un emprunteur relativement à celle des investisseurs particuliers. Comme le montrent Dorfleitner et al. (2022), l'antisélection résultant de l'importante asymétrie d'information attachée aux prêts participatifs se manifeste notamment par la médiocre performance obtenue par les investisseurs particuliers.

Un autre important courant de recherche sur le prêt participatif a pour objectif l'étude des biais comportementaux des investisseurs particuliers. Les prêteurs particuliers n'étant pas des investisseurs professionnels, de nombreux travaux académiques montrent qu'ils sont, de ce fait, plus enclins à voir leurs décisions d'investissement influencées par des biais comportementaux. Pour n'en citer que quelques-uns, Ceyhan et al. (2011) décrivent le comportement des investisseurs particuliers comme étant grégaire en début et en fin d'enchère. Hervé et Schwienbacher (2018) montrent que les prêteurs particuliers sont affectés par un biais co-

⁷Lire Moritz et Block (2016) pour une revue de la littérature sur le financement participatif.

⁸Lire Ribeiro-Navarrete et al. (2021) pour une revue exhaustive de la littérature sur le prêt participatif.

gnitif les conduisant à prêter de l'argent à des taux d'intérêt arrondis. Enfin, Lin et Viswanathan (2016) mettent en lumière que les investisseurs particuliers américains sont gouvernés par le biais domestique, i.e., ces derniers sont plus enclins à prêter à des emprunteurs vivant dans le même état qu'eux, et ce sans détenir un avantage informationnel quant à leur probabilité de défaut.

.1.5. Chapitre 1: *Geographical-Proximity Bias and Enhanced Attention in P2B Crowdlending Strategies*

Ce chapitre, co-écrit avec Madame le Professeur Carole Gresse, vise en premier lieu à prouver l'existence d'un biais comportemental conduisant des investisseurs non professionnels à être plus enclins à prêter des fonds aux entreprises localisées à proximité de leur lieu de résidence. Ce biais, nommé biais de proximité géographique, fait partie de la famille des biais de familiarité incitant les investisseurs affectés à investir plus fortement dans des actifs leur étant familiers. Dans le cas du biais de proximité géographique, le sentiment de familiarité naît de la proximité géographique entre l'investisseur et l'actif. En second lieu, ce chapitre a pour objectif d'étudier l'impact d'un tel biais sur le processus de découverte des prix conduisant à l'établissement du taux de financement des emprunteurs sur une plateforme de prêt participatif.

Pour mener cette étude, nous utilisons des données fournies à titre gracieux par Unilend, une plateforme française de prêt participatif à destination des petites et moyennes entreprises françaises⁹. Cette plateforme a la particularité d'opérer un système d'enchère à la hollandaise pour collecter les fonds nécessaires à l'origination d'un prêt participatif. Nous tirons parti de l'implémentation d'un algorithme soumettant des offres à la place des investisseurs, afin d'établir une stratégie d'identification nous permettant de prouver l'existence d'un biais de proximité géographique. En interprétant l'implémentation de l'algorithme de soumission d'offres comme une diminution exogène de la présence des biais comportementaux au cours des enchères,

⁹La plateforme Unilend, déclarée en faillite en octobre 2018, a depuis été rachetée par la plateforme Pretup.

nous montrons que les investisseurs particuliers sont d'autant plus enclins à prêter de l'argent à une entreprise si cette dernière est localisée dans leur département de résidence. Nous montrons ensuite que les investisseurs locaux prêtant aux entreprises proches de leur lieu de résidence ne détiennent pas d'avantage informationnel relativement aux autres investisseurs, ce qui nous permet de conclure à l'existence du biais de proximité géographique. Quant à l'impact de ce biais sur le processus de découverte des prix, nous montrons que la présence d'investisseurs affectés par un tel biais est associée à une augmentation du coût d'emprunt de l'entreprise levant des fonds sur la plateforme. Cette augmentation du coût de financement s'explique par la présence, dans l'enchère, d'investisseurs résidant dans le même département que l'emprunteur et ayant participé plusieurs fois par le passé à des enchères visant à financer des entreprises à proximité de leur lieu de résidence. Nos résultats suggèrent que le sentiment de familiarité découlant de la proximité géographique entre les investisseurs et l'emprunteur a renforcé l'attention de ces derniers durant les enchères, leur permettant de comprendre plus efficacement la dynamique du flux de soumissions dans les enchères des entreprises localisées à proximité de leur lieu de résidence. Forts de cet avantage informationnel obtenu par apprentissage, les investisseurs expérimentés sont alors capables d'anticiper, avec une précision accrue, l'offre de financement propre aux enchères des emprunteurs de leur département de résidence, et de soumettre en conséquence une offre gagnante à un taux proche du taux d'équilibre, faisant ainsi croître le coût de financement de l'emprunteur. Nous montrons ainsi que la propension accrue des investisseurs locaux à sur-prêter aux entreprises localisées à proximité de leur lieu de résidence est un biais comportemental durant les premières enchères auxquelles lesdits investisseurs participent, puis devient une stratégie rationnelle au fil des expériences acquises.

Les résultats présentés dans ce chapitre nous permettent d'émettre une recommandation en matière de régulation des plateformes de prêt participatif. Notre étude montre que l'utilisation d'un algorithme de soumission d'offres pour le compte des investisseurs conduit à une nette réduction des biais comportementaux. Toutefois,

l'algorithme de soumission d'offres a eu pour effet majeur de faire notablement diminuer les taux d'intérêt auxquels les investisseurs se rémunéraient. Les investisseurs ainsi découragés par la baisse de rémunération ont été dissuadés de continuer à investir sur la plateforme, mettant en péril sa stabilité financière. Nous pensons que l'algorithme de soumission d'offres est soutenable dans les cas où le taux d'intérêt est en adéquation avec le niveau de risque du projet, c'est-à-dire pour les projets peu risqués dont l'analyse est de faible complexité. Au contraire, nous pensons qu'un algorithme de soumission d'offres n'est pas désirable pour les projets risqués ou complexes à analyser méritant un taux de financement plus élevé.

.1.6. Chapitre 2: *Learning by Doing in Crowdfunding Auctions*

Afin de lever les fonds nécessaires au financement des divers projets proposés aux investisseurs, la majeure partie des plateformes de prêt participatif fixe unilatéralement le taux de rémunération des prêteurs. Toutefois, certaines plateformes ont recours au système de l'enchère à la hollandaise, mettant ainsi les prêteurs en concurrence les uns avec les autres. Lors d'une enchère à la hollandaise, l'investisseur rationnel cherche à maximiser le taux de rentabilité des fonds prêtés tout en s'assurant de pouvoir gagner l'enchère. La concurrence entre investisseurs contraint alors un tel investisseur à recourir à l'utilisation de stratégies de soumissions d'offres afin d'atteindre l'objectif souhaité. L'objet premier de ce chapitre consiste à concevoir une classification exhaustive des stratégies de soumission d'offres dans une enchère à la hollandaise. Son second objectif est de vérifier empiriquement si une telle classification fait sens en utilisant les données d'une plateforme française de prêt participatif à destination des petites et moyennes entreprises. Enfin, nous tentons également de déterminer l'impact de l'expérience des investisseurs avec le système d'enchère sur le type de stratégies adoptées.

La classification proposée aboutit à la définition de six stratégies type. Les trois premières stratégies sont considérées comme non sophistiquées car leur rémunéra-

tion n'atteint pas un niveau que nous jugeons suffisant. Les stratégies mentionnées sont utilisées par des investisseurs non-stratégiques, voire irrationnels. Les trois autres stratégies apportent aux investisseurs les adoptant un taux de rentabilité élevé et sont, de ce fait, considérées comme sophistiquées. Les investisseurs informés, les suiveurs stratégiques et les *snipers* sont les trois types d'investisseurs identifiés adoptant de telles stratégies. Empiriquement, nous trouvons que les investisseurs particuliers utilisent de façon prédominante des stratégies sophistiquées en matière de soumission d'offres. Ce résultat est particulièrement intéressant car il va à l'encontre de la vision généralement adoptée par les chercheurs quant au degré de sophistication, présumé faible, des investisseurs non professionnels. De plus, nous trouvons qu'il existe une corrélation positive entre l'expérience d'un investisseur avec le système d'enchère et sa probabilité d'adopter une stratégie sophistiquée. Les investisseurs inexpérimentés semblent faire le plus de progrès au fil de leurs expériences, ce qui paraît naturel puisque ce sont ceux ayant la plus grande marge de progression. Enfin, nous montrons que les investisseurs ayant été les premiers à investir sur la plateforme ont acquis une plus grande expérience que le reste des investisseurs par le biais de l'observation. Ils utilisent cette expérience afin d'adopter des stratégies informées, et non à des fins de *sniping*. Enfin, nous mettons en lumière l'existence d'un groupe d'investisseurs potentiellement informés parmi ces investisseurs pionniers.

.2. La gouvernance d'entreprise avec conseil d'administration à mandats échelonnés

Après avoir exposé les principes de la théorie de l'agence, je m'attache, dans cette section, à définir une structure particulière du conseil d'administration : le conseil d'administration à mandats échelonnés, sur lequel porte le troisième chapitre de cette thèse.

.2.1. La théorie de l'agence

La gouvernance d'entreprise se définit comme un ensemble de règles, de pratiques et de processus par lesquels une entreprise est dirigée et contrôlée. La gouvernance d'entreprise a pour objectif principal la satisfaction des intérêts des actionnaires, traditionnellement considérés comme étant d'ordre purement pécuniaire.

Les actionnaires n'ayant pas les compétences, l'appétence ou le temps pour gérer leur entreprise mandatent une équipe de gestionnaires à cet effet. Naît alors une relation d'agence, comme définie par Ross (1973) et Jensen et Meckling (1976), i.e., un contrat par lequel une personne, le principal, engage une autre personne, l'agent, dans le but d'exécuter un certain nombre de tâches. Ce contrat requiert la délégation d'une partie du pouvoir décisionnel du principal à l'agent. Cette délégation de pouvoir décisionnel met de fait les actionnaires à distance de la gestion courante de l'entreprise. Les gestionnaires disposent alors d'un avantage informationnel relativement aux actionnaires, couplé à un certain degré de liberté d'actions leur permettant d'en tirer profit pour satisfaire leurs propres intérêts. L'hypothèse centrale de la théorie de l'agence stipule que les intérêts du principal – i.e., des actionnaires – ne sont pas alignés sur ceux de l'agent – c'est-à-dire des gestionnaires. Il en résulte la naissance de difficultés, ou de problèmes d'agence, détrimentaires aux intérêts des actionnaires. Chargée de satisfaire les intérêts des actionnaires, la gouvernance d'entreprise a pour rôle la prévention et la gestion de ces problèmes.

Le principal organe responsable de la gouvernance d'entreprise est le conseil d'administration, composé d'administrateurs élus par les actionnaires. Le conseil d'administration est mandaté pour nommer et contrôler le directeur général – responsable de la gestion opérationnelle et stratégique de l'entreprise –, pour établir les règles de rémunération de l'équipe gestionnaire et pour convenir de la politique de distribution des dividendes aux actionnaires. L'alignement des intérêts des gestionnaires sur ceux des actionnaires est notamment obtenu par le biais de règles de rémunération fixées par le conseil d'administration corrélant positivement le salaire des gestionnaires à la performance de l'entreprise. En pratique, cela se traduit par

l'octroi de primes d'intéressement et de participation étant fonction du degré de performance de l'entreprise, ou encore par l'attribution de contrats dérivés dont la valeur est positivement corrélée au cours de bourse de l'action de l'entreprise.

.2.2. Le conseil d'administration à mandats échelonnés: définition et effets

Le conseil d'administration joue donc un rôle essentiel dans l'application de la gouvernance d'entreprise, et la façon dont il est structuré peut avoir d'importants impacts sur son efficacité.

Deux structures distinctes sont possibles pour le conseil d'administration. La structure conventionnelle est celle dans laquelle le mandat de l'ensemble des administrateurs composant le conseil d'administration est renouvelé chaque année par le vote des actionnaires. Ainsi, si la majorité des actionnaires n'est pas satisfaite du travail de surveillance, d'analyse et de conseil d'un administrateur, les actionnaires peuvent alors démettre ce dernier de ses fonctions lors du vote en assemblée générale annuelle. Le conseil d'administration peut également être structuré de telle sorte que les mandats des administrateurs soient échelonnés dans le temps. Un conseil d'administration à mandats échelonnés est composé de plusieurs groupes d'administrateurs¹⁰ – généralement au nombre de trois –, chaque groupe disposant de son propre terme. Ainsi, seul un groupe d'administrateurs est soumis au vote des actionnaires chaque année, tandis que les administrateurs rattachés aux autres groupes n'y sont pas soumis. De ce fait, la durée du mandat d'un administrateur faisant partie d'un conseil d'administration à mandats échelonnés est de plusieurs années, généralement trois.

Le conseil d'administration à mandats échelonnés est une mesure anti-OPA¹¹, c'est-à-dire qu'elle a pour effet de rendre plus difficile ou coûteuse une prise de contrôle non désirée par les actionnaires déjà en place. En admettant qu'un nouvel

¹⁰Aussi appelés classes d'administrateurs.

¹¹Offre Publique d'Achat.

actionnaire réussisse à détenir la majorité des droits de vote d'une entreprise dont le conseil d'administration est à mandats échelonnés, ce dernier ne pourrait pas prendre le contrôle effectif de l'entreprise dans le cas où les administrateurs lui seraient hostiles. Dans un tel contexte, l'actionnaire majoritaire devra généralement attendre deux élections, soit un à deux ans, pour remplacer la majorité des administrateurs non coopératifs et prendre ainsi le contrôle effectif de l'entreprise. De plus, le conseil d'administration à mandats échelonnés peut rendre l'acquisition de l'entreprise administrée bien plus coûteuse lorsqu'il est couplé à une pilule empoisonnée. Une pilule empoisonnée est une clause qui s'active lorsqu'un acquéreur hostile détient un nombre d'actions supérieur à un seuil fixé. Elle confère le droit à l'ensemble des actionnaires, excepté l'acquéreur hostile, d'acheter des actions de leur entreprise à un prix significativement plus faible que leur valeur de marché, voire de s'en voir distribué à titre gratuit. Il en résulte une dilution des positions de l'acquéreur hostile, devant alors acheter de nouvelles actions afin d'obtenir la majorité des droits de vote. Le conseil d'administration étant seul décisionnaire quant à l'emploi d'une pilule empoisonnée, l'acquéreur hostile ne pourra donc pas la retirer avant d'avoir remplacé la majorité des administrateurs.

.2.3. Deux théories en opposition: l'enracinement et l'engagement

Un large pan de la littérature se rapportant aux conseils d'administration à mandats échelonnés s'est penché sur son degré d'efficacité en tant que mesure anti-OPA. Pound (1987) et Bates et al. (2008) montrent que la présence d'un conseil d'administration à mandats échelonnés réduit la probabilité d'être la cible d'un acquéreur hostile. Toutefois, ils montrent que la probabilité que la firme soit acquise conditionnellement à avoir été ciblée n'est pas statistiquement différente de la probabilité d'acquisition d'une entreprise gouvernée par un conseil d'administration à structure conventionnelle. En d'autres termes, le conseil d'administration à mandats échelonnés dissuade les potentiels acquéreurs hostiles mais ne constitue pas une

mesure défensive absolue.

Le caractère dissuasif du conseil d'administration à mandats échelonnés a interrogé nombre de chercheurs quant à son impact sur la valeur de l'entreprise. Deux théories, en opposition, liant la présence d'un conseil d'administration à mandats échelonnés à la valeur de l'entreprise ont émergé. Manne (1965) est à l'origine de la théorie de l'enracinement, stipulant que la menace d'acquisition de l'entreprise a la vertu de discipliner l'équipe gestionnaire. En effet, l'équipe gestionnaire d'une entreprise nouvellement acquise peut être partiellement, voire totalement, remplacée. Cette menace incite donc l'équipe gestionnaire à diriger l'entreprise efficacement de sorte à ne pas se voir remerciée dans le cas où l'entreprise serait acquise par un nouvel actionnaire. Selon la théorie de l'enracinement, les mesures anti-OPA telles que le conseil d'administration à mandats échelonnés limitent l'effet disciplinant associé à la menace de remplacement de l'équipe gestionnaire puisqu'elles réduisent sa probabilité d'occurrence. Il en résulte l'apparition de problèmes d'aléa moral ayant un impact négatif sur la valeur de la firme. La théorie de l'enracinement est vérifiée empiriquement par les travaux de Bebchuk et al. (2002).

La théorie de l'engagement, ou *bonding theory*, suggérée par Knoeber (1986) et Shleifer et Summers (1988), stipule, au contraire, que la diminution de la menace d'acquisition de l'entreprise engendre des externalités positives accroissant sa valeur. La réduction de la probabilité d'acquisition causée par la présence d'un conseil d'administration à mandats échelonnés s'accompagne d'une diminution du risque de cessation des engagements que l'entreprise a noué avec diverses parties prenantes. De ce fait, les parties prenantes de l'entreprise – clients, fournisseurs ou encore employés – sont plus enclines à renforcer leurs liens économiques avec l'entreprise, notamment en consentant à réaliser des investissements spécifiques, à accepter des termes contractuels plus favorables, ou encore, dans le cas des employés, en augmentant leur productivité. Cremers et al. (2017) trouvent des résultats empiriques corroborant cette théorie.

.2.4. Chapitre 3: *Staggered Boards and Firm Value After the Sarbanes-Oxley Act*

La popularité des conseils d'administration à mandats échelonnés n'a pas été constante au cours du temps. En effet, cette provision anti-OPA était couramment utilisée par les firmes composant l'indice boursier S&P1500¹² dans les années 90 et jusqu'au début des années 2000. Toutefois, le conseil d'administration à mandats échelonnés a été progressivement abandonné à partir de 2005 lorsque la loi Sarbanes-Oxley, communément appelée SOX, a été adoptée. Ainsi, environ 60% des entreprises du S&P1500 étaient gouvernées par un conseil d'administration à mandats échelonnés entre 1990 et 2005. Seulement 20% de ces firmes dispose encore d'un conseil d'administration à mandats échelonnés en 2018¹³. SOX a été créée à la suite des scandales financiers d'Enron et WorldCom qui avaient éclaté au début des années 2000, afin de rétablir la confiance des actionnaires envers les divers organes de gouvernance d'entreprise. Cette loi crée *de facto* un environnement réglementaire défavorable à toute stratégie d'enracinement en requérant que la majorité des administrateurs siégeant au conseil d'administration soit indépendante de l'entreprise administrée. Le conseil d'administration à mandats échelonnés, du fait de sa structure rigide, rend le respect de cette règle d'indépendance plus difficile et coûteuse puisqu'il faut nommer une majorité d'administrateurs indépendants qui le resteront durant l'entièreté de la durée de leur mandat, généralement trois fois plus longue que la durée de mandat d'un administrateur dans un conseil à structure conventionnelle. L'augmentation du coût associé au conseil d'administration à mandats échelonnés à la suite de l'adoption de SOX explique donc la soudaine et continue vague d'abandons de la provision anti-OPA. Ce chapitre a pour premier objectif la découverte des facteurs responsables de la suppression du conseil d'administration à mandats échelonnés au sein de la firme après l'adoption de la loi

¹²L'indice S&P1500, ou Standard & Poor's 1500 Index, est un indice boursier constitué par les 1500 entreprises américaines les plus importantes en termes de capitalisation boursière.

¹³Voir Figure 3.1.

Sarbanes-Oxley. Le second objectif de ce chapitre consiste à déterminer la relation de causalité entre la présence d'un conseil d'administration à mandats échelonnés et la valeur de l'entreprise dans un contexte réglementaire défavorable aux stratégies d'enracinement.

En premier lieu, j'analyse les votes des actionnaires aux assemblées générales annuelles et montre un changement significatif autour de l'adoption de la loi Sarbanes-Oxley. Les actionnaires ont ainsi une propension plus faible à proposer et à voter en faveur de l'adoption d'un conseil d'administration à mandats échelonnés après l'adoption de la loi. Au contraire, ces derniers sont plus enclins à voter pour la suppression de la provision anti-OPA si leur firme en est dotée. Il apparaît également que l'équipe gestionnaire de l'entreprise est à l'origine de la totalité des propositions d'adoption du conseil d'administration à mandats échelonnés, alors que cela est rarement le cas lorsqu'il s'agit de proposer la suppression de cette provision en assemblée générale. En second lieu, je montre que les firmes ayant des relations privilégiées et créatrices de valeur avec leurs parties prenantes ont une probabilité plus faible de renoncer au conseil d'administration à mandats échelonnés après l'adoption de la loi. Ce résultat est particulièrement prononcé pour les firmes ayant plusieurs relations privilégiées avec des parties prenantes, notamment avec leurs employés et leurs clients. Enfin, en analysant la relation liant la valeur de l'entreprise à la présence d'un conseil d'administration à mandats échelonnés après l'adoption de la loi Sarbanes-Oxley, je montre que la causalité est à double sens. D'une part, les firmes ayant un conseil d'administration à mandats échelonnés après l'adoption de la loi sont de bonnes firmes. Du fait de leur qualité supérieure, elles ont les moyens de conserver un conseil à mandats échelonnés malgré son plus grand coût. D'autre part, cette structure non conventionnelle du conseil d'administration a un impact positif sur leur valeur à long terme, et ce malgré les coûts additionnels engendrés par la loi.

L'intérêt de ce chapitre est quadruple. Il présente tout d'abord des statistiques descriptives concernant les votes des actionnaires en assemblée générale avant et

après l'adoption de la loi Sarbanes-Oxley. De plus, cet article contribue à la littérature en montrant que la motivation principale des firmes à conserver leur conseil d'administration à mandats échelonnés après l'adoption de la loi réside dans la protection des relations privilégiées et créatrices de valeur de la firme avec d'importantes parties prenantes, notamment les employés et les clients de l'entreprise. Ce chapitre contribue également à la littérature en montrant que le conseil d'administration à mandats échelonnés a un impact positif sur la valeur de la firme après l'adoption de SOX, et ce même après avoir pris en considération le biais d'endogénéité potentiel. Enfin, ce troisième chapitre contribue au débat portant sur l'effet du conseil d'administration à mandats échelonnés sur la valeur d'entreprise en se positionnant en faveur de la théorie de l'engagement après l'adoption de SOX.

Partie 1

Le prêt participatif aux entreprises

Chapitre 1

Geographical Proximity and Enhanced Attention in P2B Crowdlending Strategies

joint work with Carole Gresse, Université Paris Dauphine - PSL

Abstract :

Using data from a peer-to-business crowdlending platform that runs an auction-driven system to fund corporate loans, we show that nonprofessional investors invest more heavily in borrowers located close to their place of residence despite not being better informed about their creditworthiness. Unexpectedly, this geographical-proximity bias is associated with an increase in loan rates. This effect results from the greater ability of experienced local investors to submit winning bids at an early stage. This ability is gained from their experience in previous auctions of local borrowers. This suggests that the feeling of familiarity stemming from geographical closeness increases investor attention, and thereby improves lenders' knowledge of the dynamics of the order flow in local borrowers' auctions. All in all, overinvesting in local firms is behavioral at first, but it becomes rational with experience. Those effects disappear when an automated bidding algorithm is introduced.

1.1. Introduction

While small and medium businesses (SMBs) are important to any economy, accessing funds is usually a major issue for them.¹ For instance, SMBs accounted for 99.9% of businesses and 47.5% of the total number of employees in the U.S. in 2018.² However, their access to financial markets is fairly limited. They therefore depend on banks to finance their operating needs and investments. Peer-to-business crowdfunding³ help alleviate this difficulty by allowing investors to finance SMBs directly, without intermediation, on electronic platforms, either via equity (equity crowdfunding), or via debt (crowdlending), in the hope of obtaining financial gains.⁴ Since crowdfunding platforms offer numerous projects to fund, investors must screen and select firms that they deem likely to yield positive returns. In the case of crowdlending, positive returns are ensured by the full repayment of loans, and hence borrowers' creditworthiness should be at the heart of investors' screening strategies. However, given that the average financial literacy of nonprofessional investors participating in crowdlending is by nature weaker than that of professional lenders, we fear that behavioral biases are strong on those platforms and cause overinvestment or underinvestment issues.

In this chapter, we investigate the decision-making process of nonprofessional investors to check whether this process is influenced by a behavioral bias that we designate as the *geographical-proximity bias*. This bias resembles home bias at the international level but is quite different in essence. Home bias, i.e., the tendency to overinvest in domestic assets relative to foreign assets, can be caused by exoge-

¹Abraham and Schmukler (2017) address this issue and suggest some solutions to overcome it.

²Further details on the data on American SMBs are available at <https://www.sba.gov/sites/default/files/advocacy/2018-Small-Business-Profiles-US.pdf>.

³Crowdfunding can be defined as a way of raising funds from a large number of investors, outside the banking system, generally through an internet platform. In peer-to-business crowdfunding, fund raisers are corporations, while in peer-to-peer crowdfunding, fund raisers are individual borrowers.

⁴Peer-to-business crowdfunding should not only be seen as a way to raise funds for firms. Belleflamme et al. (2013) show that some entrepreneurs use crowdfunding for marketing purposes. Chemla and Tinn (2020) elaborate the idea that firms use crowdfunding to analyze consumers' preferences and to gauge demand for their products.

nous factors such as transaction costs, foreign exchange risk, fiscal barriers, and a lack of information about foreign assets. Conversely, geographical-proximity bias does not relate to such external factors. It pertains to a broader notion, known as familiarity bias, which consists in overinvesting in assets we are more familiar with. In geographical-proximity bias, familiarity stems from geographical closeness. In other words, if investors are subject to this bias, they would overinvest in firms located near their place of residence because geographical closeness would provide them with a feeling of familiarity. Overinvesting in neighbors could also be driven by other biases such as altruism toward neighbors or the willingness to support the local economy. Our analysis does not distinguish among those different motivations, and our concept of familiarity covers all those behaviors.

Using data from a French peer-to-business crowdlending platform that uses an auction system to fund loans, we examine whether geographical closeness between lenders and borrowers creates biases in the bidding strategies of lenders. Our identification strategy relies on the implementation of a bidding algorithm that submits bids on behalf of investors. We interpret the implementation of the bidding algorithm as an exogenous decrease in geographical-proximity bias, provided that this bias exists. We find evidence that investors have a preference for firms that are located in the same administrative division as them but only during the period before the implementation of the bidding algorithm. Investors located in the same administrative division as the borrower are more likely than other investors to participate in the auction, and they are also more likely to win it. We then investigate whether this preference to lend money to geographically close borrowers is information-driven or purely behavioral. By analyzing loan performance, we find that investors who lend money to borrowers located in their administrative division are as likely as other investors to experience a default on those loans. This proves that investors do not possess privileged information on the creditworthiness of closely located firms, but it supports the idea that they develop a feeling of familiarity toward these firms. Last, we investigate whether geographical-proximity bias reduces the efficiency of the loan

rate discovery process during the auction. We find that the presence of geographically close investors in auctions is associated with an increase in the borrowers' cost of funding. We explain this result by the fact that closely located investors time their bids differently from other investors. They participate earlier in the auction and then become passive in the final moments, when the competition on the borrowing rate takes place. This decreases the level of competition between bidders in the pricing mechanism and thereby increases the borrower's cost of funding. We also find that the positive link between borrowing rates and the weight of local investors in auctions is driven by the weight of local investors who have already participated in previous local auctions. This suggests that those investors have inferred information on the order flow of local auctions from their previous experience. This knowledge, probably resulting from increased attention due to a feeling of familiarity, allows them to submit winning bids at higher rates in subsequent local auctions, which in turn tends to increase the borrowing rates of those auctions. There lies the main contribution of our work. Familiarity related to geographical closeness increases investor attention, and thereby enhances investors' ability to master the trading mechanisms they use, so that investing experience makes investing more in local projects a rational strategy.

The remainder of the chapter is structured as follows. Section 1.2 reviews the relevant literature and presents our hypotheses. Section 1.3 describes the data and the strategy used to identify geographical-proximity bias. Section 1.4 tests for the existence of geographical-proximity bias, and Section 1.5 analyzes its impact on the efficiency of the price discovery process in the auction system. We provide robustness checks in Section 1.6. Section 1.7 concludes the chapter.

1.2. Literature review and hypothesis development

A substantial extent of the literature on crowdfunding⁵ has focused on investors' behavioral biases. [Ceyhan et al. \(2011\)](#) study the dynamics of investors' bidding

⁵See [Moritz and Block \(2016\)](#) for a detailed literature review on crowdfunding.

behavior in an auction-driven crowdlending platform. They show that investors exhibit herding behavior at the beginning and at the end of each auction. [Dorfleitner et al. \(2022\)](#) show that investors stop investing on a peer-to-business crowdlending platform after experiencing a default, which leads to portfolio underdiversification. [Hervé and Schwienbacher \(2018\)](#) show that investors are more likely to use round numbers when uncertainty increases on an equity crowdfunding platform. More broadly, [Adhami et al. \(2019\)](#) investigate the return of investors on a peer-to-business crowdlending platform and show that returns are inversely related to loan risk. We contribute to this growing literature by examining a behavioral bias that has been scarcely investigated in this context: geographical-proximity bias.

1.2.1. Geographical-proximity bias and related literature

Geographical-proximity bias is a specific form of a broader concept: familiarity bias, which can be defined as a tendency to prefer what is familiar. For instance, [Heath and Tversky \(1991\)](#) show that individuals prefer betting on their own judgment when they are familiar with the matter. Such behaviors exist in stock markets. For example, [Frieder and Subrahmanyam \(2005\)](#) show that individual investors hold portfolios that are overweighted toward stocks with high visibility whereas institutional investors' holdings are more related to firm size and beta. Familiarity bias can also distort investors' expectations; as [Benartzi \(2001\)](#) shows, investors that are "very familiar" with a specific stock are more likely to extrapolate past performance to future performance. This type of familiarity bias can be termed geographical-proximity bias when familiarity results from geographical closeness. Such a bias has already been identified in financial markets. [Huberman \(2001\)](#) shows that investors tend to invest a relatively large portion of their portfolios in their local phone company. [Seasholes and Zhu \(2010\)](#) show that investors hold portfolios that are overly weighted toward local stocks while they do not earn abnormally higher returns on those stocks. This suggests that investors' preferences for local stocks is a behavioral bias. [Wolf \(2000\)](#) finds evidence of home bias in commodity trades in the U.S. at

the state level, which suggests that international trade barriers do not fully explain the higher propensity of agents to trade locally. [Coval and Moskowitz \(1999\)](#), [Coval and Moskowitz \(2001\)](#), [Kang and Kim \(2008\)](#), [Baik et al. \(2010\)](#), and [Hochberg and Rauh \(2013\)](#) show that U.S. institutional investors overweight their investment portfolios toward local companies and local private equity funds. Except for [Hochberg and Rauh \(2013\)](#), these papers find evidence suggesting that institutional investors have an informational advantage as their local investments tend to produce positive abnormal returns. Using data from two U.S. brokerage firms, [Zhu \(2002\)](#) and [Ivković and Weisbenner \(2005\)](#) show that individual investors are more likely to invest in local public companies. [Zhu \(2002\)](#) shows that this preference for local stocks is not information-driven but rather behavioral as such investors invest all the more in local companies if they spend heavily on advertising. On the contrary, [Ivković and Weisbenner \(2005\)](#) find evidence that individual investors earn positive abnormal returns on their local investments, which suggests that such investors possess private information on local companies they invest in.

Familiarity bias in general and geographical-proximity bias in particular are also present in online markets. [Hortaçsu et al. \(2009\)](#) use data from two auction sites, eBay and Mercadolibre, and find that transactions are more likely to occur between counterparts located in the same city. [Agrawal et al. \(2011\)](#) highlight the existence of familiarity bias on a crowdfunding platform that connects artists and investors. They show that this bias is mainly driven by the family and friends of the artists. [Lin and Viswanathan \(2016\)](#) exploit the moves of borrowers across states to demonstrate the existence of home-state bias on Prosper, one of the leading U.S. peer-to-peer crowdlending platforms. They also find evidence that this bias is mainly behavioral. This chapter takes part of this literature on the impact of geographical proximity on crowdfunding investment strategies. It is novel in that (1) we analyze a peer-to-business crowdlending system in which borrowers are corporations and not individuals, and (2) more important, the crowdlending platform we study runs an auction system in which loan rates are determined by investors' bids. Those

specific features allow us to investigate the impact of potential behavioral biases on the quality of the interest rate discovery process on the platform. Furthermore, the granularity of our data allows us to measure geographical proximity at a much finer geographical level than in the aforementioned studies. Consistent with other studies, we find that investors that are more familiar with certain firms because of their geographical proximity are more likely to lend to them. We contribute to the literature by showing that, although overinvesting in local firms is a behavioral bias at first, it then becomes a rational strategy with experience on the platform. Geographical proximity with borrowers increases investor attention in such a way that they acquire specific knowledge on the order flow dynamics of local auctions. This experience effect allows them to submit winning bids at higher rates in the next local auctions, which makes investing more in these auctions rational. Those effects disappear when an automated bidding algorithm is introduced.

Geographical-proximity bias resembles the widely documented home bias⁶ in the sense that both biases result in overinvesting in home assets, home being the home country in one case and a more restricted local area in the other. However, their determinants radically differ. Although some authors such as [Lewis \(1999\)](#) fail to explain the home bias in U.S. equity markets with rational factors, it is generally acknowledged that home bias is caused by exogenous factors such as trading costs, fiscal barriers, or a lack of information. For instance, [Ahearne et al. \(2004\)](#) explain the home bias in equity holdings by the presence of information asymmetries. By contrast, geographical-proximity bias is fully behavioral and not related to information. For that reason, finding a preference for local borrowers among investors on crowdlending platforms does not suffice to prove the existence of that bias. We also need to check that this preference is not driven by superior information held on closely located firms. This point is important for two reasons. First, there are examples in the literature of apparent familiarity biases that proved to

⁶For instance, [Disdier and Head \(2008\)](#) conduct a broad study to show that home bias is persistent across different markets, methodologies, and time periods. Similarly, [Hau and Rey \(2008\)](#) show that mutual funds from various countries are affected by home bias.

be information-based choices. For example, [Massa and Simonov \(2006\)](#) show that Swedish investors heavily invest in stocks related to their nonfinancial income. They however find that this bias is not behavioral but rather information-driven. Similarly, [Ivković and Weisbenner \(2005\)](#) show that U.S. individual investors earn positive abnormal returns when owning local public companies' stocks. Second, several papers show that rational creditworthiness screening or rational information inference may explain patterns observed on crowdfunding platforms. [Zhang and Liu \(2012\)](#) find that investors do not passively follow the actions of other investors but instead actively attempt to infer the creditworthiness of borrowers by observing the lending decisions of other investors. They interpret such behavior as rational herding. [Vallée and Zeng \(2019\)](#) study the adverse selection issue arising from heterogeneous levels of sophistication between investors on a crowdlending platform. They show that sophisticated investors lose part of their outperformance relative to unsophisticated investors after a substantial decrease in the borrowers' public information reported by the platform. Comparably, [Mohammadi and Shafi \(2017\)](#) show that institutional investors have better performance than individual lenders because of the greater ability to screen on a peer-to-business crowdlending platform. This chapter opposes and complements this strand of literature by showing that (1) the propensity of individual crowdlenders to invest more in geographically close borrowers is a behavioral bias in a first stage; (2) geographical proximity enhances investors' attention on auctions' dynamics; and (3) this increased attention modifies their bidding strategies in the subsequent auctions of closely located borrowers such that their greater investment in local borrowers becomes rational with experience.

1.2.2. Hypothesis development

Our main a priori hypothesis is that geographical proximity affects the decision-making process of nonprofessional investors. We test it by exploiting the data of a leading French crowdlending platform. These data are particularly well suited for our research for two reasons: first, the introduction of an algorithm on the platform

during our observation period provides us with an exogenous shock to potential behavioral biases, which facilitates our identification strategy; second, the information included in the data on the place of residence of borrowers and crowdlenders allow us to measure geographical closeness at a relatively fine level.

To determine whether an investor is located close to a borrower, we use the geographic administrative divisions of the French national territory. France has three levels of geographic administrative divisions, of which the highest is the *région* or region.⁷ *Régions* are divided into *départements*, which are in turn composed of cities, named *communes* in French. On average, the surface area of a *département* is four times that of a county in the U.S., and *communes* are equivalent to U.S. municipalities. We consider a lender to be geographically close to a borrower if the lender lives in the same administrative division as the borrower, with the administrative division level under consideration being the *département*.⁸

Based on this definition of geographical closeness, we expect investors to invest more aggressively in projects located in their administrative division, and we construct the two following testable hypotheses:

H1: Investors located in the same administrative division as the borrower are more likely to participate in the borrower's auction.

H2: Investors located in the same administrative division as the borrower are more likely to win the borrower's auction.

Finding evidence in support of H1 and H2 would not be enough to prove the existence of geographical-proximity bias because investors being more likely to lend to borrowers located close to them could be explained by an informational advantage about the borrowers' creditworthiness over the rest of the investors. As shown by [Iyer et al. \(2016\)](#) with data from Prosper, peer lenders use both hard and soft information to predict the rate of default of borrowers, and in our case, local investors may well have privileged access to soft information about the borrowers in their

⁷Until 2015, there were 25 *régions* in France. In 2015, their number was reduced to 18. In our analysis, we exclusively consider the pre-2015 administrative division.

⁸Unfortunately, our data do not allow us to pursue the analysis at a finer level, namely at the city level.

administrative division. We therefore compare two theoretical hypotheses: (1) the view that investing more heavily in nearby borrowers is the outcome of a behavioral bias, referred to as the behavioral hypothesis, and (2) the view that those greater investments are due to informational advantages, referred to as the rational hypothesis. According to the rational hypothesis, lenders located close to the borrower should have a greater ability than other lenders to avoid underperforming loans. Under the behavioral explanation, investors close to the borrower do not have more information about the creditworthiness of the borrower. They should therefore have either an equal or a higher probability of experiencing a default on the loan than the rest of the investors. To distinguish between the two hypotheses, we test H3.

H3: Investors located in the same administrative division as the borrower are less likely to experience a default than the rest of the investors.

Not rejecting H3 would validate the rational hypothesis, while rejecting H3 would validate the behavioral hypothesis. Specifically, rejecting H3 after finding evidence in support of H1 and H2 would prove the existence of geographical-proximity bias.

Finally, we attempt to determine whether geographical-proximity bias affects the efficiency of the price discovery process in the auction system. Under the rational hypothesis, the presence of local investors, i.e., investors from the same administrative division as the borrower, should improve the efficiency of the auction's price discovery process because their bids would be more informative. Conversely, under the behavioral hypothesis, the presence of local investors either, at best, has no impact on or deteriorates the efficiency of the price discovery process of the auction system by overinvesting in local firms' loans. To investigate this issue, we model theoretical fundamental loan rates as a function of common loan rate determinants in a first stage, and in a second stage, we examine how loan rate deviations from those fundamental values relate to the presence of local investors in auctions. This translates into the following hypothesis.

H4: Loan rate deviations from their fundamental values increase with the pres-

ence of local investors in auctions.

1.3. Data and identification strategy

The data come from Unilend, a French peer-to-business crowdlending platform that provides French SMBs with unsecured fixed-rate amortizing loans. These data are particularly appropriate for our research for three reasons. First, Unilend was a major actor in the crowdlending market over our observation period. Unilend was created in 2013 and was the first peer-to-business crowdlending platform in France. As of the end of 2016, it had become the third-largest crowdlending platform in France, with a market share slightly exceeding 15% of total lent money.⁹ Second, contrary to many other crowdlending platforms, such as Prosper in the U.S. or Lendix in France, on which both retail and institutional investors fund loans, Unilend only targets retail investors as potential lenders.¹⁰ Third, Unilend is one of the few platforms on which loan rates are set by investors in Dutch auctions. All other platforms with sizable market shares¹¹ use fixed-rate procedures in which investors bid at a rate previously determined by the platform according to the loan maturity and credit risk.

1.3.1. The Unilend auction system and bidding algorithm

On Unilend, loans are funded through a Dutch auction system where investors place bids with the amount of money they are willing to lend and the interest rate they are willing to receive. Investors may submit multiple bids. The amount of the loan, its term, and the auction's starting time and its end time are announced on the platform

⁹At present, Unilend remains an important player. It has the typical business model of a marketplace, which requires a critical mass of lenders and a steady flow of borrowers to be profitable. Due to a lack of borrowers, it went bankrupt in October 2018 and was acquired by another crowdlending platform, named Pretup, in December 2018.

¹⁰A minority of investors on the platform are non-physical lenders. The size of each of their investments is relatively small, making it highly unlikely that they are professional lenders or institutional investors.

¹¹In France, the PrêtStory platform also operates Dutch auctions but its market share is very small.

before the auction starts. Once the auction starts, investors bid in competition with each other at rates bounded between 4 and 10%, with a 0.1% tick. At the end of the auction, bids are sorted in ascending order of interest rates, and bids' amounts are cumulated from the lowest interest rate up to the first rate at which the loan amount can be cleared. All bids submitted at a rate strictly lower than the clearing rate are served. Bids submitted at the clearing rate are served on a first-come first-served basis. Each winning investor lends the amount of her winning bid(s) and receives the monthly service of the loan at the rate she bid. The maximum winning interest rate in an auction, i.e., the clearing rate, will be referred to as the equilibrium rate of the loan in our analysis. The funding rate of the borrower is computed as the average of all winning bids' rates weighted by the corresponding bid amounts. It will be referred to as the average rate in the remainder of the chapter. In the event that bids are inadequate to clear the loan amount, the loan is not funded.

Auctions' durations can be decomposed into two periods: the coverage period during which the cumulated bid amounts do not clear the loan amount and the competition period that starts as soon as an additional bid can clear the loan amount. During the coverage period, every bidder is a winner, and there is no competition between bidders. During the competition period, bidders compete with one another on rates, and only bids with the lowest rates submitted potentially win the auction. We further consider the ratio of the competition period duration divided by the total duration of the auction as a measure of the competitive intensity in the auction.

A specific feature of our data is the implementation of a bidding algorithm by the platform during the sample period. This algorithm, named Autolend, bids on behalf of investors according to parameters they preset on the platform. After the implementation of this algorithm, bids can be either manual or automated. Investors can freely activate or deactivate Autolend. When activating Autolend for the first time, investors must declare their reservation rate, i.e., the minimum interest rate at which they will agree to lend, for all possible loan maturity/credit rating combinations. Once those parameters are set, the algorithm automatically

bids on their behalf at the maximum rate accepted in an auction any time this maximum rate is higher than or equal to their reservation rate. When a bid is outbid, the algorithm bids again at a new rate equal to the previous bid rate minus one tick, provided that this new rate is compatible with the investor's reservation rate.

1.3.2. Available information about borrowers

Before the start of each auction, the platform provides information about the borrower and its project. Specifically, Unilend publishes the borrower's name and geographical location, as well as its income statements and balance sheets¹² up to two fiscal years before the year of the auction.¹³ Unilend also describes the borrower's business and the reason that it is seeking funds. In addition, Unilend credit analysts assign each loan a credit rating by using both hard information from the balance sheets and income statements and soft information from interviews with the firm's management, generally the CEO. Unilend uses a rating grid ranging from zero to five stars with an increment of 0.5 stars, with the number of stars decreasing with default risk. Only projects with a credit rating above or equal to three stars are offered to investors. Since we expect investors to rely on those credit ratings to assess the riskiness of the borrowers, we check, as a preliminary test, to what extent those ratings are actually related to financial variables known to be meaningful about creditworthiness. We run an ordered logistic regression in which the borrower's credit rating is the dependent variable, and firm size, cash holdings, leverage, and profitability measures are the regressors. Our estimates show that Unilend ratings significantly relate with all tested variables in the expected way. Firm size, cash scaled by total assets, and the operating margin are all positively and significantly correlated with the borrower's credit rating, while the gearing ratio has a negative and statistically significant impact on that rating. Those findings confirm that the ratings advertised to investors on the platform are reliable synthetic measures of credit risk.

¹²The income statements and balance sheets communicated to investors are not always audited.

¹³Only the year before the auction starts is generally provided.

1.3.3. Sample and descriptive statistics

The initial sample provided by Unilend comprises 318 auctions run on their platform from November 2013 to October 2016 and accounting for a total of 1.6 million bids. Nine of those auctions were not completed because of insufficient demand from investors. They were thus removed from the sample. The Autolend algorithm was first used in April 2016. 247 loans were completed¹⁴ before its implementation, and 62 loans were completed thereafter. We also removed the auctions for which we had no data either on the size of total assets or the sales of the borrowing firm one fiscal year before the auction. This leaves us with a final sample of 290 completed auctions. Those 290 auctions account for 1,470,365 bids submitted by 9,059 unique investors. Of the bidders, 11.8% are nonphysical investors, i.e., companies. Men account for 89% of nonprofessional investors. For nonprofessional investors, the data include age and place of residence in addition to gender.

We can identify from the data the *département* of residence of borrowers and investors, which is instrumental to study geographical proximity. The borrowers in our sample are located in 63 different *départements*.¹⁵ Active investors, i.e., investors that have submitted at least one bid in one of the 290 auctions composing our final sample, are located in 100 different *départements*. Bids submitted by investors located in the same *département* as the borrower represent 3.42% of the total number of bids.

Table 1.1 reports the descriptive statistics on the characteristics of the loans, the borrowers, the auctions, and the investors for our 290 sampled auctions. Loan amounts range from €10,000 to €400,000, with an average close to €75,000. Loan maturities range from 12 to 60 months, with an average of 42 months. Borrowers have on average a total asset size of 1.72 million euros and sales equal to 1.88 million euros in the fiscal year preceding the auction. Investors are on average 43.6 years

¹⁴An auction is completed if it has received enough bids to reach the loan's amount.

¹⁵The information provided is the location of the borrower's headquarters. If a borrower has other operating sites, we are not able to take them into consideration. However, given the very small size of the businesses in our sample, it is very unlikely that those potential alternative sites are located outside the headquarters' *département*.

old at the time they submit their bids.

In Table 1.2, we compare auctions completed before the implementation of Autolend with auctions completed thereafter. We test the difference in mean and median between the two groups of auctions for the main variables used in this chapter. While the economic characteristics of borrowers and funded projects are relatively similar over the two subperiods, the characteristics of the bids in the auctions are completely different.

Borrowers are similar in terms of total assets, sales, leverage,¹⁶ and Unilend credit rating. The differences in loan size and loan maturity are statistically significant, with the average loan amount and the average loan term being slightly smaller in the post-Autolend period, but those differences remain small in economic terms.

In contrast with the stability of loan and borrower characteristics, the bidding frequency is much higher in the auctions completed after the implementation of the bidding algorithm. Both the average number of distinct bidders and the average number of bids per auction substantially increase, with 719 distinct investors and 1,461 bids per auction on average in the period before the implementation of Autolend versus 1,467 investors and 20,845 bids thereafter. This bidding frequency increase is a direct consequence of bid automation. Furthermore, the algorithm monitors all auctions with equal attention, whereas investors may not realize or may forget that the auctions they were interested in have opened.¹⁷ The constant monitoring by the Autolend algorithm leads to a higher level of competition between investors during the auctions. To provide evidence on this increased competition, we compute the relative proportion of the auction duration in which bidders are in competition with each other, i.e., the ratio competition period duration over auction total duration, referred to as the competition degree in the rest of the chapter. For auctions completed before the implementation of Autolend, the competition period represents 45% of the total auction duration, while the competition period represents

¹⁶We define debt leverage as the sum of supplier debts, financial debts and other debts divided by total assets.

¹⁷Investors receive an e-mail when a new auction opens and when their last bid in a live auction has been outbid.

Table 1.1: Summary statistics

This table reports the mean, the median, the standard deviation, the minimum value, and the maximum value of several characteristics of the 290 loans of our sample, their auctions, and their borrowers. Among those characteristics, accounting items are those of the fiscal year preceding the auction. Leverage designates the ratio of total debts over total assets. The loan rating is the credit notch assigned to the loan by Unilend. For auctioned loans, those notches range from 3 to 5, with a 0.5 increment, 5 being the best creditworthiness. The equilibrium rate is the clearing rate of the auction. The average borrowing rate is the weighted average rate of the bids served in the auction, i.e., the rate paid by the borrower on its loan. The auction duration is that announced on the platform before the start of the auction. The competition degree is the duration of the competition period - that is the phase of the auction during which the cumulative amount of bids already clears the loan and investors compete in rate - divided by the total duration of the auction.

	N	Mean	Median	St. Dev.	Min	Max
Loan amount	290	74,367.240	55,000.000	55,103.330	10,000.000	400,000.000
Loan term (in months)		41.979	36.000	13.458	6.000	60.000
Total assets (in millions)		1.722	0.591	4.205	0.000	46.694
Sales (in millions)		1.880	0.754	5.531	0.000	83.532
Leverage		0.550	0.563	0.183	0.008	0.906
Loan rating		3.259	3.000	0.349	3.000	4.000
Number of bids		5,070.224	1,531.500	8,206.224	217.000	39,690.000
Number of distinct bidders		858.266	754.500	519.120	159.000	3,240.000
Investor age (in years)		43.599	43.559	0.871	40.316	46.105
Average borrowing rate (in %)		7.890	8.211	1.573	4.000	9.903
Equilibrium rate (in %)		8.137	8.450	1.642	4.000	10.000
Auction duration (in hours)		247.000	195.000	189.000	0.070	1,083.517
Competition degree		0.527	0.570	0.342	0.000	1.000

Table 1.2: Comparing loans before and after the implementation of Autolend

This table compares the means of several characteristics of the 290 loans of our sample, their auctions, and their borrowers, before and after the implementation of the Autolend algorithm. Among those characteristics, accounting items are those of the fiscal year preceding the auction. Leverage designates the ratio of total debts over total assets. The loan rating is the credit notch assigned to the loan by Unilend. For auctioned loans, those notches range from 3 to 5, with a 0.5 increment, 5 being the best creditworthiness. The equilibrium rate is the clearing rate of the auction. The average borrowing rate is the weighted average rate of the bids served in the auction, i.e., the rate paid by the borrower on its loan. The auction duration is that announced on the platform before the start of the auction. The competition degree is the duration of the competition period - that is the phase of the auction during which the cumulative amount of bids already clears the loan and investors compete in rate - divided by the total duration of the auction. We test the difference in means between the two subsamples with a t -test and the difference in medians with a Wilcoxon test, and we report the associated p -value.

	Pre-Autolend period	Post-Autolend period	t -test	Wilcoxon test
N	236.000	54.000		
Loan amount	76,854.450	63,497.220	0.089	0.023
Loan term (in months)	43.182	36.722	0.004	0.003
Total assets (in millions)	1.792	1.416	0.387	0.613
Sales (in millions)	1.978	1.451	0.268	0.743
Leverage	0.552	0.541	0.666	0.676
Loan rating	3.250	3.296	0.404	0.413
Number of bids	1,460.801	20,844.741	0.000	0.000
Number of distinct bidders	718.873	1,467.463	0.000	0.000
Investor age	43.643	43.408	0.040	0.081
Average borrowing rate (in %)	8.226	6.425	0.000	0.000
Equilibrium rate (in %)	8.499	6.552	0.000	0.000
Auction duration (in hours)	285.947	78.267	0.000	0.000
Competition degree	0.445	0.884	0.000	0.000

88% of the total auction duration after the introduction of Autolend.

Because the algorithm constantly monitors auctions, it allows loans to be funded rapidly, sometimes in less than one second, which in turn increases the relative share of the competition period in the total auction duration. Consequently, the duration of auctions completed after the implementation of Autolend is much shorter, with an average of three days against 12 days for auctions completed before Autolend.

As a consequence of this increased competition, both the average and the equilibrium rates are lower for the auctions completed after the implementation of the algorithm. The average funding rate decreased, on average, from 8.23% for the pre-Autolend subsample to 6.42% for the post-Autolend subsample. We compare those relatively high interest rates with the rates at which banks lent money to French SMBs for similar loan terms and loan amounts between 2013 and 2016.¹⁸ On average, banks lent money to SMBs at 2.22% during the period before Autolend and at 1.71% during the period after Autolend. Although some of the difference between bank rates and crowdlending rates can be attributed to the fact that bank loans are secured, the large difference between the two categories of rates suggests that crowdlending is essentially used by SMBs that cannot access bank loans because they are considered too risky. An alternative explanation may be that SMBs prefer to borrow money through crowdlending platforms rather than banks because the borrowing process is lighter and faster. For instance, income statements and balance sheets do not need to be audited to borrow money through a crowdlending platform, and firms receive the loan's principal in their bank account a couple of days after the end of the auction. However, the difference in funding rates makes this second explanation hardly credible, and we believe that crowdlending is complementary to banks rather than being a substitute. Crowdlending platforms mainly finance SMBs that banks are not willing to lend to because they are deemed too risky. This is consistent with the findings of [Tang \(2019\)](#), who shows that peer-to-peer crowdlending

¹⁸This analysis is based on the data from *Banque de France*, available at <https://www.banque-france.fr/statistiques/credit/credit/taux-des-credits-aux-entreprises>. Each completed loan is matched with the aggregated data on loan rates for SMBs from *Banque de France*.

is a complement to bank lending for small loans. It also confirms the prediction of the model of [de Roure et al. \(2022\)](#) that loans originated through crowdlending are, on average, riskier than bank loans.

1.3.4. Identification strategy

Our identification strategy relies on the implementation of Autolend. This algorithm was implemented by the Unilend crowdlending platform to improve bidding mechanisms and accelerate their auction procedures. With Autolend, investors set in advance the parameters of their bids, i.e., at their reservation rate for a given loan maturity and credit rating. Their bids are then automatically submitted according to those preset parameters, so that they do not need to monitor the platform. Because geographical location is not part of the Autolend parameters, bids submitted by the algorithm on behalf of investors are free of any geographical-proximity bias. For auctions that were completed after the implementation of Autolend, automated bids represent on average 94.11% of the total number of bids in each auction. Automated bids represent 51.72% of winning bids, and they fund 47.74% of the loan amount on average. Thus, the impact of bias-free automated bids is large. As a consequence, geographical-proximity bias should be much more present in auctions completed before the introduction of the bidding algorithm than in auctions completed thereafter. Our identification strategy is therefore based on the comparison between auctions completed before the implementation of the bidding algorithm, for which we should observe geographical-proximity bias if it exists, and the auctions completed after the implementation of Autolend, which are supposed to be less impacted by this bias. This assumption is based on the fact that automated bids largely outnumber manual ones after Autolend implementation. While bids were solely manual before Autolend, automated bids are the vast majority after its introduction. This results in dramatically changing the way auctions unfold. This is the reason why we run separate regressions for the two sub-periods. Thereby, we avoid regime change issues.

A concern about our identification strategy is that active investors may differ between the two periods. Indeed, if investors differed between the two periods, then the difference in the intensity of the geographical-proximity bias in both periods would not necessarily be caused by the implementation of the bidding algorithm but could rather result from the difference in the profile of active investors. Fortunately, most of the investors that were active before the implementation of the algorithm remained active thereafter. Before the implementation of Autolend, there were 7,908 active investors against 5,707 active¹⁹ investors in the post-Autolend period. Of the 5,707 investors that were active after the implementation of the bidding algorithm, 4,548 investors (79.69%) were already active in the period before. In addition, as reported in Table 1.2, the two populations of investors are similar in terms of age.

1.4. Testing for the existence of geographical-proximity bias

We begin this section by showing that investors prefer investing in closely located companies, i.e., companies located in their *département* of residence, further designated as local companies. We then investigate whether this preference is information-based or behavioral.

1.4.1. Testing for the existence of investor preferences for local companies

To investigate whether crowdlending investors are subject to geographical-proximity bias, we examine their likelihood of participating in an auction in the following

¹⁹An investor is considered to be active if she has submitted at least one bid in the auctions of the period considered.

logistic regression:

$$\begin{aligned} Participation_{i,j} = & \alpha_1 \cdot Geographical\ Closeness_{i,j} \\ & + \alpha_2 \cdot Auction\ Duration_j + \alpha_3 \cdot Age_i + \alpha_4 \cdot X_j + \epsilon_{i,j} \end{aligned} \quad (1.1)$$

where $Participation_{i,j}$ is a dummy equal to one if investor i bids at least once in auction j , and zero if investor i does not bid in auction j at all. To be considered, investor i must have already registered with the platform at the time of the auction. Our main variable of interest is the dummy $Geographical\ Closeness_{i,j}$, which equals one if investor i participating in auction j is located in the same administrative division as the borrower (i.e., the same *département*), zero otherwise. Investors for whom this dummy equals one will further be designated as local investors, the term "local" being defined with respect to the borrower's place of residence. We control for the preannounced duration of the auction, taken in logarithms and denoted $Auction\ Duration_j$, because investors are more likely to participate in auctions that last longer. We use Age_i , the age of investor i taken in logarithms, as a control for investor i 's wealth and investing experience. We expect it to positively impact the probability of participation. X_j is a vector of control variables at the loan level. This vector includes the loan amount and the loan maturity, both taken in logarithms, plus three dummies representing the credit rating of the loan. Each of those dummies, further denoted $Rating\ n$, equals one if the credit rating is n stars, zero otherwise, with n being alternatively 3.5, 4, and 5 and the base case being a three-star rating. The rationale for the controls composing X_j is as follows. Due to the finite number of investors registered on the platform, large-size loans take longer to be cleared in an auction. For that reason, the larger the loan amount, the easier it is to participate in the auction. All things being equal, loan maturity is expected to negatively impact the decision to participate in an auction, as a longer maturity means both a longer time before recovering the funds invested and a longer exposure to default risk. Last, rating dummies provide a synthetic assessment of the riskiness of the investment. They should thus have an impact on the decision to participate

in the auction. We also introduce fixed effects by administrative divisions to account for the differences in the economic development of those divisions. As an illustration, the Paris area and the eastern part of France have much denser industrial networks than the rest of the country. The number of auctions in those more economically active geographical areas is thus greater, which makes the likelihood of participating in auctions in those areas statistically greater, all things being equal. Therefore, finding a significantly positive α_1 coefficient in Regression (1.1) would support the hypothesis that investors participate more in the auctions of local companies (H1).

The full sample of auctions is divided into two groups: the first group is composed of the auctions completed before the implementation of the bidding algorithm, and the second group is composed of the auctions completed thereafter. As discussed in the previous section, our identification strategy relies on the comparison of those two groups, since the first group of auctions should be more impacted by that bias than the second. As illustrated by the statistics in Table 1.2, the number of bids and the number of unique bidders per auction are much higher after the implementation of Autolend. Indeed, the automation of bid submissions completely changes the way auctions unfold. For those reasons, we run logistic regression (1.1) on both subsamples, and we expect α_1 to be significantly positive for pre-Autolend auctions but statistically insignificant for the other group of auctions.

The results reported in Table 1.3 are in line with expectations. Local investors are significantly more likely than others to participate in auctions before the implementation of the bidding algorithm, but this effect disappears after the implementation of Autolend. These findings are in support of H1. Regarding control variables, an investor is more likely to participate in the auction if she is older. Age can be seen as a proxy for personal wealth here. The wealthier the investor is, the higher her likelihood of participating. As expected, investors' participation likelihood is positively correlated with the duration of the auction. The correlation between the likelihood of participating in the auction and the size of the loan is unclear as the coefficients are of opposite signs over the two subperiods.

Table 1.3: Investor likelihood of participating in an auction

This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if, for a given investor and a given auction, the investor has participated in the auction, 0 otherwise. Column 'Pre-Autolend period' and column 'Post-Autolend period' present the results for the pre-Autolend and the post-Autolend subsamples respectively. *Geographical closeness* equals 1 for local investors, 0 for others. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Investor age*, *Auction duration*, *Loan amount* and *Loan term* are expressed in years, hours, euros, and months respectively, and taken in logarithm. Standard errors are reported in parentheses. ***, **, and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Pre-Autolend period (1)	Post-Autolend period (2)
Geographical closeness	0.064*** (0.014)	0.033 (0.023)
Investor age	0.551*** (0.009)	0.475*** (0.013)
Auction duration	0.554*** (0.011)	0.007** (0.004)
Loan amount	-0.053*** (0.011)	0.228*** (0.013)
Rating 3.5	0.098*** (0.007)	0.361*** (0.018)
Rating 4	0.162*** (0.013)	0.444*** (0.022)
Rating 4.5	-0.018 (0.030)	
Loan term	-0.109*** (0.008)	-0.071*** (0.017)
Intercept	-5.841*** (0.093)	-5.781*** (0.131)
Fixed effects	Administrative division	Administrative division
Number of observations	951,364	465,398

As expressed in H2, we also expect investors from the same administrative division as the borrower to be more likely to win the auction. We test this by conducting the following logistic regression at the bid level:

$$\begin{aligned} \text{Winning Bid}_{i,j,t} = & \beta_1 \cdot \text{Geographical Closeness}_{i,j} + \beta_2 \cdot \text{Age}_i + \beta_3 \cdot X_j \\ & + \beta_4 \cdot X_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \quad (1.2)$$

where $\text{Winning Bid}_{i,j,t}$ is a dummy equal to one if the bid of investor i submitted at time t in auction j is served at equilibrium and ultimately funds the loan, zero otherwise. If H2 holds, β_1 should be significantly positive for the group of projects funded before the implementation of Autolend and statistically insignificant for the other group of projects. X_j is the vector of controls already used in Equation (1.1), which comprises the loan amount, the loan term, and rating dummies. $X_{i,j,t}$ is a vector of controls at the bid level. It includes the interest rate and the timing of the bid. The interest rate obviously determines the probability of winning the auction because in a Dutch auction, the bids with the lowest rates have priority. The bid timing also impacts the likelihood of winning the auction because the visibility of the potential clearing rate increases at the end of the auction. Submitting late thus allows investors to fine-tune their bid rates with the most up-to-date information on the actual demand for the loan and thereby to have a higher chance of winning the auction. The timing of a bid submitted at time t by investor i in auction j is computed as a score in which the numerator is the difference between the submission time of the bid under consideration and the time of the first bid submitted in the auction, and the denominator is the time elapsed between the first bid and the last bid submitted in the auction. This score, which ranges from zero to one, decreases with the earliness of the bid.

The results are reported in Table 1.4. For the group of auctions completed before the implementation of Autolend, bids submitted by local investors are significantly more likely to win the auction (β_1 significantly positive), but β_1 is statistically insignificant for the auctions completed after the introduction of the bidding algo-

rithm. Those results support H2. The estimated coefficients of the controls are as expected. The lower the interest rate of a bid and the later its submission, the more likely the bid is to win the auction. The likelihood of winning an auction decreases with the credit rating of the loan. This can be explained by the fact that riskier loans attract fewer investors. Most risk-averse investors may consider that, over a certain level of risk, projects are not worth investing at less than 10%, the maximum interest rate permitted on the platform. As a consequence, a lower rating leads to reduce competition between investors which, in turn, increases a bid's likelihood of winning the auction. A similar explanation can be offered to explain the positive correlation found between the term of the loan and the bid's likelihood of winning the auction, as longer terms are associated with higher default risk. Last, the likelihood of winning an auction increases with the loan amount due to the limited elasticity of the funds' total offer available on the platform.

1.4.2. Preferences for local companies: informed investing or behavioral bias?

In the previous section, we demonstrated that crowdlenders invested more heavily in the loans of local companies in the pre-Autolend period. We now investigate whether this is rational investing based on superior information held on nearby companies (rational hypothesis) or whether this is a familiarity bias related to geographical closeness (behavioral hypothesis). To this end, we follow the methodology of [Lin and Viswanathan \(2016\)](#) and analyze the performance of pre-Autolend loans after issuance.

Data on loan performance are available for 204 of the 236 loans auctioned before the implementation of Autolend. Of these, 164 loans were fully repaid at maturity; five loans are considered delinquent, i.e., the payment of the principal was late by more than 90 days but less than 9 months; and 35 loans are in default. A loan is considered to be in default in the following four cases: (1) the payment of the principal is late by more than 9 months; (2) the loan is under a recovery

Table 1.4: Bid likelihood of winning an auction

This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if the bid of a given investor in a given auction submitted at a given time is served in the auction. Column 'Pre-Autolend period' and column 'Post-Autolend period' present the results for the pre-Autolend and the post-Autolend subsamples respectively. *Geographical closeness* equals 1 for local investors, 0 for others. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Interest rate* is the interest rate of the bid submitted. It ranges from 4% to 10% in the coverage period, i.e., as long as the cumulated bid amount does not clear the loan. *Bid timing* measures the earliness of the bid in the auction by a ratio ranging from 0 to 1, 0 corresponding to the timing of the first submission and 1 corresponding to the last one. *Investor age*, *Loan amount*, and *Loan term*, measured in years, euros, and months respectively, are taken in logarithm. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Pre-Autolend period (1)	Post-Autolend period (2)
Geographical closeness	0.224*** (0.022)	0.009 (0.037)
Interest rate	-0.680*** (0.005)	-1.556*** (0.009)
Bid timing	1.226*** (0.013)	4.242*** (0.029)
Investor age	-0.220*** (0.014)	0.200*** (0.019)
Rating 3.5	-0.709*** (0.010)	-0.649*** (0.018)
Rating 4	-1.024*** (0.016)	-1.412*** (0.026)
Rating 4.5	-1.821*** (0.049)	
Loan term	1.976*** (0.013)	1.476*** (0.017)
Loan amount	1.924*** (0.010)	1.489*** (0.016)
Intercept	-23.212*** (0.120)	-16.458*** (0.161)
Number of observations	338,492	1,110,209

procedure; (3) the borrowing firm went bankrupt; or (4) the borrowing firm is going into receivership. In total, 40 of the 204 (19.60%) sampled loans are delinquent or in default.²⁰ Finally, of these 40 distressed loans, 28 had a credit rating of 3 stars, 8 were rated 3.5 stars, and 4 loans had a rating of 4 stars. Unfortunately, our data include neither the exact date of the delinquency or the default, nor the recovery rate in case of a default.

We investigate the likelihood of auction winners of investing in delinquent or defaulting loans by running the following logistic regression:

$$Default_{i,j} = \gamma_1 \cdot Geographical\ Closeness_{i,j} + \gamma_2 \cdot Age_i + \gamma_3 \cdot X_j + \epsilon_{i,j} \quad (1.3)$$

where subscript i identifies an investor who has successfully participated in auction j . $Default_{i,j}$ is a dummy equal to one if the borrower of auction j has subsequently defaulted on its loan, zero otherwise. We also study the case where dummy $Default_{i,j}$ includes delinquent loans. We control for investor age (Age_i) and for the same loan characteristics as in previous regressions (vector X_j), namely loan term, loan rating, and loan amount. We include fixed effects per administrative division. Under hypothesis H3, we expect γ_1 to be significantly negative.

The results are reported in Table 1.5. Regarding the control variables, a lender is less likely to experience a default as the loan's rating increases. The probability of investing in a defaulting loan increases with the loan amount. As expected, loans with longer terms are more likely to become delinquent or to be in default. In columns (2) and (4) of Table 1.5, we add a variable that measures the degree of competition in the auction by the ratio of the duration of the competition period over the total auction duration.²¹ We add this covariate to account for potential herding behavior that led investors to blindly follow the crowd and fund a borrower because of high demand coming from other investors. A higher degree of competition during

²⁰As a means of comparison, the ratio of nonperforming bank loans subscribed by French SMBs was 4.05% in 2011 and 3.90% in 2015 according to the OECD. This confirms that the loans originated through crowdlending platforms are riskier than bank loans.

²¹The competition period corresponds to the auction time period when the loan amount can already be cleared with submitted bids, and bidders compete on rate.

the auction is associated with a lower probability of default, which suggests that the crowd is informed and that investors are subject to rational herding behavior.²²

Regarding our main variable of interest, the γ_1 coefficients are not found to be significantly negative. Investors that funded a borrower located close to their place of residence are statistically as likely as other lenders to have invested in a subsequently defaulting or delinquent loan, which leads us to reject H3. This means that local investors do not possess privileged information about the creditworthiness of the borrower. As a consequence, the higher probability of investors to win the auctions of borrowers located close to their place of residence is not information-driven (rejection of the rational hypothesis), and it should be considered a behavioral bias (behavioral hypothesis). This result also rules out the alternative hypothesis that geographical-proximity bias could be a proxy for a local network effect based on personal relationships between lenders and managers from the same geographical area. If lenders geographically close to the borrower personally knew its managers, they would have private information about the creditworthiness of the borrower, and they would experience a significantly lower rate of default when investing in local companies. Therefore, rejecting H3 rules out all kinds of information-based explanations, including that based on potential local networks. On the contrary, it supports the hypothesis that the geographical-proximity bias is mainly behavioral.

Now that we have demonstrated that the tendency of investors to over-lend to geographically close borrowers is not driven by superior information but is rather behavioral, we investigate whether this bias impacts the efficiency of the price discovery process in the auction system.

²²According to [Chemla and Timm \(2021\)](#), in light of the recent literature, crowdfunding harnesses the wisdom of crowds when investors' valuations are independent from one another. We consider that this is the case in Unilend auctions, where the characteristics of each investor's bids are not visible to other participants.

Table 1.5: Likelihood to invest in a defaulting or delinquent loan

This table reports the results of logistic regressions in which the dependent variable is set to 1 for a given auction winner and a given loan if the loan is in default (columns 1 and 2) or the loan is either in default or considered delinquent (columns 3 and 4). A loan is considered delinquent if the repayment of its principal is late by more than 60 days but less than 9 months. A loan is considered in default if: (1) the repayment of its principal is late by more than 9 months; (2) the loan is under a recovery procedure; (3) the borrower went bankrupt; or (4) the borrowing firm is going into receivership. We only consider loans completed before the implementation of Autolend and for which we have information about their performance. *Geographical closeness* equals 1 for local investors, 0 for others. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Competition degree* is the duration of the competition period - that is the phase of the auction during which the cumulative amount of bids already clears the loan and investors compete in rate - divided by the total duration of the auction. *Investor age*, *Loan amount*, and *Loan term*, measured in years, euros, and months respectively, are taken in logarithm. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Default		Default or delinquent	
	(1)	(2)	(3)	(4)
Geographical closeness	0.008 (0.055)	0.007 (0.056)	-0.009 (0.054)	-0.010 (0.054)
Rating 3.5	-0.386*** (0.037)	0.049 (0.041)	-0.914*** (0.036)	-0.608*** (0.038)
Rating 4	0.390*** (0.051)	0.718*** (0.054)	0.267*** (0.051)	0.524*** (0.053)
Rating 4.5	-21.995 (1,179.405)	-21.457 (1,179.398)	-22.175 (1,179.404)	-21.601 (1,179.400)
Investor age	0.008 (0.043)	0.034 (0.043)	0.007 (0.042)	0.028 (0.042)
Loan amount	0.164*** (0.028)	-0.727*** (0.042)	0.397*** (0.026)	-0.304*** (0.037)
Loan term	1.331*** (0.051)	0.714*** (0.056)	1.789*** (0.052)	1.250*** (0.056)
Competition degree		-2.094*** (0.076)		-1.811*** (0.072)
Intercept	-8.119*** (0.425)	4.515*** (0.615)	-12.327*** (0.402)	-2.133*** (0.560)
Fixed effects	Administrative division	Administrative division	Administrative division	Administrative division
Number of observations	80,778	80,778	80,778	80,778

1.5. The impact of geographical-proximity bias on the price discovery process

In this section, we examine how geographical-proximity bias impacts the efficiency of the price discovery process in the auction system. Given that geographically close lenders are subject to a behavioral bias, their presence in an auction may draw the clearing rate away from its fundamental value. We investigate this issue with a two-stage methodology: we first estimate the deviations of observed loan rates from their fundamental values; we then analyze how those deviations relate to geographical-proximity bias.

1.5.1. Test design

We start our analysis by comparing observed loan rates with their fundamental values. Since fundamental rates are unobservable, we model them by regressing the observed average borrowing rate and the observed equilibrium rate of each auction on several characteristics of the loan and the borrower, deemed essential in the formation of interest rates. Those rate determinants include the loan amount, the loan maturity, the borrowing firm size measured by total assets in logarithms, credit rating dummies, and four dummies identifying the purpose of the loan, i.e., the type of project for which the firm borrows money. Dummy *Commercial development* equals one for activity-growth projects, zero otherwise; dummy *Intangible investment* equals one for loans funding R&D or any other type of intangible assets, zero otherwise; dummy *Tangible investment* equals one for loans funding tangible assets, zero otherwise; dummy *Financial operations* equals one for loans financing the repayment or restructuring of liabilities, zero otherwise; and the base case in the regression corresponds to firms borrowing money to finance their working capital. In addition, we add year fixed effects to account for general trends in interest rates over time and potential changes in the demand for crowdlending loans.

The estimates of this predictive model are reported in Table 1.6, where column (1) displays the estimates for average borrowing rates and column (2) displays the estimates for equilibrium rates. Average borrowing rates and equilibrium rates are positively correlated with the loan amount, positively correlated with the term of the loan, and negatively correlated with the borrower's credit rating. The size of the borrowing firm does not appear to have any impact on the rates. We find that loans funding commercial development obtain a higher borrowing rate and a higher equilibrium rate, on average, than loans funding other types of project. Borrowing money to invest in intangible assets (a new website for instance), tangible assets (e.g., a new production machine), or to carry out financial operations such as debt restructuring has no effect on the borrowing rate or the equilibrium rate of the auction. Error terms extracted from this model are then considered to be pricing errors, or in other words, deviations from fundamental values.

In a second stage, we test whether geographical-proximity bias affects the efficiency of the price discovery process (H4) by running the following quantile regression:

$$\text{Loan Rate Deviation}_j = \theta_1 \cdot \text{Closeness Degree}_j + \theta_2 \cdot \text{Rating}_j + \epsilon_j \quad (1.4)$$

where $\text{Loan Rate Deviation}_j$ is the difference between the equilibrium (average) rate resulting from auction j and the estimated fundamental value of that equilibrium (average) rate. $\text{Closeness Degree}_j$ is a measure of the relative weight of local investors in auction j . Under the generic notation $\text{Closeness Degree}_j$, we use three different metrics of the degree of presence of local investors. The first metric, named *Local funding*, is the total amount of funds coming from local investors divided by the loan amount. The second metric, named *Local bid amount*, is the cumulative amount of all bids submitted by local investors divided by the cumulative amount of all bids submitted in the auction. The third metric, named *Local bid number*, is the number of bids submitted by local investors divided by the total number of bids submitted in the auction. While the first variable only accounts for winning bids, the

Table 1.6: Modelling fundamental interest rates

This table reports the estimates of OLS regressions run to model the fundamental values of loan rates. The dependent variable is alternatively the observed average borrowing rate (Column 1) or the observed auction equilibrium rate (Column 2). Rating n equals 1 if the loan's rating is n , 0 otherwise. *Commercial development*, *Intangible investment*, *Tangible investment*, and *Financial operations* are dummies identifying the type of project for which the firm borrows money. *Loan amount*, *Loan term*, and *Total assets* are expressed in euros, months, and million euros respectively, and are taken in logarithm. Robust standard errors are reported in parentheses. ***, ** and * denote significance of the parameter estimates at the 1%, 5% and 10% level, respectively.

	Average rate (1)	Equilibrium rate (2)
Loan amount	0.927*** (0.096)	1.032*** (0.100)
Loan term	1.360*** (0.149)	1.394*** (0.154)
Rating 3.5	-0.584*** (0.111)	-0.606*** (0.116)
Rating 4	-0.749*** (0.183)	-0.753*** (0.196)
Rating 4.5	-1.690*** (0.574)	-1.494** (0.600)
Total assets	-0.009 (0.025)	-0.014 (0.027)
Commercial development	0.297** (0.151)	0.308* (0.158)
Intangible investment	0.284 (0.201)	0.319 (0.210)
Tangible investment	0.043 (0.148)	0.059 (0.155)
Financial operations	0.676 (0.422)	0.674 (0.441)
Intercept	-6.611*** (1.157)	-6.985*** (1.226)
Fixed effects	Year	Year
Number of observations	290	290
Adjusted R ²	0.745	0.744

other two variables include both winning and losing bids. By definition, those three variables are positively correlated with the intensity of the geographical-proximity bias in an auction. If bids submitted by investors who are subject to geographical-proximity bias reduce the efficiency of the price discovery process (H4), we expect θ_1 to be significantly different from zero. We also control for the loan's credit rating because the deviation from efficiency may depend on risk-aversion.

We estimate the coefficients of Regression (1.4) by using a quantile model because we expect the relation between the outcome variable and the degree of the presence of geographically close investors in the auction to be nonlinear. First, the outcome variable of the regression and the variables gauging the degree of the presence of geographically close investors in the auction are not normally distributed. Second, we expect the relation between the dependent variable and the presence of local investors to be characterized by threshold effects, in the sense that the impact of geographical-proximity bias on rate deviation could become significant only once the weight of geographically close investors in the auction is high enough and that the impact might be a jump rather than a proportional response.

1.5.2. Results

Whereas the predictive model of loan rates' fundamental values is estimated over the full sample, the second-stage regressions of loan rate deviations (Regressions (1.4)) are only conducted on the subsample of auctions completed before the implementation of Autolend. The results are reported in Table 1.7. Columns (1), (3) and (5) analyze the deviations of equilibrium rates, while columns (2), (4) and (6) analyze the deviations of average borrowing rates, a deviation being defined as the observed value minus the estimated fundamental value. All coefficients of the variables gauging the presence of local investors in the auction are positive and statistically significant. The intensity of geographical-proximity bias in pre-Autolend auctions thus reduces the efficiency of the price discovery process by increasing the borrower's rate of funding. While this is in support of H4, the sign of the relation

is unexpected. We conduct additional tests to investigate this phenomenon.

1.5.3. Interpretation

The positive relation between geographical-proximity bias and loans' funding rates is puzzling, especially in light of the finding that local investors are more likely to win an auction as shown in Table 1.4. On the one hand, the positive link between the weight of local investors and funding rates would suggest that local investors bid at higher rates than others. On the other hand, local investors' higher likelihood of winning the auction would suggest that they bid at lower rates. To solve this puzzle, we analyze the bidding strategies of geographically close investors by examining three characteristics of those strategies: the bid interest rate, the bid timing, and the number of bids submitted in each auction.

We start by analyzing the interest rate of winning bids with the following quantile regression:

$$\begin{aligned}
 \text{Bid Rate Deviation}_{i,j,t} = & \psi_1 \cdot \text{Geographical Closeness}_{i,j} \\
 & + \psi_2 \cdot \text{Bid Timing}_{i,j,t} + \psi_3 \cdot \text{Bid Timing}_{i,j,t}^2 + \psi_4 \cdot \text{Age}_i + \psi_5 \cdot \text{Rating}_j + \epsilon_{i,j,t}
 \end{aligned} \tag{1.5}$$

where $\text{BidRateDeviation}_{i,j,t}$ is the difference between the interest rate of the winning bid of investor i submitted at time t in auction j and the estimated fundamental value of the average rate of auction j . We control for the timing of the bid. The later the bid is submitted, the more competitive on the rate it has to be to win against competitors. We also add the square of the bid's timing as a covariate because the relationship between the timing of the bid and the interest rate of the bid is not linear. We control for age as a proxy for investing experience. We expect older investors to be less prone to discount bid rates to win auctions. We also control for the credit rating of the borrower by including vector Rating , which comprises the three rating dummies already used in previous regressions. The coefficients of Regression (1.5) are estimated by using a quantile regression because the outcome variable is not normally distributed.

Table 1.7: Impact of the geographical-proximity bias on the rate discovery process

This table reports the estimates of quantile regressions of loan rate deviations from their fundamental values on measures of the geographical-proximity bias intensity. Our dependent variable is the difference between the observed rate and the rate predicted by the model of Table 1.6. For each loan, the interest rate considered is alternatively the average borrowing rate (Columns 2, 4, and 6) and the auction equilibrium rate (Columns 1, 3, and 5). Loans considered are those completed before the implementation of Autolend. *Local funding* is the share of the loan amount funded by local investors. *Local bid amount* is the share of the auction's total cumulative bid amount submitted by local investors. *Local bid number* is the number of bids submitted by local investors divided by the total number of bids submitted in the auction. Rating n equals 1 if the loan's rating is n , 0 otherwise. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Equilibrium rate (1)	Average rate (2)	Equilibrium rate (3)	Average rate (4)	Equilibrium rate (5)	Average rate (6)
Local funding	1.909*** (0.685)	2.174* (1.260)				
Local bid amount			1.871*** (0.454)	2.039*** (0.555)		
Local bid number					2.538** (0.987)	2.756*** (1.034)
Rating 3.5	0.043 (0.101)	0.038 (0.129)	0.049 (0.107)	0.028 (0.113)	0.015 (0.116)	-0.006 (0.116)
Rating 4	0.128 (0.357)	0.232 (0.248)	0.180 (0.350)	0.234 (0.215)	0.195 (0.354)	0.198 (0.219)
Rating 4.5	0.051 (0.524)	-0.040 (0.338)	0.112 (0.592)	0.031 (0.274)	0.262 (0.795)	0.185 (0.480)
Intercept	0.046 (0.077)	-0.039 (0.087)	0.039 (0.071)	-0.039 (0.074)	0.053 (0.079)	-0.013 (0.082)
Number of observations	236	236	236	236	236	236

The results are reported in Table 1.8. Local investors obtain significantly higher interest rates than other winning investors. The aforementioned results only hold for the group of auctions completed before the introduction of Autolend as the coefficient of dummy *Geographical Closeness* is not statistically significant for the group of auctions completed after the implementation of the bidding algorithm. This finding is consistent with the results reported in Table 1.7, according to which the presence of geographically close investors increases the cost of funding for borrowers. Regarding the control variables, as expected, late submissions are associated with lower interest rates, and the interest rates of winning bids increase with the age of the investor and default risk.

Table 1.8: Impact of geographical closeness on accepted bids' rates

This table reports the estimates of quantile regressions in which the dependent variable is the difference between the interest rate of each winning bid in a given auction and the fundamental value of the average borrowing rate as predicted by the model of Table 1.6 for that auction. Column (1) and Column (2) present the results for the pre-Autolend and the post-Autolend periods respectively. *Geographical closeness* equals 1 for local investors, 0 for others. *Bid timing* measures the earliness of the bid in the auction by a ratio ranging from 0 to 1, 0 corresponding to the timing of the first submission and 1 corresponding to the last one. *Investor age* is taken in logarithm. Rating n equals 1 if the loan's rating is n , 0 otherwise. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Pre-Autolend period (1)	Post-Autolend period (2)
Geographical closeness	0.152*** (0.019)	0.001 (0.009)
Bid timing	-0.142*** (0.040)	-1.379*** (0.054)
Bid timing ²	0.113*** (0.037)	1.783*** (0.042)
Investor age	0.058*** (0.010)	-0.0001 (0.005)
Rating 3.5	0.040*** (0.007)	0.155*** (0.004)
Rating 4	0.188*** (0.009)	-0.238*** (0.003)
Rating 4.5	0.071*** (0.007)	
Intercept	-0.141*** (0.038)	-0.560*** (0.023)
Number of observations	111,602	42,311

The results reported in Table 1.8 still cannot explain local investors' bids being more likely to win the auction. This leads us to study their timing and their

frequency. For the group of auctions completed before the implementation of Autolend, we compare the average timing of bids submitted by geographically close investors with the average timing of bids submitted by other investors. The results are reported in panel A of Table 1.9. No difference in timing appears between the two groups of investors when considering both accepted and rejected bids, but when considering winning bids only, we find that geographically close investors submit their bids earlier than the rest of the crowd. Specifically, local investors submit their last bid in the auction earlier than others. In panel B of Table 1.9, we compare the average number of bids submitted per auction for the two groups of investors. Although both groups of investors submit a similar number of bids during each auction, we find that local investors participate more during the coverage period of the auction and less during the competition period. The fact that local investors participate more during the coverage period than other investors explains why they earn significantly higher interest rates as there is no competition in rate during that period. Moreover, by participating less during the competition period, they reduce the level of competition at a crucial time for equilibrium rate formation. This explains the increase in the borrowers' cost of funding associated with their presence in the auction.

The findings displayed in Tables 1.8 and 1.9 mean that local crowdlenders are able to win the auctions of local borrowers with early bids at higher rates than other winners. To investigate this phenomenon, we divide the investor population into two groups: (1) those who have already participated in at least two auctions of local borrowers, referred to as experienced local investors, and (2) all others, i.e., those who have participated in at most one auction of a local borrower. Our definition of experienced investors is very similar to that used by [Petit and Wirtz \(2022\)](#) to define expert investors in reward-based crowdfunding.²³

Then, in the regressions in Table 1.7, we divide each of our three measures of

²³[Petit and Wirtz \(2022\)](#) define expert backers as participants who have backed at least three projects on a reward-based crowdfunding platform. They show that the participation of expert backers impacts the funding dynamics and the success of the campaign they participate in, as well as the pool of future backers.

Table 1.9: Comparing the bidding strategies of local and non-local investors

This table compares the bidding strategies of local and non-local investors in auctions completed before the implementation of Autolend. Panel A reports, for local and non-local investors, the average timing of their bids, their accepted bids, their first bid, and their last bid submitted in an auction. The timing of a bid is the earliness of that bid in the auction, measured by a score between 0 and 1, 0 corresponding to the timing of the first submission and 1 corresponding to the last one. Panel B reports, for local and non-local investors, the average number of bids submitted per auction as well as the average of three ratios, the number of bids submitted in the coverage period divided by the total number of bids, the number of bids submitted in the competition period divided by the total number of bids, and the number of bids submitted in the coverage period divided by the number of bids submitted in the competition period. The coverage period is the phase of the auction during which cumulated bid amounts do not clear the loan amount and each bidder is a winner. The competition period starts as soon as the cumulated bid amount clears the loan. In that phase, only bidders with bid rates lower than or equal to the clearing rate are winners. The differences in means between local and non-local investors are tested with t -tests which p -values are reported in the last column.

	Local investors	Non-local investors	t -test
Panel A : Average bid timing			
All bids	0.6012	0.5996	0.595
Accepted bids	0.6891	0.7172	0.000
First bid in the auction	0.4441	0.4450	0.837
Last bid in the auction	0.6655	0.6804	0.001
Panel B : Average number of bids			
Total # of bids	1.9890	2.0338	0.135
# bids coverage period / Total # of bids	0.4802	0.4372	0.000
# bids competition period / Total # of bids	0.5198	0.5628	0.000
# bids coverage period / # bids competition period	0.2990	0.2840	0.078

the degree of the presence of local investors into two variables: one measuring the presence of experienced local investors and the other measuring the presence of inexperienced local investors. The results reported in Table 1.10 show that the positive relation between auction rates and the weight of local investors is entirely driven by the weight of the experienced investors. In addition, we run Regression (1.5) separately for experienced investors and inexperienced local investors. The results indicate that inexperienced local investors win the auction by submitting lower rates than others, whereas experienced local investors win the auction even though their bid rates are relatively high. We therefore conclude that experienced local investors have extracted information about the dynamics of the order flow in previous auctions of local borrowers. They are then able to submit winning bids at higher rates than other winners, at an early stage, in subsequent local borrowers' auctions. This suggests that a feeling of familiarity for geographically close businesses strengthens investor attention and learning abilities and thereby improves investor knowledge about the dynamics of local auctions' order flow. In the end, over-lending to local borrowers is a behavioral bias in the first local auctions an investor participates in, but it becomes rational after experiencing a few local auctions.

In summary, geographical proximity creates a behavioral bias in the first local auctions in which an investor bids. This bias is irrational in that it leads the investor to invest more heavily at lower rates. Nevertheless, the investor's attention is enhanced in those auctions for which she has familiarity bias. As a result, she develops superior knowledge about the order flow dynamics in those auctions, so that she is able to submit winning bids at relatively high rates in subsequent local auctions. Consequently, after experiencing a few local auctions, investing more heavily in local borrowers becomes rational because it achieves higher lending rates.

To ensure that this experience effect is generated by geographical closeness, we test whether a similar effect exists for experienced non-local investors. In the regressions in Table 1.7, we replace the three variables measuring the weight of local investors with similar variables measuring the weight of experienced non-local

Table 1.10: Impact of local lenders on loan rates: experienced versus inexperienced local lenders

This table reports the estimates of quantile regressions of loan rate deviations from their fundamental values on measures of the weight of local investors in auctions. Our dependent variable is the difference between the observed rate and the rate predicted by the model of Table 1.6. For each loan, the interest rate considered is alternatively the average borrowing rate (columns 2, 4, and 6) and the auction equilibrium rate (columns 1, 3, and 5). Loans considered are those completed before the implementation of Autolend. *Local funding* is the share of the loan amount funded by local investors. *Local bid amount* is the share of the auction's total cumulative bid amount submitted by local investors. *Local bid number* is the number of bids submitted by local investors divided by the total number of bids submitted in the auction. The subpopulation of local investors is divided into two groups: (1) those who have already participated in at least two auctions of local borrowers, referred to as experienced local investors, and (2) all others, i.e., those who have participated in one auction of a local borrower at most. Rating n equals 1 if the loan's rating is n , 0 otherwise. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level, respectively.

	Equilibrium rate (1)	Average rate (2)	Equilibrium rate (3)	Average rate (4)	Equilibrium rate (5)	Average rate (6)
Local funding Experienced	3.220*** (0.828)	4.100*** (0.403)				
Local funding Inexperienced	0.970 (2.401)	-1.741 (2.152)				
Local bid amount Experienced			3.021*** (0.908)	3.105*** (1.029)		
Local bid amount Inexperienced			1.377 (1.997)	1.547 (2.582)		
Local bid number Experienced					4.322*** (1.538)	4.973*** (1.435)
Local bid number Inexperienced					1.852 (3.371)	2.199 (3.345)
Rating 3.5	0.098 (0.113)	0.083 (0.117)	0.121 (0.117)	0.053 (0.110)	0.058 (0.124)	-0.007 (0.118)
Rating 4	0.247 (0.329)	0.224 (0.184)	0.277 (0.378)	0.246 (0.183)	0.229 (0.369)	0.256 (0.232)
Rating 4.5	0.220 (0.864)	0.450 (0.540)	0.233 (0.749)	0.093 (0.491)	0.322 (0.795)	0.247 (0.477)
Intercept	-0.002 (0.084)	-0.024 (0.081)	-0.032 (0.080)	-0.050 (0.086)	-0.0002 (0.093)	-0.069 (0.096)
Number of observations	236	236	236	236	236	236

investors in each auction, and we find that the weight of experienced non-local investors has no significant impact on auction rates. This confirms that the experience effect observed for local investors in Table 1.7 is the outcome of enhanced attention related to geographical proximity.

1.6. Robustness checks

Our identification strategy relies on the comparison between two groups of auctions that did not take place during the same time period. The statistical significance of the geographical-proximity bias in the period before the implementation of Autolend could therefore be driven by time-specific unobserved variables. To address this concern, we run the regressions in Table 1.3, Table 1.4, and Table 1.8 by reducing the sample to auctions completed in 2016, the year when the Autolend algorithm was launched. In that year, 38 auctions were completed before the implementation of Autolend, and 54 were completed after the algorithm's implementation. Notwithstanding the small size of the subsample, the results are qualitatively the same as those obtained with the full sample.

Our identification strategy also relies on the fact that the samples before and after the implementation of Autolend are comparable. However, the sample size for the period after Autolend is significantly smaller than that for the period before Autolend in Tables 1.3 and 1.8. One could therefore suspect the absence of statistical significance for the coefficients identifying the geographical-proximity bias in the post-Autolend regressions in Tables 1.3 and 1.8 to be caused by the smaller size of the post-Autolend subsample. We show that this is not the case in two ways. First, as previously mentioned, our findings are robust to reducing the observation period to the year 2016 for which the pre-Autolend subsample and the post-Autolend subsample are comparable in size. Second, we use the bootstrapping technique to make the pre-Autolend and the post-Autolend subsamples similar in size. Specifically, we run bootstrapped regressions in the period before the implementation of Autolend, i.e., for column (1) in Tables 1.3 and 1.8, using the same sample size as for the

regressions in the period after the implementation of Autolend. The coefficient of dummy *Geographical Closeness* remains positive and statistically significant at the 1% level in both tables before the implementation of Autolend. The difference in statistical significance of the coefficient of dummy *Geographical Closeness* between the two periods in Tables 1.3 and 1.8 is therefore not explained by differences in sample sizes.

Furthermore, all results hold when we exclude from the pre-Autolend projects the top five percent in terms of the weight of the local investors in the amount funded. Our conclusions are therefore not driven by extreme values.

At another level, it could be argued that the behavior of local investors results from the media influence of the local press. To check this point, we have extracted from Factiva all articles published on Unilend auctions in local newspapers. Of the 20 articles retrieved, only two focused on local projects. We reran our analysis without the three borrowers covered by those two articles, and our conclusions remained unchanged.

Last, we test whether geographical-proximity bias exists at larger distances by considering the next-level administrative division, i.e., the French *régions* instead of the *départements*.²⁴ On average, the surface area of a *région* is seven times larger than that of a *département*. When running all regressions at the *région* level, we find that geographical-proximity bias also exists at that level but with almost no impact on the price discovery process. This confirms that geographical closeness is crucial in explaining our findings.

1.7. Conclusion

This chapter investigates whether individual investors are subject to geographical-proximity bias by testing whether the fund lenders of a peer-to-business crowd-lending platform over-lend to firms located close to their place of residence. Using the implementation of a bidding algorithm that submits bids on behalf of investors as

²⁴For a definition of French *régions*, cf. Section 1.2.2.

an exogenous shock to behavioral biases, we provide evidence that geographical-proximity bias exists. Investors located in the same administrative division as borrowers are more likely to participate and win their auctions and, thus, to lend them funds.

We then show that creditors located in the same administrative division as borrowers are as likely as creditors located farther away to experience a default on their claims. This invalidates the hypothesis that investors would lend more to closely located borrowers because they possess more information about the latter's creditworthiness. On the contrary, it suggests that the preference to lend money to geographically close borrowers is behavioral to such an extent that it might hamper the auction's price discovery process. We investigate whether this is the case and find that geographical-proximity bias indeed has a significant impact on the quality of equilibrium loan rates. The presence of geographically-biased investors in the auction is associated with an increase in the borrower's cost of funding. This result is likely to be explained by how such investors time their bids. Geographically close investors submit their bids early, and they become passive toward the end of the auction. By not participating at the end of the auction, when the competition between bidders is at its peak, geographically close investors decrease the level of competition in the auction and therefore increase the borrower's cost of funding.

Furthermore, we find that the positive link between auction rates and the weight of local investors is driven by experienced local investors, i.e., local investors who have already participated in at least two auctions of local borrowers. We infer from this finding that investor attention and learning capacities are increased when participating in the auctions of geographically close borrowers. This allows crowdlenders to acquire some specific knowledge about the dynamics of the order flow of local auctions. They are then able to submit winning bids at higher rates in subsequent local auctions, which in turn tends to increase both their returns and the borrowing rates of those auctions. Consequently, this specific knowhow - i.e., know how to submit winning bids at higher rates in local auctions - makes investing more heavily

in local auctions rational with experience.

Whether the increase in loan rates generated by the presence of experienced local lenders is good or bad for borrowing firms is debatable. At first glance, it seems unfavorable as it means higher funding costs. Yet, in the long-run, it may encourage experienced crowdlenders to keep investing on the platform regularly. The long-term effect would then be beneficial to future projects and the platform. In the case of Unilend, the introduction of the Autolend bidding algorithm made loan rates decrease substantially, to an extent that has probably dissuaded investors from investing in regards to the default rates of borrowers. In light of this example, our recommendation regarding bidding algorithms is twofold. On the one hand, automated bidding eliminates human behavioral biases and intensifies competition among investors in a way that immediately benefits borrowers. Yet the benefits are sustainable in the long run only if the resulting equilibrium interest rates are high enough in regards to risks. In that sense, we believe that bidding algorithms are more appropriate for low-risk and low-complexity investments. On the other hand, if the equilibrium interest rates resulting from the algorithm are too low in regards to borrowers' credit risk, the bidding algorithm may jeopardize the platforms' sustainability. For that reason, we consider that manual bidding is preferable for high-risk and complex projects. In that case, our research shows that, in auctions with manual bidding, behavioral biases can quickly change into rational investing, thanks to learning-by-doing, provided that investor attention is stimulated by familiarity. We thus recommend crowdfunding platforms to provide investors with such stimuli to help them develop their financial literacy and their expertise on auction mechanisms.

Last, this chapter highlights that feelings of familiarity, including familiarity stemming from geographical proximity, distort investment decisions, but that they also accelerate learning-by-doing in investing experiences in a way that develop investors' financial expertise. We believe that this finding based on crowdlending data has external validity for any financial activity involving fund offerings by nonprofes-

sional investors. We expect individual investors: (1) to invest more heavily in assets that are familiar to them in many contexts including bond, stock, or real estate investments, but also (2) to learn more from those investing experiences.

Chapitre 2

Learning by Doing in Crowdlending Auctions

joint work with Carole Gresse, Université Paris Dauphine - PSL

Abstract :

We construct a novel taxonomy of bidding strategies in crowdlending Dutch auctions by mapping the auction process into six areas, each area representing a specific winning bidding strategy. These strategies are associated with five types of investors: non-strategic, irrational, informed, strategic followers, and snipers. Applying this classification to peer-to-business crowdlending data, we find that retail investors mostly use sophisticated strategies, and that their bidding behavior changes as they gain experience in auctions. More specifically, the more they win in auctions, the more likely they are to adopt rewarding sophisticated bidding strategies.

2.1. Introduction

Crowdlending is a relatively new asset class allowing retail investors to lend money to small and medium businesses, associations, or retail borrowers to fund their various projects through an internet platform. In most cases, the interest rate of the loan is fixed by the platform, but some of them choose to use a Dutch auction system instead. Crowdlending platforms that use an auction system to fund loans foster competition between investors. The rational goal of an investor, once she has decided to lend money to a specific borrower, is to do so at the highest possible interest rate. However, submitting bids at high-interest rates increases the probability of losing the auction as the competition is fierce at such interest rates. Investors may therefore adopt bidding strategies in order to win the auction while lending at the maximum interest rate possible.

In this chapter, we theoretically determine six different bidding strategies in Dutch auctions by mapping the auction process along two key characteristics of the last submitted bid of a winner investor: the interest rate and the relative timing of her bid. Less rewarding strategies in terms of interest rates are considered non-sophisticated and are used by either non-strategic or irrational investors. On the contrary, we consider highly rewarding strategies as sophisticated. They are used by either informed investors, strategic followers, and snipers. Using data from a French peer-to-business crowdlending platform that funds loans using a Dutch auction system, we observe the frequency of use of each type of strategy between 2013 and 2016. Although retail investors are often thought of as unsophisticated by practitioners and academics, we find that such investors mostly use sophisticated strategies. We also observe that the number of strategic followers and snipers increases over the years, suggesting that the degree of sophistication of investors increases with time. This observation leads us to investigate the link between investor experience in auctions and the degree of sophistication of the adopted strategies. We find that investors become more likely to adopt rewarding sophisticated bidding strategies as they win

more auctions. Moreover, we find that beginners, i.e., inexperienced investors, are the ones to gain the most from experience in auctions. Last, we find that pioneer investors, i.e., those who invested early in the platform, gained additional knowledge through the observation of the loan rate formation process. Interestingly, they use this acquired knowledge to adopt informed strategies, but do not use it for sniping strategies. Furthermore, we find that a subgroup of pioneer investors has consistently been able to adopt informed strategies with significantly higher probabilities than the rest of the investors. This result suggests that some pioneer investors possess privileged information about loan rates' fundamental values.

This chapter contributes to the literature in two ways. We develop a new methodology to classify bidding strategies in Dutch auctions without relying on data-mining techniques. Moreover, we provide evidence of the impact of investor experience on investment decisions. More specifically, we identify learning effects from auction participation, which lead retail investors to change their bidding behaviors.

The remainder of the chapter is structured as follows. Section 2.2 reviews the literature. Section 2.3 presents the data and the auction system used to fund loans. Section 2.4 develops the classification of bidding strategies and presents descriptive statistics. Section 2.5 presents and tests the hypotheses relative to the link between investor experience in auctions and bidding behavior. Section 2.6 concludes.

2.2. Literature review

[Bapna et al. \(2000\)](#) construct a theoretical model to understand the bidding dynamics in multi-item auctions¹ and are the first to observe bidding strategies using data from an online retailer. They classify investors as evaluators – i.e., early one-time bidders who have a clear idea of the item's fundamental value –, participators – that is, investors who derive utility from the process of participating in the auction

¹A multi-item auction is an auction in which several homogeneous items are sold. Crowdfunding auctions fall into this category.

itself –, or opportunists who are seeking buying opportunities. [Shah et al. \(2002\)](#) use data-mining techniques to identify investors' bidding strategies in eBay auctions and discover five different bidding strategies: late bidding – i.e., the investor submits only one bid towards the end of the auction –, sniping – which is essentially late bidding in the last seconds of the auction –, skeptic – when the bidder submits multiple bids at the minimum increment over the ask price –, evaluation, and unmasking when the bidder submits a series of closely placed bids to try exposing the reserve price of a competitor. Using the data-mining methodology of [Shah et al. \(2002\)](#), [Puro et al. \(2011\)](#) examine bidding strategies on the Prosper peer-to-peer crowdlending² platform. They find evaluation and late bidding to be commonly used strategies. Using the same platform data, [Zhang and Liu \(2012\)](#) find that investors do not passively follow the actions of other investors but instead actively attempt to infer the creditworthiness of borrowers by observing the lending decisions of other investors. Similarly, [Edelman and Ostrovsky \(2007\)](#) show evidence of strategic bidding behavior in first-price auctions for search engines. From a theoretical perspective, the literature has supported the existence of non-homogeneous bidding behaviors between investors. [Roth and Ockenfels \(2002\)](#) develop rational arguments to explain late bidding and sniping in hard-close auctions, most notably to avoid bidding wars with incremental bidders. Late bidding and sniping can also be explained as a collusive equilibrium in which agents implicitly agree to wait until the end of the auction to submit their bids. [Bajari and Hortag su \(2003\)](#) incorporate a model of common-value to explain late bidding. [Hopenhayn and Saeedi \(2016\)](#) show that investors in eBay auctions are incited to shade their bids – i.e., to bid at a lower price than the investor's estimate of the item's fundamental value – because of the existence of the option of rebidding and the possibility of information arrival throughout the auction. Our work contributes to this strand of the literature as we theoretically construct a novel classification of bidding strategies based on a

²As our work relates to the crowdfunding literature, see [Moritz and Block \(2016\)](#) for a detailed literature review on crowdfunding.

two-dimensional decomposition of the auction.³

Investors usually make multiple investments during their investing career. As they do, both their experience and their financial knowledge increase, which may have an impact on their subsequent investment decisions. The literature on individuals' investment decision-making process has focused on the impact of investment experience. [Kaustia and Knüpfer \(2008\)](#) show that positive returns in past IPOs appear to increase the investor's likelihood to participate in future IPOs. This result is consistent with the reinforcement learning theory which states that an individual repeats behaviors that produce favorable outcomes and avoids behaviors that have produced unfavorable outcomes.⁴ [Chiang et al. \(2011\)](#) tracked individual investors in Taiwanese IPO auctions between 1995 and 2000 and find that the performance of investors decreases with experience, which is consistent with the naive reinforcement learning theory, according to which investors become overly optimistic about their ability to generate positive records after having good performance. [Choi et al. \(2009\)](#) show that individual investors change their saving behavior based on their past investing experience, with positive experiences tending to increase the saving rate. [Andersen et al. \(2019\)](#) find that negative personal experiences can have a substantial effect on the investor's risk-taking profile. Similarly, [Dorfleitner et al. \(2022\)](#) show that investors on a German peer-to-business platform stop investing after experiencing a default, which leads to portfolio under-diversification. Lastly, [Nicolosi et al. \(2009\)](#) find that portfolio returns of individual investors increase as they gain experience. The experience of individual investors has also been shown to impact the way investors bid during auctions. [Kagel \(1995\)](#) show that the performance of participants on a series of experimental auctions improved as they gained experience. [Wilcox \(2000\)](#) find that experienced investors in eBay auctions are more likely to become snipers and submit fewer bids during the same auction. This chapter also contributes to this strand of the literature as we examine the impact of experience on the choice of bidding strategies made by individual investors in crowdlending

³See Figure 2.1.

⁴[Cross \(1973\)](#) is the first to apply the reinforcement learning theory to economics.

auctions.

2.3. Data

The data come from Unilend, a French peer-to-business crowdlending platform that provides French SMBs with unsecured fixed-rate amortizing loans. These data are particularly appropriate for our research for three reasons. First, Unilend was a major actor in the crowdlending market over our observation period. Unilend was created in 2013 and was the first peer-to-business crowdlending platform in France. As of the end of 2016, it had become the third-largest crowdlending platform in France, with a market share slightly exceeding 15% of total lent money.⁵ Second, Unilend is one of the few platforms on which loan rates are set by investors in Dutch auctions. All other platforms with sizable market shares⁶ use fixed-rate procedures in which investors bid at a rate previously determined by the platform according to the loan maturity and credit risk. Third, contrary to many other crowdlending platforms, such as Prosper in the U.S. or Lendix in France, on which both retail and institutional investors fund loans, Unilend only targets retail investors as potential lenders.⁷

2.3.1. The Unilend auction system

On Unilend, loans are funded through a Dutch auction system where investors place bids with the amount of money they are willing to lend and the interest rate they are willing to receive. Investors may submit multiple bids. The amount of the loan, its term, and the auction's starting time and its end time are announced on the platform

⁵At present, Unilend remains an important player. It has the typical business model of a marketplace, which requires a critical mass of lenders and a steady flow of borrowers to be profitable. Due to a lack of borrowers, it went bankrupt in October 2018 and was acquired by another crowdlending platform, named Pretup, in December 2018.

⁶In France, the PrêtStory platform also operates Dutch auctions but its market share is very small.

⁷A minority of investors on the platform are non-physical lenders. The size of each of their investments is relatively small, making it highly unlikely that they are professional lenders or institutional investors.

before the auction starts. Once the auction starts, investors bid in competition with each other at rates bounded between 4 and 10%, with a 0.1% tick. At the end of the auction, bids are sorted in ascending order of interest rates, and bids' amounts are cumulated from the lowest interest rate up to the first rate at which the loan amount can be cleared. All bids submitted at a rate strictly lower than the clearing rate are served. Bids submitted at the clearing rate are served on a first-come-first-served basis. Each winning investor lends the amount of her winning bid(s) and receives the monthly service of the loan at the rate she bid. The maximum winning interest rate in an auction, i.e., the clearing rate, will be referred to as the equilibrium rate of the loan in our analysis. The funding rate of the borrower is computed as the average of all winning bids' rates weighted by the corresponding bid amounts. In the event that bids are inadequate to clear the loan amount, the loan is not funded.

Auctions' durations can be decomposed into two periods: the coverage period during which the cumulated bid amounts do not clear the loan amount and the competition period which starts as soon as an additional bid can clear the loan amount. During the coverage period, every bidder is a winner, and there is no competition between bidders. During the competition period, bidders compete with one another on interest rates, and only bids with the lowest interest rates submitted may win the auction.

2.3.2. Available information about borrowers

Before the start of each auction, the platform provides information about the borrower and its project. Specifically, Unilend publishes the borrower's name and geographical location, as well as its income statements and balance sheets⁸ up to two fiscal years before the year of the auction.⁹ Unilend also describes the borrower's business and the reason that it is seeking funds. In addition, Unilend credit analysts assign each loan a credit rating by using both hard information from the balance sheets and income statements and soft information from interviews with the firm's

⁸The income statements and balance sheets communicated to investors are not always audited.

⁹Only the year before the auction starts is generally provided.

management, generally the CEO. Unilend uses a rating grid ranging from zero to five stars with an increment of 0.5 stars, with the number of stars decreasing with default risk. Only projects with a credit rating above or equal to three stars are offered to investors. Since we expect investors to rely on those credit ratings to assess the riskiness of the borrowers, we check, as a preliminary test, to what extent those ratings are actually related to financial variables known to be meaningful about creditworthiness. We run an ordered logistic regression in which the borrower's credit rating is the dependent variable, and firm size, cash holdings, leverage, and profitability measures are the regressors. Our estimates show that Unilend ratings significantly relate to all tested variables in the expected way. Firm size, cash scaled by total assets, and the operating margin are all positively and significantly correlated with the borrower's credit rating, while the gearing ratio has a negative and statistically significant impact on that rating. Those findings confirm that the ratings advertised to investors on the platform are reliable synthetic measures of credit risk.

2.3.3. Sample selection

A specific feature of our data is the implementation of a bidding algorithm by the platform during the sample period. This algorithm, named Autolend, bids on behalf of investors according to parameters they preset on the platform. After the implementation of this algorithm, bids can be either manual or automated. Investors can freely activate or deactivate Autolend.

Because the algorithm constantly monitors auctions, it allows loans to be funded rapidly, sometimes in less than one second, which in turn increases the relative share of the competition period in the total auction duration. Consequently, the duration of auctions completed after the implementation of Autolend is much shorter, with an average of three days against 12 days for auctions completed before Autolend. Hence, the implementation of the bidding algorithm substantially modifies auctions dynamics. We therefore decide to exclude auctions completed after the implementation of Autolend from our sample. We also remove from our sample the auctions

for which we had no data either on the size of total assets or the sales of the borrowing firm one fiscal year before the auction, and auctions not completed because of insufficient demand from investors. This leaves us with a final sample of 236 auctions completed from November 2013 to April 2016. Those 236 auctions account for 113,949 winning bids submitted by 7,321 investors. Loan amounts range from €10,000 to €400,000, with an average of €76,854. Loan maturities range from 6 to 60 months, with an average of 43 months. The average borrowing rate is equal to 8.226%. Borrowers have on average a total asset size of 1.79 million euros and sales equal to 1.98 million euros in the fiscal year preceding the auction. Investors are on average 43.6 years old at the time they submit their bids.

2.4. A taxonomy of crowdenders' bidding profiles in Unilend auctions

To characterize investor bidding strategies, the literature has extensively used data-mining techniques. In other words, bidding strategies were discovered empirically after observing the actions of investors in auctions. While this way of characterizing bidding strategies is perfectly valid, we choose to follow a different path. We first define bidding strategy classes, and we then check how investors' actions fall into those classes.

In this section, we start by designing a taxonomy of bidding strategies, and then we present descriptive statistics relative to investors' bidding behavior in Unilend's auctions in correspondence with our taxonomy.

2.4.1. A taxonomy of bidding strategies

A bid submitted by an investor in a Dutch auction has two major characteristics: an interest rate and a timing during the auction. We determine different bidding strategy classes by mapping the auction process according to those two characteristics, as shown in Figure 2.1.

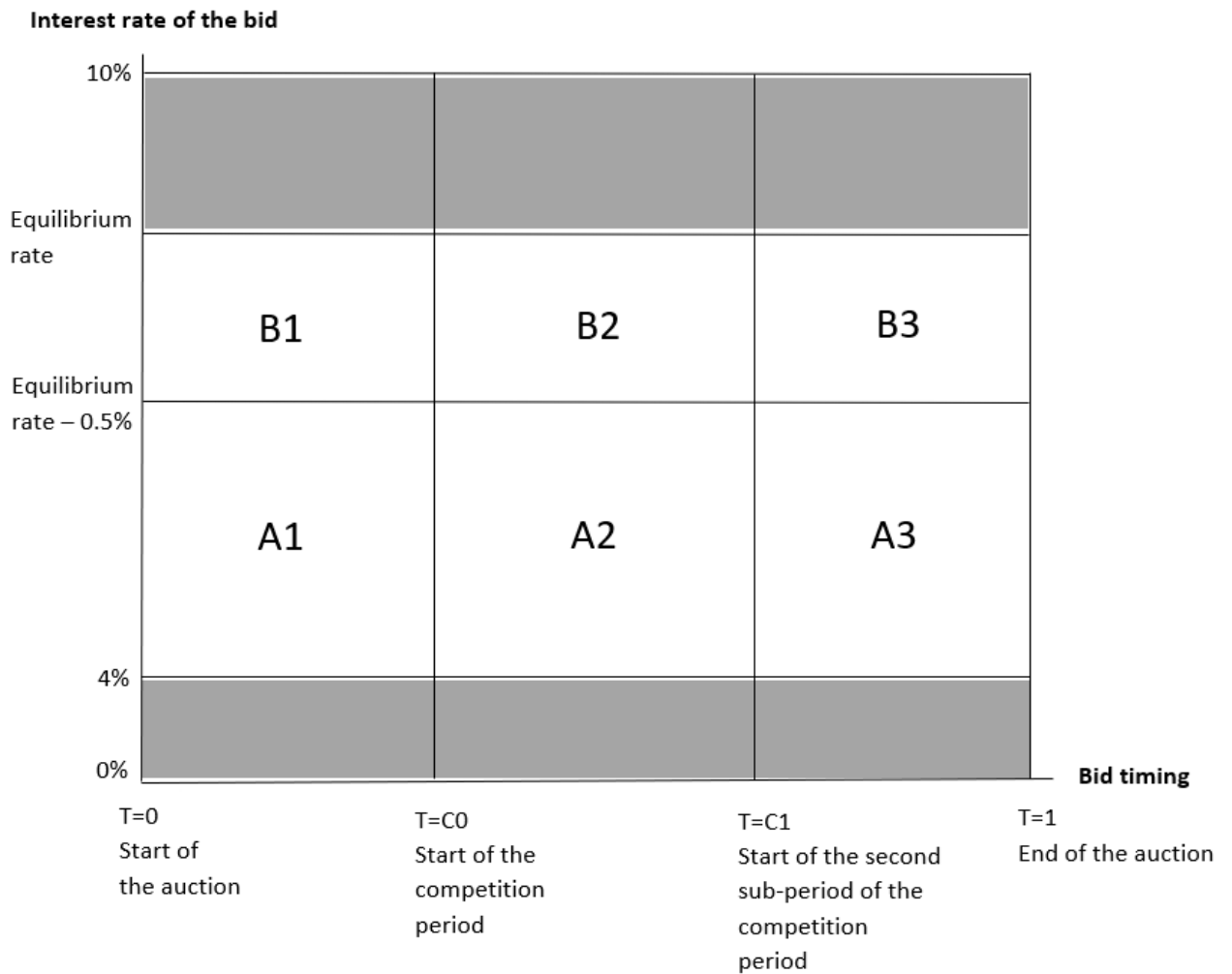


Figure 2.1: A taxonomy of bidding strategies in crowdending auctions

This figure represents the decomposition of a Dutch auction in peer-to-business crowdending platform Unilend along two components: the interest rate of an investor's bid (y-axis), and the relative timing of the investor's bid in the auction (x-axis). The auction process is mapped into six different areas, each area corresponding to a specific bidding strategy. A winning investor in an auction can only follow one of the six strategies, which is determined by her last submitted bid in the auction. Strategies A1, A2, and A3 are considered unsophisticated bidding strategies whereas strategies B1, B2, and B3 are considered to be sophisticated.

The x-axis represents the auction time in relative terms. We divide the auction time into three sub-periods: the coverage period, the first part of the competition period, and its second part. As there is no competition between bidders during the coverage period, investors can submit bids at any interest rate they want. The competition period starts as soon as an additional bid can clear the loan amount. We divide the competition period into two sub-periods. The first sub-period represents the vast majority of the competition period, while the second one grasps the final moments of the auction. The second part of the competition period lasts between 5 minutes and one hour, depending on the total duration of the competition period. If the competition period lasts for more than 2 hours, the second sub-period lasts for one hour; if the competition period lasts for less than 2 hours, the second sub-period duration is equal to half the full duration of the competition period, with a minimum being set at 5 minutes. The idea behind this rule is that the final moments of the auction, in which the degree of competition between bidders is at its highest, will certainly last longer if the competition period lasts two days rather than three hours for example.

The y-axis represents the interest rate of a bid submitted by an investor. In the Unilend auction system, the range of interest rates of winning bids goes from 4% to the equilibrium rate of the auction. We divide this range into two sub-ranges: the first range accounts for bids whose interest rates are between the equilibrium rate and the equilibrium rate minus five ticks included (0.5%). This sub-range accounts for the most competitive bids in terms of interest rate. The other sub-range goes from 4% to the equilibrium rate minus five ticks excluded. This sub-range accounts for the non-competitive bids.

Mapping the auction this way allows us to define six different bidding strategies. We consider that each winning investor in an auction can only follow one strategy at a time. This strategy is identified by considering her last submitted winning bid only. We divide the six different strategies into two groups: the group of sophisticated strategies, and the group of unsophisticated ones. The group of

unsophisticated strategies is composed of strategies denoted A1, A2, and A3 in Figure 2.1. Investors who adopt strategy A1 bid early in the auction when there is no competition, and they do so at interest rates significantly lower than the equilibrium rate of the auction. We consider these investors as non-strategic as they are not able to correctly estimate the equilibrium rate of the auction. Those investors are similar to participators in [Bapna et al. \(2000\)](#)'s paper as they certainly bid at a significantly lower rate, perhaps at their reservation rate, at the beginning of the auction to have a high likelihood of winning the auction without having to monitor it. Investors adopting strategy A2 bid at non-competitive interest rates during the first sub-period of the competition period. We also consider them non-strategic investors. Last, investors adopting strategy A3 bid at non-competitive interest rates although they manage to participate in the last moments of the auction. Investors adopting such a strategy either do not understand the auction system mechanism or, if they do, are irrational.

The group of sophisticated strategies is composed of rewarding strategies B1, B2, and B3. Investors using strategy B1 bid early in the auction at highly competitive interest rates. Either those investors are lucky, or they are able to anticipate the equilibrium rate long before the end of the auction. We therefore consider such investors as potentially informed. Investors adopting strategy B2 submit their last bid at a highly competitive interest rate during the first sub-period of the competition period. Although they are similar to investors using strategy B1, we consider them strategic followers because they certainly had to wait for the competition period to start to be able to gauge demand and estimate the equilibrium rate of the auction. Last, investors adopting strategy B3 submit highly competitive bids in the last moments of the auction. This strategy is typically used by snipers. We also construct two sub-strategies for strategies B1 and B3 and call them B1+ and B3+. An investor falls into the B1+ (B3+) category if she is labeled B1 (B3) in auction j while she submitted only one bid in that auction. These two sub-categories are supposed to gather truly informed, or expert, investors as they do not need to

submit multiple bids during a given auction to implement a sophisticated strategy. Although B2 is also part of sophisticated strategies, we believe it is mainly used by uninformed investors who follow the expert investors adopting B1 strategies. Investors adopting B2 strategies are therefore a notch less sophisticated than investors adopting B1 strategies, which is the reason why we do not create a B2+ category.

2.4.2. Descriptive statistics relative to the frequency of use of strategies

After designing a taxonomy of bidding strategies in Unilend auctions, we check for the frequency of use of those different strategies. For each auction, we select the last bid of each winning investor and we classify it in one of the bidding strategy classes of Figure 2.1. We then compute the proportion of use of each strategy among all winning investors. We report the associated descriptive statistics in Table 2.1. Strategy A1, used by non-strategic investors, represents on average 10.28% of the total number of strategies adopted by winning investors. The frequency of use of this strategy has steadily decreased over the years as it represented 11.42% of all winning strategies in auctions completed in 2014 and 7.10% in auctions completed in 2016. Strategy A2, also adopted by non-strategic investors, represents 6.32% of the total number of winning strategies in auctions and has increased over the years. As we consider both investors adopting strategies A1 and investors adopting strategies A2 as non-strategic, we add their associated frequencies of use and find that their representation is quite stable over the years at around 16% of all winning strategies. Strategy A3, the last non-sophisticated strategy adopted by irrational investors, is only used in 0.57% of cases by winner investors. Regarding sophisticated strategies, they appear to be more frequently used than unsophisticated ones. Strategy B1, used by potentially informed investors that are able to estimate the equilibrium rate of the auction during the coverage period, represents 22.23% of winning strategies on average. The frequency of use of such a strategy has, however, drastically decreased over the years, from 36.80% in 2014 to 7.59% in 2016. Interestingly, the frequency of

use of sub-strategy B1+ is quite close to strategy B1's, meaning that, in most cases, winning investors that adopted strategy B1 did so by submitting only one bid in the auction. Strategy B2 represents 38.56% of winning strategies on average and its use has increased over the years. Last, the sniping strategy is used in 22.03% of cases and its use has also increased over the years. Contrary to strategy B1, strategy B3 is mostly used by investors who bid multiple times in the auction.

Table 2.1: Summary statistics - auction level

This table reports the mean, 25th percentile value, median, and 75th percentile value of the proportion of each bidding strategy in each auction. The proportion of strategy i in auction j is the number of investors who adopted strategy i in auction j divided by the number of winning investors in auction j . The mean statistic is reported for the full sample period (column *Mean*), for the year 2014 (column *Mean(2014)*), for the year 2015, and for the year 2016. Our sample is composed of 236 auctions completed between 2013 and 2016. Bidding strategies are defined in Figure 2.1 and Section 2.4.1.

Statistic	N	Mean	Mean(2014)	Mean(2015)	Mean(2016)	Pctl(25)	Median	Pctl(75)
A1	236	10.28	11.42	9.85	7.10	1.22	5.11	12.97
A2		6.32	5.27	5.68	8.92	2.87	4.87	7.83
A3		0.57	0.23	0.61	1.17	0.00	0.34	0.75
B1		22.23	36.80	17.20	7.59	3.40	14.50	33.91
B1+		19.06	32.09	14.61	6.05	2.83	11.44	28.55
B2		38.56	31.50	42.40	44.00	20.75	40.46	55.10
B3		22.03	14.80	24.30	31.20	8.29	21.99	32.92
B3+		6.08	3.81	6.48	9.75	2.74	5.49	8.99

The fact that strategy B1 is the only sophisticated strategy that has known a decrease in its use is puzzling. Indeed, the fact that the frequency of use of all other sophisticated strategies increases, especially strategy B3, suggests that the degree of sophistication of investors has increased over the years. If this is the case, then the relatively high use of strategy B1 during the early days of Unilend is certainly due to luck rather than privileged information for the most part.

2.5. Effects of learning by doing on crowdenders' bidding strategies

As investors participate in more auctions, they gain experience and knowledge about the way they unfold. Descriptive statistics reported in Section 2.4.2 suggest that investors have adopted more sophisticated strategies with time. The goal of the rest of the chapter is to investigate whether experience in auctions impacts the choice of strategies adopted by investors.

2.5.1. Hypothesis development

With experience, investors may gain valuable knowledge about the auction system. For instance, they may become better at gauging the offer of funds from lenders and, therefore, at estimating the equilibrium rate of an auction before its end. This experiential knowledge may have an impact on the choice of strategies made by investors. The main *a priori* hypothesis, supported by the studies of [Kagel \(1995\)](#) and [Wilcox \(2000\)](#), is that investors' performance in auctions should increase with experience. We therefore expect investors to be more likely to adopt rewarding sophisticated strategies (B-type) as they gain more experience with crowdending auctions. For any given auction, we measure an investor's experience with auctions as the number of auctions she has previously won before participating in the current auction. We construct the following testable hypothesis.

H1: The investor's likelihood to adopt a sophisticated strategy of type B during an auction increases with the number of auctions previously won by the investor.

Financial literacy and degree of sophistication in auctions vary across investors. We can expect that investors capable of adopting sophisticated strategies from the first auction they participate in have certainly less to learn with experience than unsophisticated investors who do not have a good understanding of the auction system during their first auction participation. In other words, we can expect the

increase in absolute terms in the likelihood of adopting a sophisticated strategy of type B coming from experience to be higher for unsophisticated beginners than for the rest of the crowd. We consider an investor to be unsophisticated in the first auctions she participates in if she adopts an unsophisticated strategy of type A at least 3 times during her first 5 auctions. We construct the following testable hypothesis:

H2: The increase, in absolute terms, in the likelihood of adopting a sophisticated strategy of type B coming from experience in auctions is higher for unsophisticated beginners than for other investors.

Unilend was amongst the first French crowdlending platforms, and it was the first platform to operate an auction system to fund loans. Early investors, i.e., investors who joined the platform in 2013 and 2014, can certainly be considered pioneers as (1) they invested money in a relatively new asset class (peer-to-business crowdlending), and (2) they lent money through an auction system. Pioneers have had more time than the rest of the investors to observe the formation of interest rates in auctions and may have gathered experience that is not necessarily captured by the number of past auctions they won. If pioneers have gathered more experience in auctions through observation than the rest of the investors, we expect these investors to have a higher likelihood of adopting a sophisticated strategy of type B.

H3: Pioneer investors are more likely to adopt a sophisticated strategy of type B during an auction than the rest of the investors.

2.5.2. Results

To investigate whether crowdlending investors change their bidding strategies and become more sophisticated as they gain experience with the auction system, we examine their bidding likelihood of adopting a sophisticated strategy of type B in an auction using the following logistic regression:

$$\text{Strategy B - type}_{i,j} = \alpha_1 \cdot \text{Auction Rank}_{i,j} + \alpha_2 \cdot \text{Age}_i + \alpha_3 \cdot X_j + \epsilon_{i,j}, \quad (2.1)$$

where *Strategy B – type_{*i,j*}* is a dummy equal to one if investor *i* wins auction *j* and her last submitted bid falls into one of the B-type categories, 0 otherwise. Our main variable of interest is *Auction Rank_{*i,j*}* which is equal to *n* if auction *j* is the *n*th auction investor *i* participates in and wins. This variable measures the experience of investor *i* with auctions. We use *Age_{*i*}*, the age of investor *i* taken in logarithms, as a control for investor *i*'s wealth and investing experience. We expect it to positively impact the probability of adopting a sophisticated strategy in the auction. *X_{*j*}* is a vector of control variables at the loan level. This vector includes the loan amount and the loan maturity, both taken in logarithms, the year of the auction as a fixed effect, plus three dummies representing the credit rating of the loan. Each of those dummies, further denoted *Rating n*, equals one if the credit rating is *n* stars, zero otherwise, with *n* being alternatively 3.5, 4, and 5, and the base case being a three-star rating. The rationale for the controls composing *X_{*j*}* is as follows. Due to the finite number of investors registered on the platform, the offer of funds is limited. For that reason, the larger the loan amount, the easier it is to win the auction with a bid close to the equilibrium rate, i.e., to adopt a sophisticated strategy of type B. The loan maturity and the credit rating of the borrower may affect the offer of funds from lenders, which in turn impacts the level of competition in the auction and the probability to adopt a sophisticated strategy. Year fixed effects control for yearly changes in the offer of funds from lenders. Last, *Busy Area_{*j*}* is a dummy equal to one if borrower *j* is located in the most two active economic areas of the French territory, in terms of crowdlending borrowers and lenders.¹⁰ We add this control to account for the fact that such borrowers may be more well-known to lenders, and therefore attract more attention, which in turn increases the level of competition during the auction. Finding a significantly positive α_1 coefficient in Regression (2.1) would be in support of H1.

Results are reported in Table 2.2. In Column (1), the dependent variable is a dummy equal to one if investor *i* wins the auction and her last submitted bid

¹⁰The two aforementioned areas are the city of Paris and its west suburb.

falls into any of the B-type categories. Columns (2) to (6) report the results for strategies B1, B2, B3, B1+, and B3+ respectively. Results are mostly in line with expectations: the probability of an investor adopting a sophisticated strategy of types B1, B2, or B3 increases as experience is gained in auctions. However, the probability to adopt B1 and B3 strategies by submitting only one bid (B1+ and B3+) in the auction decreases with experience. Overall, these results are in support of H1. As for the coefficients of the control variables, the coefficient of investor age is significantly positive, which means that the probability of adopting a sophisticated strategy is positively correlated with investment experience. The probabilities of adopting strategies B1 and B1+ increase with the risk of the loan (Rating 3), its amount, and its duration and they are higher when the borrower is located in a busy area. On the opposite, the probabilities of adopting strategies B2 and B3 decrease with the risk of the loan (Ratings 3.5 and 4), its amount, and its duration, and they are lower when the borrower is located in a busy area. Those findings suggest that investors who adopt strategies B1 hold fundamental information about loans' quality, while investors adopting B2 or B3 do not. B1 investors are therefore drawn to high-risk and long-term loans, which are more complex to analyze. In contrast, B2 and B3 investors are relatively less prone to invest on them.

As expressed in H2, we expect unsophisticated beginners to benefit the most from experience with regard to the probability of adopting a sophisticated strategy of type B in auctions. We test this hypothesis by conducting the same logistic regression as in Regression (2.1), on the subsample of investors that were using mostly unsophisticated strategies in the first auctions they won. Results are reported in Table 2.3. The probability that an unsophisticated beginner adopts any kind of sophisticated strategies increases with experience, and coefficient α_1 is of much greater magnitude than the one displayed in the full sample regression in Table 2.2. These elements suggest that unsophisticated beginners benefit the most from experience, which is in support of H2.

Table 2.2: Investor likelihood of adopting a sophisticated bidding strategy - Full sample

This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if, for a given investor and a given auction, the investor has adopted a strategy of type B - that is, either B1, B2, B3, B1+, or B3+ - in the auction, 0 otherwise. *Auction rank* measures the experience of a given investor for a given auction. It is equal to n if the auction is the n th auction the investor wins. The loan rating is the credit notch assigned to the loan by Unilend. For auctioned loans, those notches range from 3 to 5, with a 0.5 increment, with 5 being the best creditworthiness. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Investor age*, *Loan amount*, and *Loan term* are expressed in years, euros, and months, respectively, and taken in logarithms. Year n equals 1 if the auction's year of completion is n , 0 otherwise. *Busy area* equals 1 if the borrowing firm is located in France's two most active economic areas, 0 otherwise. Bidding strategies are defined in Figure 2.1 and Section 2.4.1. Standard errors are reported in parentheses. ***, **, * and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level, respectively.

	Any B-type strategy					
	(1)	(2)	(3)	(4)	(5)	(6)
Auction rank	0.008*** (0.0004)	0.001*** (0.0004)	0.001*** (0.0003)	0.005*** (0.0003)	-0.001*** (0.0004)	-0.001* (0.001)
Investor age	0.216*** (0.027)	-0.028 (0.028)	-0.082*** (0.023)	0.420*** (0.029)	-0.033 (0.029)	0.353*** (0.049)
Rating 3.5	0.153*** (0.019)	-0.597*** (0.019)	0.498*** (0.016)	0.070*** (0.020)	-0.676*** (0.020)	0.025 (0.034)
Rating 4	0.135*** (0.030)	-0.852*** (0.031)	0.628*** (0.026)	0.264*** (0.033)	-1.005*** (0.033)	0.098* (0.057)
Rating 4.5	-0.276*** (0.062)	-2.010*** (0.068)	-0.150* (0.084)	-1.053*** (0.130)	-2.268*** (0.078)	-0.615*** (0.187)
Loan amount	-0.949*** (0.015)	1.241*** (0.016)	-0.908*** (0.013)	-0.934*** (0.015)	1.123*** (0.017)	-0.688*** (0.025)
Loan term	-0.445*** (0.026)	0.723*** (0.029)	-0.403*** (0.020)	-0.431*** (0.023)	0.764*** (0.031)	-0.235*** (0.038)
Year 2014	2.285*** (0.097)	1.200*** (0.141)	1.455*** (0.145)	-0.226* (0.134)	1.509*** (0.177)	-0.342 (0.223)
Year 2015	1.820*** (0.096)	0.302** (0.142)	1.794*** (0.145)	0.217 (0.133)	0.629*** (0.177)	0.117 (0.221)
Year 2016	1.489*** (0.097)	-0.569*** (0.143)	1.789*** (0.146)	0.390*** (0.134)	-0.252 (0.179)	0.455** (0.222)
Busy area	-0.554*** (0.019)	0.167*** (0.020)	-0.298*** (0.017)	-0.144*** (0.021)	0.139*** (0.021)	0.023 (0.035)
Intercept	11.065*** (0.229)	-18.059*** (0.263)	9.531*** (0.226)	8.681*** (0.247)	-17.320*** (0.292)	4.227*** (0.401)
Number of observations	98,447	98,447	98,447	98,447	98,447	98,447

Table 2.3: Investor likelihood of adopting a sophisticated bidding strategy - Unsophisticated investors only

This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if, for a given investor and a given auction, the investor has adopted a strategy of type B – that is, either B1, B2, B3, B1+, or B3+ – in the auction, 0 otherwise. *Auction rank* measures the experience of a given investor for a given auction. It is equal to n if the auction is the n th auction the investor wins. The loan rating is the credit notch assigned to the loan by Unilend. For auctioned loans, those notches range from 3 to 5, with a 0.5 increment, with 5 being the best creditworthiness. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Investor age*, *Loan amount*, and *Loan term* are expressed in years, euros, and months, respectively, and taken in logarithms. Year n equals 1 if the auction's year of completion is n , 0 otherwise. *Busy area* equals 1 if the borrowing firm is located in France's two most active economic areas, 0 otherwise. Unsophisticated investors, i.e., investors who have invested in at least 5 auctions and adopted at least 3 times an unsophisticated strategy of type A during their 5 first auctions, are the only investors included in the sample. Bidding strategies are defined in Figure 2.1 and Section 2.4.1. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level, respectively.

	Any B-type strategy					
	(1)	(2)	(3)	(4)	(5)	(6)
	B1	B2	B3	B1+	B3+	
Auction rank	0.022*** (0.001)	0.007*** (0.001)	0.004*** (0.001)	0.016*** (0.001)	0.006*** (0.001)	0.007*** (0.001)
Investor age	0.409*** (0.060)	0.042 (0.073)	0.126* (0.065)	0.952*** (0.109)	0.084 (0.076)	1.169*** (0.200)
Rating 3.5	0.247*** (0.038)	-0.417*** (0.045)	0.625*** (0.042)	0.126* (0.067)	-0.470*** (0.048)	0.027 (0.127)
Rating 4	0.147** (0.059)	-0.608*** (0.072)	0.739*** (0.065)	0.160 (0.112)	-0.727*** (0.077)	0.314 (0.201)
Rating 4.5	-0.248 (0.185)	-1.770*** (0.224)	-0.078 (0.254)	-0.812** (0.388)	-2.093*** (0.270)	-0.962 (0.728)
Loan amount	-0.943*** (0.031)	0.602*** (0.036)	-1.145*** (0.034)	-1.037*** (0.052)	0.561*** (0.038)	-0.708*** (0.092)
Loan term	-0.713*** (0.055)	0.276*** (0.069)	-0.630*** (0.054)	-0.674*** (0.078)	0.339*** (0.073)	-0.357*** (0.136)
Year 2014	2.128*** (0.220)	1.774*** (0.344)	1.785*** (0.300)	0.903 (0.586)	1.857*** (0.387)	0.424 (1.015)
Year 2015	1.802*** (0.221)	1.124*** (0.345)	2.002*** (0.301)	1.175** (0.586)	1.212*** (0.388)	1.155 (1.010)
Year 2016	1.882*** (0.223)	0.520 (0.348)	2.261*** (0.302)	1.327** (0.588)	0.597 (0.392)	1.710* (1.012)
Busy area	-0.451*** (0.041)	0.016 (0.049)	-0.295*** (0.045)	-0.266*** (0.074)	-0.003 (0.052)	-0.028 (0.132)
Intercept	9.711*** (0.491)	-10.642*** (0.624)	11.475*** (0.561)	6.434*** (0.931)	-10.768*** (0.670)	-0.463 (1.644)
Number of observations	17,128	17,128	17,128	17,128	17,128	17,128

However, the large difference in magnitude between the coefficients of the proxy variable for investor i 's experience in auctions in Tables 2.2 and 2.3 may indicate that unsophisticated beginners drive the results for the full sample. To check whether this is the case, we run Regression (2.1) excluding unsophisticated beginners from the sample. Results are reported in Table 2.4. Although the economic magnitude of the coefficients is lower than that in Table 2.3, we still find a positive correlation between investor experience and the probability of adopting a sophisticated strategy in Column (1), which appears to be driven by the sniping strategy (B3). These results therefore show that unsophisticated beginners mostly explain the overall results reported in Table 2.2 and that the likelihood of adopting a sniping strategy is positively correlated to auction experience for all types of investors.

Last, we test H3 by checking whether pioneer investors are more experienced than the rest of the investors. To test this hypothesis, we run the following logistic regression:

$$\begin{aligned} \text{Strategy } B - \text{type}_{i,j} = & \beta_1 \cdot \text{Pioneer}_i + \beta_2 \cdot \text{Pioneer } B1_i + \beta_3 \cdot \text{Auction Rank}_{i,j} \\ & + \beta_4 \cdot \text{Age}_i + \beta_5 \cdot X_j + \epsilon_{i,j}, \end{aligned} \quad (2.2)$$

where Pioneer_i is a dummy equal to one if investor i won at least one auction in 2013 or 2014, 0 otherwise. $\text{Pioneer } B1_i$ is a dummy equal to one if investor i is a pioneer investor who adopted strategy B1 more frequently than the median pioneer investor in 2013 and 2014, 0 otherwise. We divide the population of pioneer investors into two sub-populations to check whether pioneer investors that adopted more frequently B1 strategies than the rest of the pioneer investors are indeed better informed. If H3 holds, we expect β_1 to be positive. As all active investors in the auctions completed in 2013 and 2014 are defined as pioneers, we restrict the sample to auctions completed in 2015 and 2016.

Results are reported in Table 2.5. In Column (1), we still find that investor experience is positively correlated with the likelihood of adopting a sophisticated strategy. However, this result appears to be driven by the B3 strategy as the co-

Table 2.4: Investor likelihood of adopting a sophisticated bidding strategy - Unsophisticated investors excluded

This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if, for a given investor and a given auction, the investor has adopted a strategy of type B – that is, either B1, B2, B3, B1+, or B3+ – in the auction, 0 otherwise. *Auction rank* measures the experience of a given investor for a given auction. It is equal to n if the auction is the n th auction the investor wins. The loan rating is the credit notch assigned to the loan by Unilend. For auctioned loans, the notch ranges from 3 to 5, with a 0.5 increment, with 5 being the best creditworthiness. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Investor age*, *Loan amount*, and *Loan term* are expressed in years, euros, and months, respectively, and taken in logarithms. Year n equals 1 if the auction's year of completion is n , 0 otherwise. *Busy area* equals 1 if the borrowing firm is located in France's two most active economic areas, 0 otherwise. Unsophisticated investors, i.e., investors who have invested in at least 5 auctions and adopted at least 3 times an unsophisticated strategy of type A during their 5 first auctions, are excluded from the sample. Bidding strategies are defined in Figure 2.1 and Section 2.4.1. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level, respectively.

	Any B-type strategy					
	(1)	(2)	(3)	(4)	(5)	(6)
	B1	B2	B3	B1+	B3+	
Auction rank	0.006*** (0.0004)	-0.0002 (0.0004)	0.0005 (0.0003)	0.003*** (0.0003)	-0.003*** (0.0005)	-0.002*** (0.001)
Investor age	0.320*** (0.033)	-0.005 (0.030)	-0.093*** (0.025)	0.430*** (0.030)	-0.025 (0.032)	0.339*** (0.050)
Rating 3.5	0.178*** (0.023)	-0.655*** (0.021)	0.486*** (0.018)	0.077*** (0.021)	-0.740*** (0.022)	0.035 (0.035)
Rating 4	0.197*** (0.037)	-0.934*** (0.034)	0.619*** (0.028)	0.283*** (0.035)	-1.093*** (0.037)	0.082 (0.060)
Rating 4.5	-0.190*** (0.070)	-2.148*** (0.073)	-0.174* (0.089)	-1.079*** (0.139)	-2.388*** (0.083)	-0.579*** (0.194)
Loan amount	-1.067*** (0.019)	1.392*** (0.018)	-0.872*** (0.014)	-0.932*** (0.016)	1.253*** (0.019)	-0.684*** (0.025)
Loan term	-0.430*** (0.031)	0.820*** (0.032)	-0.370*** (0.022)	-0.417*** (0.025)	0.854*** (0.034)	-0.226*** (0.040)
Year 2014	2.374*** (0.125)	0.875*** (0.159)	1.201*** (0.169)	-0.621*** (0.145)	1.248*** (0.201)	-0.659*** (0.232)
Year 2015	1.404*** (0.123)	-0.155 (0.159)	1.514*** (0.168)	-0.261* (0.144)	0.256 (0.201)	-0.314 (0.230)
Year 2016	1.005*** (0.124)	-1.066*** (0.161)	1.476*** (0.169)	-0.058 (0.145)	-0.664*** (0.203)	0.025 (0.231)
Busy area	-0.609*** (0.023)	0.202*** (0.022)	-0.297*** (0.019)	-0.130*** (0.022)	0.173*** (0.023)	0.033 (0.036)
Intercept	12.701*** (0.280)	-19.692*** (0.296)	9.409*** (0.252)	9.182*** (0.263)	-18.722*** (0.328)	4.740*** (0.416)
Number of observations	81,319	81,319	81,319	81,319	81,319	81,319

efficient of *Auction Rank* is negative in all other specifications. Hence, we find that there is a positive correlation between auction experience and the likelihood of adopting a sniping strategy for all types of investors. Although coefficient β_1 of *Pioneer* is not statistically significant in Column (1), it is significantly positive for B1 and B1+ strategies and significantly negative for B3 and B3+ strategies. This result means that pioneers are more likely to be informed investors and less likely to adopt sniping strategies with experience. We can therefore conclude that, on average, pioneer investors gained some additional experience through the observation of the loan rate formation process, but do not use such knowledge to snipe. This result is therefore partially in support of H3. As for the potentially-informed pioneer investors, these investors are more likely to adopt B1 and B2 strategies, and less likely to snipe. The fact that this subgroup of pioneer investors has consistently been able to adopt B1 and B1+ strategies with significantly higher probabilities than the rest of the investors rules out, at least partially, the luck factor explanation. This suggests that this subgroup of pioneer investors may have privileged information about loan rates' fundamental values.

A caveat of our analysis relative to the potentially-informed group of pioneer investors is that there are two possible explanations for this result. The first explanation is the one used to construct hypothesis H3: pioneer investors had more time than the rest of the investors to learn about auction dynamics and loan rate formation. Another explanation is that pioneer investors self-selected and became pioneers because they knew that their level of bidding sophistication was higher than the rest of the investors. Unfortunately, we cannot think of a means to check which of these explanations is true.

Table 2.5: Investor likelihood of adopting a sophisticated bidding strategy - Pioneers regressions, years 2015 and 2016 only

This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if, for a given investor and a given auction, the investor has adopted a strategy of type B – that is, either B1, B2, B3, B1+, or B3+ – in the auction, 0 otherwise. *Pioneer* is equal to 1 if a given investor was already active on the platform in 2013 and 2014. *Pioneer B1* is equal to 1 if a given investor is a pioneer on the platform, and adopted strategy B1 more frequently than the median adoption of such a strategy in years 2013 and 2014. *Auction rank* measures the experience of a given investor for a given auction. It is equal to n if the auction is the n th auction the investor wins. The loan rating is the credit notch assigned to the loan by Unilend. For auctioned loans, those notches range from 3 to 5, with a 0.5 increment, with 5 being the best creditworthiness. Rating n equals 1 if the loan's rating is n , 0 otherwise. *Investor age*, *Loan amount*, and *Loan term* are expressed in years, euros, and months, respectively, and taken in logarithms. Year n equals 1 if the auction's year of completion is n , 0 otherwise. *Busy area* equals 1 if the borrowing firm is located in France's two most active economic areas, 0 otherwise. Only auctions completed in 2015 and 2016 are included in the sample. Bidding strategies are defined in Figure 2.1 and Section 2.4.1. Standard errors are reported in parentheses. ***, ** and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level, respectively.

	Any B-type strategy (1)	B1 (2)	B2 (3)	B3 (4)	B1+ (5)	B3+ (6)
Pioneer	0.004 (0.034)	0.239*** (0.036)	0.048 (0.030)	-0.299*** (0.039)	0.293*** (0.038)	-0.127** (0.061)
Pioneer B1	0.596*** (0.040)	0.152*** (0.040)	0.251*** (0.034)	0.073* (0.043)	0.139*** (0.042)	-0.222*** (0.070)
Auction rank	0.001*** (0.0005)	-0.004*** (0.0005)	-0.002*** (0.0004)	0.007*** (0.0004)	-0.007*** (0.001)	0.002*** (0.001)
Investor age	0.259*** (0.031)	-0.008 (0.033)	-0.087*** (0.026)	0.418*** (0.032)	0.010 (0.036)	0.300*** (0.052)
Rating 3.5	0.197*** (0.022)	-0.528*** (0.024)	0.441*** (0.018)	-0.056** (0.022)	-0.655*** (0.026)	-0.010 (0.037)
Rating 4	0.431*** (0.037)	-1.172*** (0.045)	0.685*** (0.032)	0.457*** (0.038)	-1.221*** (0.050)	0.338*** (0.063)
Rating 4.5	0.205*** (0.067)	-1.981*** (0.072)	-0.137 (0.085)	-1.101*** (0.129)	-2.243*** (0.082)	-0.628*** (0.187)
Loan amount	-1.242*** (0.019)	1.263*** (0.020)	-0.926*** (0.014)	-0.914*** (0.017)	1.130*** (0.021)	-0.702*** (0.027)
Loan term	-0.523*** (0.028)	0.616*** (0.032)	-0.373*** (0.022)	-0.321*** (0.025)	0.724*** (0.036)	-0.172*** (0.040)
Year 2016	-0.257*** (0.023)	-0.702*** (0.028)	0.053*** (0.019)	0.115*** (0.022)	-0.725*** (0.031)	0.254*** (0.035)
Busy area	-0.580*** (0.022)	0.073*** (0.024)	-0.286*** (0.019)	-0.166*** (0.023)	0.072*** (0.026)	0.044 (0.037)
Intercept	16.296*** (0.251)	-17.700*** (0.280)	11.414*** (0.198)	8.365*** (0.228)	-16.810*** (0.299)	4.495*** (0.363)
Number of observations	74,509	74,509	74,509	74,509	74,509	74,509

2.6. Conclusion

In this chapter, we present a novel way of determining investors' bidding strategies in Dutch auctions. Although the literature has extensively used data-mining techniques to describe investors' strategies, we choose to define, a priori, typical bidding strategies that investors can use. To do so, we map the auction process into six areas using two major bid features: the interest rate of the bid and its relative timing in the auction. Each area of this map is then associated with a specific strategy. Of the six strategies created, we consider three of them to be unsophisticated, also called the A-type strategies, and the three others to be sophisticated, the B-type strategies. Our taxonomy of bidding strategies leads us to categorize investors as the following: non-strategic investors (corresponding to the investors adopting strategies A1 and A2), irrational investors (A3), informed investors (B1), strategic followers (B2), and snipers (B3).

Although retail investors are often thought of as unsophisticated by academics and practitioners, we observe that sophisticated strategies are actually used by most retail investors as they represent around 86% of winning strategies. We also observe that strategies B2 and B3, adopted by strategic followers and snipers respectively, have been used more and more by investors over the years. This result suggests that the degree of sophistication of investors increases with experience. We test this hypothesis by analyzing the link between investor experience in auctions and the likelihood of adopting a sophisticated strategy and we find a significantly positive correlation. Furthermore, we find that investors that adopted unsophisticated strategies most of the time during their first auctions benefited the most from experience as they had more to learn than the rest of the investors. We also show that pioneer investors who lent money during the early days of Unilend gained additional knowledge through the observation of the loan rate formation process. They use this additional knowledge to adopt informed strategies, but do not use it for sniping strategies. Last, we find that there is a group of potentially-informed investors

among pioneer investors. These investors are more likely to adopt a sophisticated bidding strategy than the rest of the investors. More specifically, they are more likely to behave as informed participants (B1), or as strategic followers (B2), but they do not snipe (B3) more than others.

Partie 2

La gouvernance d'entreprise avec conseil d'administration à mandats échelonnés

Chapitre 3

Staggered Boards and Firm Value After the Sarbanes-Oxley Act

Abstract :

A steady decline in the use of staggered boards (SB) by S&P 1500 firms has been observed since the Sarbanes-Oxley Act (SOX) was enforced. This paper aims to understand this phenomenon by investigating: (1) the motivations for keeping a SB after SOX, and (2) the impact of this choice on the firm's value. I find that the main motive for keeping a SB is to protect important stakeholder relationships, in particular those with employees and customers, and that having a SB is value-enhancing after SOX, even when controlling for a potential selection bias. My results, fully consistent with the bonding theory, rule out the entrenchment theory after SOX, proving SOX to be efficient in precluding entrenchment.

3.1. Introduction

In a conventional board of directors, all directors are up for reelection every year, so that shareholders have the power to replace them all at once if needed. Alternatively, shareholders may decide to adopt a staggered board of directors. Staggered boards, also known as classified boards, are a governance provision that groups directors into classes, each class of directors having its own reelection term. Directors are traditionally grouped into three classes and each class of directors has a term lasting three years. In that case, only one-third of the directors can be replaced in a given year. This arrangement is a powerful takeover defense as a hostile acquirer would have to win two annual elections to replace a majority of board directors. The impact of the deterrent power of staggered boards on the value of the firm has been a source of debate. On the one hand, the entrenchment theory advocates that staggered boards have a negative impact on the value of the firm. The entrenchment theory states that takeover defenses limit the power of the market for corporate control, which allows managers to redirect their firm's resources to their own benefit. This theory has been supported by early empirical studies as well as proxy advisors, who have historically advised their clients to vote against the use of staggered boards.¹ On the other hand, the bonding theory states that staggered boards have a positive impact on the value of the firm. This theory states that takeover defenses limit the risk of termination of important bonds between the firm and its stakeholders. This incentivizes the firm to make relationship-specific investments which are more value-creating.

In practice, the popularity of staggered boards has changed over time. They were relatively popular in the 1990s and the early 2000s, but they have been pro-

¹As an example, annual voting guidelines of Institutional Shareholders Services (ISS), a proxy advisor, are available from 2013 to 2020 at <https://www.issgovernance.com/search/voting+guidelines>. ISS have always advised their clients to vote against staggered boards, i.e., either to vote against their adoption or to vote for their removal. The stance of ISS towards staggered boards is even older as Patrick S. McGurn, ISS's Special Counsel, is the author of an article published in 2002 and called "*Classification Cancels Corporate Accountability*" (McGurn, 2002).

gressively abandoned by many S&P1500 firms since 2005, when the Sarbanes-Oxley Act (SOX) was adopted, in the aftermath of the Enron and WorldCom financial scandals.² As stated by [Linck et al. \(2009\)](#), "[SOX] signifies a turning point in the corporate governance landscape" as it creates an anti-entrenchment regulatory environment. In particular, it makes the choice of having a staggered board more costly because meeting the SOX requirement that requires a majority of independent directors on the board is more difficult. As a consequence, numerous firms have started to remove their staggered board since 2005, and this dynamic has gone on ever since. The goal of this chapter is twofold. First, it aims to understand the determinants of staggered board removals after the adoption of SOX. Second, it investigates the relation between staggered boards and the value of the firm in an anti-entrenchment regulatory environment such as SOX.

As governance choices are decided by shareholders, I first analyze shareholders' votes at annual general meetings of S&P 1500 firms. I find a significant change after the adoption of the Sarbanes-Oxley Act. First, shareholders became less likely to propose the adoption of a staggered board. Second, they became more likely to propose and vote for its removal if their firm had one in place. Moreover, I find that proposals in favor of the adoption of a staggered board are systematically sponsored by the management of the firm, while proposals to remove the takeover defense are sponsored, in the vast majority of cases, by non-executive shareholders. Then, looking at the determinants of staggered board removals, I find that firms for which the staggered board brings benefits are less likely to remove it after the adoption of SOX. More specifically, firms having important stakeholder relationships that would lose value in the case of a takeover are more likely to keep the provision after the adoption of SOX. After controlling for potential endogeneity issues by using a [Heckman \(1979\)](#) correction procedure, I find that staggered boards have a positive

²See Figures 3.1 and 3.2. Interestingly, [Guernsey et al. \(2022\)](#) show that this dynamic is only true for S&P1500 firms as the proportion of non-S&P1500 firms having a staggered board has risen from 40% to 53% throughout the 1995-2020 period. They attribute the decrease in the popularity of staggered boards to increasing attention to governance and rising index ownership for S&P1500 firms.

impact on the long-term value of firms after SOX despite the associated costs.

I contribute to the literature in several ways. First, I provide descriptive statistics relative to proxy votes around the adoption of the Sarbanes-Oxley Act. Second, I show that the main motivation for keeping a staggered board after SOX, despite the regulation making it more costly, is to have substantial relationships with stakeholders, especially employees and customers. Third, I show that firms with a staggered board after SOX have greater values than others, meaning that those specific stakeholder relationships are value-enhancing. This finding holds after controlling for endogeneity. Last, it contributes to the debate relative to the relation between staggered boards and the value of the firm by finding clear support in favor of the bonding theory in the post-SOX period.

The remainder of the chapter is structured as follows. Section 3.2 reviews the literature. Section 3.3 describes SOX and stylized facts relative to firms having a staggered board around the adoption of the law. Section 3.4 presents the testable hypotheses. Section 3.5 describes the data and reports descriptive statistics. Section 3.6 exposes the empirical tests, and Section 3.7 concludes.

3.2. Literature review

The literature on staggered boards has focused on three questions: (1) the efficiency of the staggered as an anti-takeover provision, (2) the determinants explaining the choice of a staggered board at the firm level, and (3) the impact of that provision on the value of the firm. While the last two questions have often been addressed simultaneously in the same papers, the first one has been addressed in a distinct strand of the literature.

3.2.1. Efficiency of staggered boards as anti-takeover provisions

Takeover defenses, such as staggered boards, are any provisions installed in the charter or bylaws used in order to increase the cost of hostile takeovers. They are very frequently used as 99% of S&P1500 firms had at least one in 2018. The most commonly used takeover defenses are limits to amend charter, limits to amend bylaws, and golden parachutes which were used respectively by 96.9%, 92.4%, and 83.5% of firms in 2018.

In theory, a staggered board makes it more difficult for an acquirer to take over a firm because a staggered board insulates directors from immediate removal, even if an acquirer manages to own the majority of the firm's voting rights. As a consequence, a hostile acquirer may have to wait for up to two years before replacing the majority of directors and thus taking effective control of the firm. A staggered board can also increase the cost of hostile takeovers when combined with a shareholders' rights plan, also known as poison pill. Poison pills are triggered when a hostile acquirer accumulates outstanding shares of a target company above a preset threshold. In such an event, all shareholders of the target company except the hostile bidder are either distributed with free shares or can buy them at a significant discount. As a result, the hostile bidder's holdings are diluted. Hence, the hostile bidder has to buy more shares than initially intended in order to own the majority of the firm's voting rights.³ Because the board of directors of the target company decides whether to add, keep, or remove a poison pill, the hostile acquirer will only be able to redeem the pill after replacing the majority of the directors. A staggered board is, at least in theory, a powerful takeover defense. From an empirical point of view, [Bates et al. \(2008\)](#) show that staggered boards reduce the probability of being

³As described by [Coates IV \(2000\)](#), the poison pill does not need to be adopted before the hostile bid, as the board of directors can always adopt it after. [Coates IV \(2000\)](#) names this possibility the "shadow poison pill". This possibility may explain the large decrease in the use of poison pills by S&P1500 firms. The proportion of those firms using poison pills fell from 50.9% in 1990 to less than 2% in 2018.

targeted by a hostile takeover bid. They however show that once targeted, a firm having a staggered board is as likely to be acquired as firms having a conventional board. This is also shown by Pound (1987), who adds that staggered boards do not increase the premium received by targets' shareholders. This suggests that staggered boards harm deal activity and reduce shareholders' wealth. Bebchuk et al. (2002) show that all hostile bidders lost against "effective" staggered boards between 1996 and 2000.⁴ They also show that the shareholders of target firms having a staggered board lost wealth by not accepting the offer. More recently, Cuñat et al. (2020) find that takeover defenses both reduce the likelihood of a takeover and, conditionally on being targeted, the premium. These findings suggest that staggered boards effectively protect firms from hostile takeovers, at the expense of shareholders.

3.2.2. Impact of staggered boards on firm value

The effect of having a staggered board on the value of the firm is a matter of debate, with two main theories opposing: (1) the entrenchment theory and (2) the bonding theory. Manne (1965) explains that the market for corporate control disciplines managers, and that any takeover defense used to reduce the effectiveness of such control entrenches managers. Entrenched managers may allocate the firm's resources for their own interest rather than that of shareholders. A staggered board would therefore have a negative impact on the value of the firm. This theory has found early empirical support. Although not specifically related to the staggered board provision, academics have also studied the association between the number of takeover defenses used by the firm and its value. Using the G-index constructed by Gompers et al. (2003),⁵ Masulis et al. (2007) find a negative correlation be-

⁴A staggered board is considered effective if it is installed in the charter and not in the bylaws. In such a case, directors can only be removed for cause.

⁵The G-index, or governance index, counts all shareholder rights provisions at the firm-year level. Bebchuk et al. (2009) transform the G-index into the E-index -or entrenchment index- by counting the most powerful takeover defenses only. The staggered board provision is included in both indexes. Karpoff et al. (2022) have recently shown that only four of the provisions composing the G-index are negatively and consistently related to the probability of a takeover over the 1995-2020 period. Although they find the staggered board to be negatively related to the likelihood of a takeover at the start of their sample period, the effect does not persist in more recent years. They attribute this result to be possibly caused by activism which led to a drop in the proportion

tween the magnitude of an acquirer stock return when announcing an acquisition and the number of anti-takeover provisions the acquirer has. This suggests that investors discount the acquisition news because entrenched managers may be involved in empire-building. Using hand-collected data over a 30-year period, [Cremers and Ferrell \(2014\)](#) find a negative effect of anti-takeover provisions on the value of the firm only after the Delaware Supreme Court approved the use of takeover defenses in 1985. More specifically, they find that the value of the firm is reduced by approximately 5% after the adoption of a poison pill. They also show that the negative effects of anti-takeover provisions are higher for firms in industries with a high level of mergers and acquisitions activity. Finally, [Johnson et al. \(2022\)](#) show that the entrenchment costs associated with takeover defenses increase as the firm grows, while their benefits decrease. As a consequence, they show that young firms benefit the most from anti-takeover provisions. They also show that firms tend to keep their anti-takeover provisions even though they become more costly with time because of high adjustment costs. In their seminal paper, [Bebchuk and Cohen \(2005\)](#) find that, consistent with the entrenchment theory, staggered boards are associated with lower firm value. [Faleye \(2007\)](#) finds that firms operating under a staggered board have lower CEO turnover and lower CEO pay-performance sensitivity, which suggests managerial entrenchment. [Guo et al. \(2008\)](#) find that the stock price of firms announcing that they will remove their staggered board increases by 1%, suggesting that investors perceive this provision as detrimental to the value of the firm.

The second theory on the impact of a staggered board on the value of the firm, known as the bonding theory, was first proposed by [Knoeber \(1986\)](#) and [Shleifer and Summers \(1988\)](#). The firm's stakeholders, such as employees, customers, and suppliers, may make relationship-specific investments that would lose value if the firm were to change its operating strategy in the case of a takeover. According to the bonding theory, takeover defenses bond the firm with its important stakeholders. By reducing the likelihood of a takeover, takeover defenses limit the risk of termination

of firms having a staggered board, as shown in Figure 3.1.

of the firm's commitments with its various stakeholders. In turn, stakeholders may be more likely to further invest in their relationship with the firm such as accepting more favorable contracting terms. Staggered boards would therefore have a positive impact on the value of the firm. This theory has received recent empirical support. [Johnson et al. \(2015\)](#) show that takeover defenses bring value to IPO firms when they have important business relationships such as a large customer, a dependent supplier, or a strategic alliance with another firm. [Cen et al. \(2016\)](#) show that firms that have important relationships with large customers experience higher operating performance when the threat of a takeover decreases. As stated by [Adams et al. \(2010\)](#), "governance structures arise endogenously because economic actors choose them in response to the governance issues they face". [Cremers et al. \(2017\)](#) address the endogeneity issue of the board structure and show that staggered boards have a positive effect on the value of the firm. Their findings, consistent with the bonding theory, suggest that the stronger commitment of the firm to its important stakeholders, enabled by the staggered board, is the source of value creation. Although they do not provide evidence in favor of the bonding theory, [Daines et al. \(2021\)](#) and [Field and Lowry \(2022\)](#) show that staggered boards benefit IPO firms with high information asymmetries by decreasing market myopia. This allows managers to focus on innovation and long-term investments.

In an attempt to bring an end to the debate on the impact of staggered boards on the value of the firm, [Amihud et al. \(2017\)](#) show that prior studies do not include important explanatory variables in their econometric models. They find support for neither theory and rather claim that the effect of the staggered board on the value of the firm is idiosyncratic. As a response, [Cremers et al. \(2019\)](#) show that the findings of [Cremers et al. \(2017\)](#) are robust to the critics of [Amihud et al. \(2017\)](#). The question of the impact of the staggered board on the value of the firm is therefore still open.

3.3. The Sarbanes-Oxley Act and related stylized facts

To protect investors and restore shareholders' trust in corporate governance after the scandals of Enron and WorldCom, the Sarbanes-Oxley Act, commonly designated as SOX, was enacted in 2002. SOX seeks to bolster the independence of the board of directors, reduces the degree of financial opacity, and increases executives' accountability. In brief, SOX has the purpose to create an anti-entrenchment regulatory environment. To reach its goals, SOX requires listed firms to have a majority of independent directors on their board, and to have their audit, nomination, and compensation committees exclusively composed of independent directors. SOX also increases the reporting duties of firms and the sanctions firm executives can face if responsible for fraud. Firms operating under a staggered board had until the end of year 2004 to comply with those requirements, whereas other firms needed to be in compliance with SOX by the end of 2003. The requirement relative to the independence of the majority of the board's directors is especially costly for firms having a staggered board. Indeed, directors of staggered boards must stay independent for a substantially longer time period as their mandate is usually three times longer than a director mandate in a conventional board.

To highlight the consequences of the enforcement of SOX, in 2005 for firms having a staggered board, Figure 3.1 illustrates the annual change in the proportion of S&P 1500 firms having a staggered board. The data comes from the governance database provided by Institutional Shareholder Services (ISS). I use a balanced panel of S&P 1500 firms which reported the structure of their boards of directors from 1990 to 2018. While the proportion of firms operating under a staggered board remained stable around 60% between 1990 and 2004,⁶ the proportion of firms using a staggered board in the S&P 1500 index has steadily decreased since 2006 to reach 19% in 2018.

⁶The lack of board structure variation before the year 2006 certainly explains why early studies such as [Bebchuk and Cohen \(2005\)](#) do not include firm fixed effects in the panel regressions linking the presence of a staggered board to the value of the firm.

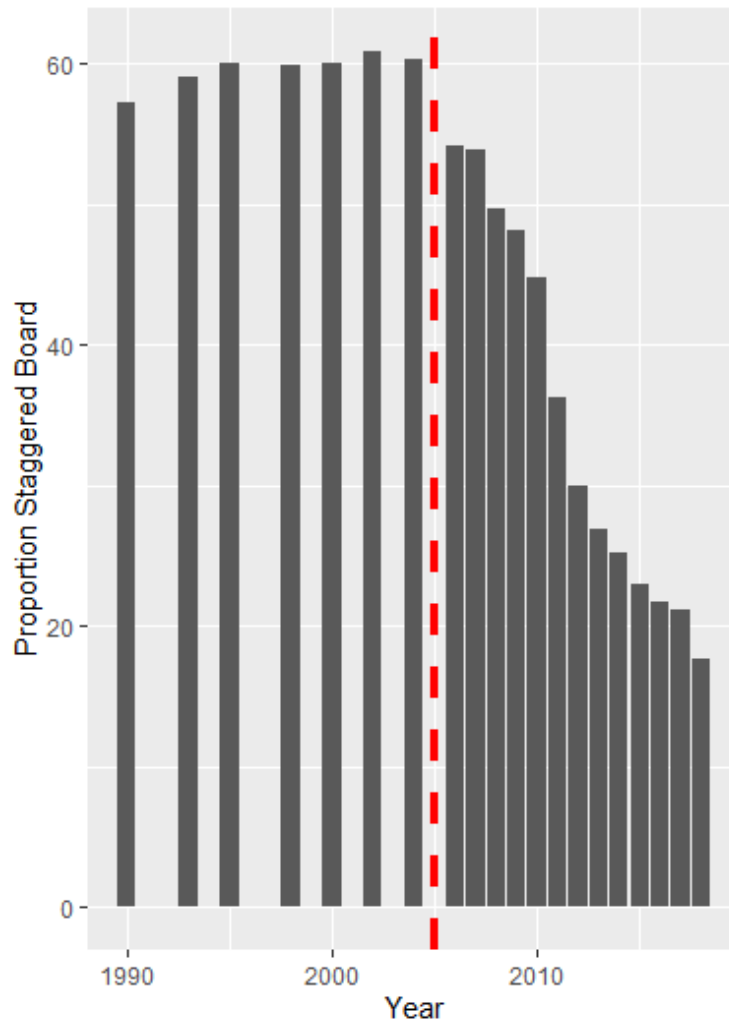


Figure 3.1: Time evolution of the proportion of firms in the S&P 1500 index that operate under a staggered board

This figure shows the annual percentage of S&P 1500 firms having a staggered board of directors between 1990 and 2018. The red vertical dotted line signals the date of the enforcement of the Sarbanes-Oxley Act, i.e., 2005 for firms with a staggered board. For the time period between 1990 and 2006, the data relative to the presence of a staggered board is collected only for the following years: 1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006.

To better understand the causes of the decrease in the proportion of firms using a staggered board, I provide, in Figure 3.2, the annual change in the proportion of S&P 1500 firms that adopt a staggered board (upper panel), and the annual change in the proportion of firms that remove their staggered board (lower panel) using the same panel data as in Figure 3.1. The proportion of firms that decide to adopt a staggered board suddenly decreased in 2006 and the following years, while the proportion of firms that remove their staggered board increased. The decrease in the proportion of S&P 1500 firms having a staggered board shown in Figure 3.1 is

therefore explained by a halt in staggered board adoptions combined with a surge in staggered board removals.

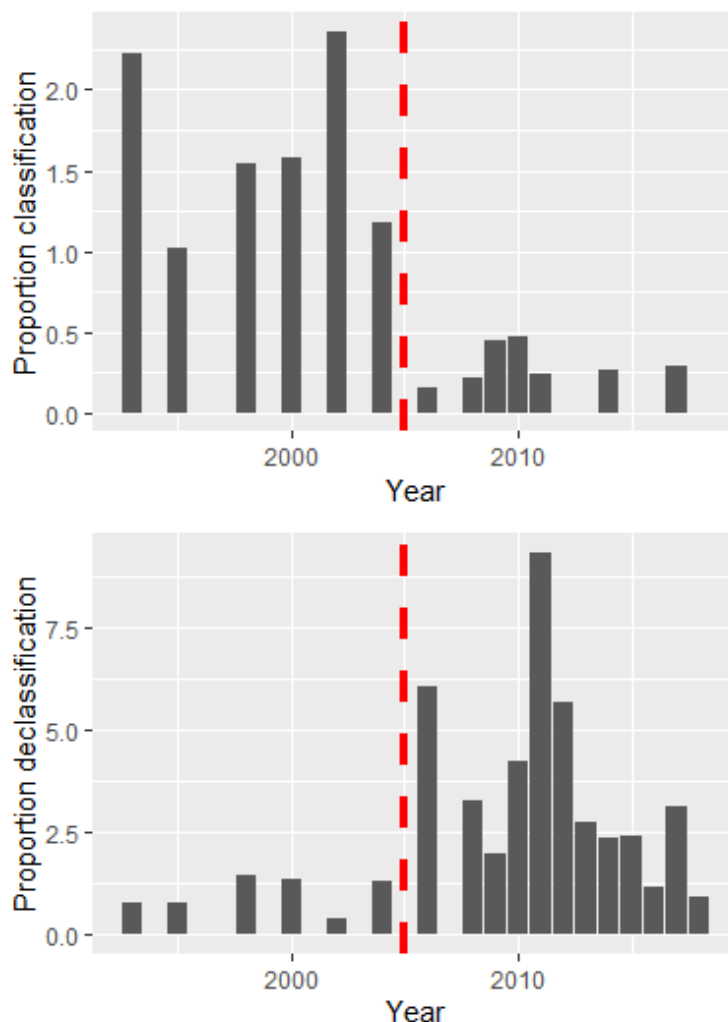


Figure 3.2: Time evolution of the proportion of firms in the S&P 1500 index that adopt, or remove, a staggered board

The upper figure shows the annual percentage of S&P 1500 firms that adopt a staggered board between 1991 and 2018. The figure at the bottom shows the annual percentage of S&P 1500 firms that remove their staggered board between 1991 and 2018. The red vertical dotted line signals the date of the enforcement of the Sarbanes-Oxley Act, i.e., 2005 for firms with a staggered board.

Since the decision to change the structure of the board of directors rests on shareholders at each annual general meeting, I investigate shareholders' proposals and votes before and after the adoption of SOX using data collected by Institutional Shareholder Services.⁷ This dataset is unique as it gathers characteristics about

⁷ISS collects firm-level data relative to the characteristics of shareholders' proposals and their associated voting result. This data is available under the tab "Voting Analytics". I use the legacy database, available under the tab "Other" - "Company Vote Results (Legacy)", as it covers both

shareholders' proposals and votes during annual general meetings. Unfortunately, the sample period for this dataset is relatively short, as it starts in 1997 and ends in 2006. For that reason, this dataset is only used to produce the descriptive statistics of Table 3.1. For the rest of the chapter, I use a larger dataset. In Table 3.1, I compare the means and medians for several characteristics of shareholders' proposals before versus after the adoption of SOX. Panel A of Table 3.1 reports the number and proportion of shareholders' proposals to remove, or to adopt, a staggered board. Proposals to remove the staggered board represent a significantly higher proportion of all shareholders' proposals after the adoption of SOX than before, while it is the opposite for proposals to adopt a staggered board. Panel B reports the winning rates of such proposals for the two time periods. The average winning rate of proposals to remove the staggered board increases after the adoption of SOX. This increase cannot be attributed to a global increase in the winning rate of all shareholders' proposals as, on the contrary, the average winning rate of all shareholders' proposals decreased after the adoption of SOX. In other words, not only proposals to remove the staggered board are more numerous after the adoption of SOX, but they are also more likely to be approved by shareholders. Lastly, I report statistics relative to the sponsors of shareholders' proposals in panel C. The average number of shareholders' proposals by firm and year is mainly composed of proposals sponsored by the management of the firm. Interestingly, the management of the firm is always the sponsor for proposals to adopt a staggered board, but very rarely for proposals to remove it. Proposals to remove the staggered board are mainly sponsored by non-executive shareholders. Those statistics raise the question of the motivations leading a firm to use a staggered board. The fact that the management of the firm always sponsors proposals to classify the board of directors suggests that the staggered board mainly benefits them.

All in all, results reported in Table 3.1 are consistent with the findings shown in

the pre and post-SOX time periods. Furthermore, it is the only shareholders' proposals dataset indicating whether the proposal has been sponsored by the management of the firm or by non-executive shareholders.

Table 3.1: Comparing shareholders' proposals before and after the adoption of the Sarbanes-Oxley Act

This table compares the means and medians of several characteristics relative to shareholders' proposals in annual general meetings of firms in the S&P 1500 index before and after the adoption of the Sarbanes-Oxley Act (SOX). The full sample period, which starts in 1997 and ends in 2006, is divided into two sub-periods: before the enforcement of SOX (1997-2004) and after (2005-2006). The term *classification* refers to the adoption of a staggered board, while the term *declassification* refers to its removal. Panel A reports, for the full sample and the two sub-periods, the number and proportion of shareholders' proposals to remove or to adopt a staggered board. Panel B reports, for the full sample and the two sub-periods, the winning rate of such shareholders' proposals as well as the winning rate of all shareholders' proposals. Panel C reports, for the full sample only, the proportion of all shareholders' proposals sponsored by the management of the firm, and the proportion of shareholders' proposals to remove or to adopt a staggered board sponsored by the management of the firm. I test the difference in means between the two sub-periods with a *t*-test and the difference in medians with a Wilcoxon test, and I report the associated *p*-value.

	1997-2006	Before SOX	After SOX	<i>t</i> -test	Wilcoxon test
Panel A: Proportion of classification/declassification proposals					
# declassification proposals	582.000	435.000	147.000		
# classification proposals	38.000	38.000	0.000		
Proportion declassification proposals	2.766 %	2.345 %	5.899 %	0.000	0.000
Proportion classification proposals	0.181 %	0.205 %	0.000 %	0.000	0.024
Panel B: Winning rates of shareholders' proposals					
Winning rate of all proposals	86.170 %	87.277 %	77.929 %	0.000	0.000
Winning rate of declassification proposals	65.460 %	56.552 %	91.837 %	0.000	0.000
Winning rate of classification proposals	65.790 %	65.790 %	0.000 %	0.000	0.000
Panel C: Sponsor of shareholders' proposals					
Proportion of all proposals sponsored by management	76.040 %				
Proportion of declassification proposals sponsored by management	11.170 %				
Proportion of classification proposals sponsored by management	100.000 %				

Figures 3.1 and 3.2, and they show that non-executive shareholders are responsible for the surge in staggered board removals after the adoption of SOX.

3.4. Testable hypotheses

The stylized facts reported in Section 3.3 highlight the fact that the additional costs associated with SOX for firms having a staggered board have led numerous firms to remove the provision. Yet, many firms have also decided to keep the staggered board provision. This chapter first aims to understand the determinants of the decision to keep or remove the staggered board in the post-SOX anti-entrenchment regulatory environment. Second, the goal of this chapter is also to determine the link between the staggered board provision and the value of the firm in such a regulatory environment.

I assume that a firm chooses to have a staggered board if related benefits exceed related costs. Following this assumption, a staggered board-governed firm should decide to switch to a traditional board after SOX if the total costs associated with a staggered board after SOX outweigh the associated benefits. Because the costs of having a staggered board are difficult to measure at the firm level, I prefer to focus on the benefits drawn from the provision. [Cremers et al. \(2017\)](#) show that staggered boards create value for firms having important stakeholder relationships that would lose value if those firms were to be taken over. This finding, in support of the bonding theory, leads me to construct the following testable hypothesis.

H1: Firms having important stakeholder relationships are less likely to remove their staggered board provision after the adoption of the Sarbanes-Oxley Act.

The stakeholders considered are customers, suppliers, and employees. Finding evidence in support of H1 would prove that firms for which the staggered board is value-enhancing are more likely to keep the provision after the enforcement of SOX, while other firms are more likely to abandon it. Indeed, having a staggered board reduces the firm's probability of being acquired, which therefore limits the risk that relationships with important stakeholders will be terminated. As a consequence,

the firm's stakeholders are incited to pursue relationship-specific investments that are value-enhancing. All things equal, the group of firms having a staggered board after the adoption of SOX should have a greater value than the rest of firms. The associated testable hypothesis stands as follows.

H2: Firms having a staggered board after the enforcement of SOX have a greater value than others.

Finding evidence in support of H2 would mean that having a staggered board is value-enhancing after the adoption of SOX. In regards to the literature debate on the impact of staggered boards on the value of the firm, finding support for both H1 and H2 would be consistent with the bonding theory and would rule out the entrenchment theory after SOX.

3.5. Data and descriptive statistics

I begin this section by describing the data used to test hypotheses H1 and H2. I then present descriptive statistics. Last, I check that my sample produces results that do not differ from those found in past studies.

3.5.1. Data and sample

Governance data, and more specifically the information about the type of board (staggered or standard) firms have chosen to put in place, are collected from Institutional Shareholders Services (ISS). This database, formerly known as RiskMetrics or IRRC, lists all anti-takeover provisions at the firm-year level for S&P 1500 firms as of 1990. From 1990 to 2006, the database does not provide data every year but does so from 2007.⁸ Following [Bebchuk and Cohen \(2005\)](#), I fill the missing data by assuming that the firm's board structure, i.e., whether the firm operates under a staggered board, in any given year, is the same as the one reported the year after. This dataset differs from the dataset used in Section 3.3 for the analysis of share-

⁸For the time period between 1990 and 2006, the data is collected only for the following years: 1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006.

holders' votes. While the dataset on shareholders' votes also indicates whether the firm uses a staggered board, it covers a narrower time period than the dataset used to construct the sample to test H1 and H2. Furthermore, in the dataset relative to shareholders' votes, firms are identified by their company name and ticker, which leads to mismatches and a sizeable loss of observations when merging it with other sources of data. Accounting data are collected from Compustat, while mergers and acquisitions activity data are collected from Thomson One Banker and CRSP. Data relative to firms' stakeholder relationships are collected from Compustat's Customer Segment, Thomson Reuters Institutional Holdings (13F), and the U.S. Bureau of Labor Statistics.

Firms not headquartered in the U.S., Real Estate Investment Trusts (REITs), and financial and utility firms are removed from the sample.⁹ The final sample is a panel composed of 3,461 unique firms composing the S&P 1500 index from 1993 to 2018, with an average of 1,032 firm observations per year.

I use Tobin's Q to measure firm value. I construct this variable in the same way as [Kaplan and Zingales \(1997\)](#), [Gompers et al. \(2003\)](#), and [Bebchuk and Cohen \(2005\)](#) did. The variable accounting for the mergers and acquisitions activity in a specific industry for a given year is constructed as the ratio of the number of mergers and acquisitions by industry and year divided by the total number of active firms by industry and by year. I use four different proxies to account for the firm's important stakeholder relationships. Following [Johnson et al. \(2015\)](#), the first measure is an indicator equal to 1 if the firm has at least one large customer accounting for 10% or more of the firm's annual sales. According to the bonding theory, relationship-specific investments are more likely to be made by the firm and its customer if their substantial economic relationship is not likely to be endangered by a hostile takeover thanks to takeover defenses such as the staggered board. The second measure is an indicator equal to 1 if the firm is a large customer of another firm, i.e., if the firm

⁹Empirical studies focusing on the impact of the staggered board provision on firm value generally keep financial and utility firms in their final sample. I remove them from my sample because the regulation that applies to those firms has changed during my observation period. When I include them in the sample as a robustness check, results remain unchanged.

accounts for 10% or more of the supplier's annual sales. In other words, the second measure indicates whether the firm has a dependent supplier which is certainly more likely to make relationship-specific investments if it is confident that their economic relationship will not be terminated because of a takeover. Firms may also consider their employees, managers, and executive directors as important stakeholders if they have long-term commitments with them, as noted by [Pontiff et al. \(1990\)](#). Protecting these commitments by the use of takeover defense provisions such as a staggered board may incite employees, managers, and executive directors to invest their time and energy to nurture skills specifically benefiting their employer. The third measure used to account for the firm's important stakeholder relationships is an indicator equal to 1 if the firm owns a pension fund that has more funds than needed to cover current and future benefits to employees. A hostile acquirer can terminate an overfunded pension and replace it with a plan that lowers employees' benefits. Reducing the probability of a takeover may assure employees that they will obtain full retirement benefits, which in turn may encourage them to develop employer-specific skills that would increase their productivity. Lastly, as suggested by [Titman and Wessels \(1988\)](#), firms part of low employee turnover industries certainly invest more in human capital than the rest of firms. Employees of these firms are *de facto* important stakeholders. Conversely, employees of such firms may be more likely to develop firm-specific skills. Having a staggered board reduces the risk of layoffs following a takeover, inciting both the firm and its employees to further invest in their relationship. The fourth measure is therefore an indicator equal to 1 if the firm belongs to an industry having an employee turnover below the median across all industries.

3.5.2. Descriptive statistics

Table 3.2 reports descriptive statistics on several characteristics of the firms composing the sample. 51.4% of firm-year observations have a staggered board provision. Firms have, on average, a total asset size of 1.6 billion dollars, a return on assets

equal to 14.7%, a growth in sales equal to 10.3%, and a debt ratio equal to 23.2% of their balance sheet. With respect to important stakeholder relationships, 66.7% of firm-year observations correspond to firms having a large customer, i.e., a customer representing more than 10% of their annual sales, and 6.50% of firm-year observations have a dependent supplier. For 30.6% of firm-year observations, the firm owns a retirement fund that has more funds than needed to cover current and future benefits to employees. For 26.3% of firm-year observations, the firm belongs to an industry in which the turnover of employees is low. Aggregating the four previous indicators, firms have on average 1.31 important stakeholder relationships.

In Table 3.3, I compare firms having a staggered board with firms having a conventional board. I test the difference in mean and median between the two groups of firms for the main variables used in this chapter. On average, firms having a staggered board have significantly lower value, lower total asset size, and less leverage than the rest. However, firms having a staggered board experience higher growth in sales. Such firms also belong to industries with significantly lower activity in terms of mergers and acquisitions, which can be surprising as one could expect that firms would adopt the staggered board all the more if the market for corporate control is active in their industry.¹⁰ Although the Student's *t*-tests indicate that firms having a staggered board have lower profitability measured by return on assets, and higher research and development expenses scaled by sales than the rest of the sample, these results are not supported by the signed-rank tests. This means that the group of firms having a staggered board is composed of firms having either a significantly lower return on assets or a significantly higher research and development expenses to sales ratio than the median staggered board-governed firm. As a consequence, I believe that, overall, firms having a staggered board do not have a significantly different return on assets and R&D expenses to sales ratio than firms

¹⁰This observation may mean that firms having a staggered board belong to different industries than those operating under a conventional board. I use a paired Student's *t*-test to check whether the distribution of firms having a staggered board across industries is different from the industry distribution of firms having a conventional board of directors. I find that industry distributions are not statistically different between the two groups of firms.

Table 3.2: Summary statistics

This table reports the mean, the median, the standard deviation, the minimum value, and the maximum value of several characteristics of the 24,762 firm-year observations composing the sample in this chapter. This sample covers firms in the S&P 1500 index from 1993 to 2018, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Staggered board* indicates whether the firm operates under a staggered board of directors. *Tobin's Q* is used to proxy for the value of the firm. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Leverage* is the ratio of total debts over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Industry M&A activity* is, for each Fama-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . *Large customer* indicates whether the firm has a customer representing at least 10% of its sales in year t . *Dependent supplier* indicates whether the firm is disclosed as the large customer of another firm in year t . *Pension fund overfunded* indicates whether the firm's retirement plan has more funds than needed to cover current and future benefits to employees. *Low employee turnover* indicates whether the firm belongs to an industry whose employee turnover is below the median in year t . The number of important stakeholder relationships is computed by adding up the four previous indicators. All continuous variables are winsorized at their 1% and 99% values.

	N	Mean	Median	St. Dev.	Min	Max
Staggered board	24,762	0.514	1.000	0.500	0.000	1.000
Tobin's Q	24,762	2.033	1.594	1.637	0.513	115.426
log(Total assets)	24,762	7.386	7.282	1.461	1.971	10.318
Return on assets	24,762	0.147	0.145	0.141	-3.954	0.567
Capital expenditure intensity	24,762	0.053	0.037	0.053	0.000	0.426
Leverage	24,762	0.232	0.214	0.206	0.000	3.892
Sales growth	24,762	0.103	0.069	0.352	-0.977	6.741
R&D expenses to sales	24,762	0.117	0.004	0.905	0.000	17.000
Industry M&A activity	24,762	0.344	0.234	0.311	0.053	1.561
Important stakeholder relationships						
Large customer	24,762	0.667	1.000	0.471	0.000	1.000
Dependent supplier	24,762	0.065	0.000	0.246	0.000	1.000
Pension fund overfunded	12,496	0.306	0.000	0.461	0.000	1.000
Low employee turnover industry	7,220	0.263	0.000	0.440	0.000	1.000
# of important stakeholders	2,582	1.314	1.000	0.932	0.000	4.000

Table 3.3: Comparing staggered board-governed firms with conventionally governed firms

This table compares the means of several characteristics between the group of firms operating under a conventional board of directors -i.e., in which all directors are up for reelection each year- and the group of firms using a staggered board in the sample of study. This sample covers firms in the S&P 1500 index from 1993 to 2018, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Tobin's Q* is used to proxy for the value of the firm. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Leverage* is the ratio of total debts over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Industry M&A activity* is, for each Fama-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . *Large customer* indicates whether the firm has a customer representing at least 10% of its sales in year t . *Dependent supplier* indicates whether the firm is disclosed as the large customer of another firm in year t . *Pension fund overfunded* indicates whether the firm's retirement plan has more funds than needed to cover current and future benefits to employees. *Low employee turnover* indicates whether the firm belongs to an industry whose employee turnover is below the median in year t . The number of important stakeholder relationships is computed by adding up the four previous indicators. All continuous variables are winsorized at their 1% and 99% values. I test the difference in means between the two subsamples with a t -test and the difference in medians with a Wilcoxon test, and I report the associated p -value. ***, **, and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Conventional board	Staggered board	t -test	Wilcoxon test
N	12,036	12,726		
Tobin's Q	2.075	1.993	0.000***	0.000***
log(Total assets)	7.573	7.209	0.000***	0.000***
Return on assets	0.149	0.144	0.003**	0.250
Capital expenditure intensity	0.052	0.053	0.095*	0.000***
Leverage	0.238	0.227	0.000***	0.020**
Sales growth	0.098	0.108	0.039**	0.000***
R&D expenses to sales	0.102	0.131	0.012**	0.415
Industry M&A activity	0.357	0.331	0.000***	0.000***
Important stakeholder relationships				
Large customer	0.680	0.655	0.000***	0.000***
Dependent supplier	0.076	0.054	0.000***	0.000***
Pension fund overfunded	0.256	0.352	0.000***	0.000***
Low turnover industry	0.247	0.279	0.002***	0.002***
# of important stakeholders	1.187	1.451	0.000***	0.000***

with a standard board of directors.¹¹ Firms that operate under a staggered board appear to have a statistically higher number of important stakeholder relationships than others. They are more likely to own an overfunded pension fund and to be part of an industry exhibiting a relatively low turnover rate of employees than the rest of firms. They are however less likely to have a large customer or a dependent supplier.

3.5.3. Sample validity test

In order to show that my sample produces similar results as those found in past studies on staggered boards, I run the main regressions of [Bebchuk and Cohen \(2005\)](#) and [Cremers et al. \(2017\)](#) over my sample period. Those regressions test the link between the value of the firm and the presence of a staggered board. The main difference between the two papers lies in the fact that [Cremers et al. \(2017\)](#) add firm fixed effects to the regression to account for firm-specific time-invariant omitted variables, whereas [Bebchuk and Cohen \(2005\)](#) do not. I replicate both papers over my observation period using the following linear regression:

$$Q_{i,t+1} = \alpha_1 \cdot \text{Staggered board}_{i,t} + \alpha_2 \cdot X_{i,t} + \epsilon_{i,t} \quad (3.1)$$

where $Q_{i,t+1}$ is firm i 's Tobin's Q in year $t + 1$. The main variable of interest is dummy $\text{Staggered board}_{i,t}$ which equals one if firm i operates under a staggered board in year t and zero otherwise. $X_{i,t}$ is a vector of controls traditionally used in the literature at the firm level in year t . This vector includes the firm's total assets, taken in logarithm, return on assets, capital expenditure over total assets, growth in sales between year $t - 1$ and year t , total debts over total assets, research and development expenses over sales, a dummy variable indicating whether the firm is incorporated in the state of Delaware, and the number of mergers and acquisitions scaled by the number of active firms in the firm's industry in year t . The Delaware

¹¹Still, as a precautionary measure, these two variables are used as control variables in all regressions.

dummy variable is only used as a control variable when no firm fixed effects are added as it is extremely rare that a firm changes its state of incorporation over its lifetime. I also introduce year fixed effects in Regression (3.1) to account for unobserved factors that affect the value of all firms in the sample for a given year. Lastly, robust standard errors are clustered by firm to account for potential correlation between residuals across time at the firm level.¹²

Results are reported in Table 3.4. In Column (1), I report the results of the regression without firm fixed effects, as in [Bebchuk and Cohen \(2005\)](#), and in Column (2) I report those of the regressions with firm fixed effects, as in [Cremers et al. \(2017\)](#). I find similar results over my observation period as the two aforementioned studies, that is: (1) a negative association between having a staggered board and firm value when firm fixed effects are not included in the regression, and (2) a positive association between the two variables when including firm fixed effects. These results show that my sample produces similar results found in past studies. I believe that the methodology used by [Cremers et al. \(2017\)](#) is more robust than [Bebchuk and Cohen \(2005\)](#)'s as the latter may be biased because of omitted variables. I therefore conclude that there is a positive association between having a staggered board and firm value over my observation period. With regard to the control variables, I find the value of the firm to be negatively correlated to its size while being positively associated with its return on assets. Contrary to the results found by [Cremers et al. \(2017\)](#), I do not find a negative and statistically significant association between firm value and the activity of mergers and acquisitions in the firm's industry.

3.6. Empirical tests

In this section, I first investigate the determinants of the corporate decision to switch from a staggered board to a conventional board of directors after the adoption of SOX. Then, after describing my identification methodology, I test the link between

¹²As noted by [Petersen \(2009\)](#), the correlation between residuals across time at the firm level is more likely to occur when variables' time variation is low.

Table 3.4: Firm value and staggered boards

This table reports the estimates of pooled OLS regressions in which the dependent variable is the *Tobin's Q* of the firm in year $t+1$. Independent variables account for several characteristics of the firm in year t . This sample covers firms in the S&P 1500 index from 1993 to 2018, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Staggered board* indicates whether the firm operates under a staggered board of directors. *Total assets* is taken in logarithm. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Leverage* is the ratio of total debts over total assets. *Delaware* indicates whether the firm is incorporated in Delaware. *Industry M&A activity* is, for each Fama-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . All continuous variables are winsorized at their 1% and 99% values. Both specifications include year fixed effects, and the specification reported in column (2) also includes firm fixed effects. Robust standard errors clustered by firm are reported in parentheses. ***, **, and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	$Q_{i,t+1}$	
	(1)	(2)
Staggered board $_{i,t}$	-0.086** (0.041)	0.149** (0.059)
Total assets $_{i,t}$	-0.119*** (0.018)	-0.557*** (0.051)
Return on assets $_{i,t}$	2.946*** (0.360)	2.746*** (0.347)
Capital expenditure intensity $_{i,t}$	-1.527*** (0.292)	0.061 (0.352)
Sales growth $_{i,t}$	0.408*** (0.080)	0.044 (0.119)
Leverage $_{i,t}$	-0.319 (0.220)	0.104 (0.148)
R&D expenses to sales $_{i,t}$	0.268*** (0.037)	0.077 (0.118)
Delaware $_{i,t}$	0.110** (0.048)	
Industry M&A activity $_{i,t}$	-0.050 (0.080)	0.195* (0.118)
Intercept	2.118*** (0.121)	3.865*** (0.290)
Year indicators	Yes	Yes
Firm indicators	No	Yes
Number of observations	22,910	22,910
Adjusted R ²	0.127	0.604

the firm's value and the presence of a staggered board in the post-SOX regulatory environment. Last, I present robustness checks.

3.6.1. Determinants of staggered board removals after SOX

In order to test H1, i.e., to investigate the determinants of the firm-level decision to remove the staggered board after the adoption of SOX, I run the following logistic regression:

$$\begin{aligned} \text{Decision to remove the staggered board}_{i,t+1} = & \\ \beta_1 \cdot \text{Important stakeholder relationship}_{i,t} + \beta_2 \cdot X_{i,t} + \epsilon_{i,t} & \end{aligned} \quad (3.2)$$

where the dependent variable is a dummy equal to one if firm i operates under a staggered board in year t and under a conventional board of directors in year $t + 1$, zero otherwise. The sample for this regression is therefore restricted to firms having a staggered board in year t . The main variable of interest in Regression (3.2), denoted *Important stakeholder relationship* $_{i,t}$, is alternatively one of the four dummies defined in Subsection 1.3.3 that account for firm i 's important stakeholder relationships, namely *Large customer* $_{i,t}$, *Dependent supplier* $_{i,t}$, *Pension fund overfunded* $_{i,t}$, and *Low turnover industry* $_{i,t}$. The regression is also run by introducing these four dummies simultaneously. On top of these four dummies, I also build three other dummies which account for the number of important stakeholder relationships that firm i has: the “*1 important stakeholder* $_{i,t}$ ” dummy which equals 1 if the firm has one important stakeholder relationship in year t , the “*2 important stakeholders* $_{i,t}$ ” dummy which equals 1 if the firm has two important stakeholder relationships, and the “*3 and more important stakeholders* $_{i,t}$ ” dummy which equals 1 if the firm has three or four. I then estimate Regression (3.2) by taking those three dummies as the regressors of interest. $X_{i,t}$ is the same vector of firm-level controls as in Equation (3.1). As the surge in staggered board removals started after the adoption of SOX, the determinants of staggered board removals are certainly different before and after the law's enforcement. For that reason, I only include firm-year observations start-

ing in the year 2005, when SOX requirements became compulsory for firms having a staggered board.¹³ Under hypothesis H1, I expect to find a negative relation between the presence of important stakeholder relationships and the decision to remove the staggered board, i.e., β_1 to be significantly negative.

Results are reported in Table 3.5. In Column (6), the coefficients of the three “*important stakeholder*” dummies are significantly negative. This shows that having at least one important stakeholder relationship negatively affects the probability of switching from a staggered board to a conventional board after SOX. In addition, the values of the three coefficients increase in the number of relationships that each corresponding dummy represents. This means that the higher the number of important stakeholder relationships a firm has in a given year, the less likely it is to remove its staggered board the year after. Yet not all types of stakeholders play the same role. When introducing distinct dummies by type of stakeholders, as in Column (5), all coefficients except that of the “*Dependent supplier*” dummy are negative and statistically significant. Then, the coefficient of the “*Low turnover industry*” dummy is significantly negative at the 10% statistical level only. The most significant coefficients are those of dummies “*Large customer*” and “*Pension fund overfunded*”. Last, when the four stakeholder relationship dummies are separately introduced in the regression (cf. Columns (1) to (4) in Table 3.5), the “*Pension fund overfunded*” turns out to have a stronger statistical significance at the 5% level. This indicates that a strong relationship between the firm and its employees, materialized through overfunded pension funds, is a major determinant of the decision to keep a staggered board. This also suggests that among other stakeholder relationships, the employee relationship is probably the most bonding.

Overall, results in Table 3.5 show that (1) strong relationships with employees and customers are drivers of the corporate decision to keep a staggered board after SOX, and (2) that the higher the number of important stakeholder relationships a firm has, the more likely it is to keep the provision. These results are in support of

¹³An additional argument in favor of this choice is that staggered board removals are relatively scarce before 2005.

Table 3.5: Determinants of the decision to remove the staggered board after the adoption of the Sarbanes-Oxley Act
This table reports the results of logistic regressions in which the dependent variable is a dummy equal to 1 if the firm operates under a staggered board in year t and under a conventional board of directors in year $t + 1$, i.e., if the firm removes the staggered board provision. Independent variables account for several characteristics of the firm in year t . This sample covers firms in the S&P 1500 index from 2005 to 2017, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Large customer* indicates whether the firm has a customer representing at least 10% of its sales in year t . *Dependent supplier* indicates whether the firm is disclosed as the large customer of another firm in year t . *Pension fund overfunded* indicates whether the firm's retirement plan has more funds than needed to cover current and future benefits to employees. *Low employee turnover* indicates whether the firm belongs to an industry whose employee turnover is below the median in year t . *Large customer*, *Dependent supplier*, *Pension fund overfunded*, and *Low employee turnover* account for firm i 's important stakeholder relationships with customers, suppliers, and employees respectively. On top of these four dummies, I also build three other dummies which account for the number of important stakeholder relationships that firm i has: the "*1 important stakeholder_{i,t}*" dummy which equals 1 if the firm has one important stakeholder relationship in year t , the "*2 important stakeholders_{i,t}*" dummy which equals 1 if the firm has two important stakeholder relationships, and the "*3 and more important stakeholders_{i,t}*" dummy which equals 1 if the firm has three or four. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Leverage* is the ratio of total debts over total assets. *Industry M&A activity* is, for each Panna-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . All continuous variables are winsorized at their 1% and 99% values. Standard errors are reported in parentheses. ***, **, * and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Decision to remove the staggered board _{$i,t+1$}					
	(1)	(2)	(3)	(4)	(5)	(6)
Large customer _{i,t}	-0.201 (0.148)				-0.892** (0.401)	
Dependent supplier _{i,t}		0.003 (0.205)			0.645 (0.526)	
Pension fund overfunded _{i,t}			-0.798*** (0.299)		-2.525*** (1.038)	
Low turnover industry _{i,t}				-0.367 (0.230)	-0.601* (0.325)	-1.065** (0.473)
1 important stakeholder _{i,t}						-1.456*** (0.477)
2 important stakeholders _{i,t}						-1.703** (0.676)
3 and more important stakeholders _{i,t}						
Total assets _{i,t}	0.561*** (0.051)	0.563*** (0.053)	0.585*** (0.072)	0.634*** (0.085)	0.769*** (0.168)	0.748*** (0.163)
Return on assets _{i,t}	-0.453 (0.744)	-0.404 (0.747)	-0.958 (1.161)	1.810* (1.070)	1.551 (2.230)	0.532 (2.222)
Capital expenditure intensity _{i,t}	-2.672** (1.351)	-2.515* (1.339)	-2.714 (2.181)	-5.451** (2.658)	-5.691 (4.806)	-6.966 (5.104)
Sales growth _{i,t}	-0.722** (0.350)	-0.732** (0.350)	-0.404 (0.452)	-1.307** (0.635)	-0.424 (0.946)	-0.132 (0.951)
Leverage _{i,t}	-0.028 (0.375)	-0.005 (0.377)	0.114 (0.564)	0.459 (0.425)	0.326 (1.116)	0.122 (1.116)
R&D expenses to sales _{i,t}	-0.274 (0.541)	-0.337 (0.577)	0.916 (1.499)	0.771 (2.278)	3.834 (6.741)	4.000 (6.757)
Industry M&A activity _{i,t}	0.257 (0.198)	0.231 (0.198)	0.288 (0.258)	0.172 (0.288)	0.629 (0.458)	0.547 (0.434)
Intercept	-6.926*** (0.457)	-7.108*** (0.448)	-7.283*** (0.634)	-7.713*** (0.788)	-8.299*** (1.523)	-7.764*** (1.462)
Number of observations	5,534	5,534	2,836	1,986	733	733
Pseudo R ²	0.066	0.065	0.063	0.084	0.133	0.106

H1.

As for the coefficients of the control variables, I find that larger firms and firms with low growth in sales are more likely to remove their staggered board after the adoption of SOX. More mature firms therefore appear to be more likely to remove their staggered board, which echoes the work of [Johnson et al. \(2022\)](#), who find that takeover defenses create value when a firm is young but become costly as the firm ages due to entrenchment costs increasing.

3.6.2. Impact of having a staggered board on the firm's value after SOX

Firms that have important stakeholder relationships are the most prone to keep a staggered board after SOX, most probably because a hostile takeover would certainly put those relations at risk of termination. The question of whether protecting those relationships by keeping a staggered board is value-enhancing, then naturally arises. To analyze the link between the presence of a staggered board and the value of the firm, I run the following linear regression :

$$Q_{i,t+1} = \gamma_1 \cdot \text{Staggered board}_{i,t} + \gamma_2 \cdot \text{Staggered board}_{i,t} \times \text{Post SOX}_t + \gamma_3 \cdot \text{Post SOX}_t + \gamma_4 \cdot X_{i,t} + \epsilon_{i,t} \quad (3.3)$$

where $Q_{i,t+1}$ is the Tobin's Q of firm i in year $t + 1$; Post SOX_t is a dummy equal to one in the post-SOX period starting in 2005, zero before; and $\text{Staggered board}_{i,t}$ is a dummy equal to one if firm i operates under a staggered board in year t , zero otherwise. $X_{i,t}$ is the vector of firm-level controls used in Equations (3.1) and (3.2). Regression (3.3) is also run by taking $Q_{i,t+2}$ and $Q_{i,t+3}$ as the dependent variable in order to check whether a long-term relation can be found between the value of the firm and the choice of having a staggered board after the adoption of SOX. I also include year and firm fixed effects. Robust standard errors are clustered by firm.

In this specification, γ_1 measures the impact of having a staggered board in year t on the firm's value in year $t + 1$ in the pre-SOX period. The coefficient

of the interaction term, γ_2 , measures the differential impact on $Q_{i,t+1}$ of having a staggered board in the post-SOX period relative to having it pre-SOX. As a result, quantity $\gamma_1 + \gamma_2$ measures the difference in value in year $t + 1$ between firms having a staggered board in year t and firms having a conventional board of directors, for the post-SOX period only. Finding $\gamma_1 + \gamma_2$ to be significantly positive would be in support of H2. Finding γ_2 to be significantly different from zero would prove the SOX regulatory environment affects firms' strategies relative to the use of staggered boards. As SOX is an anti-entrenchment law, I expect the bonding theory to be more prominent after SOX, and γ_2 to be significantly positive.

Results are reported in Table 3.6. For the three specifications considered, coefficient γ_1 is positive but not statistically significant, while coefficient γ_2 is significantly positive, so that, in total, quantity $\gamma_1 + \gamma_2$ is always significantly positive. This allows me to make two statements. First, in the pre-SOX period, no clear link exists between the presence of a staggered board and the value of the firm in the following years. Second, my empirical evidence are in support of H2, according to which the staggered-board governance is value-enhancing after SOX. This result holds whatever the time horizon considered between one and three years for the value impact. I conclude from there that the result of Table 3.4 - found by [Cremers et al. \(2017\)](#) and replicated with my sample in Column (2) of Table 3.4 - according to which the staggered-board governance has a positive impact on the value of the firm is completely generated by the post-SOX period. This means that the enforcement of SOX has changed firms' strategies regarding the use of staggered boards. It has created a regulatory environment that discourages managers' entrenchment strategies in an effective way, and it has thereby favored the bonding theory.

In regard to the coefficients of control variables, the firm value is negatively associated with its size, and positively related to its return on assets, as in Table 3.4.

The choice of a board structure is an essential corporate decision taken by shareholders. Such a decision is therefore supposed to be non-random. The results

Table 3.6: Impact of having a staggered board on the firm's value after SOX

This table reports the estimates of pooled OLS regressions in which the dependent variable is the *Tobin's Q* of the firm in year $t+1$, $t+2$, and $t+3$. Independent variables account for several characteristics of the firm in year t . This sample covers firms in the S&P 1500 index from 1993 to 2018, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Staggered board* indicates whether the firm operates under a staggered board of directors. *Post SOX* is a dummy equal to one in 2005 - the year of the adoption of the Sarbanes-Oxley Act for firms having a staggered board - and the years after, 0 otherwise. *Total assets* is taken in logarithm. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Leverage* is the ratio of total debts over total assets. *Industry M&A activity* is, for each Fama-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . All continuous variables are winsorized at their 1% and 99% values. All specifications include year fixed effects and firm fixed effects. Robust standard errors clustered by firm are reported in parentheses. ***, **, and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	$Q_{i,t+1}$	$Q_{i,t+2}$	$Q_{i,t+3}$
	(1)	(2)	(3)
Staggered board $_{i,t}$	0.007 (0.080)	0.019 (0.076)	0.012 (0.078)
Post SOX $_t$	1.220*** (0.151)	1.009*** (0.144)	0.829*** (0.145)
Total assets $_{i,t}$	-0.559*** (0.050)	-0.510*** (0.043)	-0.408*** (0.043)
Return on assets $_{i,t}$	2.755*** (0.347)	1.976*** (0.277)	0.907*** (0.251)
Capital expenditure intensity $_{i,t}$	0.049 (0.352)	-0.489 (0.341)	-0.751** (0.304)
Sales growth $_{i,t}$	0.040 (0.119)	-0.179** (0.089)	0.027 (0.071)
Leverage $_{i,t}$	0.109 (0.146)	0.236 (0.160)	0.176 (0.151)
R&D expenses to sales $_{i,t}$	0.077 (0.120)	0.198 (0.134)	-0.019 (0.053)
Industry M&A activity $_{i,t}$	0.179 (0.117)	0.088 (0.119)	0.085 (0.120)
Staggered board $_{i,t}$ x Post SOX $_t$	0.222*** (0.068)	0.164*** (0.064)	0.144** (0.063)
Intercept	3.963*** (0.289)	3.970*** (0.270)	3.551*** (0.272)
Year indicators	Yes	Yes	Yes
Firm indicators	Yes	Yes	Yes
Number of observations	22,910	20,180	18,261
Adjusted R ²	0.605	0.628	0.655

reported in Table 3.6 are in support of the bonding theory in the post-SOX period. Let us remind that, according to this theory, having a staggered board is value-enhancing because it bonds the firm with its important stakeholders by discouraging hostile takeovers. The firm then benefits from a greater commitment from those stakeholders. According to my findings in Table 3.5, the relevant stakeholders are, by order of importance, employees and customers. Regarding employees, a possible explanation is that bonding employees with overfunded pension funds increases productivity. Regarding customers, value may be created through relationship-specific investments that the firm is incited to make when the risk of termination of the specific relationship is low. However, the positive impact of staggered boards on firm value could also be the outcome of a selection bias. The adoption of SOX is associated with additional costs for having a staggered board due to the requirement of having a majority of independent directors on the board. If we consider that keeping a staggered board becomes more costly indeed with SOX, we can expect two side effects of SOX: (1) SOX governance requirements explain the loss of interest for staggered boards after SOX; (2) firms that keep a staggered board after SOX are those which have the financial means to withstand the additional costs, i.e., the firms with higher values. In that case, Equation (3.3) might be plagued by reverse causality due to a selection bias. In order to deal with this endogeneity issue, I apply a Heckman (1979) correction procedure to Equation (3.3). In a first stage, I model the likelihood of having a staggered board and I compute the associated inverse Mills ratio at the firm-year level. Then, in a second stage, I add this inverse Mills ratio as a control variable in Equation (3.3). The inverse Mills ratio is derived from a logistic regression, which models the probability of having a staggered board as follows:

$$Staggered\ board_{i,t+1} = \delta_1.Delaware_{i,t} + \delta_2.Post\ SOX_{i,t} + \delta_3.Q_{i,t} + \delta_4.X_{i,t} + \epsilon_{i,t} \tag{3.4}$$

$Delaware_{i,t}$, $PostSOX_{i,t}$, and $Q_{i,t}$ are the main variables of interest in this equation.

The state of Delaware has historically been considered more friendly than other states regarding the use of anti-takeover provisions such as the staggered board. I therefore expect to find a positive relation between the presence of a staggered board and the incorporation in Delaware. As the Sarbanes-Oxley Act is an anti-entrenchment law that increases the costs of having a staggered board, I naturally expect firms to be less likely to have a staggered board after SOX, i.e., the coefficient of $Post\ SOX_{i,t}$ is expected to be significantly negative. The Tobin's Q of the firm is used to take into account the aforementioned endogeneity issue. If only good firms can afford to have a staggered board, coefficient δ_3 of $Q_{i,t}$ is expected to be significantly positive. $X_{i,t}$ is the same vector of firm-level controls used in previous equations. The regression is run over the full sample, i.e., over the 1993-2018 time period in order to maximize the number of observations and increase the predictive power of the model. Results are reported in Table 3.7. As expected, a firm is more likely to have a staggered board if it is incorporated in the state of Delaware, and it is less likely to have one after the coming into force of SOX. Firms of smaller size have a higher likelihood to have a staggered board, which is in line with the results of [Johnson et al. \(2022\)](#). The likelihood of having a staggered board is greater if the firm belongs to an active industry in terms of mergers and acquisitions. This result also makes sense as a firm would certainly be more likely to protect itself from takeovers if the probability of occurrence of such events is higher. Last, lower-value firms are more likely to have a staggered board, as opposed to what was expected. This last finding reduces endogeneity concerns.

Using Regression (3.4), I compute an inverse Mills ratio which I introduce in Equation (3.3). If only good firms choose to have a staggered board, the coefficient of the inverse Mills ratio should be positive and statistically significant. Since the inverse Mills ratio controls for endogeneity, quantities γ_1 , γ_2 , and $\gamma_1 + \gamma_2$ in Regression (3.3) can, now, be interpreted with no ambiguity regarding causality. If hypothesis H2 holds, $\gamma_1 + \gamma_2$ should be significantly positive. Results are reported in Table 3.8. They confirm that only good firms choose to have a staggered board as the coefficient

Table 3.7: The likelihood to choose a staggered board - Heckman procedure first stage

This table reports the results of a logistic regression in which the dependent variable is a dummy equal to 1 if the firm has a staggered board in year $t+1$. Independent variables account for several characteristics of the firm in year t . This sample covers firms in the S&P 1500 index from 1993 to 2018, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Delaware* is a dummy equal to one if the firm is incorporated in the state of Delaware, 0 otherwise. *Post SOX* is a dummy equal to one in 2005 - the year of the adoption of the Sarbanes-Oxley Act for firms having a staggered board - and the years after, 0 otherwise. *Large customer* indicates whether the firm has a customer representing at least 10% of its sales in year t . *Dependent supplier* indicates whether the firm is disclosed as the large customer of another firm in year t . *Q* is the Tobin's Q of the firm. *Total assets* is taken in logarithm. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Leverage* is the ratio of total debts over total assets. *Industry M&A activity* is, for each Fama-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . All continuous variables are winsorized at their 1% and 99% values. Standard errors are reported below the coefficients in parentheses. ***, **, and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	Staggered board $_{i,t+1}$
Delaware $_{i,t}$	0.401*** (0.055)
Post SOX $_t$	-0.457*** (0.037)
Large customer $_{i,t}$	-0.030 (0.034)
Dependent supplier $_{i,t}$	-0.104* (0.063)
Q $_{i,t}$	-0.059*** (0.011)
Total assets $_{i,t}$	-0.190*** (0.011)
Return on assets $_{i,t}$	-0.096 (0.119)
Capital expenditure intensity $_{i,t}$	0.222 (0.275)
Sales growth $_{i,t}$	0.052 (0.041)
Leverage $_{i,t}$	-0.096 (0.077)
R&D expenses to sales $_{i,t}$	0.004 (0.018)
Industry M&A activity $_{i,t}$	0.142*** (0.054)
Intercept	1.777*** (0.091)
Year indicators	No
Firm indicators	No
Number of observations	19,721
Pseudo R ²	0.026

Table 3.8: Impact of having a staggered board on the firm's value after SOX - Heckman procedure second stage

This table reports the estimates of pooled OLS regressions in which the dependent variable is the *Tobin's Q* of the firm in year $t+1$, $t+2$, and $t+3$. Independent variables account for several characteristics of the firm in year t . This sample covers firms in the S&P 1500 index from 1993 to 2018, excluding firms not headquartered in the USA, REITs, financial, and utility firms. *Staggered board* indicates whether the firm operates under a staggered board of directors. *Post SOX* is a dummy equal to one in 2005 - the year of the adoption of the Sarbanes-Oxley Act for firms having a staggered board - and the years after, 0 otherwise. *IMR* is the inverse Mills ratio constructed on the specification reported in Table 3.7. *Total assets* is taken in logarithm. *Return on assets* is the operating income before depreciation of the firm in year t divided by the total assets of the firm in year $t - 1$. *Capital expenditure intensity* is the ratio of capital expenditure over total assets. *Sales growth* designates the growth in sales of the firm between year $t - 1$ and year t . *Leverage* is the ratio of total debts over total assets. *Industry M&A activity* is, for each Fama-French 48 industries, the number of acquisitions divided by the number of listed firms in year t . All continuous variables are winsorized at their 1% and 99% values. All specifications include year fixed effects and firm fixed effects. Robust standard errors clustered by firm are reported in parentheses. ***, **, and * denote the statistical significance of the parameter estimates at the 1%, 5%, and 10% level respectively.

	$Q_{i,t+1}$	$Q_{i,t+2}$	$Q_{i,t+3}$
	(1)	(2)	(3)
Staggered board $_{i,t}$	-0.031 (0.079)	0.025 (0.080)	-0.009 (0.085)
Post SOX $_t$	0.495*** (0.164)	0.686*** (0.145)	0.624*** (0.150)
IMR $_{i,t}$	1.952*** (0.274)	0.976*** (0.181)	0.671*** (0.171)
Total assets $_{i,t}$	-0.739*** (0.059)	-0.618*** (0.049)	-0.502*** (0.049)
Return on assets $_{i,t}$	2.755*** (0.354)	1.907*** (0.265)	0.812*** (0.267)
Capital expenditure intensity $_{i,t}$	0.177 (0.349)	-0.498 (0.325)	-0.817** (0.337)
Sales growth $_{i,t}$	0.063 (0.153)	-0.058 (0.047)	0.088 (0.081)
Leverage $_{i,t}$	0.179 (0.154)	0.201 (0.159)	0.155 (0.162)
R&D expenses to sales $_{i,t}$	0.202* (0.119)	0.102 (0.082)	-0.001 (0.072)
Industry M&A activity $_{i,t}$	0.321*** (0.113)	0.142 (0.117)	0.162 (0.121)
Staggered board $_{i,t}$ x Post SOX $_t$	0.243*** (0.072)	0.164** (0.070)	0.176** (0.071)
Intercept	4.176*** (0.299)	4.185*** (0.280)	3.803*** (0.291)
Year indicators	Yes	Yes	Yes
Firm indicators	Yes	Yes	Yes
Number of observations	17,919	15,559	13,884
Adjusted R ²	0.621	0.638	0.638

of the inverse Mills ratio is significantly positive for the three specifications. However, taking into account this endogenous link does not change my findings on the causal link between staggered boards and firm value. Coefficient γ_1 is not statistically significant, meaning that having a staggered board has no effect on the value of the firm before SOX enforcement. At the opposite, quantity $\gamma_1 + \gamma_2$ remains positive and statistically significant as in Table 3.6, which means that staggered boards increase the short-term and long-term value of firms after the coming into force of SOX. This result is in support of H2.

When considering the relation between the value of the firm and the choice of having a staggered board after the adoption of SOX, the causal link goes both ways: (1) good firms are more likely to keep a staggered board after SOX; and (2) having a staggered board after SOX has a positive impact of the firm's value. Indeed, good firms can afford the higher cost of having a staggered board after the enforcement of SOX, and they accept to bear such cost because it benefits them both in the short term and long term. The management stability ensured by the staggered board increases their value through a higher commitment from their important stakeholders. Hence, I find evidence for both hypotheses H1 and H2. My results are consistent with the bonding theory, as those found by [Cremers et al. \(2017\)](#), but only in the post-SOX period. Regarding the pre-SOX period, results in Table 3.8 show that, on average, the staggered board has no impact on firm value before the adoption of SOX. This may have two explanations. On the one hand, it may be explained by the fact that there are very few intra-firm variations in board structure during that time period. Firm fixed effects included in Regression (3.3) may therefore capture the effect of staggered boards on firm value during that time period. On the other hand, it may also be the case that both the entrenchment theory and bonding theory are at play during that time period, and that they cancel each other out in the regression.

To conclude, I show that good firms having important stakeholder relationships are more likely to keep a staggered board after SOX. Their motivation for using a

staggered board, be it before the adoption of SOX or after, is to protect their important stakeholder relationships from the risk of termination associated with takeovers. At the opposite, firms that removed their staggered board after SOX did so because the associated costs became too high and exceeded the associated benefits. Staggered board removals after SOX suggest that the takeover defense provided some firms with very few to no benefits. This observation, combined with the fact that no clear link between staggered boards and firm value can be found before SOX leads me to suspect that the staggered board provision was used to entrench managers and directors in the pre-SOX period, and that SOX altered such strategies in an effective way.

3.6.3. Robustness checks

My findings are by and large robust to the following four robustness checks. First, the 2008 financial crisis is an important event that might have disproportionately affected firms that have a staggered board. If so, the financial crisis might drive the findings in the regression analysis. To address this concern, I run all regressions after excluding all observations of the years 2008, 2009, and 2010. Although the results of Table 3.5 are statistically weaker compared with the full sample results, very probably as a result of the smaller sample size, all other results are similar.

Second, following [Bebchuk and Cohen \(2005\)](#), I exclude from the sample all firms having a dual-class stock structure as it is also considered a powerful anti-takeover defense that may drive results. All results are robust to this exclusion.

Third, I reconsider the exclusion of financial and utility firms. These firms were initially excluded from the sample as they are part of heavily regulated industries during the time period of this chapter. However, studies close to this chapter generally include such firms in their sample. For a robustness check, I reintroduce those firms in the sample. Results differ for Table 3.5 as only the variables that account for important relationships with employees are statistically significant in Columns (1) to (4). Results reported in Columns (5) and (6) of Table 3.5 are quite similar,

although the statistical significance of the important stakeholder relationship variables' coefficients is lower than that in the full sample. All other results are robust to the inclusion of financial and utility firms in the sample.

Last, I run all regressions after excluding firms that are not traded on the NYSE, NASDAQ, or AMEX, as these stock exchanges are the only ones to add corporate governance requirements for listed firms relative to the Sarbanes-Oxley Act by the end of 2003. Results remain unchanged.

3.7. Conclusion

The coming into force of SOX at the beginning of 2005 made staggered boards more costly to keep in place by imposing new regulatory requirements regarding the independence of board directors. As a consequence, staggered board adoptions came to a halt, and staggered board removals sponsored by non-executive shareholders surged. Therefore, a first objective of my research was to identify the motivations for maintaining a staggered board in this new regulatory environment. I find that the higher the number of value-enhancing relationships the firm has with specific stakeholders, the more likely it is to keep its staggered board after SOX enforcement. The most relevant stakeholders are, by order of importance, employees and customers.

I then investigate the link between the value of the firm and the choice of having a staggered board in the post-SOX. In this investigation, I tackle endogeneity issues by using a [Heckman \(1979\)](#) correction procedure. I find that the causal link goes both ways, that is: (1) mostly good firms choose to have a staggered board after SOX, and (2) the staggered board has a positive impact on the value of the firm after the enforcement of SOX, both in the short term and long term.

Hence, this chapter shows that only good firms can afford the cost of having a staggered board after SOX, and they pay those costs because the staggered board provision creates long-term value through an increased commitment from their important stakeholders. This opens the question of whether firms that choose the

staggered-board governance after SOX do so to signal themselves as good firms in preparation for future issues. Under this hypothesis, good firms that plan to raise funds would choose to pay the cost of having a staggered board after SOX so as to signal their quality to the market, while bad firms would not be able to replicate that signal. As testing this hypothesis is out of the scope of this chapter, I leave it for future research.

All in all, my results on the impact of staggered boards on the value of the firm are in line with the findings of [Cremers et al. \(2017\)](#) for the post-SOX time period only. Regarding the pre-SOX period, I show that the value of firms with a staggered board is not significantly different from the value of firms having a conventional board before the adoption of SOX. It means that, on average, having a staggered board does not contribute to create additional value before SOX. My interpretation of this finding is that both the entrenchment theory and the bonding theory are most probably at play during that time period, so that they cancel each other out in the regression. SOX, by strengthening governance requirements, makes board directors' entrenchment more difficult to handle and discourages directors' entrenchment strategies in an effective manner. As a result, the bonding theory becomes prominent in the post-SOX period.

Conclusion générale

Le premier chapitre a permis de mettre en lumière l'existence d'un biais comportemental conduisant les investisseurs particuliers à favoriser le financement des petites et moyennes entreprises localisées à proximité de leur lieu de résidence sans détenir d'avantage informationnel concernant la probabilité de défaut des emprunteurs. L'analyse de l'impact des prêteurs locaux sur le taux de financement des emprunteurs a toutefois révélé un résultat inattendu. En effet, nous montrons que la présence de prêteurs locaux dans l'enchère est associée à un coût de financement plus élevé pour les emprunteurs. Ce résultat s'explique par le comportement stratégique d'investisseurs locaux expérimentés pendant l'enchère, le terme « expérimentés » faisant référence aux investisseurs ayant déjà participé à des enchères d'emprunteurs locaux. Nous interprétons ce phénomène comme un effet d'apprentissage sur le fonctionnement des enchères lié à une attention accrue lors des enchères d'emprunteurs locaux. Plus précisément, le sentiment de familiarité découlant de la proximité géographique d'un emprunteur accroît certainement le niveau d'attention des investisseurs lors des enchères d'emprunteurs locaux. Cette attention accrue leur permet alors de mieux mémoriser la dynamique du flux d'ordres soumis dans ces enchères. De ce fait, ils développent une aptitude à soumettre des offres à des taux d'intérêt proches du taux d'équilibre relativement tôt dans les enchères d'emprunteurs locaux. Les investisseurs locaux expérimentés utilisent donc cette aptitude acquise avec l'expérience afin d'augmenter la rémunération de leurs investissements, ce qui accroît le coût de financement des emprunteurs locaux. Et ce qui était initialement identifié comme un biais comportemental devient une stratégie rationnelle avec

l'expérience. L'apport principal de ce premier chapitre de thèse réside dans le résultat qu'un biais comportemental, en l'occurrence le biais de proximité géographique, peut devenir rationnel au fil des expériences des investisseurs.

Le second chapitre propose une classification originale et exhaustive des stratégies de soumission d'offres des investisseurs dans une enchère à la hollandaise. Cette classification aboutit à l'identification de cinq types d'investisseurs : les non-stratégiques, les irrationnels, les informés, les suiveurs stratégiques, et les *snipers*. L'analyse empirique des comportements stratégiques des investisseurs particuliers dans des enchères à la hollandaise révèle la prévalence de l'utilisation de stratégies sophistiquées à rémunération élevée, à rebours de la vision généralement admise par les chercheurs quant au degré de sophistication de ce type d'investisseurs. De plus, nous montrons que la probabilité qu'un investisseur adopte une stratégie sophistiquée en matière de soumission d'offres est positivement corrélée au nombre d'enchères gagnées par l'investisseur en question. Ainsi, nos résultats suggèrent l'existence d'effets d'apprentissage en matière de soumission d'offres dans les enchères à la hollandaise, notamment chez les investisseurs les moins expérimentés. Enfin, nous montrons que les investisseurs ayant été les premiers à investir sur la plateforme, aussi appelés pionniers, ont acquis une expérience additionnelle par l'observation du processus de formation des prix. Ce gain d'expérience se traduit par une probabilité plus élevée que le reste des investisseurs à adopter une stratégie informée. Cette expérience n'est toutefois pas utilisée à des fins de *sniping*. Enfin, nous montrons qu'il existe un sous-groupe d'investisseurs potentiellement informés parmi les pionniers.

Le dernier chapitre de cette thèse montre que les firmes du S&P1500 conservant un conseil d'administration à mandats échelonnés après la mise en application de la loi Sarbanes-Oxley (SOX) aux Etats-unis sont des firmes ayant établi d'importantes relations les engageant sur le long terme avec diverses parties prenantes, plus particulièrement avec leurs employés et avec leurs clients. En utilisant la procédure de Heckman (1979) afin de corriger un potentiel biais de sélection, je montre que la relation de causalité entre la valeur de la firme et la présence

d'un conseil d'administration à mandats échelonnés est à double sens. D'une part, les firmes choisissant d'avoir un conseil d'administration à mandats échelonnés après la mise en application de la loi sont majoritairement de bonnes firmes, et, d'autre part, la provision anti-OPA en question a un impact positif et durable sur la valeur de ces dernières. L'apport principal de ce papier à la littérature réside dans sa contribution au débat relatif à l'impact du conseil d'administration à mandats échelonnés sur la valeur de la firme. En effet, je montre que les résultats avancés par les études les plus récentes en faveur de la théorie de l'engagement ne sont valables que pour la période temporelle postérieure à l'application de SOX. Pour ce qui est de la période temporelle antérieure, mes résultats suggèrent que la théorie de l'engagement et la théorie de l'enracinement sont toutes deux vérifiées.

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RÉSUMÉ

Cette thèse est constituée de trois travaux empiriques, répartis en trois chapitres. Deux chapitres sont consacrés à l'étude des comportements d'investisseurs particuliers sur une plateforme française de prêt participatif fonctionnant avec un système d'enchère pour organiser le financement des projets de petites et moyennes entreprises, tandis que le troisième chapitre se rattache au thème de la gouvernance d'entreprise.

Le premier chapitre s'attache à analyser un éventuel biais comportemental des investisseurs individuels en faveur des emprunteurs locaux, et l'impact de ce biais sur les taux d'emprunt. Le deuxième chapitre propose une classification exhaustive des comportements des investisseurs individuels en matière de soumission d'offres dans les enchères à la hollandaise.

Le troisième chapitre porte, quant à lui, sur l'impact du conseil d'administration à mandats échelonnés, une mesure anti-OPA, sur la valeur de l'entreprise après l'adoption de la loi Sarbanes-Oxley aux Etats-Unis. Je montre que cette structure de conseil d'administration a un impact positif sur la valeur de l'entreprise à long terme dans un contexte réglementaire défavorable aux stratégies d'enracinement.

MOTS CLÉS

prêt participatif, investisseur individuel, biais comportemental, conseil d'administration à mandats échelonnés

ABSTRACT

This dissertation is constituted of three chapters corresponding to three empirical articles. Two of them are focused on the analysis of retail investors' behavior in the crowdlending auctions of a French platform that raises funds for small and medium businesses. The third one focuses on corporate governance.

The first chapter analyzes a potential behavioral bias leading retail investors to be more likely to fund local borrowers, and the impact of this bias on borrowing rates. The second chapter provides an exhaustive classification of retail investors' bidding strategies in Dutch auctions.

The third chapter of this thesis analyzes the impact of having a staggered board, an anti-takeover provision, on the value of the firm after the adoption of the Sarbanes-Oxley Act in the United States. I show that this provision has a positive impact on the long-term value of the firm in a regulatory environment that is detrimental to entrenchment strategies.

KEYWORDS

crowdlending, retail investor, behavioral bias, staggered board

